

# Empirical Evaluation of Search Algorithms for Satisficing Planning

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# GBFS

- Best-first search:
  - $f(s)$  to find the most promising state to expand.
- GBFS:
  - $f(s) = h(s)$

# Misleading heuristics

- Exploration of states not leading to a goal.
- Plateaus:
  - Many states are explored.
  - No improvement of  $h(s)$ .

## Random Exploration:

- Explore random States from the open list.

## Local Exploration:

- Start a search on a limited subset of states.

# Search enhancements

## Deferred evaluation:

- States are inserted with the heuristic value of their parent.
- Evaluated when they are explored.

## Preferred Operators:

- Operators most probable part of a solution.
- Alternate open lists.

# $\epsilon$ -GBFS

- Extension of standard GBFS.
  - Probability  $\epsilon$  select a state uniformly randomly from the open list.
  - Probability  $1 - \epsilon$  use standard behaviour of GBFS.

# Type-based exploration

- States are inserted into buckets based on  $h(s)$ ,  $g(s)$ ,  $const(1)$ , ....
- Buckets are selected uniformly randomly as well as the states in the buckets.
- Used alternating with a standard open list.

# Enforced hill climbing

- Standard GBFS until a better  $h(s')$  value is found or the search fails.
- Run a new GBFS on state  $s'$ .

# Monte-Carlo random walks

- Random exploration:
  - Multiple random walks:
    - Random operators are applied.
    - Only the end point is evaluated.
  - The path providing the best improvement is added to the global path.
- Configurations:
  - Helpful actions
  - Dead end avoidance
  - Iterative deepening
  - Acceptable progress



# Local exploration

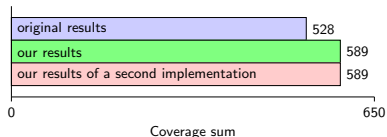
- Start a standard GBFS.
- If the heuristic value was not improved over a period of steps, start a local search.
- Depth of local search is limited.
- Close list is shared.
- Local search ends if:
  - the configured depth is reached.
  - a state  $s'$  with  $h(s') < h(s)$  is found.
  - the local search fails, the local open list is empty.
- Remaining states are merged.
- Alternate configuration: Local Random Walks

# Diverse best-first search

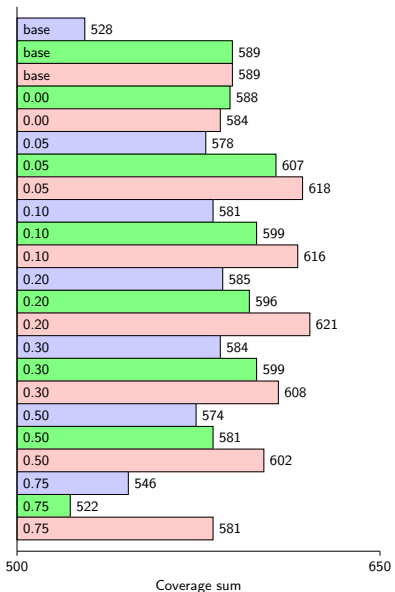
- Global open list:
  - Probabilistic selection of states, based on their  $h(s)$  and  $g(s)$  value.
  - Smaller  $g(s)$  and  $h(s)$  are preferred.
- Local open list:
  - Standard open list.
- Only local searches.
- Local search is limited by the initial  $h(s)$  .
- Remaining states are merged into the global open list.
- Next local search is started.

# Experiments

- All experiments were run on the same benchmark sets as in the original papers.
- Results named *base* are those of a standard GBFS.

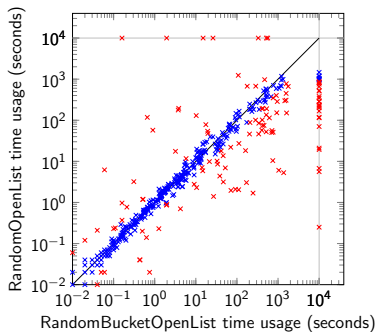


## ε-GBFS



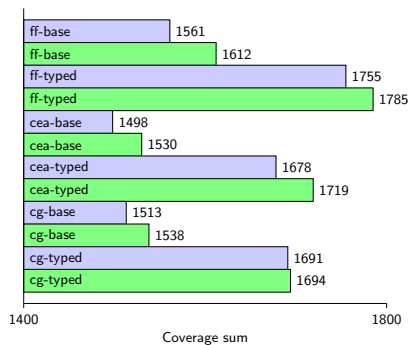
- Results:
  - Scale similar.
- Two implementations:
  - Bucket based
  - Heap based
    - FIFO by ID.

# $\epsilon$ -GBFS



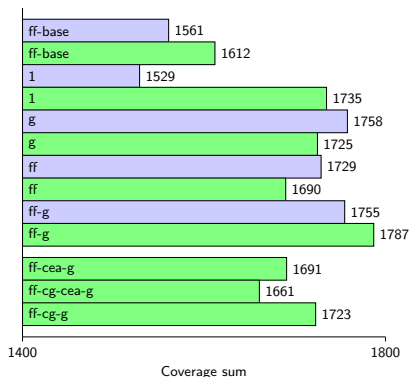
Action	RandomBucketOpenList	RandomOpenList
Insert state	$O(1)$	$O(\log(n))$
Remove random state	$O(m)$	$O(\log(n))$
Remove min state	$O(1)$	$O(\log(n))$

# type-based-GBFS



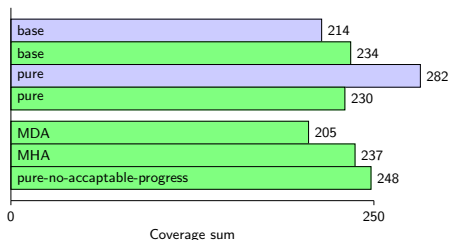
- Results:
  - Results scale similar.
- Implementation:
  - Reduced complexity  $O(1)$  instead of  $O(m)$  to the number of buckets.
    - Vector containing buckets.
    - Map pointing to buckets.

# type-based-GBFS: Multiple heuristics



- ff-cea-g, ff-cg-cea-g, ff-cg-g are additions on our side.
- Longer keys lead to more evaluations resulting in worse results.
- Even the const(1) performs better.

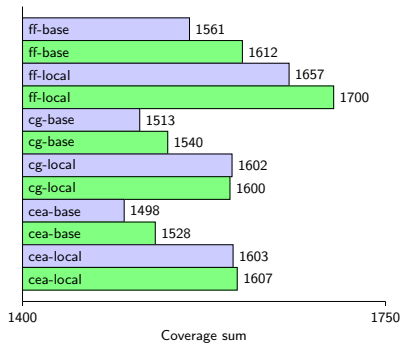
# Monte-Carlo random walks



- Results:
  - Number estimated from percentage results.
  - Good MHA results.
- Implementation:
  - Support for multiple configurations
    - Helpful actions
    - Dead end avoidance
    - Iterative deepening
    - Acceptable progress

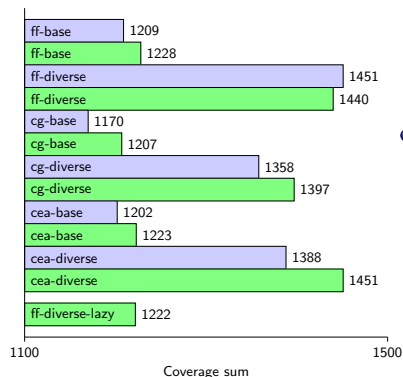


# Local exploration



- Results:
  - The results scale similar to the original results.
- Implementation:
  - Abstract wrapper
  - Combinations of different search engines possible.

## DBFS

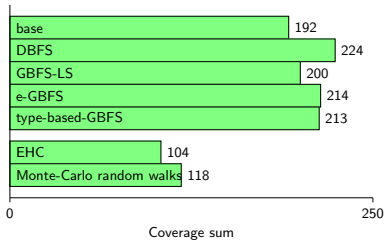


- Results:
  - Good results.
  - Bad results for deferred evaluation.
- Implementation:
  - Three open lists:
    - DiverseOpenList
    - ProbabilisticOpenList (global open list)
    - Any open list (local open list)
  - ProbabilisticOpenList modified algorithm
    - Only iterate over existing values.

# Comparison

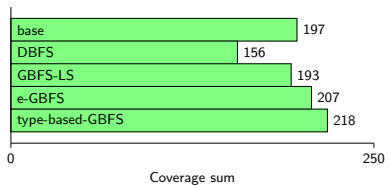
- Comparison of all algorithms.
- On IPC 2011 benchmarks.
- Standard (eager) search.
- Deferred (lazy) search where applicable.

# Eager



- All new algorithms improve results compared to standard GBFS.
- Random walks and EHC can not compete with the current algorithms.
- Simple randomisation leads to a similar improvement ( $\epsilon$ -GBFS, type-based-GBFS).

# Lazy



- Deferred evaluation leads to worse results in most cases.

# Conclusion

- All algorithms perform as good as announced.
- Simple randomisation can massively improve the results.
- For  $\epsilon$ -GBFS improvements showed their potential.

# Future Work

- Try to combine.
- Try new configurations.
- We could try a single bucket randomisation with the alternating open list.
- Optimise.
- Comparison on a bigger benchmark set.