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Memory Mapping and Parallelizing Random Forests for Speed and Cache Efficiency

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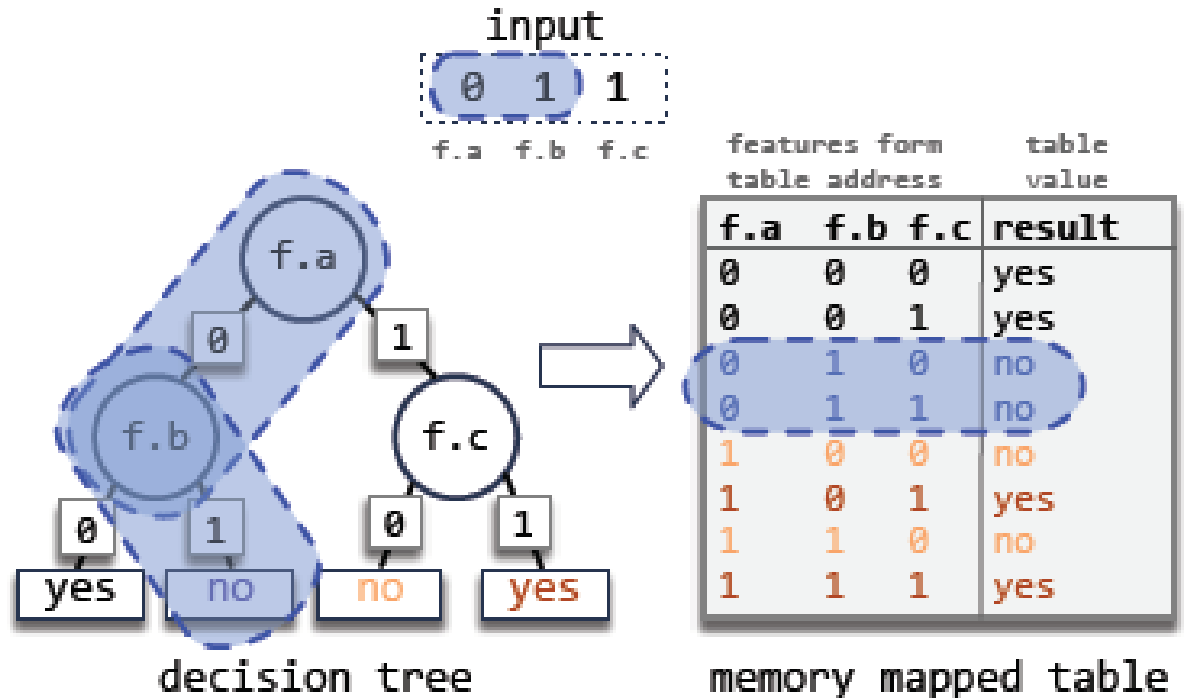
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Background – Memory Mapping

Memory mapping as a Depth-first alternative to tree traversal.

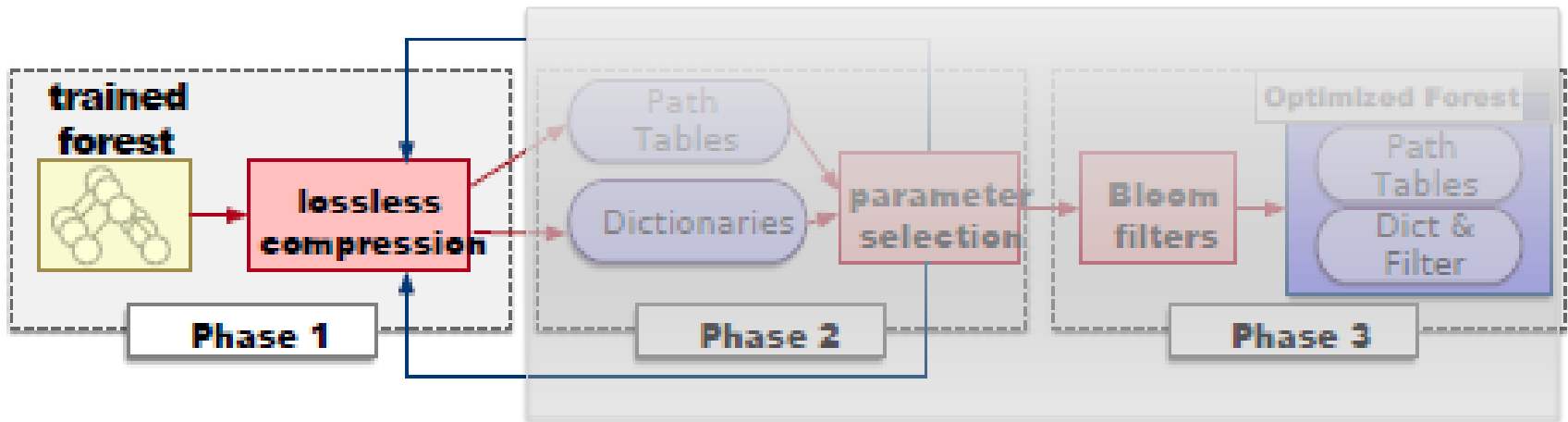
Table size grows exponentially





Design

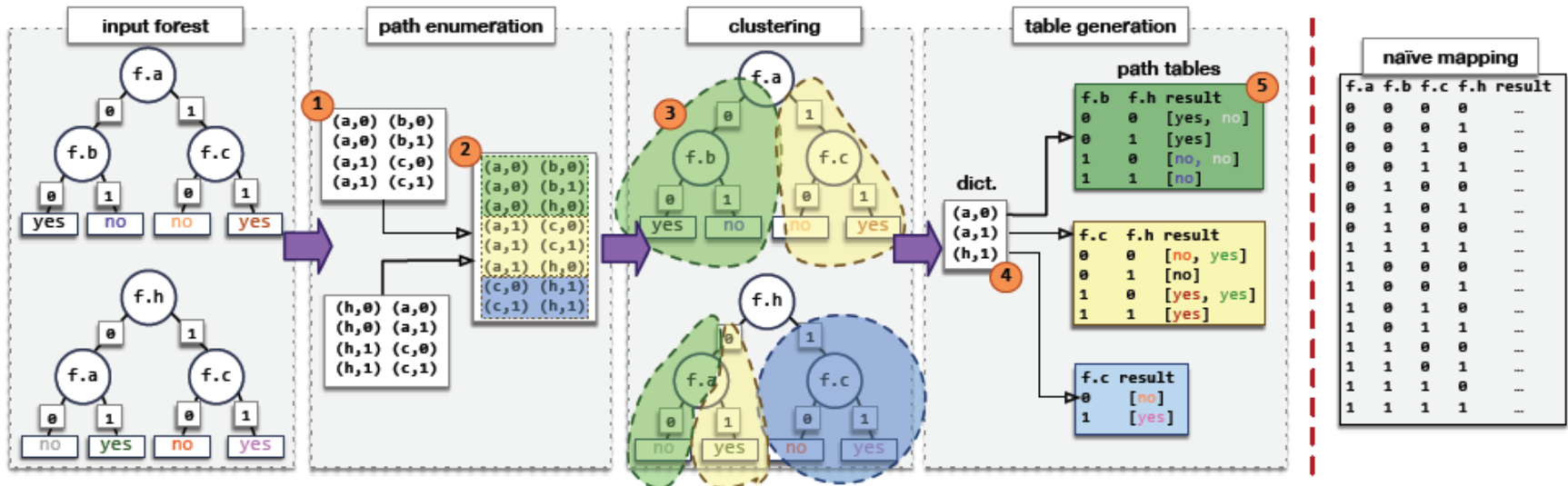
Overview:





Phase 1 – Clustering & Compression

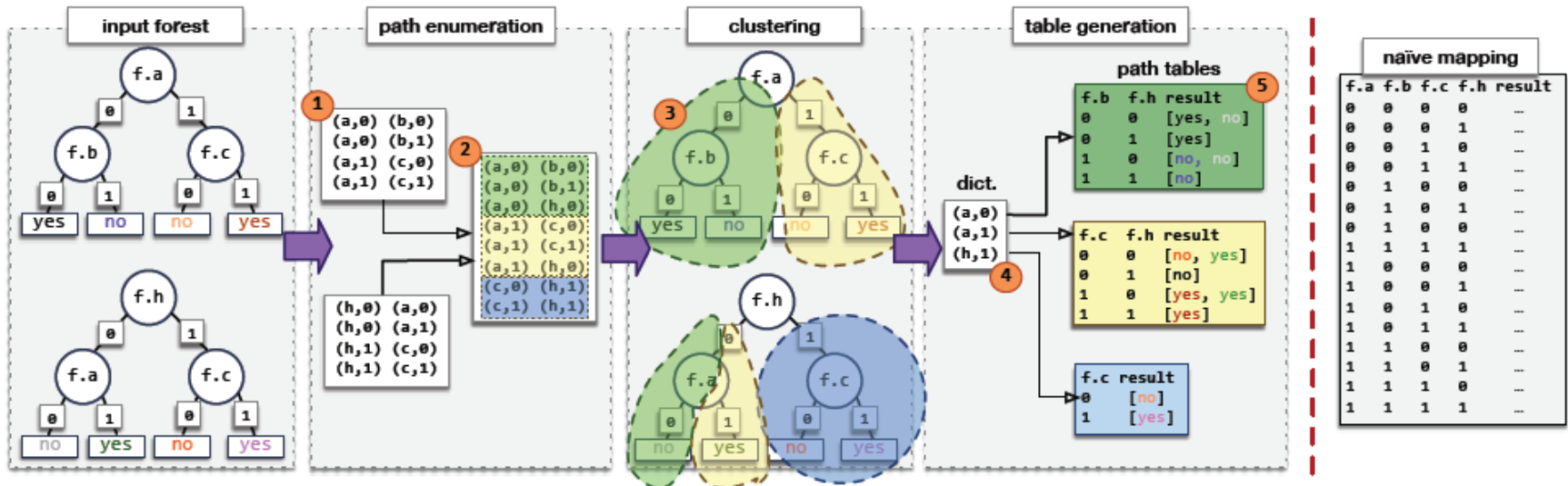
- List all paths in the forest.
- Sort features in each path.
- Sort all paths.





Phase 1 – Clustering & Compression

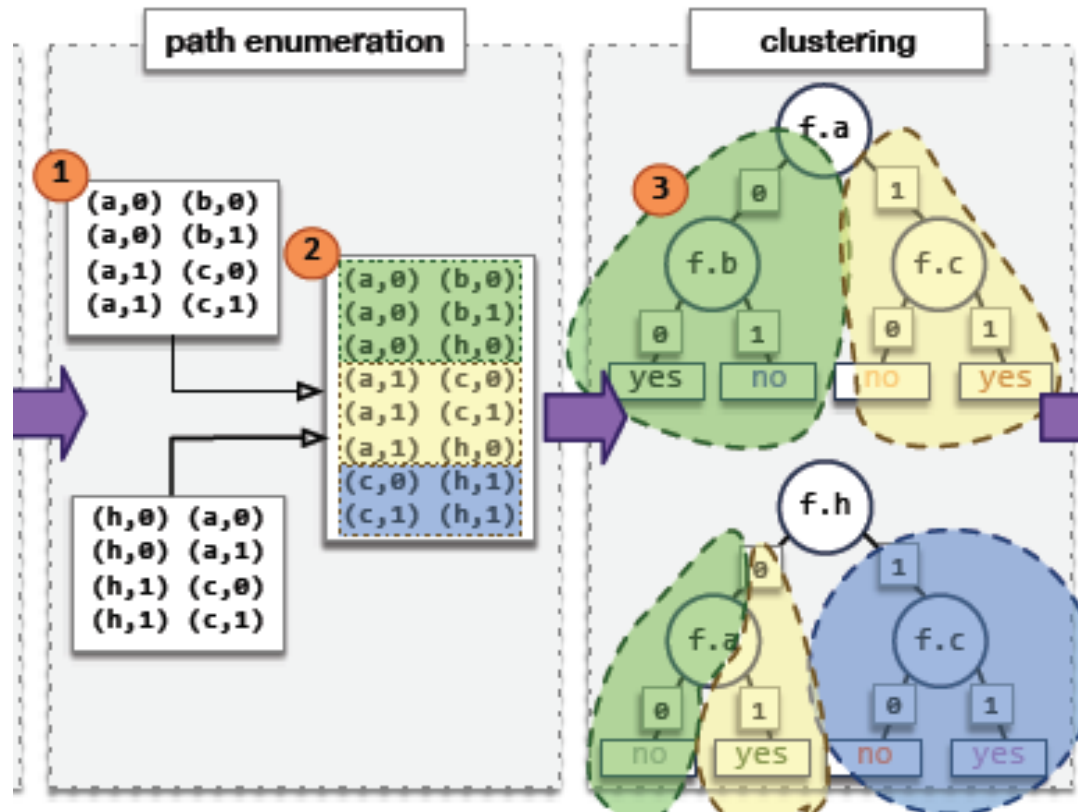
- Assign paths to clusters.
- Create table from each cluster
- Resulting table size < naïve table





Phase 2: Parameter selection

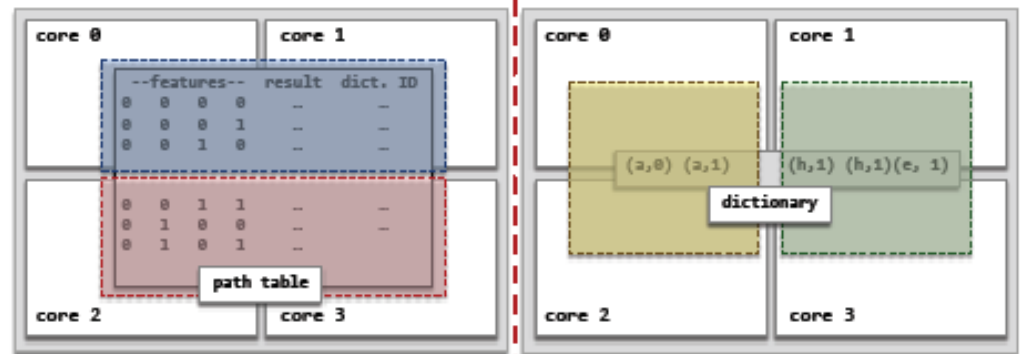
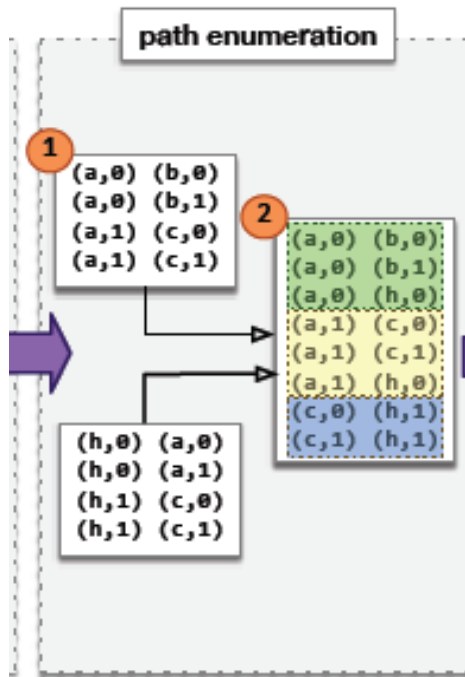
How are clusters divided?





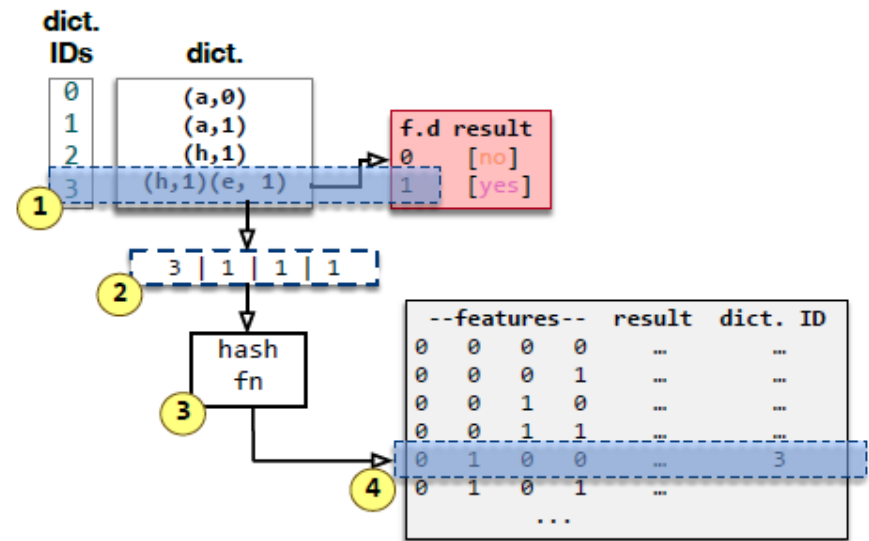
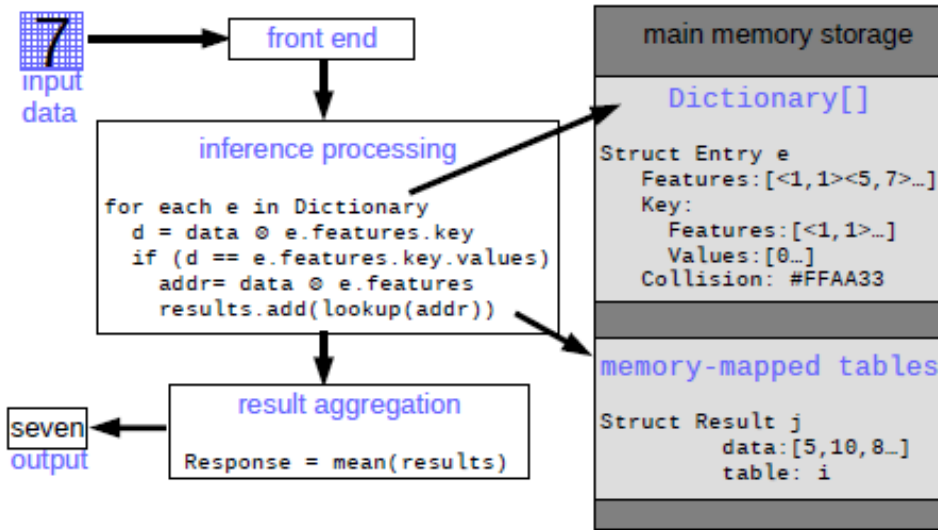
Phase 2: Parameter selection

- Tunable cluster size
- Assign tables and/or dictionaries to different clusters





Inference Overview



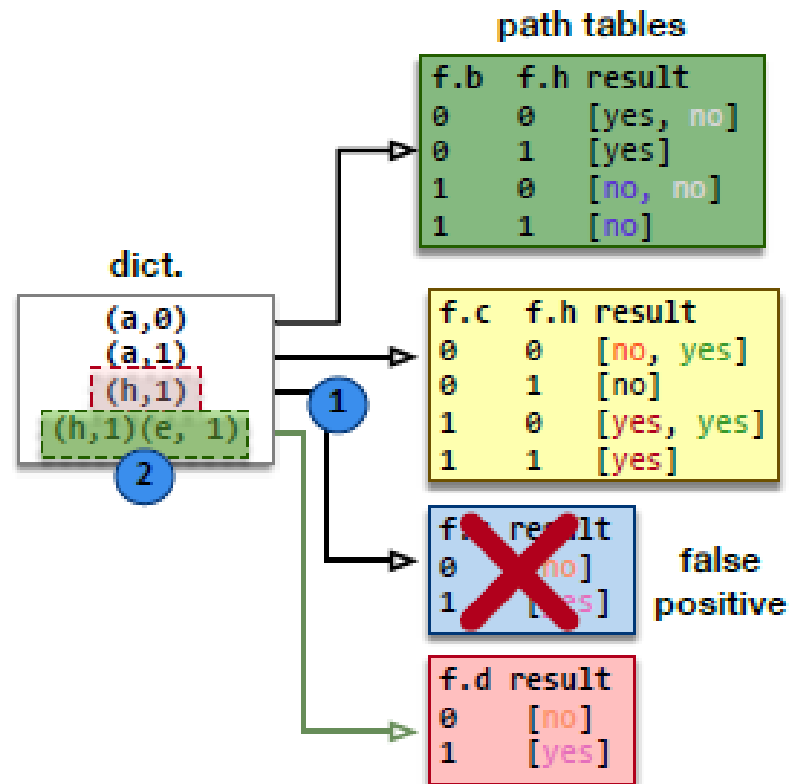


Phase 3: Improving Path Table selection

Could this model lead to false positives?
Yes. Hence Dictionary ID.

Bloom filter: Fast and Safe.

--features--				result	dict. ID
0	0	0	0
0	0	0	1
0	0	1	0
0	0	1	1
0	1	0	0	...	3
0	1	0	1
...					





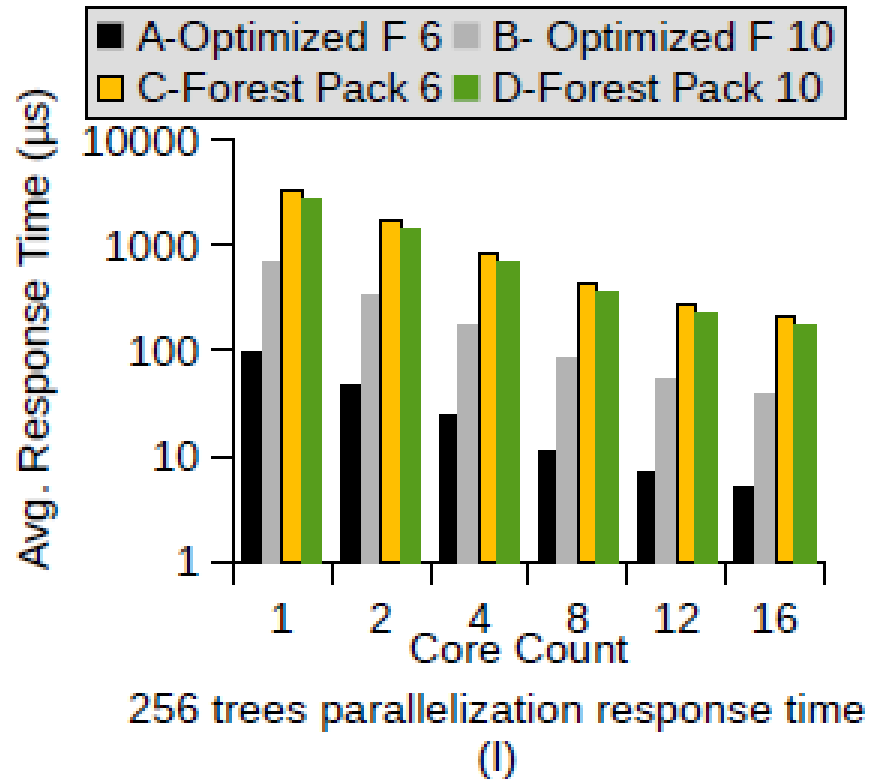
Early Results

MNIST Results:

Orders of magnitude faster than alternative approaches.

Multiple number of cores.

Two settings for max tree height.





Future Work

Search space methods

Optimization modeling

Explore datasets

Test interpretability benchmarks



References

J. Browne, D. Mhembere, T. M. Tomita, J. T. Vogelstein, and R. Burns. Forest packing: Fast parallel, decision forests. In Proceedings of the 2019 SIAM International Conference on Data Mining, pages 46–54. SIAM, 2019.