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Combining Novelty-Guided and Heuristic-Guided Search

Master Thesis

Natural Science Faculty of the University of Basel
Department of Mathematics and Computer Science
Artificial Intelligence
ai.cs.unibas.ch

Examiner: Prof. Dr. Malte Helmert
Supervisor: Dr. Thomas Keller

Dario Maggi
dario.maggi@stud.unibas.ch
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Abstract

Greedy Best-First Search (GBFS) is a prominent search algorithm to find solutions for planning tasks. GBFS chooses nodes for further expansion based on a distance-to-goal estimator, the *heuristic*. This makes GBFS highly dependent on the quality of the heuristic. Heuristics often face the problem of producing *Uninformed Heuristic Regions* (UHRs). GBFS additionally suffers the possibility of simultaneously expanding nodes in multiple UHRs.

In this thesis we change the heuristic approach in UHRs. The heuristic was unable to guide the search and so we try to expand *novel* states to escape the UHRs. The novelty measures how "new" a state is in the search.

The result is a combination of heuristic and novelty guided search, which is indeed able to escape UHRs quicker and solve more problems in reasonable time.

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1 Introduction

Classical Planning, also known as *Planning* is a branch in Artificial Intelligence engaging in finding actions that lead an agent from an initial state to a goal state. In Classical Planning, the environment is known beforehand and does not change while we make our decisions. Additionally, the environment is deterministic and totally observable - actions and their outcome are predefined and known in advance. An example of such a classical planning task is the 8-puzzle of Figure 1.1. Initial state is a scrambled board. The 8 tiles are movable and can be slid into the open space. An agent has to decide in which order the tiles should be moved in order to reach the goal state. The goal state is reached when the tiles are in ascending order.

Classical Planning engages in formalizing such problems and developing algorithms to find sequences of actions leading to a goal state.

Greedy Best-First Search (GBFS) is a widely used algorithm for Classical Planning. GBFS looks at states and selects the most promising one for further evaluation. The ranking is based on a distance-to-goal estimator, the *heuristic*. Thus, GBFS depends on the quality of its heuristic. A common problem of GBFS is to get stuck in *plateaus*. A plateau occurs if the actions considered by GBFS do not lead to an improved heuristic. GBFS has to consider all states with equal heuristic values in order to escape the plateau. States of a plateau do not necessarily lie in one coherent region. A plateau might consist of states with unconfined distances between them.

Xie et al. (2014, 2015) propose the use of local-GBFS or random walk to escape a single region of the plateau.

A different idea for solving classical planning tasks was introduced by Lipovetzky and Geffner (2012). Their *Iterated Width (IW)* algorithm does not try to assess the quality of a state. Instead, IW only includes states if their *novelty* is below a threshold. If no solution is found, the threshold is increased and the search is restarted. Lipovetzky and Geffner (2014) also present extensions to narrow the performance gap to state of the art planners.

The goal of this paper is to use GBFS until a plateau is encountered. In order to escape the plateau we switch to a novelty based local search. After the escape we continue the GBFS

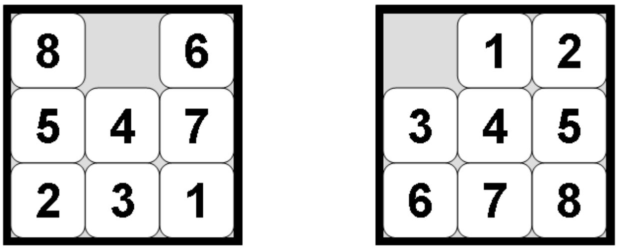


Figure 1.1: Problem of the 8-puzzle: Initial state on the left and goal state on the right.

search. This approach is implemented and evaluated in the Fast Downward Planning System of Helmert (2006).

This thesis is structured as follows: Chapter 2 introduces definitions, notations and algorithms used in this thesis. Chapter 3 describes the implementation of the introduced algorithms in the Fast Downward Planning System. In Chapter 4 we combine the heuristic and novelty based searches and evaluate them in Chapter 5. Chapter 6 concludes the findings and points at future work.

2

Background

This chapter introduces definitions, notations and algorithms the thesis is based on. First we define the planning task and state spaces before describing heuristics and their use in the relevant algorithms. The chapter ends with the introduction of novelty based algorithms.

2.1 Planning

Planning is the task of finding actions leading from an initial state to a goal state. To be able to apply methods and findings to a variety of different problems, planning in artificial intelligence is desired to be domain-independent. One simple and powerful encoding of planning tasks is STRIPS, introduced by Fikes and Nilsson (1972). We extend the original STRIPS marginally with a cost function over the operators.

Definition 1 (Extended STRIPS Planning Task)
Our extended STRIPS planning task is a 4-tuple $\Pi = \langle V, O, I, G \rangle$ where

- V is a finite set of propositional state variables, called *atoms*.
- O is a finite set of operators. Each operator $o \in O$ has preconditions $pre(o) \subseteq V$, add-effects $add(o) \subseteq V$, delete-effects $del(o) \subseteq V$ and costs $cost(o) \in \mathbb{R}_0^+$.
- $I \subseteq V$ is the initial state.
- $G \subseteq V$ is the goal state.

STRIPS planning tasks aim for a complete representation of planning problems and are usually not very compact. This makes planning tasks unsuitable for theoretical analysis. However, STRIPS planning tasks induce a *state space*, which simplifies conceptual work.

Definition 2 (State Space)
A State Space is a 6-tuple $\mathcal{S} = \langle S, A, cost, T, s_0, S_G \rangle$ where

- S is a finite set of states.
- A is a finite set of actions.
- *cost* is a function, assigning costs to each action $a \in A$ with $cost(a) \in \mathbb{R}_0^+$
- $T \subseteq S \times A \times S$ is a finite set of transitions. A transition $t \in T$ can be written as $s \xrightarrow{a} s'$ or $s \rightarrow s'$ if the action is irrelevant. Transitions are deterministic in the first two arguments, i.e $\langle s, a \rangle$ deterministically defines s'.
- $s_0 \in S$ is the initial state.
- $S_G \subseteq S$ is a set of goal states.

An action a is *applicable* if it can be applied in a state s, i.e there exists a transition $s \xrightarrow{a} s' \in T$ for some state s'.

A solution to the planning problem is a path that ends in a goal state.

Definition 3 (Path)
Let $\mathcal{S} = \langle S, A, cost, T, s_0, S_G \rangle$ be a state space, $s^{(0)}, \dots, s^{(n)} \in S$ states and $a_1, \dots, a_n \in A$ actions such that $s^{(0)} \xrightarrow{a_1} s^{(1)}, \dots, s^{(n-1)} \xrightarrow{a_n} s^{(n)}$.

The path from $s^{(0)}$ to $s^{(n)}$ is defined as:

$$\alpha = \langle a_1, \dots, a_n \rangle \tag{2.1}$$

The length of the path is given by $|\alpha| = n$, the cost by $cost(\alpha) = \sum_{i=1}^{n} cost(\alpha_i)$.

Definition 4 (Solution)
Let $\mathcal{S} = \langle S, A, cost, T, s_0, S_G \rangle$ be a state space. A solution for $\mathcal{S}$ is a path $\pi = \langle \pi_1, \dots, \pi_n \rangle$ generating a sequence $s^{(0)} \xrightarrow{\pi_1} s^{(1)}, \dots, s^{(n-1)} \xrightarrow{\pi_n} s^{(n)}$ such that $s^{(0)} = s_0$ and $s^{(n)} \in S_G$.

A solution with minimal cost among all solutions is an optimal plan.

Solving planning tasks without any further information than its state space or encoded model is called *uninformed* or *blind search*. Ideally, states that are close to a goal should be prioritized in the search. *Heuristics* are a common approach to assess the favorability of a state.

Definition 5 (Heuristic)
Let $\mathcal{S}$ be a state space with a set of states S. A heuristic function for a state space $\mathcal{S}$ is a function

$$h : S \rightarrow \mathbb{R}_0^+ \cup \{\infty\} \tag{2.2}$$

which assigns each state $s \in S$ a non-negative number or infinity.

The purpose of a heuristic $h(s)$ is to estimate the distance to a goal state based on s. Heuristics enable us to prioritise promising states in the search.

Algorithm 1: SearchNode

```
create_initial_node()
begin
    n ← new SearchNode
    n.parent ← none
    n.state ← s_0
    n.action ← none
    n.g ← 0 ;                  // g holds the path cost to reach this SearchNode
    return n
make_node(parent: SearchNode, a: Action, s: State)
begin          // creates SearchNode with state s' of a transition s -a-> s'
    n ← new SearchNode
    n.parent ← parent
    n.state ← s
    n.action ← a
    n.g ← parent_node.g + cost(a)
    return n
extract_path(n: SearchNode)
begin
    path ← empty list of Actions
    while n.action ≠ none do
        path.push_back(n.action)
        n ← n.parent
    return path
```

Heuristics often induce *Uninformed Heuristic Regions* (UHRs) in a state space. An Uninformed Heuristic Region (UHR) consists of states in the state space that are connected by actions and have equal heuristic values. Search Algorithms may run into the problem of getting stuck in multiple UHRs simultaneously.

2.2 Search

In *forward searches*, algorithms apply actions beginning at the initial state and try to work themselves into the direction of the goal state. The process of generating states by applying applicable actions is known as *state expansion*. Expanding states can be seen as exploration of *search nodes* in a graph, our state space. A search node is a construct that holds a state, its parent node, the action used to reach it and the cost of the path to the search node (notated by g). The implementation of a search node can be seen in the pseudo code of Algorithm 1.

Planning algorithms can be divided into two classes. *Informed planners*, which use heuristics to expand promising nodes first, and *blind planners* which make no assumptions of the quality of an expanded state. Different algorithms yield different properties for search and solution. For informed search, these properties depend additionally on the used heuristic.

Algorithm 2: Greedy Best-First Search (GBFS)

```
Input  : Π: Planning Task
         h: heuristic
Result: π: solution or unsolvable
open ← FIFO priority queue of SearchNodes ordered by h
closed ← empty set of States
if h(s_0) < ∞ then
    open.insert(create_initial_node() )
while open is not empty do
    node ← open.pop_min()
    if node.state ∈ closed then
        continue
    closed.insert(node.state)
    if G ⊆ node.state then
        return extract_path(node)                    // Goal found
    foreach ⟨a, s'⟩ with node.state -a-> s' do       // Expand node
        if h(s') ≤ ∞ then
            n' ← make_node(node, a, s')
            open.insert(n')
return unsolvable
```

Definition 6 (Complete, Semi-Complete, Sound, Satisficing, Optimal)
A search algorithm is:

- Complete, if it finds a solution in case one exists. If there exists no solution the algorithm will report this.
- Semi-Complete, if it returns a solution in case one exists. In the case of no existing solution the algorithm may not terminate.
- Sound, if anytime it returns a result, the result is correct.
- Satisficing[1], if plans are found without violating any constraints on time, resources and quality of the solution.
- Optimal, if returned solutions have optimal i.e shortest paths.

2.2.1 Greedy Best First Search (GBFS)

Greedy Best-First Search (GBFS) is a class of informed algorithms which expands nodes in order of their heuristic value. GBFS is a satisficing method and is shown in Algorithm 2.

[1] The term *satisficing* was introduced by Simon (1965) as the combination of *satisfy* and *suffice*.

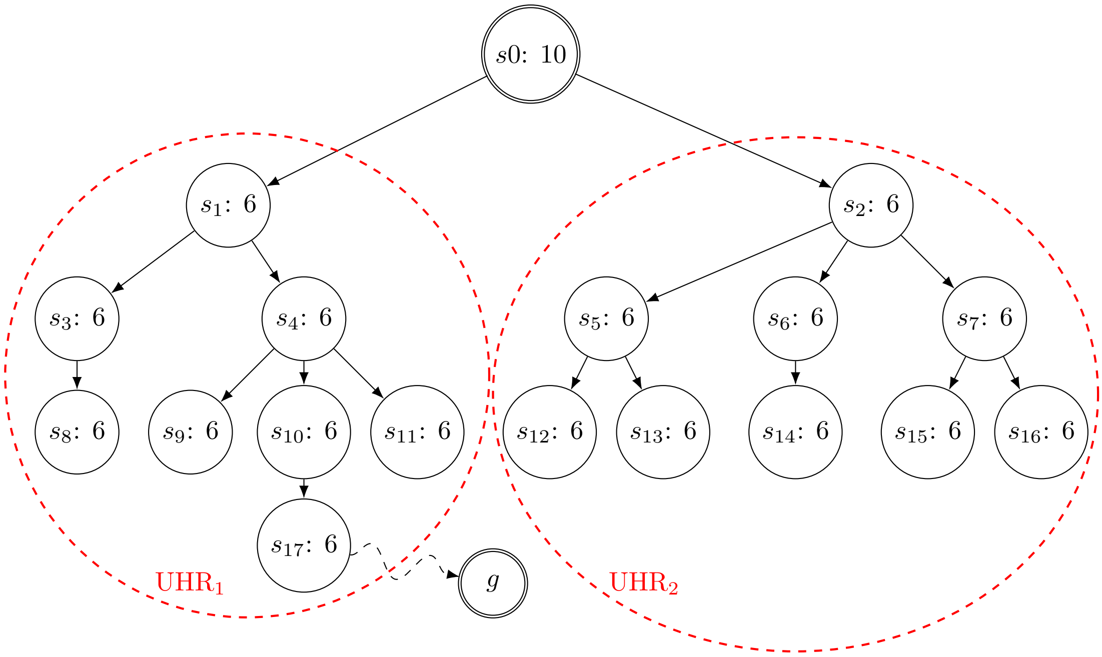


Figure 2.1: Example of GBFS getting stuck in two UHRs.

2.2.2 Local Exploration

Heuristics can induce UHRs. In GBFS this leads to exploration of many nodes without improvement of the heuristic value, decreasing the advantage of the heuristic. This problem is aggravated by GBFS' potential to get stuck in multiple UHRs simultaneously as shown in Fig. 2.1. In this example, GBFS expands states of two UHRs simultaneously. The heuristic value of a state is noted inside the state. The expansion order is from top to bottom, left to right (in the order of the states' names). GBFS encounters two UHRs (circled red) and has to expand both until s_{17} is expanded. Child nodes of s_{17} have a better heuristic value and point into the direction of the goal. A local exploration can prove to be helpful as it tries to escape only a single UHR. The local explorations introduced by Xie et al. (2014, 2015) are a local-GBFS, resulting in GBFS-LGBFS and a random walk. A UHR is detected if the heuristic value does not change over a threshold number of expansions.

2.3 Novelty Based Algorithms

Various attempts have been made to introduce a width notion for classical planning. However none of these definitions explain why current benchmarks are seemingly simple and can be solved in short times. Lipovetzky and Geffner (2012) introduced a new width definition and the blind planners *Iterated Width* and the serialized form *Serialized Iterated Width* based on this width. Their research and definitions are based on the STRIPS setting.

2.3.1 Iterated Width (IW)

Lipovetzky and Geffner (2012) show empirically that the width of many existing domains is bound and low when goals are restricted to *single atoms*. A classical planning problem is solvable in time exponential to its width. The *Iterated Width* (IW) algorithm tries to take advantage of these two findings. IW is a blind search algorithm, implementing a pruned breadth-first search. The pruning is based on the *novelty* of a state. The novelty of a state in the STRIPS setting is defined as:

Definition 7 (Novelty)
Let $\Pi = \langle V, O, I, G \rangle$ be a STRIPS planning task.
Let $T_i \subseteq \mathcal{P}(V)$ which is created iteratively during the search as:

- $T_0 = \{\emptyset\}$
- $T_{i+1} = T_i \cup \mathcal{P}(s_{i+1})$,

where s_{i+1} is the $(i+1)$-th expanded state and $\mathcal{P}(s_{i+1})$ produces the power set of s_{i+1}.
The novelty of s_{i+1} is:

$$nov(s_{i+1}) = \begin{cases} |V| + 1 & \text{if } \mathcal{P}(s_{i+1}) \setminus T_i = \emptyset \\ \min\limits_{t \in \mathcal{P}(s_{i+1}) \setminus T_i} |t| & \text{otherwise.} \end{cases} \tag{2.3}$$

In other words, the novelty of a state s_{i+1} is the size of the smallest subset of s_{i+1} that is not contained in T_i, where T_i contains all power sets of already encountered states.

The Iterated Width algorithm uses the novelty to prune the search space. In the first iteration only states with novelty 1 are expanded. These are states where atoms are true that have never been true before in the search. If the first iteration finds no solution, the next iteration examines variable sets of size 2. All pairs of true atoms are checked whether this combination has already been encountered in the iteration. IW can be seen as iterative calls to IW(i), where i denotes the size of examined variable sets. We call i the *novelty-bound*. The concept for IW is shown in Fig. 2.2. The pseudo code for IW is given in Algorithm 3 and Algorithm 4 shows IW(i). IW is sound and complete. For a problem of width w, IW(w) finds optimal solutions. However IW is not optimal since a solution can be found in an iteration smaller than its actual width[2].

[2] Lipovetzky and Geffner (2012) provide a simple example with a goal G of width 2:

- Initial State: $\{p_1, q_1\}$
- Actions (without delete effects):
  $a_i : p_i \rightarrow p_{i+1}$ and $b_i : q_i \rightarrow q_{i+1} \quad | \; i \in \{1, \ldots 5\}$,
  $a_6 : p_6 \rightarrow G$,
  $c : \{p_3, q_3\} \rightarrow G$
- Goal State: G

IW achieves goal G in a path of size 6, with IW(1) by applying $a_1, \ldots a_6$. IW(2) returns the optimal path of size 5 by applying the action c. IW(1) is unable to apply action c since it prunes states with pairs such as $\{p_2, q_3\}$ and $\{p_3, q_2\}$ because each variable was *true* before in the search.

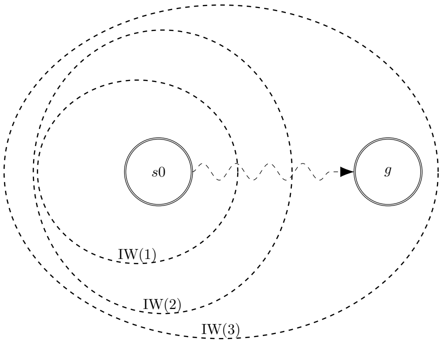


Figure 2.2: Concept of IW: Novelty-bound is increased in each iteration until the goal can be reached.

Algorithm 3: Iterated Width (IW)

```
  Input  : Π: Planning Task
  Result: π: solution or unsolvable
1 foreach i ∈ { 1, . . . , number of variables in Π} do
2     solution ← IW(i)                                  // call IW(i)
3     if solution ≠ unsolvable then
4         return solution
5     if not IW(i).states_pruned then
          /* If IW(i) pruned no states, IW is in a dead-end    */
6         return unsolvable
7 return unsolvable
```

The line 5 of Algorithm 3 makes sure that IW(i) is not unnecessarily invoked. If IW(i) does not find a solution and has not pruned any states, IW is stuck in a dead end and returns unsolvable.

2.3.2 Serialized Iterated Width (SIW)

Lipovetzky and Geffner (2012) show empirically that the width of common benchmark problems is bound and low if the goal is reduced to a **single atom** of the goal. IW is able to solve these reduced problems in time exponential to their width.

The problem is however not solved by reaching only one atom of the goal. But these findings motivate the introduction of the *Serialized Iterated Width* (SIW) algorithm. SIW uses IW to automatically split the problem into smaller problems of single atom goals. This is done by starting IW until one single atom of the goal is reached. IW is then started from this state and tries to add a second atom of the goal state, and so on. SIW calls IW to iteratively construct the solution out of single atoms that are part of the goal. It is important to note that the single atoms reached by IW have to be *consistent*. Meaning, they do not need to be undone to find a solution.

Algorithm 4: IW(i)

```
Input  : Π: Planning Task
         i: novelty-bound ℕ≠0
Result: π: solution or unsolvable with width i
open ← FIFO priority queue of SearchNodes ordered by g
open.insert(create_initial_node())
states_pruned ← false
while open is not empty do
    node ← open.pop_min()
    if G ⊆ node.state then
        return extract_path(node)                       // Goal found
    foreach ⟨a, s'⟩ with node.state -a-> s' do
        n' ← make_node(node, a, s')
        if novelty(n'.state) > i then                   // Prune by Novelty
            states_pruned ← true
        else
            open.insert(n')
return unsolvable
```

In the STRIPS settings SIW is defined as:

Definition 8 (Serialized Iterated Width (SIW))
Serialized Iterated Width (SIW) over a STRIPS planning task $\Pi = \langle V, O, I, G\rangle$ consists of a sequence of calls to IW over the problems $\Pi_k = \langle V, O, I_k, G_k\rangle, k = 1, \ldots, |G|$, where:

- $I_1 = I$
- G_k is the first consistent set of atoms achieved from I_k, such that $G_{k-1} \subset G_k \subseteq G$ and $|G_k| = k; G_0 = \emptyset$
- I_{k+1} represents the state where G_k is achieved, $1 < k < |G|$.

The states containing G_k are called subgoals.

Definition 9 (Subgoal)
Given a STRIPS planning task Π with a set of propositional goal variables G, a subgoal is a state s which shares variables of the goal G, $s \cap G \neq \emptyset$. The size of the subgoal is given by $|s \cap G|$.

The concept of SIW is displayed in Fig. 2.3. IW is used to reach subgoals and paths between them. The subgoals are s_u and s_p. The subgoal s_p has to contain the previously found subgoal s_u and increase it. Additionally the subgoals have to be consistent.

SIW commits to subgoals. If the consistency property does not hold, SIW can commit to a dead end state, rendering SIW incomplete as shown in Example 1.

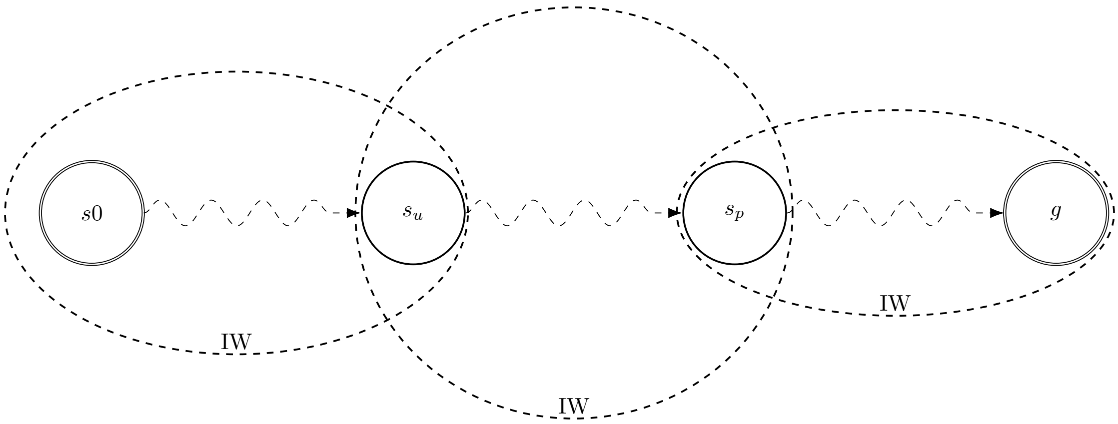


Figure 2.3: Concept of SIW: Use IW to increase consistent subgoals. Subgoal s_p must contain all variables that s_u shares with the goal.

Example 1: Incompleteness of SIW by disregarding the consistency of subgoals:

- Variables: {p, v, w}
- Initial State: {p}
-

action	preconditions	add-effects	delete-effects
a_1	p	v	p
a_2	p	w	

- Goal State: {v, w}

SIW can apply action a_1 to generate the inconsistent subgoal {v}. Committing to this state, SIW is stuck in a dead-end since there are no more applicable actions. No solution will be found.

SIW forces two modifications on the IW(i) implementation in Algorithm 4: Firstly, the starting point needs to vary since searches start from subgoals. Secondly, the goal checking has to be modified, because we are creating increasing consistent subgoals. This is shown in Algorithm 5. The function `subgoal_is_consistent(State s)` checks a subgoal for consistency. Properties and implementation of the consistency check are explained in the Section 3.4.

The way SIW(i) is used to build SIW is shown in Algorithm 6.

2.3.3 Extended Iterated Width (IW+) and Extended Serialized Iterated Width (SIW+)

Lipovetzky and Geffner (2014) present IW+, an extensions to IW with a change in its pruning criteria. IW+ works similar to IW by calling IW+(i), where i is the increasing novelty-bound.

IW+ is not a purely blind search engine as it computes a relaxed plan for the start state s_0. The atoms that are made true on the path of the relaxed plan and are not true in s_0 are called *relaxed plan atoms*. These relaxed plan atoms are then used for the new pruning criteria. The

Algorithm 5: SIW(i)

Input : Π: Planning Task
i: novelty-bound $\mathbb{N}_{\neq 0}$
$start\_node$: SearchNode
Result: sub_goal : SearchNode, new consistently increased subgoal or none
$states\_pruned$: boolean indicating if states were pruned due to their novelty

$open \leftarrow$ FIFO priority queue of SearchNodes ordered by g
$open$.insert($start\_node$)
$states\_pruned \leftarrow false$
$starts\_goal\_variables \leftarrow start\_node.state \cap G$
while $open$ is not empty **do**
    $node \leftarrow open$.pop_min()
    if $G \subseteq node.state$ **then**
        return $\langle node,\ states\_pruned \rangle$ // Goal found
    $node\_goal\_variables \leftarrow node.state \cap G$
    if $starts\_goal\_variables \subsetneq nodes\_goal\_variables$ **then**
        /* The new subgoal needs to contain the previous subgoal and increase in size */
        if subgoal_is_consistent($node.state$) **then**
            return $\langle node,\ states\_pruned \rangle$
    foreach $\langle a, s' \rangle$ with $node.state \xrightarrow{a} s'$ **do** // Similar to IW(i)
        $n' \leftarrow$ make_node($node, a, s'$)
        if novelty($n'.state$) $> i$ **then** // Prune by Novelty
            $states\_pruned \leftarrow true$
        else
            $open$.insert(n')
return $\langle$none, $states\_pruned\rangle$

new pruning criteria of a search node s considers an extended tuple $\langle t, m \rangle$, where t is a set of atoms of s and m is the number of relaxed plan atoms that were made true on the path reaching s. For a search node s not to be pruned in IW+(i) it must be the first node of the search to make an extended tuple $\langle t, m \rangle$ true where the number of atoms in t is at most i.

One can visualize the new novelty check as multiple layers of autonomous novelty checks. The number of reached relaxed plan atoms (m) is the layer in which the state will be checked for its novelty.

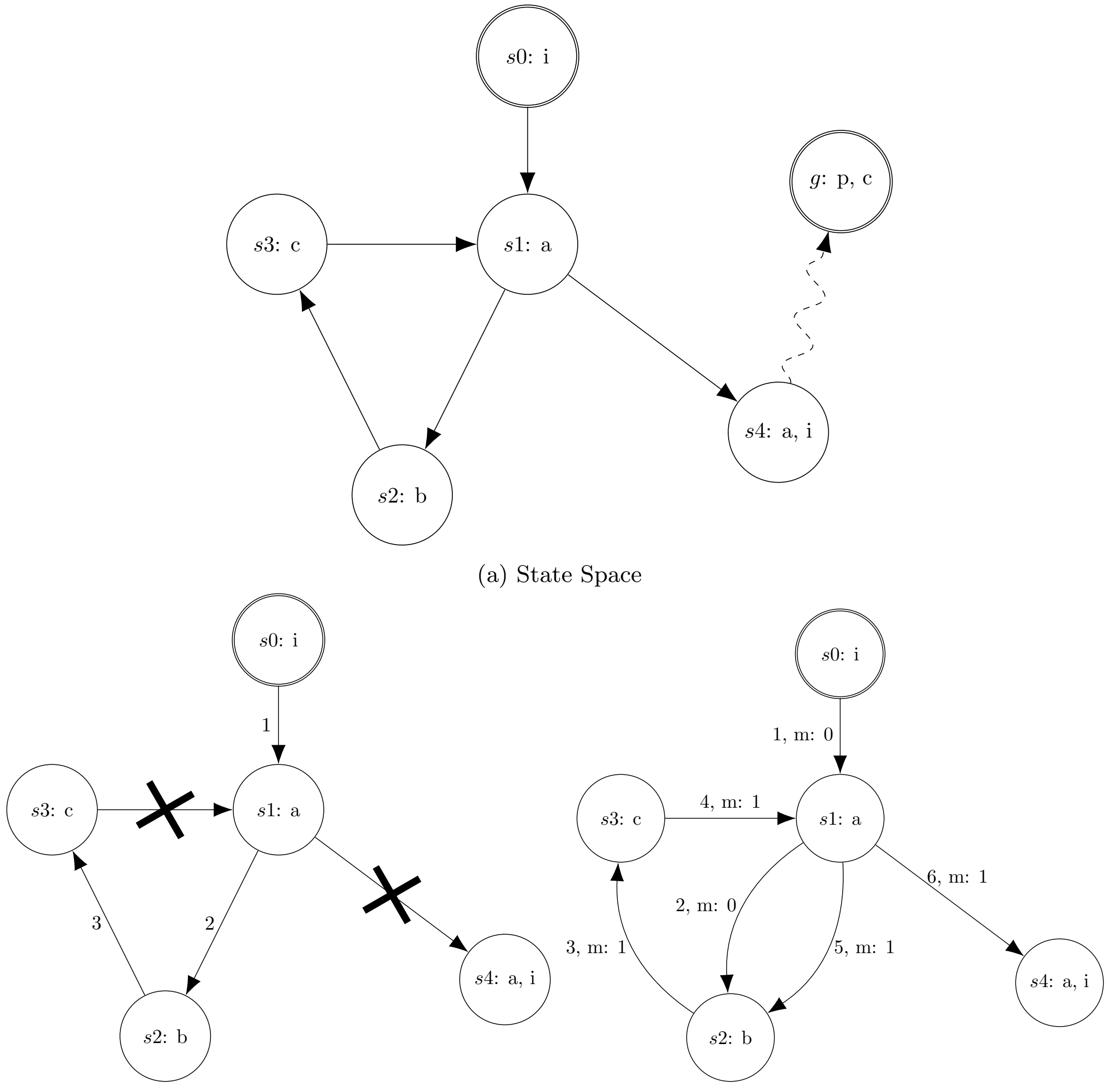
IW+(i) is fundamentally different from IW in that a state can be expanded multiple times. An example for this behaviour is shown in Fig. 2.4. This example shows a small part of a state space and the expansion order of IW(1) and IW+(1). A node represents a state and the variable that are true in that state. The arrows in the state space represent applicable actions and numbers mark the order they are applied in the search. IW(1) starts by expanding s_0 and s_1. By expanding s_1 the state s_4 gets pruned, since both atoms have already been encountered. IW+(1) expands these states differently. Lets assume the facts of the relaxed plan consists only of the variable "c". By expanding s_1 the state s_4 gets pruned for now. The search continues

Algorithm 6: Serialized Iterated Width (SIW)

```
Input  : Π: Planning Task
Result: π: solution or FAILED
i ← 1                                                        // novelty_bound
start_node ← create_initial_node()
while i ≤ number of variables in Π do
    ⟨end_node, states_pruned⟩ ← SIW(Π, i, start_node)        // calling SIW(i)
    if end_node is none then
        // SIW(i) did not find a bigger consistent subgoal.
        if not states_pruned then
            return FAILED
        i ← i + 1
    else
        // SIW(i) did find a bigger consistent subgoal.
        if G ⊆ end_node.state then
            // SIW(i) found a solution
            return extract_path(end_node)
        else
            // Start next SIW(i) from new subgoal, with a i of 1
            start_node ← end_node
            i ← 1
return FAILED
```

with the state s_2. By expanding s_2 we generate the state s_3. This state makes one atom of the relaxed plan atoms true and is checked for its novelty on the layer $m = 1$. On this layer the atom "a" has not been seen and therefore s_1 gets expanded a second time. The second expansion of s_1 does not prune s_4 because the atom "i" is new on the layer $m = 1$. Algorithm 7 shows the implementation of IW+(i).

SIW+ works similar to SIW, but uses IW+ instead of IW to serialize the problem.



(a) State Space

(b) IW(1) expansion order

(c) IW+(1) expansion order.

Figure 2.4: (a) displays states by their names and atoms that are true in them. Arrows represent applicable actions between states. (b) shows the expansion order of IW(1). (c) shows the expansion order of IW+(1) if the relaxed plan consist only of the atom “c”.

Algorithm 7: IW+(i)

```
Input  : Π: Planning Task
         i: novelty_bound ℕ≠0
Result: π: solution or unsolvable for width i
// To store the atoms of the relaxed plan that were made true on the way
   to a SearchNode the open-list holds pairs ⟨SearchNode, set of relaxed
   plan atoms⟩.
open ← FIFO priority queue of ⟨SearchNodes, set of relaxed plan atoms⟩ ordered by g
relaxed_plan_atoms ← compute_relaxed_plan_atoms()
open.insert(⟨create_initial_node(), {}⟩)
while open is not empty do
    ⟨node, nodes_relaxed_plan_atoms⟩ ← open.pop_min()
    if G ⊆ node.state then                                         // Goal found
        return extract_path(node)
    foreach ⟨a, s'⟩ with node.state →a s' do
        n' ← make_node(node, a, s')
        // Which relaxed plan atoms hold in the generated state s'
        new_relaxed_plan_atoms ← n.state ∩ relaxed_plan_atoms
        /* Merge the two sets:
           1.  Already reached relaxed plan atoms on the path to node
           2.  Atoms of the relaxed plan which hold in the new created node
           n'
           remove duplications                                              */
        current_relaxed_plan_atoms ←
            nodes_relaxed_plan_atoms ∪ new_relaxed_plan_atoms
        m ← |current_relaxed_plan_atoms|
        if novelty(n'.state, m) > i then                 // Extended novelty check
            states_pruned ← true                                // Prune by Novelty
        else
            open.insert(⟨n', current_relaxed_plan_atoms⟩)
return unsolvable
```

3
Implementation

This chapter introduces the Fast Downward Planning System (FD) in which the combination of heuristic and novelty guided search will be implemented. The Fast Downward Planning System uses a Multi-Value Planning Task instead of STRIPS, such that previously defined ideas and definitions have to be adapted. After the adaption we present data structures and their use in the implementations of FD.

3.1 Fast Downward (FD)

The Fast Downward Planning System (FD) was introduced by Helmert (2006). It is an open-source[3] framework written in `C++`. Fast Downward uses a Multi-Value Planning Task (MPT) which is introduced in Definition 10. The MPT of FD is slightly more sophisticated as it additionally supports axioms.

The Fast Downward Planning System supports multiple search algorithms and heuristics and enables users to easily combine them over a command line interface.

FD is capable of using improvements such as *combining multiple heuristics* introduced by Röger and Helmert (2010), use of *helpful actions* or *preferred operators* introduced by Hoffmann and Nebel (2001) and *deferred evaluation* introduced by Richter and Helmert (2009). FD enables researchers to implement their ideas and integrate them as plug-ins into the Fast Downward Planning System.

Definition 10 (Multi-Valued Planning Task (MPT))
A multi-valued planning task (MPT) is a 5-tuple $\Pi = \langle V, dom, O, I, G, \rangle$ where

- V is a finite set of **state** variables.

[3] http://www.fast-downward.org

- *dom* is a function assigning every variable $v \in V$ a non-empty domain $dom(v)$.
  We call a variable-value assignment $\langle$var, value$\rangle$, where var $\in V$ and value $\in dom$(variable) a *fact*.
  A *partial (variable) assignment* or *partial state* is a set of consistent facts.
  A state s is a set of consistent facts, where $|s| = |V|$.

- O is a finite set of operators. Each operator $o \in O$ is a pair of $\langle \text{pre}, \text{effect} \rangle$, where pre are preconditions in the form of a partial state and effect is a function assigning a portion of variables new values of their domain.

- I is a state over V called the initial state.

- G is a partial state called the goal.
  A state that shares facts of the goal is called a subgoal.

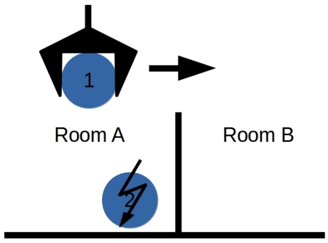
A special feature of FD is the translation of a STRIPS problem into an MPT. This is done by identifying groups of variables for which only one can be true at all times. A simple example for such a group of variables can be a truck's position in a logistics problem: A truck has to deliver multiple packets to several locations. The STRIPS setting models this by introducing a variable for each location the truck can be at. FD recognizes that the truck can only be at one place at a time through an *invariant synthesis*. FD then introduces a multi-value variable for the truck with the locations as its domain.

3.2 Adaptions for the MPT Setting

To implement the relevant algorithms in the MPT setting the novelty definition of the STRIPS has to be adapted. The novelty Definition 7 tells us to look for new sets of atoms. This definition can directly be applied to an MPT planning task by looking for new sets of facts. The power set produces now sets of facts instead of sets of atoms. The novelty is then the smallest set of the power set which hasn't been seen before, or $|V| + 1$ if all these sets are already known.

Even though we use the same novelty definition as in the STRIPS setting, IW is not equal in the STRIPS and MPT setting. An example showing the difference is given in the following proposition:

Proposition 1 (Inequality of IW in STRIPS and MPT)
FD creates MPT out of STRIPS planning tasks by grouping variables for which only one can be true at all times. But there is also a possibility that none of those variables is true in a state. For this situation FD introduces a "none of those" value. This value can make a difference if a state gets pruned or not. If a state in the MPT contains a "none of those" value for the first time it wont get pruned. This state could very well be pruned in the STRIPS setting, as setting variables to false does not generate a new set of true variables.



Encountered atoms
ball1_in_A
ball2_in_A
agents_hand_free
agent_in_B
agent_in_A
agent_holding_ball1

Figure 3.1: Demonstration of inequality of IW(1) in the STRIPS and MPT setting. Ball 2 destroys itself if ball 1 is moved first. The resulting state gets pruned in the STRIPS setting, but will be expanded in the MPT setting.

A STRIPS and MPT example for such a case is given in Appendix A.1 and Appendix A.2. They model a modified gripper problem, where an agent with one hand has to move two balls from room A to room B. The twist for this modified gripper problem is that ball 2 destroys itself if ball 1 is moved first. The search process which leads to the state that gets pruned in the STRIPS setting but wont in the MPT is given in Appendix A.4. Fig. 3.1 shows the step that results in this controversial state. The agent started in room B, moved to room A, picked up ball 1 and wants to take ball 1 to room B. In IW(1) of the STRIPS setting the resulting state does not produce a new atom and gets pruned. In the MPT setting, the resulting state assigns ball 2 the "none of those" value for the first time and will not get pruned.

A complete prove of the inequality in the STRIPS and MPT setting would have to consider the precise procedure of the invariant synthesis producing the MPT. This is beyond the scope of this thesis. But from the provided example we can conclude:

IW(i), as introduced in this thesis, is not equivalent in the STRIPS and MPT setting.

3.3 Implementation of Iterated Width (IW)

IW calls IW(i) with iteratively increasing i. The implementation follows this semantic and creates a new search engine IW(i) in each iteration. IW(i) receives the novelty-bound i through the constructor. The fact that the novelty-bound is known before the search engine IW(i) starts the search simplifies the novelty check immensely. Algorithm 4 at line 10 computes blindly the novelty of a state. If the novelty is beyond the threshold it gets pruned. If the novelty is below or equal to the threshold the node will be expanded. We do not care what its actual novelty is. The definition of the novelty in an MPT setting tells us to look at its partial states. Given a novelty-bound i, it is sufficient to only check partial states of size i. Checking smaller partial states for smaller novelties is unnecessary. If the smaller state that establishes the smaller novelty gets expanded into a bigger partial state, this bigger partial state is still new to the search. This is demonstrated in Example 2. The MPT introduced in this example is used throughout this chapter to demonstrate operational and conceptual behaviour of implementations.

Example 2: To check whether the novelty of a state is 2 or below it is sufficient to only check partial states of size 2.

Variable Domains:

2	4	6	5

State generation order:

s_0 :	0	0	0	0
s_1 :	1	0	0	0

The MPT has 4 variables. The variable domains are given on the left. The first entry means that the first variable can only take on two different values: 0 or 1. The second variable can take on 4 different values . . . .

The search first generates the initial node s_0. The value of each variable in s_0 is 0. The second generated state in the search is s_1. s_1 has a novelty of 1 due to its first variable with the never before seen value of 1. However, we are only interested if the novelty is 2 or below. Every partial state of size 2 containing the first variable lets us conclude that the novelty of s_1 is in fact 2 or below. The actual novelty is irrelevant.

Only checking whether a state's novelty is below or equal a threshold is not enough in order for IW to work. All encountered partial states of given size have to be stored in a data structure. This data structure should be optimized for lookups and insertions.

The chosen implementation consists of multiple coherent arrays: `vectors` of the `C++` standard library. At the beginning all subsets of size novelty-bound are created and stored in a `vector<int>`. Each `int` in the array points at a variable of a state. The subsets are used to create the partial states of size novelty-bound from a given state.

Every possible partial state of size novelty-bound gets its place in a `vector<bool>` called `lookup`. The mapping between a partial state and its position in `lookup` is done with the help of another `vector<int>` called `offsets`. `offsets` is filled during creation of the subsets and provides a jumping point into `lookup`. From this jumping point we need to determine the position of the partial state compared to its other possible assignments. An example of this data structure and its initialization is displayed in Example 3. Example 4 demonstrates the use of the data structure to determine if a partial state has been encountered before in the search. To check whether a state gets pruned due to its novelty and storing partial states in the process is shown in Example 5.

Example 3: Data structure that stores encountered partial states during the search.

`variable_domains`

2	4	6	5

`subsets`		`offsets`
0	1	0
0	2	$0 + 2 * 4 = 8$
0	3	$8 + 2 * 6 = 20$
1	2	$20 + 2 * 5 = 30$
1	3	$30 + 4 * 6 = 54$
2	3	$54 + 4 * 5 = 74$

`lookup`
0
0
⋮
0
0

The size of the lookup is the number of possible partial states with size 2:
$74 + 6 * 5 = 104$

`variable_domains` is the same as in Example 2.

For each subset in `subsets` a jumping point is computed and stored in `offsets`. The first entry of `offsets` is 0 because indexing of `lookup` starts with 0. The second entry in `offsets` takes the first subset $\langle 0, 1\rangle$ to compute the jumping point. The subset $\langle 0, 1\rangle$ points at the first and second variable. These two variables are able to create $2 * 4$ different assignments. The jumping point for the second subset is therefore 8, placing it after all possible assignments of the first subset. The next jumping point computes the possible assignments of the second subset and adds these to the previous jumping point $8 + 2 * 6$. The entries in `lookup` are all initialized with $false$ or 0 because no partial state has been encountered so far.

Example 4: Checking whether a partial state has been encountered in the search or not.
Given is the initialized data structure of Example 3. The encountered state is $s = \langle 0, 3, 1, 4\rangle$. The fifth subset of `subsets`, $\langle 1, 3\rangle$ produces the partial state $\langle 3, 4\rangle$ for which we determine if it has been encountered in the search before.

Determination whether the partial state has been encountered is done by:

- taking the jumping point into `lookup` of subset $\langle 1, 3\rangle$ is taken from `offsets` and is **54**.
- computing the position of this partial state compared to other possible assignments. The first variable of the partial state is 3. Considering that 0 is a valid assignment, there are 3 different assignments of the first variable before the assigned 3. These three assignments can be combined with the domain size of the last variable: $3*5 = 15$. To these 15 possible assignments there are still an additional 4 before our partial state: $\langle\langle 3, 0\rangle, \langle 3, 1\rangle, \langle 3, 2\rangle, \langle 3, 3\rangle\rangle$. The position of this partial state compared to other possible assignments is therefore $15+4 = \mathbf{19}$.
- Whether the subset $\langle 1, 3\rangle$ creating the partial state $\langle 3, 4\rangle$ has been encountered in the search before, is stored in the boolean of `lookup` at the position: 54 + 19.

Example 5: Checking if the novelty is 2 or below and storing all partial states in the process.
Given is the data structure of Example 3. The encountered state is $s = \langle 0, 3, 1, 4\rangle$. To check whether the novelty of s is 2 or below we have to iterate over all `subsets` of the novelty data

structure. For each subset we then have to get the entry in `lookup` corresponding to the partial state created by the subset as shown in Example 4. If the boolean entry in `lookup` at this corresponding position is 0 (standing for `false`), the novelty of s is indeed 2 or below. We then have to set it to 1 (standing for `true`) for further checks.
Important is now that we must not break the iteration over the subsets. We have to set all corresponding entries for all partial states in `lookup` to true. Breaking this loop would tamper with later novelty computations, as already encountered partial states would not be recorded.

We chose a `vector<int>` for subsets because it simplifies the construction of partial states and requires less memory for small novelty-bounds than a bit-map. The vector `offsets` is stored because its values are needed in each novelty check, making this simple lookup faster than the computation. The vector `lookup` is then a simple and fast way to check and store if a partial state has been encountered. `lookup` may allocate memory for booleans (encoding partial states) that are not reachable in the MPT and will never be used. These dead spaces are negligible compared to a map-based implementations and their overheads.

We chose the presented implementation with coherent arrays because it proofed to be faster than a mapping approach of: subset $\leftrightarrow$ set of partial states. Tests of IW on a gripper problem with 10 balls showed a speedup of 4 by using coherent arrays over the map approach. The speedup even increases for bigger problems.

The implementation of IW and IW(i) is an adaption from the pseudo code of Algorithm 3 and Algorithm 4 into `C++` and the framework of the Fast Downward Planning System.

3.3.1 Improvement: Novelty check with generating operator

One can take advantage of the fact that nodes are generated by applying an operator. The operator dictates which variables get new values assigned. In the novelty check we have to only check the subsets containing these variables. During the initialization of the data structure an additional vector is created. Each entry of this vector stands for a variable and holds pointers to the subsets the variable appears in. The novelty check has then to iterate over the subsets containing a changed variable. With IW on the gripper problem with 10 balls we got a speedup of 1.1 by this approach.

3.3.2 Improvement: Taking advantage of the Fast Downward Search Nodes

The Fast Downward Planning system implements search nodes different than introduced in this thesis. Per state s there exists at maximum one search node with this state. A search node with state s has one of the following statuses:

- NEW: No node with state s has been opened before.
- OPEN: A search node with state s already exists and is open.

Algorithm 8: Fast Downward IW(i)

```
Input  : Π: Planning Task
         i: novelty-bound ℕ≠0
Result: π: solution or unsolvable with width i
open ← FIFO priority queue of SearchNodes ordered by g
open.insert(create_initial_node())
pruned_states ← false
while open is not empty do
    node ← open.pop_min()
    if node.state ∈ S_G then
        return extract_path(node)                         // Solution found
    foreach ⟨a, s'⟩ with node.state -a-> s' do
        n' ← get_node(s')               // Get FD search node from search space
        if n'.is_new() then
            n'.open(node, a)                    // make sure n' is not NEW anymore
            if novelty(n'.state) > i then                    // Prune by Novelty
                states_pruned ← true
            else
                open.insert(n')
return unsolvable
```

- CLOSED: A search node with state s already exists and has been marked closed.

A search node in FD can be created by getting the node for the state s from the search space. This node has one of the described statuses. If the status is NEW, the node can be opened by providing the parent node and the generating operator. This changes the status of the node to OPEN. If we encounter the same state s again later in the search and get the node from the search space, its status is still OPEN.

The advantage is now to be able to check if a node is new. In IW(i) a state s gets pruned if its novelty is beyond a threshold. If the status of a node with state s is not NEW, s has been encountered in the search before, has novelty $n + 1$ (where n is the number of variables) and gets pruned. Checking if a node is NEW or OPEN is faster than iterating over the data structure of the novelty check. We can further take advantage of this by opening the nodes which get pruned by the novelty check. This makes novelty checks for pruned nodes obsolete. The IW(i) taking advantage of the FD search nodes is shown in Algorithm 8.

This implementation also makes the value of the boolean variable `states_pruned` more meaningful. The normal IW(i) would report to have pruned states, if it just encountered the same state twice. This implementation only reports to have pruned states if they were actually new states.

In our gripper toy problem with 10 balls this improvement produced a speedup of 4.3.

3.4 Serialized Iterated Width (SIW)

SIW uses IW to construct subgoals of increasing size until a solution is found. The SIW(i) implementation in the Fast Downward planning system inherits from the IW(i) implementation. The difference lies in the condition when SIW(i) stops. For the Iterated Width algorithm, IW(i) needs to find the solution. SIW(i) needs to find a subgoal. The conditions on the subgoal are:

1. The subgoal needs to extend the previous subgoal, i.e the subgoal size must increase and the previous subgoal must be contained in the new one.

2. The subgoal needs to be consistent: it does not have to be undone to find a solution.

Checking the first condition is simple. But checking a subgoal for consistency is equivalent to solving the problem beginning at the subgoal. We weaken the consistency condition by using a safe heuristic for the subgoal candidate as proposed by Lipovetzky and Geffner (2012). A safe heuristic has the property that if $h(s) = \infty$ then there exists no solution for state s. Before calculating the heuristic value, operators that change the assignment of the subgoal are removed. We then check if the heuristic value is infinite or not. This check is weaker than the introduced consistency because of the safe heuristic. If this modified heuristic value tells us the distance from the subgoal to the goal is infinite, we know that the subgoal is not consistent. However, there might be cases where the heuristic value is smaller than infinite, but there still exists no path to the goal. Considering this weak consistency test we do not prune states which change already reached subgoals in SIW. Due to the weak consistency check SIW might be incomplete if there are actual dead-ends in the problem definition.

In the Fast Downward Planning System this weak consistency uses a modified relaxation heuristic which allows disabling operators and checking relaxed reachability.

3.5 IW+ and SIW+

To obtain IW+/SIW+, the implementation of IW and SIW require a few changes:

- It is required to know how many facts of the relaxed plan were made true on the path to a search node. As shown in Algorithm 7, the open list holds a tuple. In the MPT setting this tuple contains a search node as well as a set of facts. This set of facts contains those facts of the relaxed plan that were encountered on the path to the node. It is not sufficient to just keep track of the number of relaxed plan facts a node encountered on its path. This is insufficient because a new state might make relaxed plan facts true, which were already encountered on the path.

  These relaxed plan facts are stored as a vector of booleans in the open list. Each position of this vector stands for a fact of the relaxed plan. The open list is no longer a State Open List implemented by FD, but a priority queue of the `C++` standard library.

- The novelty check needs to be adapted to deal with the extended tuple $\langle t, m \rangle$. The boolean vector `lookup` needs to have multiple layers. The number of layers is the size of the relaxed plan facts + 1. The additional layer is for search nodes, which do not make any relaxed plan facts true on their path.

- The improvement of the novelty check with the generating operator as described in Section 3.3.1 has to be disabled. This is the case because the layers of the novelty check are independent. If a state is known on one layer it is not sufficient to check only the changed subsets on another layer. Eg: state $\langle 5, 3, 2 \rangle$ is known on layer 1 (it made 1 fact of the relaxed plan true on its path). If an operator changes the first entry to 1 and makes and additional fact of the relaxed plan true the novelty will be checked on layer 2. On this layer the whole state might be new and all its partial states have to be added in the layer.

- In IW+ and SIW+, a once pruned state might be expanded later in the search if it made more relaxed plan facts true on its path. Due to this property the improvement of closing nodes and checking nodes whether they are new as described in the Section 3.3.2 has to be disabled as well.

4

Iterated Width and Serialized Iterated Width on Uninformed Heuristic Regions

The basic idea of this thesis is to mix up the search when GBFS gets stuck in UHRs. The new approach expands states only if they are novel enough in order to try to escape UHRs. The intuition behind this idea is that the heuristic might assess nodes that are pretty similar with equal heuristic values. By disregarding the heuristic and expanding nodes which are novel to the search we hope to escape UHRs quicker and find solutions faster.

One precondition to implement this idea is the recognition of UHRs during the GBFS search. This is done by counting the number of consecutively expanded states with equal heuristic values as proposed by Xie et al. (2014). Once a given threshold is reached we are stuck in UHRs.

This section describes two approaches to combine GBFS with IW and SIW when GBFS encounters UHRs.

4.1 Chain of GBFS and IW/SIW

The first approach to combine GBFS with IW/SIW is similar to SIW. But instead of a subgoal, GBFS commits to a state in an UHR. This approach is shown in Fig. 4.1. GBFS counts the number of consecutive expanded states with the same heuristic value. If this number reaches a threshold, a local search is started from that state. The local search can be IW, IW+, SIW or SIW+. The difference in implementation is that GBFS has to count how many states it expanded with stationary heuristic value. The only difference in the local searches affects the goal checking. Each state that gets expanded by the local search needs to be evaluated by the heuristic. If a state improved the heuristic value, the local search escaped the UHR and a new GBFS is started from that state.

This approach has multiple short comings. The most severe might be that it commits to states in UHRs. If this quite arbitrarily chosen state is in an enormous UHR or even in a dead-

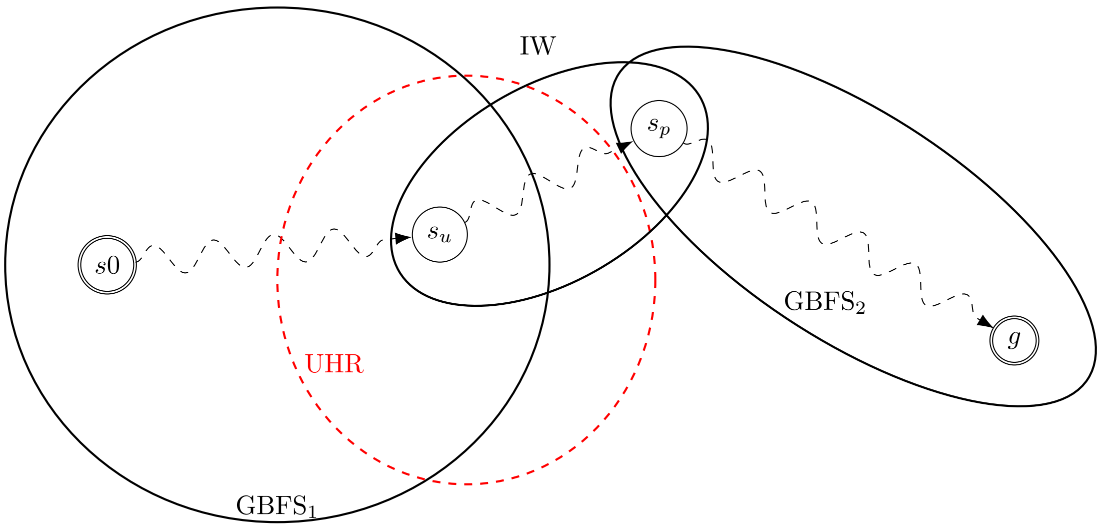


Figure 4.1: Chaining approach of GBFS and IW.

end this approach gets stuck. Another poor characteristic of this chaining idea is that GBFS and the local searches do not share any information other than the heuristic. It is possible that a state is evaluated and expanded by multiple GBFS and local searches.

4.2 Star of GBFS and Local Searches

The chaining approach of Section 4.1 is not very efficient. States might be evaluated and expanded by multiple local searches. A more efficient way would be to share information between search engines such that a state is evaluated and expanded at most once.

This can be achieved by sharing the closed list. In the Fast Downward Planning System the closed list is implemented as status in the search nodes. Search nodes are stored in the search space of FD. Thus the whole search space has to be shared, or more accurately the search engines operate on the same search space. To obtain a complete algorithm the main difference to the chain approach are the starting points of the local searches. The local searches are started from within a global GBFS and operate on its search space. The name "star" originates from its topology: A central GBFS starts local searches on the same search space to branch out in different directions. The approach is displayed in Fig. 4.2. A GBFS encounters two UHRs. IW(1) is started in one of them but is unable to escape the UHR. IW(2) is then able to escape the second UHR. The fact that IW(2) can be started in another UHR is due to the insertion order into the GBFS' open list. Local searches are started from the next node of this open list. IW(2) is able to escape its UHR and the global GBFS takes over again. The lines of GBFS, IW(1) and IW(2) are all dashed because their neighbouring nodes are known and can be expanded later in the search.

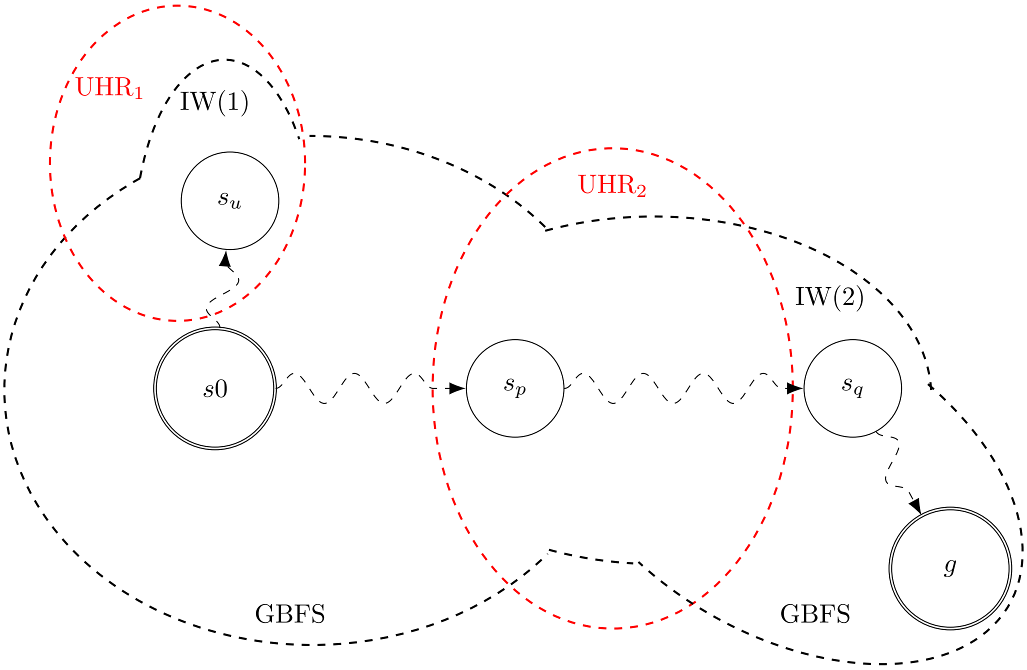


Figure 4.2: Star approach of GBFS and IW.

For implementation we have to consider that IW(i) and SIW(i) prune nodes by closing them. We have to pay special attention to these nodes. Pruned nodes need to be stored, reopened and inserted into the GBFS' open-list after the local search. Otherwise we would prune the search space and lose potential solutions. Additionally to the re-opening of the pruned nodes the open-list of the local search has to be merged with the global GBFS'.

The basics of the star approach are:

- GBFS and IW/SIW operate on the same search space (equivalent to sharing the closed list). Closed nodes will not be expanded.
- If a node is expanded by either GBFS or IW/SIW it will be closed.
- GBFS and IW/SIW hold their own separate open lists. The GBFS' open list is ordered by a heuristic. IW/SIW order their open list by g-values (path length to the state).
- After a local search finished, their open list is merged with the GBFS' open list to create a complete algorithm.
- The novelty data structure is always newly initialized with the start node of the local search. Previously, by GBFS expanded states do not influence the pruning criteria of the local search.

- IW/SIW prune nodes by closing them. These nodes are stored in an *ignored* list. After IW/SIW ended, their ignored list is merged into the GBFS' open list and said nodes statuses are set to open (equivalent to removing said nodes from a closed list).

Using IW+/SIW+ as local search is more complicated. IW+ and SIW+ prune states based on the extended novelty criteria. This may lead to multiple expansions of the same state, if the number of relaxed plan facts of its path increased since the last visit. We do not want to expand closed nodes but are not able to close nodes due to the property that a state might need to be expanded multiple times in IW+. Thus we have to store the expanded nodes of IW+ and SIW+ in a separate `closed` set. The `ignored` list is used to store nodes which were pruned by their novelty. Since a node of `ignored` can still be expanded later we have to make sure that `closed` and `ignored` are mutually exclusive by removing said nodes from `ignored`. At the end of the local search the ignored list is inserted into the GBFS' open list. The states stored in the separate closed list have to be closed in the search space for good.

If a local search fails to escape the plateau, the global GBFS resets its UHR detection and continues with its heuristic search.

This approach is complete, since it does not prune any nodes. All nodes that would be pruned by a local search are inserted into the GBFS open-list. Thus, given enough time, the whole search space can be expanded.

5

Experiments and Results

This section presents conducted experiments and their results. We start by comparing SIW and SIW+ in the STRIPS and MPT setting. We then evaluate two heuristic based GBFS approaches and compare them to our planners that combine heuristic and novelty based searches.

5.1 Setup

All benchmarks were run on a cluster of Intel® Xeon® processors running CentOS 6.5 at 2.2 GHz. Each task was executed on a single processor core with a time limit of 30 minutes and a memory limit of 2 GB. The Fast Downward was compiled with GCC 4.8.4 for a 32 bit architecture.

The benchmarks consist of 46 domains resulting in a total of 1456 satisficing planning problems.

5.2 Baseline Algorithms

First we compared SIW and SIW+ of the STRIPS setting[4] to our implementation in the MPT setting. We then proceeded to evaluate the default GBFS of FD and compared it to the GBFS that detects UHRs. Since the only difference is a counter in one of them, there was no observable difference. For further experiments we recall with GBFS the one detecting UHRs.

We then proceeded to compare the GBFS with a GBFS using preferred operators, $\text{GBFS}_{\text{preferred}}$. This modified GBFS produces in each state a set of helpful actions as proposed by Hoffmann and Nebel (2001). In the MPT helpful actions are called preferred operators. Operators that appear in the relaxed plan of the state and are applicable in it are preferred operators of said state. The intuition is that a successor state is more promising if it is generated by a preferred

[4] Source code for $\text{SIW}_{\text{STRIPS}}$ and $\text{SIW+}_{\text{STRIPS}}$ available under: https://github.com/miquelramirez/LAPKT-public.git. Tested on committed version: 6d5ce1c of May 16, 2016.

Table 5.1: Coverage of the baseline algorithms SIW and SIW+ in the STRIPS and MPT setting. $\text{SIW}_{\text{STRIPS}}$ and $\text{SIW+}_{\text{STRIPS}}$ operate on the STRIPS setting. SIW/SIW+ are the implementations embedded in the MPT of the Fast Downward.

$\text{SIW}_{\text{STRIPS}}$	SIW	$\text{SIW+}_{\text{STRIPS}}$	SIW+
1075	1040	**1167**	1162

operator. FD implements this preference with two separate open lists. One containing all successors and one containing exclusively states that are produced by preferred operator. The next state to be expanded by $\text{GBFS}_{\text{preferred}}$ is alternatingly taken from one of these two open lists. This approach proved to be helpful in domains where heuristic guidance is weak and a lot of time is spent exploring UHRs.

If not mentioned otherwise the heuristic used with GBFS and the heuristic that produces preferred operators is the *ff*-heuristic of Hoffmann and Nebel (2001).

A detailed table with the baseline results can be found in Appendix A.5.

5.2.1 SIW and SIW+ in the STRIPS and MPT setting

Table 5.1 compares the SIW and SIW+ in the STRIPS and MPT setting. In this experiment we observe that SIW+ outperforms SIW substantially in both settings. But the coverages vary in the different settings. Our implementation of SIW and SIW+ is not quite able to solve as many problems as the implementation of Lipovetzky and Geffner (2012). We suspect three reasons:

- Differing operator orders: The order of introducing a state's children to the search influences the pruning criteria and therefore the expansion order. For example: $\text{SIW}_{\text{STRIPS}}$ is not able to solve a single instance of the movie domain. These verdicts are reached in mere seconds, revealing that $\text{SIW}_{\text{STRIPS}}$ runs into dead-ends. Our SIW is able to solve all problems of this domain.
- Checking the novelty in the STRIPS setting can be more efficient: The number of tuples that need to be checked in a state might be smaller, as shown in Appendix A.3.
- The expansion order in the MPT might be different through the introduction of "none of those" values as stated by Proposition 1. This can lead to expansion of states that would be pruned in the STRIPS setting. Pruning less nodes in the MPT setting could explain why SIW in the MPT setting runs less often into dead ends but more often out of time.

5.2.2 SIW vs GBFS

By comparing SIW and SIW+ to the GBFS in Table 5.2 we observe that $\text{GBFS}_{\text{preferred}}$ performs best. The SIW+ however, is a close runner up. This is somewhat surprising since SIW+ is almost a blind planner. It would be interesting to implement complete versions of SIW

Table 5.2: Coverage of the baseline algorithms SIW, SIW+ and GBFS.

SIW	SIW+	GBFS	$GBFS_{preferred}$
1040	1162	1075	**1171**

Table 5.3: Coverage of the chaining approach of GBFS and local searches with different UHR threshold sizes. The UHR threshold notes the number of steps without improving the heuristic value in GBFS after which a local search is started. Red colours indicate high coverage and blue low coverage.

	UHR threshold								
Local Search	10	100	1000	2000	3000	4000	5000	6000	7000
IW	922	1016	1067	1092	**1102**	1100	1100	1100	1100
IW+	1006	1090	1139	1163	1166	1163	**1169**	1165	1162
SIW	984	1075	1122	1147	**1148**	1147	1146	1150	1142
SIW+	1022	1103	1152	1167	**1175**	1169	1173	1166	1168

and SIW+. These complete algorithms could backtrack in dead-ends and would not be permitted to commit to subgoals that lead them into dead ends. This improvement has the potential for SIW+ to solve 81 more problems in which the planner runs into dead ends. SIW+ might be able to surpass the performance of $GBFS_{preferred}$.

5.3 Chaining Approach

The results for the chaining approach of Section 4.1 are displayed as heat map in Table 5.3. This approach has one tunable parameter: the UHR threshold. This threshold determines the number of expansions without improvement of the heuristic value, after which a local search is started. Red colours in the table indicate high coverage and blue low coverage. Detailed domain coverages for the best configurations are given in Appendix A.6.

In these experiments we observed that the performance is highly dependant on the choice of the UHR threshold parameter. Best performances are reached if a local search is started somewhere between 2'000 and 5'000 expansions without improvement of the heuristic value. We explain these high thresholds by the choice of the state from which a local search is started. This state is chosen quite arbitrarily and might be a terrible choice. If the UHR threshold is low and we commit early in UHRs, we might pick states in dead ends. By putting off the commitment, GBFS might fully expand these dead end UHRs, such that the local search then can be started from within a promising one.

The local searches IW+ and SIW+ which use the extended pruning criteria outperform their counterparts IW and SIW. SIW+ as local search dominates in all configurations. Even with the short comings of committing to dead-ends and the possibility of expanding states multiple times, the best configuration solves more problems than $GBFS_{preferred}$ (1175 vs. 1171).

Table 5.4: Coverage for different configurations of the star approach. Novelty-Bound is the maximum novelty-bound for local searches to be started with. UHR threshold notes the number of steps without improving the heuristic value in GBFS after which a local search is started. Max Steps is the maximum number of expansions a local GBFS is allowed to perform. Red colours indicate high coverage and blue low coverage.

Local Planner	Novelty-Bound	UHR threshold 10	50	100	500	1000
IW	1	1157	1151	**1161**	1144	1140
	2	1139	1136	1151	1152	1161
	3	1105	1112	1115	1133	1150
	∞	1059	1075	1086	1108	1126
IW+	1	**1251**	1236	1232	1222	1219
	2	1209	1214	1209	1205	1206
	3	1178	1187	1195	1200	1200
	∞	1149	1171	1183	1189	1201
SIW	1	1149	1158	**1161**	1156	1071
	2	1139	1156	1149	1146	1140
	3	1100	1135	1131	1139	1141
	∞	948	996	1016	1055	1140
SIW+	1	1161	1173	1171	1171	1150
	2	1157	**1175**	1169	1172	1159
	3	1135	1157	1159	1170	1153
	∞	1028	1086	1086	1113	1113
	Max Steps					
GBFS	10	1109	1110	1110	1110	1102
	50	1126	**1128**	1124	1117	1106
	100	1124	1121	1123	1118	1116
	600	1109	1114	1110	1111	1106
	1000	1105	1109	1117	1104	1098
	∞	1044	1048	1052	1053	1057

5.4 Star Approach

The results for the star approach of Section 4.2 are displayed as heat map in Table 5.4. This approach has two parameters to tune: The UHR threshold and the range for the novelties. If the novelty-bound for a local search engine is 3, the first local search engine is started with a novelty-bound of 1. If it is not able to escape the UHR a second local search is started with a novelty-bound of 2. The starting point of the second local search is taken from the open list of the global GBFS. The novelty-bound gives the upper bound for local searches to search with. We also implemented our own GBFS-LGBFS of Xie et al. (2014). GBFS-LGBFS is implemented in the star approach. The local search engine is a GBFS that stops if it encounters a state with better heuristic value or reaches the maximum number of expansions it is allowed to perform (Max Steps).

We observe an antipodal trend to the results of the chaining approach: Performance is generally better with smaller UHR threshold sizes. This was somehow expected. In the chaining approach we run the risk of committing to dead ends. In the star approach we do not commit to states. Even starting local searches in huge UHRs or dead ends is no threat. The more often a small local search is started, the bigger the chance of starting it in a state close to the border of an UHR. If the local search is unsuccessful in escaping the UHR, the global GBFS continues for a maximum of UHR threshold number of expansions. If this UHR threshold is small, we increase the chance of starting a local search in a promising position even further. However, we cannot go too low with the UHR threshold size, since the overhead for initializing the novelty data structure would be too severe.

GBFS with local GBFS performs better than a single GBFS (1075). Again, starting multiple small GBFS seems more promising than starting a few big ones. The coverages among all GBFS-LGBFS are pretty similar. If the number of steps in the local GBFS is not bounded, the positive effect of using a local GBFS diminishes entirely.

In the results we see again, that the local searches with the extended pruning criteria usually perform better than their counterparts. Using IW or IW+ as local searches produce better coverage than their serialized counterparts. This feels somehow natural, since SIW or SIW+ can locally commit to subgoals which will be the starting point for their subsequent local searches.

Using IW+ as local search performs best. With a novelty-bound of 1 and an UHR threshold size of 10 it is able to solve 1251 problems; 80 more than $\text{GBFS}_{\text{preferred}}$.

5.5 Comparison of the best planners: $\text{GBFS}_{\text{preferred}}$ vs. Star-GBFS-IW+(1)

We compare the plan lengths and execution times of the two best planners: $\text{GBFS}_{\text{preferred}}$ and the star approach with IW+ (novelty-bound of 1 and an UHR threshold of 10). A point in the scatter plot represents two measures: One of the baseline algorithm $\text{GBFS}_{\text{preferred}}$ (x-axis) and one of Star-GBFS-IW+(1) (y-axis). Only problems which both planners were able to solve are displayed. If the result for a problem is better solved by $\text{GBFS}_{\text{preferred}}$ it will appear above the diagonal. As the figure Fig. 5.1 shows, the $\text{GBFS}_{\text{preferred}}$ usually produces shorter paths and is faster in doing so. This is somehow expected, since we solely try to escape UHRs without respect to optimality in doing so. Longer paths could then result in more time usage to expand nodes along these longer paths. These graphs are somehow misleading as they solely show that $\text{GBFS}_{\text{preferred}}$ is faster and finds better solution when both planners are able to solve the problem. These graphs do not address the number of problems which Star-GBFS-IW+(1) is able to solve that $\text{GBFS}_{\text{preferred}}$ cannot.

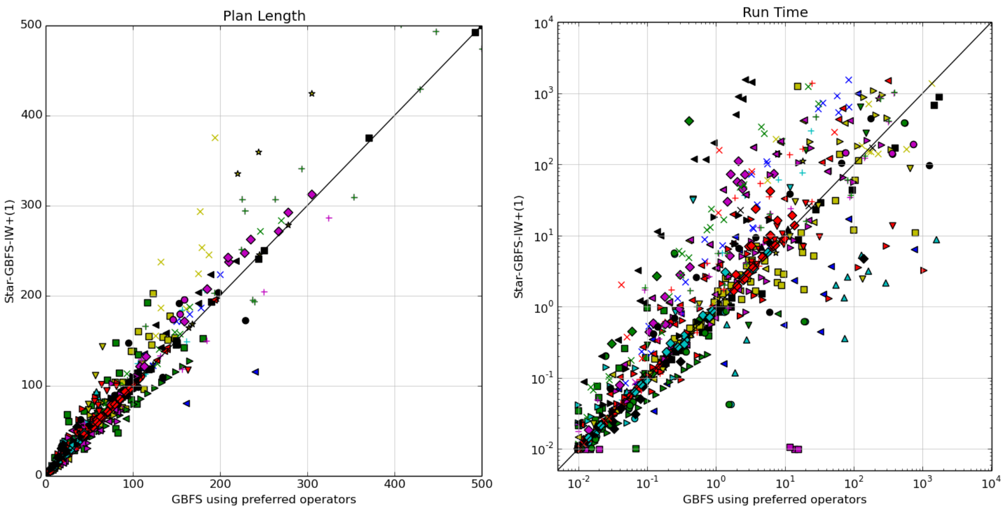


Figure 5.1: Scatter plot comparing the plan lengths (left) and the run times (right, on logarithmic scales) of the $\text{GBFS}_{\text{preferred}}$ (x-axis) and the best performing GBFS star approach with IW+(1) and an UHR threshold of 10 (y-axis). Data points appearing above the diagonal indicate that $\text{GBFS}_{\text{preferred}}$ is able to solve these problems with shorter paths and in less time. The domain for a data points is given in Fig. 5.2.

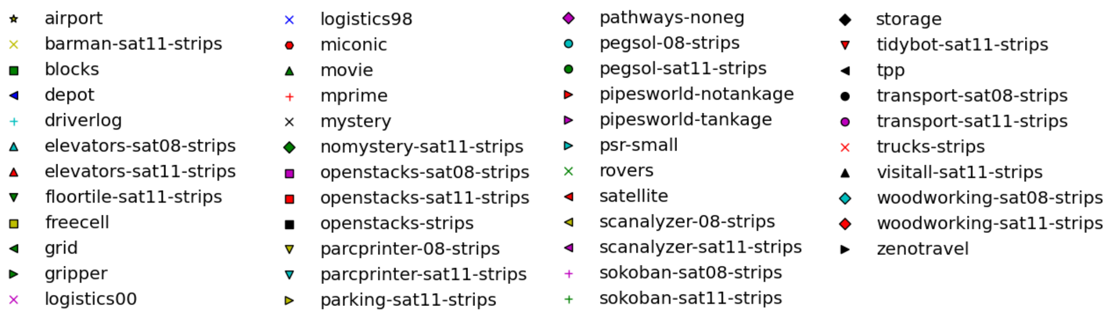


Figure 5.2: Domain Legend for Fig. 5.1

6

Conclusion and Future Work

In this thesis we discussed the blind novelty-based search algorithms *Iterated Width* (IW), *Serial Iterated Width* (SIW) and their extensions IW+ and SIW+. We adapted the novelty into the MPT setting and implemented IW, IW+ and SIW, SIW+ in the Fast Downward Planning System. We showed that the adaption in the MPT setting induces differences: The MPT may introduce "none of those" variables. These can lead to expansion of states which would be pruned in the STRIPS setting.

We then used the novelty based search engines to escape UHRs in GBFS with two approaches: The first approach is a chain of search engines which share no information. The second approach shares information of already expanded states between GBFS and local searches. This produces a complete algorithm with no re-opening of already expanded nodes (IW+ and SIW+ may locally re-open nodes).

The results show that changing the search approach to escape UHRs can be helpful. By tightly coupling the heuristic and novelty guided search, we managed to surpass the best performing GBFS by 80 problems. The increase in coverage however, may go to the expense of run time and quality of the solutions.

Possible future work includes a complete SIW/SIW+ algorithm that is able to backtrack in dead ends and does not commit to the previous malicious subgoal. This improvement is already part of BFS(f) by Lipovetzky and Geffner (2012) where they additionally use a linear combination of the heuristic and the novelty to create a new heuristic. This idea of including the novelty into a heuristic is still missing in the Fast Downward Planning System. Further, one could try to change the novelty definition in order to ignore "none of those"-values in the MPT and produce novelty-based algorithms that are equivalent to the ones in STRIPS. An other idea would be to introduce a new UHR recognition that considers the numbers of simultaneously expanded UHRs. Counting the UHRs can be achieved by determining the first expanded node of the UHR. Search nodes that have this node in their path, lie in the same UHR. Switching to a local search could then depend by the number of UHRs and their sizes.

It might even be possible to couple novelty- and heuristic-based searches even tighter by only using novelty based local searches to escape an UHR instead of switching back to GBFS for a given number of steps. It might even be successful to randomly switch between GBFS and novelty based searches.

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A
Appendix

A.1 Modified Gripper STRIPS

Given a modified gripper problem: An agent has to move two balls from room A into room B. The agent is only able to pick up and hold one ball. If ball 1 is moved before ball 2, ball 2 gets jealous and destroys itself. The STRIPS problem is given by $\Pi_S = \langle V_S, O_S, I_S, G_S \rangle$, where

- $V_S =$ {ball1_in_A, ball1_in_B, ball2_in_A, ball2_in_B, agent_in_A, agent_in_B, agent_holding_ball1, agent_holding_ball2, agents_hands_free }
- O_S:

operator	preconditions	add-effects	delete-effects
pickup_ball1_A	ball1_in_A agent_in_A agents_hand_free	agent_holding_ball1	ball1_in_A agents_hand_free
pickup_ball2_A	ball2_in_A agent_in_A agents_hand_free	agent_holding_ball2	ball2_in_A agents_hand_free
agent_move_A	agent_in_B	agent_in_A	agent_in_B
agent_move_B_empty	agent_in_A agents_hand_free	agent_in_B	agent_in_A
agent_move_ball1_B_before_ball2	agent_in_A agent_holding_ball1 ball2_in_A	agent_in_B	agent_in_A ball2_in_A
agent_move_ball1_B_after_ball2	agent_in_A agent_holding_ball1 ball2_in_B	agent_in_B	agent_in_A
agent_move_ball2_B	agent_in_A agent_holding_ball2	agent_in_B	agent_in_A
agent_drop_ball1_B	agent_in_B agent_holding_ball1	ball1_in_B agents_hand_free	agent_holding_ball1
agent_drop_ball2_B	agent_in_B agent_holding_ball2	ball2_in_B agents_hand_free	agent_holding_ball2

- I_S: {ball1_in_A, ball2_in_A, agent_in_B, agents_hand_free}
- G_S: {ball1_in_B, ball2_in_B }

A.2 Modified Gripper MPT

To transform the gripper problem Π_S of Appendix A.1 into an MPT we have to detect variable groups of which only one can be true at all times: The balls cannot be in A and B at the same time, thus introducing a variable for the ball's position. The same applies to the agent. We additionally need a third variable for the agent's hand. This leads to the MPT $\Pi_M = \langle V_M, dom, O_M, I_M, G_M \rangle$, where

- V_M and their *dom*:

variable	domain		
ball1_position	A	B	none of those
ball2_position	A	B	none of those
agent_position	A	B	
agents_hand	free	ball1	ball2

- O_M:

operator	preconditions	effects
pickup_ball1_A	ball1_position = A	ball1_position = none of those
	agent_position = A	
	agents_hand = free	agents_hand = ball1
pickup_ball2_A	ball2_position = A	ball2_position = none of those
	agent_position = A	
	agents_hand = free	agents_hand = ball2
agent_move_A	agent_position = B	agent_position = A
agent_move_B_empty	agent_position = A	agent_position = B
	agents_hand = free	
agent_move_ball1_B_before_ball2	agent_position = A	agent_position = B
	agents_hand = ball1	
	ball2_position = A	**ball2_position = none of those**
agent_move_ball1_B_after_ball2	agent_position = A	agent_position = B
	agents_hand = ball1	
	ball2_position = B	
agent_move_ball2_B	agent_position = A	agent_position = B
	agents_hand = ball2	
agent_drop_ball1_B	agent_position = B	
	agents_hand = ball1	agents_hand = free
		ball1_position = B
agent_drop_ball2_B	agent_position = B	
	agents_hand = ball2	agents_hand = free
		ball2_position = B

- I_M: {ball1_position = A, ball2_position = A, agent_position = B, agents_hand = free}
- G_M: {ball1_position = B, ball2_position = B}

A.3 Efficiency Difference of Novelty Check in STRIPS and MPT

Given the modified gripper problems of Appendix A.1 and Appendix A.2, we check the novelty of the state after the agent moved to A and picked up ball 1. The state is encoded as follows:

- STRIPS: {ball2_in_A, agent_in_A, agent_holding_ball1}

- MPT: {ball1_position = none of those, ball2_position = A, agent_position = A, agents_hand = ball1}

To check this state in the STRIPS setting for novelty 2, we have to check $\binom{3}{2} = 3$ pairs of variables. In the MPT setting we have to check $\binom{4}{2} = 6$ pairs of variables.

Generalized: For a novelty-bound i the number of partial states that need to be checked in the MPT setting is given by $\binom{n}{i}$, where n is the number of variables in the MPT. In the STRIPS setting this might be less as shown in the example. However, a state in the STRIPS setting can never have more true variables than the number of variables in the MPT. This is the case, because the MPT is created by merging mutually exclusive propositional variables into a multi-value variable.

A.4 Inequality of IW in STRIPS and MPT

Given are the modified gripper problem of Appendix A.1 and Appendix A.2. We assume a novelty-bound of 1. The agent started in B, moved to A and picked up ball 1. The atoms that were made true during this process are:

- ball1_in_A
- ball2_in_A
- agent_in_B
- agents_hand_free
- agent_in_A
- agent_holding_ball1

The operation of the agent moving to room B will be pruned by IW(1), since the atom agent_in_B has already been seen in the search. The same operation order in the MPT setting results in following known facts:

- ball1_position = A
- ball2_position = A
- agent_position = B
- agents_hand = free
- agent_position = A
- ball1_position = none of those
- agents_hand = ball1

In the MPT setting the operation of moving ball1 into room B before ball2 will not be pruned because the never seen fact ball2_position = **none of those** will be created.

A.5 Baseline Results

Table A.1: Baseline comparison. All GBFS use the ff-heuristic. $\text{GBFS}_{\text{preferred}}$ uses preferred operators of the ff-heuristic. $\text{SIW}_{\text{STRIPS}}$ and $\text{SIW+}_{\text{STRIPS}}$ work on the STRIPS setting and were implemented by Lipovetzky and Geffner (2012) (available under github.com/miquelramirez/LAPKT-public.git). SIW and SIW+ operate on the MPT of the FD. The last line reports the numbers for: stuck in dead ends, unable to solve due to lack of time, run out of memory of the SIW/SIW+. The domain "other" includes the domains blocks, gripper, logistics00, miconic and zenotravel, for which there was no difference in coverage.

Domain	Instances	GBFS	$\text{GBFS}_{\text{preferred}}$	$\text{SIW}_{\text{STRIPS}}$	SIW	$\text{SIW+}_{\text{STRIPS}}$	SIW+
airport	50	31	32	47	46	48	44
barman-sat11-strips	20	4	9	8	0	18	16
depot	22	16	19	22	21	22	22
driverlog	20	17	20	16	16	17	18
elevators-sat08-strips	30	11	12	30	29	30	21
elevators-sat11-strips	20	0	0	17	9	19	3
floortile-sat11-strips	20	8	8	0	0	0	0
freecell	80	79	80	78	73	80	78
grid	5	4	4	2	5	5	5
logistics98	35	29	32	19	16	32	26
movie	30	30	30	0	30	0	30
mprime	35	32	35	31	26	29	30
mystery	30	17	18	17	17	18	18
nomystery-sat11-strips	20	9	13	0	1	0	0
openstacks-sat08-strips	30	6	6	26	26	30	30
openstacks-sat11-strips	20	0	0	7	8	20	20
openstacks-strips	30	28	30	10	8	30	29
parcprinter-08-strips	30	22	22	30	27	30	29
parcprinter-sat11-strips	20	5	5	20	16	20	18
parking-sat11-strips	20	19	20	20	20	20	20
pathways-noneg	30	9	23	13	17	12	19
pegsol-08-strips	30	30	30	7	19	7	16
pegsol-sat11-strips	20	20	20	0	6	2	7
pipesworld-notankage	50	30	42	44	40	46	36
pipesworld-tankage	50	22	32	33	35	37	33
psr-small	50	50	50	46	45	40	45
rovers	40	26	40	32	29	40	37
satellite	36	29	31	26	23	28	22
scanalyzer-08-strips	30	28	30	26	13	25	29
scanalyzer-sat11-strips	20	18	20	16	5	15	19
sokoban-sat08-strips	30	28	28	3	6	3	4
sokoban-sat11-strips	20	18	18	0	2	0	1
storage	30	19	19	28	23	28	25
tidybot-sat11-strips	20	16	16	10	12	18	19
tpp	30	23	30	24	16	27	24
transport-sat08-strips	30	13	21	30	24	30	30
transport-sat11-strips	20	0	3	13	9	16	17
trucks-strips	30	14	17	2	3	2	3
visitall-sat11-strips	20	3	3	20	20	20	20
woodworking-sat08-strips	30	28	30	30	29	30	29
woodworking-sat11-strips	20	13	20	19	17	20	17
other	253	253	253	253	253	253	253
Sum	1456	1057	**1171**	1075	1040	1167	1162
(#dead ends, #timeouts, #memory exceeded)				(222, 46, 113)	(54, 174, 66)	(188, 28, 73)	(81, 240, 95)

A.6 Chaining approach

The best results of the chaining approach described in Section 4.1 are displayed in Table A.2.

Table A.2: Detailed coverages for the best configurations for the chaining approach of GBFS and local searches. The domain “other” contains domains for which all problems were solved by all engines: gripper, logistics00, miconic, movie, mprime, pegsol-08-strips, pegsol-sat11-strips, psr-small, scanalyzer-08-strips, scanalyzer-sat11-strips, woodworking-sat08-strips, zenotravel.

		UHR threshold size			
		3000	5000	6000	3000
Domain	Instances	IW	IW+	SIW	SIW+
airport	50	31	31	31	31
barman-sat11-strips	20	1	1	1	1
blocks	35	34	34	35	33
depot	22	16	14	14	18
driverlog	20	18	18	19	18
elevators-sat08-strips	30	10	29	22	30
elevators-sat11-strips	20	1	9	4	11
floortile-sat11-strips	20	7	7	8	7
freecell	80	79	79	79	78
grid	5	4	4	4	4
logistics98	35	31	31	31	31
mystery	30	18	18	18	18
nomystery-sat11-strips	20	7	8	8	7
openstacks-sat08-strips	30	5	30	26	29
openstacks-sat11-strips	20	0	15	7	17
openstacks-strips	30	28	28	28	28
parcprinter-08-strips	30	22	22	22	22
parcprinter-sat11-strips	20	5	5	5	5
parking-sat11-strips	20	18	18	18	18
pathways-noneg	30	20	16	21	23
pipesworld-notankage	50	43	39	46	38
pipesworld-tankage	50	30	32	29	30
rovers	40	34	38	34	39
satellite	36	28	29	29	28
sokoban-sat08-strips	30	24	24	24	24
sokoban-sat11-strips	20	14	14	14	14
storage	30	21	24	18	23
tidybot-sat11-strips	20	16	16	16	16
tpp	30	28	24	27	24
transport-sat08-strips	30	11	12	12	11
transport-sat11-strips	20	0	0	1	0
trucks-strips	30	13	14	14	13
visitall-sat11-strips	20	3	3	3	3
woodworking-sat11-strips	20	19	20	19	20
other	463	463	463	463	463
Sum	1465	1102	1169	1150	**1175**

A.7 Star approach

Best results of the star approach of Section 4.2 are displayed in Table A.3.

Table A.3: Results of the Star approach. The star approach with a local GBFS is our implementation of GBFS-LGBFS. The domain “other” contains domains for which all problems were solved by all engines: blocks, driverlog, gripper, logistics00, miconic, movie, pegsol-08-strips, pegsol-sat11-strips, psr-small, scanalyzer-08-strips, scanalyzer-sat11-strips.

		UHR threshold				
		100	10	100	50	50
		Max Novelty-Bound				max steps
		1	1	1	2	10
Domain	Instances	IW	IW+	SIW	SIW+	GBFS
airport	50	31	31	31	31	31
barman-sat11-strips	20	4	14	7	13	19
depot	22	20	22	20	22	17
elevators-sat08-strips	30	16	29	16	17	0
elevators-sat11-strips	20	1	9	1	5	0
floortile-sat11-strips	20	8	7	8	8	7
freecell	80	80	79	80	80	80
grid	5	5	5	5	5	4
logistics98	35	30	30	30	30	29
mprime	35	35	35	35	35	33
mystery	30	18	18	18	18	18
nomystery-sat11-strips	20	8	8	8	8	8
openstacks-sat08-strips	30	6	30	0	0	0
openstacks-sat11-strips	20	0	19	0	0	0
openstacks-strips	30	28	30	28	28	30
parcprinter-08-strips	30	22	24	23	21	23
parcprinter-sat11-strips	20	6	9	8	7	8
parking-sat11-strips	20	20	11	17	14	20
pathways-noneg	30	22	23	22	23	22
pipesworld-notankage	50	43	43	43	43	43
pipesworld-tankage	50	36	41	37	39	29
rovers	40	33	35	34	34	32
satellite	36	27	27	28	27	29
sokoban-sat08-strips	30	28	27	27	27	22
sokoban-sat11-strips	20	18	17	17	17	14
storage	30	27	27	26	27	20
tidybot-sat11-strips	20	16	17	16	15	17
tpp	30	26	23	25	24	30
transport-sat08-strips	30	22	28	28	28	23
transport-sat11-strips	20	3	11	9	11	3
trucks-strips	30	14	13	14	14	14
visitall-sat11-strips	20	5	6	5	5	7
woodworking-sat08-strips	30	30	30	26	27	25
woodworking-sat11-strips	20	20	20	16	19	16
other	475	475	475	475	475	475
Sum	1456	1161	**1251**	1161	1175	1126

Declaration on Scientific Integrity
Erklärung zur wissenschaftlichen Redlichkeit

includes Declaration on Plagiarism and Fraud
beinhaltet Erklärung zu Plagiat und Betrug

Author — Autor
Dario Maggi

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Declaration — Erklärung
I hereby declare that this submission is my own work and that I have fully acknowledged the assistance received in completing this work and that it contains no material that has not been formally acknowledged. I have mentioned all source materials used and have cited these in accordance with recognised scientific rules.

Hiermit erkläre ich, dass mir bei der Abfassung dieser Arbeit nur die darin angegebene Hilfe zuteil wurde und dass ich sie nur mit den in der Arbeit angegebenen Hilfsmitteln verfasst habe. Ich habe sämtliche verwendeten Quellen erwähnt und gemäss anerkannten wissenschaftlichen Regeln zitiert.

Basel, 17.7.2016

D. Maggi

Signature — Unterschrift