Proceedings of the Thirty-First AAAI Conference on Artificial Intelligence (AAAI-17)

Improving Greedy Best-First Search by Removing Unintended Search Bias (Extended Abstract)*

Masataro Asai
Graduate School of Arts and Sciences
The University of Tokyo
3-8-1 Komaba, Meguro, Tokyo, Japan, +81-3-5454-6306
guicho2.71828 @ gmail.com

Alex Fukunaga
Graduate School of Arts and Sciences
The University of Tokyo

Abstract

Recent enhancements to greedy best-first search (GBFS) improve performance by occasionally adopting a non-greedy node expansion policy, resulting in more exploratory behavior. However, previous exploratory mechanisms do not address exploration within the space sharing the same heuristic estimate (plateau) and the search bias in a breadth direction. In this abstract, we briefly describe two modes of exploration (diversification), which work *inter*-(across) and *intra*-(within) plateau, and also introduce IP-diversification, a method combining Minimum Spanning Tree and randomization, which addresses "breadth"-bias instead of the "depth"-bias addressed by the existing methods.

1 Introduction

Many search problems in AI are too difficult to solve optimally, and finding even one satisficing solution is challenging. Although GBFS ignores solution optimality, it has been shown to be quite useful when it is necessary to find some satisficing solution quickly, and GBFS has been the basis for state-of-the-art domain-independent planners (Helmert 2006). Despite the ubiquitous use of GBFS for satisficing search, previous work has shown that GBFS is susceptible to being easily trapped by undetected dead ends and huge search plateaus. These pathological behaviors are caused by the strong dependendency of search behavior of GBFS on the quality of the heuristic function.

Recently, several approaches have been proposed for alleviating this problem, e.g., DBFS (Imai and Kishimoto 2011), ϵ-GBFS (Valenzano et al. 2014) and Type-GBFS (Xie et al. 2014). They improve the search performance by occasionally expanding nodes which do not have the lowest h-value, i.e., diversifying the search. These diversified algorithms provides an opportunity to expand nodes that are mistakenly overlooked due to errors made by the heuristic functions.

Existing methods for diversification have two issues: First, previous methods all employ h-based diversification as part of their algorithms in order to avoid the bias toward the nodes with smaller estimates. However, h-based diversification cannot detect the bias *among nodes with the same h-cost*. Second, as we see later, they are based on diversification with respect to search depth (distance from the start / goal / plateau entrance), so the bias among the set of nodes with the same search depth is not removed. In this abstract, we briefly introduce two modes of exploration (diversification), which work *inter*-(across) and *intra*-(within) plateau as well as our new diversification scheme, IP-diversification, a method combining Minimum Spanning Tree and randomization, which addresses "breadth"-bias instead of the "depth"-bias addressed by the existing methods.

We first define some notation used in the paper. First, $h(n), g(n), f(n)$ for node n follows the standard terminology (heuristic cost to goal, cost from the initial state, $g + h$). A *sorting strategy* for a best first search algorithm tries to select a single node from the open list (OPEN). Each sorting strategy is denoted as a vector of several *sorting criteria*, such as [criterion$_1$, criterion$_2$, . . ., criterion$_k$], which means: First, select a set of nodes from OPEN using criterion$_1$. If there are still multiple nodes remaining in the set, then break ties using criterion$_2$ and so on, until a single node is selected. A^* which breaks ties according to h value is denoted as $[f, h]$, and GBFS is denoted as $[h]$.

In A^*, those strategies have a significant effect on the performance (Asai and Fukunaga 2016). Traditional strategies such as $[f, h, \mathit{fifo}]$ or $[f, h, \mathit{lifo}]$ have a strong bias to either the regions of smaller (*fifo*) or larger (*lifo*) search depth of the plateau, which delays the search process. They proposed a notion of *depth* and diversified the search over different depths within a plateau. A depth $d(n)$ of a node n is the step-wise distance from the *entrance* of the plateau (the most recent state which entered the plateau, along the path from the initial state).

DBFS, ϵ-GBFS and Type-GBFS are the algorithms which try to escape the local minima by relaxing the (h-based) best-first order and introduce exploration (diversity) to the search process. For example, Type-GBFS alternates GBFS and Type-based expansion, which selects a random node in a random bucket, where nodes are put in buckets indexed by h-value and g-value.

2 Intra- and Inter-plateau Diversification

Previous work on exploration for GBFS address the problem of heuristic errors by occasionally expanding nodes with high h. Since this type of diversification operates across different search plateaus, we refer to these as *inter-plateau* exploration.

*More at: guicho271828.github.io/publications/gbfs17.pdf

However, we propose another type of exploration, which we call *intra-plateau* exploration, which works within a particular plateau: This type of exploration only changes expansion order among the nodes within a plateau.

Consider a hypothetical 2-dimensional histogram (Figure 1) of the number of nodes for each pair h, h^*. If h is perfect ($h = h^*$), all nodes would be on the diagonal line $x = y$. However, in reality, h has errors relative to h^* (projected to the x-axis). Inter-plateau exploration assumes that low-h^* nodes may have high-h values and it is sometimes reasonable to expand high-h nodes. However, a single h-plateau also consists of nodes with different h^* values (projected to the y-axis). This leads to an observation that *a naive algorithm may keep expanding bad (high-h^*) nodes within an h-value plateau*. This pathology happens for each h-plateau and requires intra-plateau exploration.

Both Type-GBFS and Depth Diversification use Type-based node selection (Xie et al. 2014), but for different purposes. In Type-based node selection, nodes with equal depth-related metrics (distance from goals h, initial states g or plateau entrance d) are put in a single bucket, and the search is diversified by random bucket selection. However, the former breaks the h-based best-first ordering (inter-plateau) while the latter uses it inside each h-plateau (intra-plateau). In Table 1, we compared their performance and show that: 1. Inter- and intra-plateau exploration address orthogonal issues and have complementary performance; 2. Combining inter- and intra-plateau exploration can result in better performance than either exploration alone.

3 Breadth-Aware IP-Diversification

One problem with diversification based on path distance or heuristics (depth, Type-GBFS) is that it does not diversify with respect to breadth – nodes with equal estimated distance from goals (h), initial states (g) or plateau entrance (d) are put in a single bucket. We propose *IP-diversification*, a new diversification that addresses this type of bias. On each explorative expansion, we expand nodes following Prim's method (Prim 1957) for Minimum Spanning Tree (MST) on a graph which is isomorphic to the search space (inter-plateau) or pleateau (intra-pleateau), but has randomly assigned edge costs. This is known to simulate *Invasion Percolation* (Wilkinson and Willemsen 1983), a physical fractal phenomenon where the distribution of fluid slowly invading porous media (e.g. porous rock). Figure 2 shows an example of a 2-dimensional lattice after running this algorithm for a certain length of time (blue=expanded). The resulting structure has holes of various size that the fluid has not invaded, due to *embankments*, the high-valued edges surrounding the neighbors of the holes.

Consider a blind search on the graph shown in Figure 2. It consists of two large components, **high-b** and **low-b**. The initial node is I and the goal is L_4. Both branches have maximum depth D, and the high-b branch has maximum width B, both values being very large. It presents a pathological case for depth-diversification. Although it addresses the bias of Depth/Breadth-first Search to deeper/shallower region by distributing the effort among various depths, the probability of expanding L_2, L_4 at depths 2, 4 is $1/(B+1)$ each,

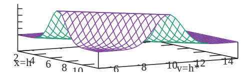

Figure 1: A conceptual view of the node distribution wrto $y = h^*$ and inadmissible $x = h$. The peak line is on $x = y$.

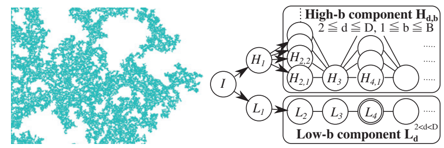

Figure 2: (Left) Invasion Percolation on 2-dimensional lattice. (Right) Example case exhibiting large bias in the branching factor depending on the subgraph.

which is small for large B. In contrast, in IP-diversification does not expand high-b branch with probability 1/5. (Let $r(n)$ the cost of the parent edge of a node n. This happens when $r(H_1) > r(L_i)$ for any of $i = 1 \ldots 4$, and $\int_0^1 dr(H_1)$ $Pr(\forall i; r(L_i) \leq r(H_1)) = \int_0^1 x^4 dx$). In this case, node H_1 is acting as an embankment.

	GBFS	hd	hD	hdD	hb	hB	hbB
total	77	84.2	84.4	**89**	77	88	**92.1**

Table 1: Number of solved IPC14 instances (5 min, 4GB RAM) using CG heuristics (Helmert 2006), mean of 10 runs. **hd/hD**: intra/inter-plateau type-based diversification $[h, \langle d \rangle]$ and $alt([h], [\langle g, h \rangle, ro])$ (Type-GBFS), **hb/hB**: intra / inter-plateau IP diversification $[h, r]$ and $alt([h], [r])$, **hdD/hbB**: A combined configuration, $alt([h, \langle d \rangle], [\langle g, h \rangle, ro])$ and $alt([h, r], [r])$.

This strategy can be used as both inter- and intra-plateau diversification and improve GBFS performance (Table 1). Complementary material contains in-depth analysis and state-of-the-art results of these methods applied to LAMA.

References

Asai, M., and Fukunaga, A. 2016. Tiebreaking Strategies for Classical Planning Using A^* Search. In *AAAI*.

Helmert, M. 2006. The Fast Downward Planning System. *J. Artif. Intell. Res.(JAIR)* 26:191–246.

Imai, T., and Kishimoto, A. 2011. A Novel Technique for Avoiding Plateaus of Greedy Best-First Search in Satisficing Planning. In *AAAI*.

Prim, R. C. 1957. Shortest connection networks and some generalizations. *Bell system technical journal* 36(6):1389–1401.

Valenzano, R. A.; Schaeffer, J.; Sturtevant, N.; and Xie, F. 2014. A Comparison of Knowledge-Based GBFS Enhancements and Knowledge-Free Exploration. In *ICAPS*.

Wilkinson, D., and Willemsen, J. F. 1983. Invasion percolation: a new form of percolation theory. *Journal of Physics A: Mathematical and General* 16(14):3365.

Xie, F.; Müller, M.; Holte, R. C.; and Imai, T. 2014. Type-Based Exploration with Multiple Search Queues for Satisficing Planning. In *AAAI*.