Additive Pattern Database Heuristics

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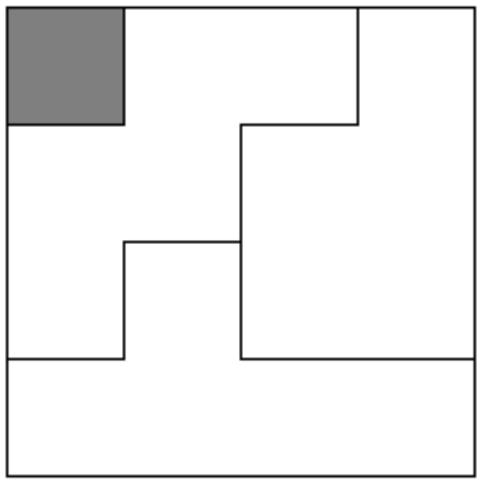
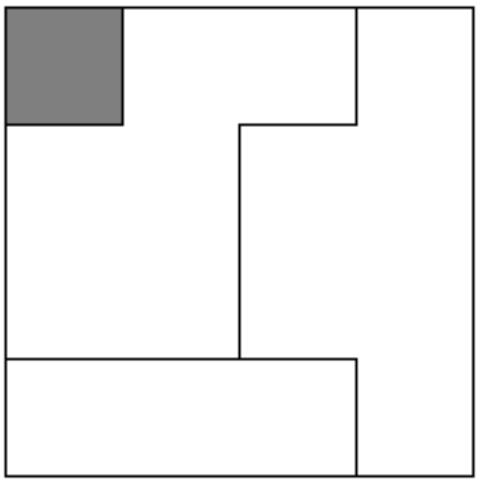
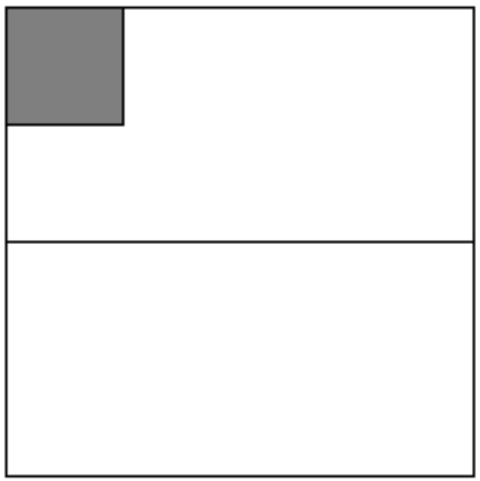
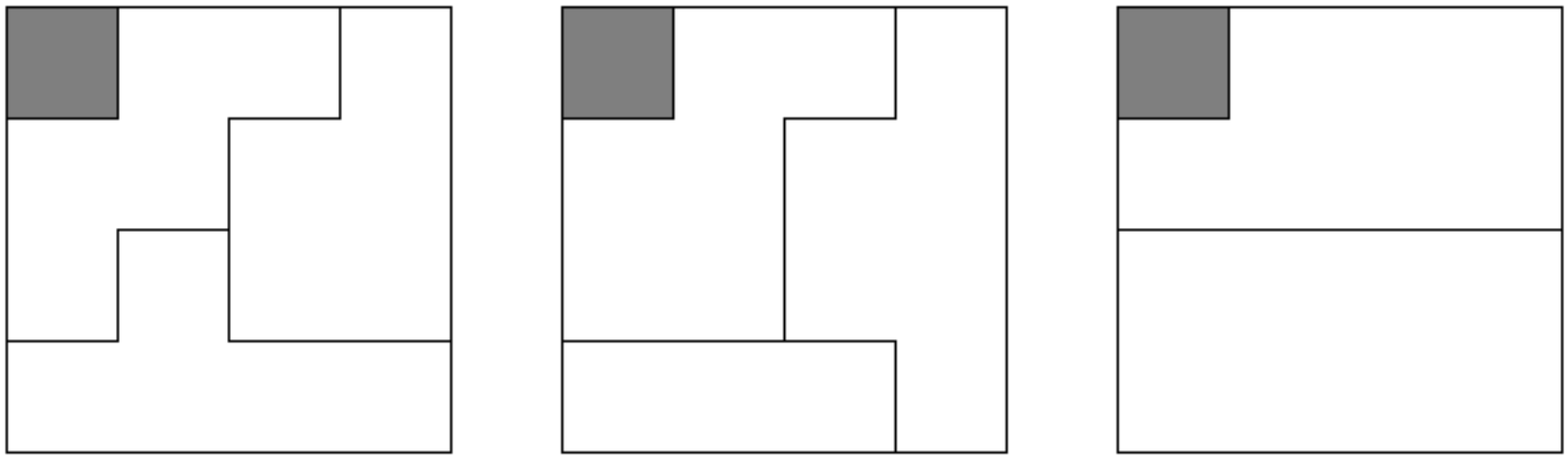
Two ways to create additive pattern databases:

- Statically-partitioned (old)
- Dynamically-partitioned (new)

Disjoint or Statically-Partitioned Additive Database Heuristic

Disjoint or Statically-Partitioned Additive Database Heuristic



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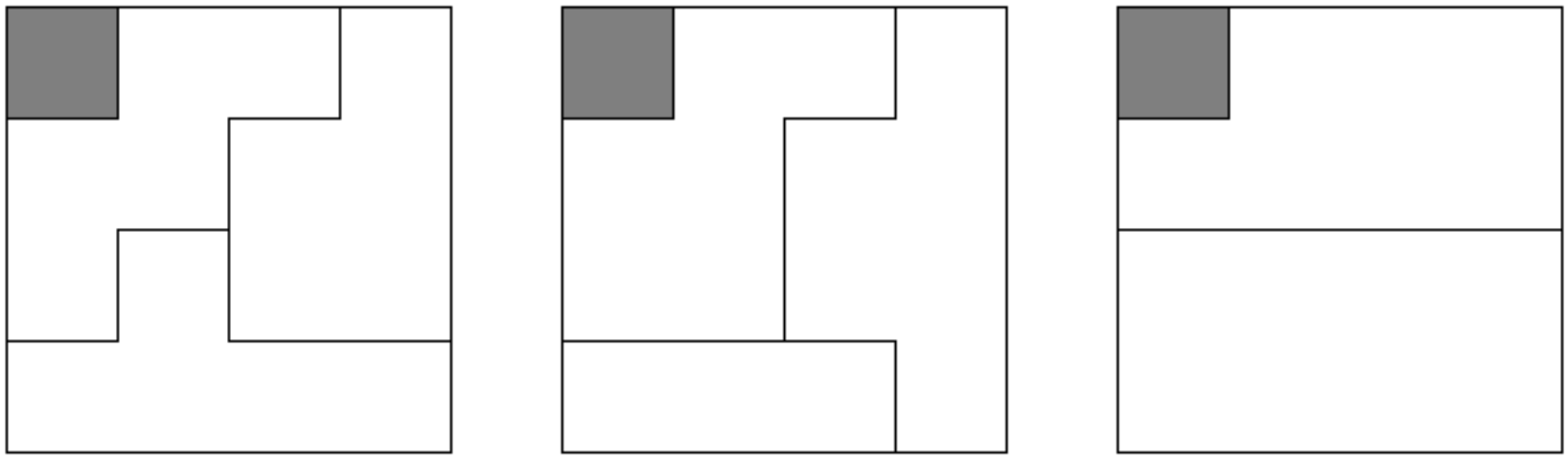

- Only count moves of the tiles within the group to avoid overestimation
- Fails to capture interactions between tiles in different groups

Dynamically-Partitioned Database Heuristics

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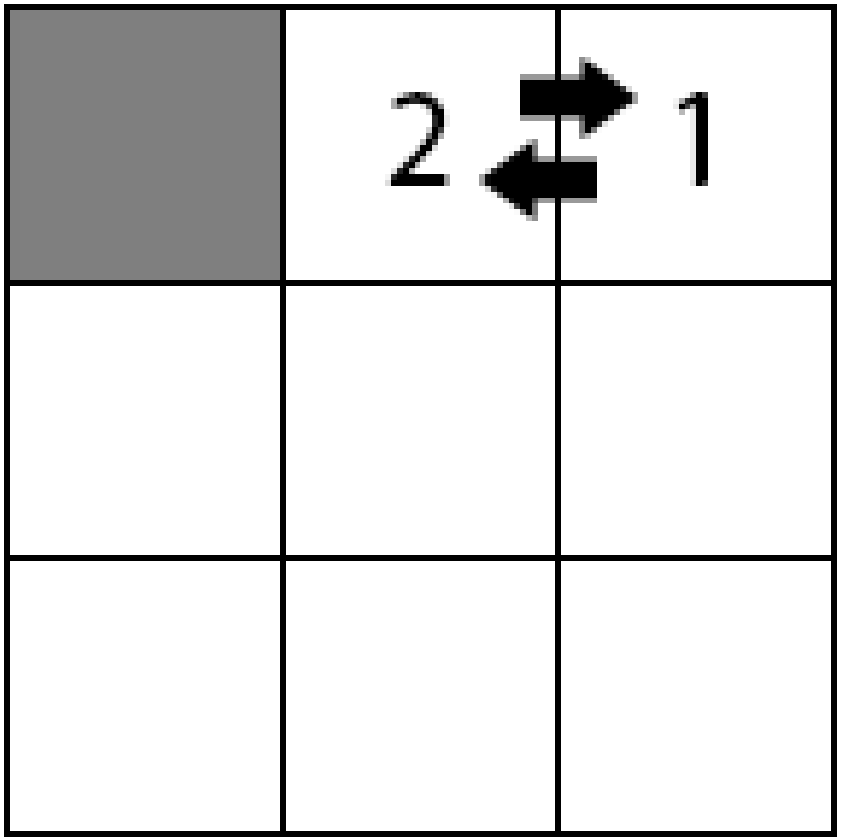
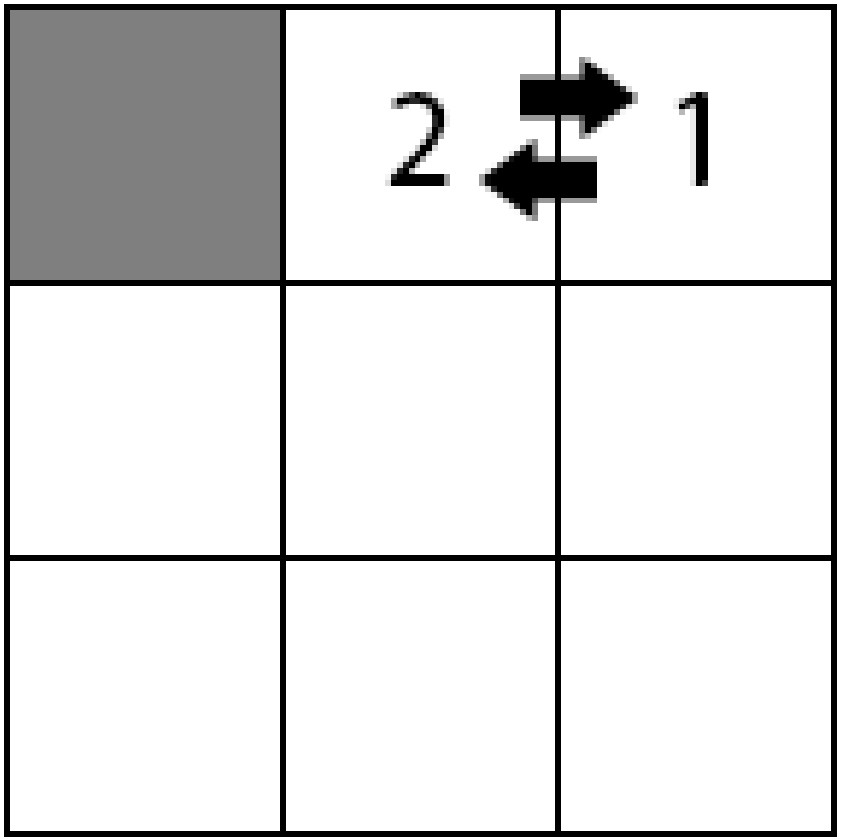
Given n tiles, there are $O(n^4)$ entries.

Linear Conflict

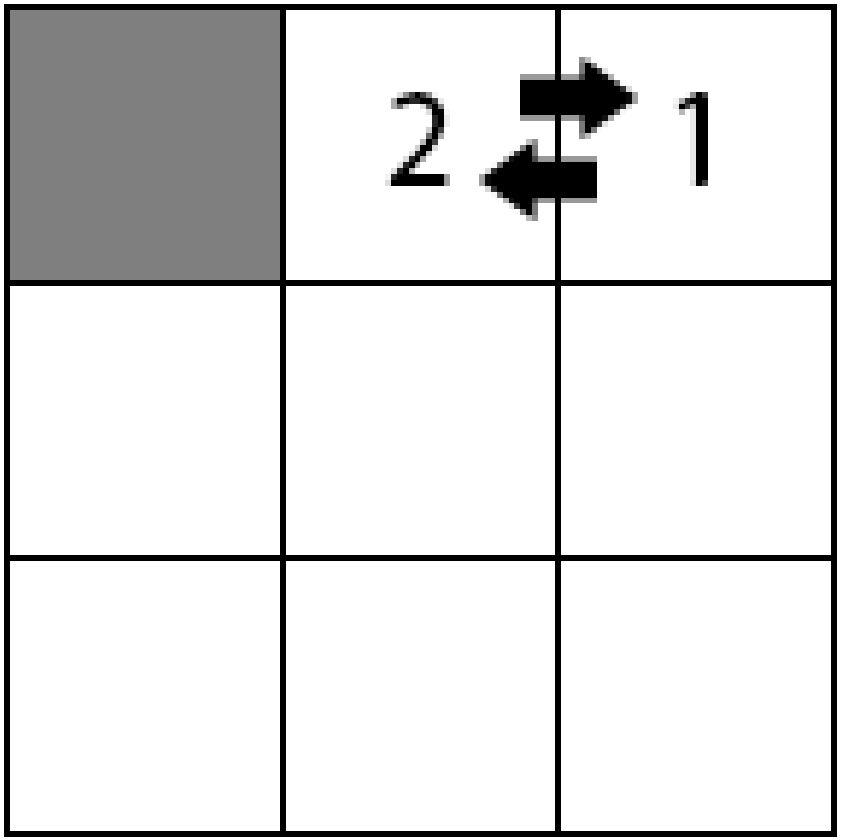


Linear Conflict



Manhattan-Distance: 2

Linear Conflict



Manhattan-Distance: 2
Considering Linear conflict: +2

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4. Rinse and repeat for all $n(n-1)/2$ different pairs.

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Mutual Cost Graphs!

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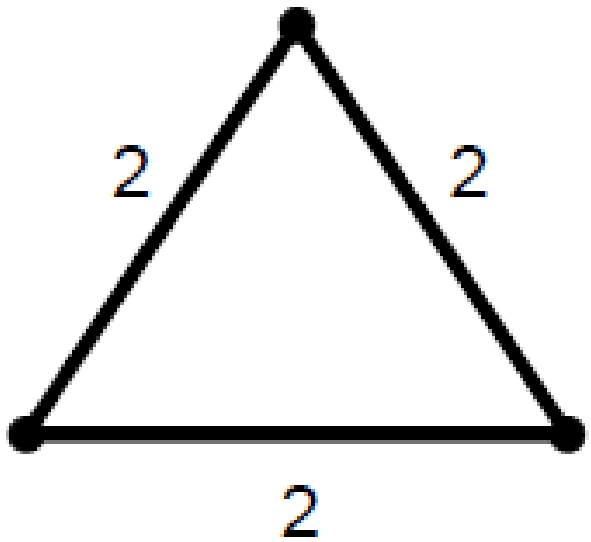
4. k-tile . . .

Weighted Vertex Cover Distance

Domain-specific enhancement:



Experimental Results

Heuristic Function	Value	Nodes	Sec.	Nodes/sec	Memory
Manhattan	36.940	401,189,630	53	7,509,527	0
Linear conflict	38.788	40,224,625	10	3,891,701	0
Dynamic, MM: pairs	39.411	21,211,091	13	1,581,848	1,000
Dynamic, MM: pairs+triples	41.801	2,877,328	8	351,173	2,300
Dynamic, WVC: pairs	40.432	9,983,886	10	959,896	1,000
Dynamic, WVC: pairs+triples	42.792	707,476	5	139,376	2,300
DWVC: pairs+triples+quadruples	43.990	110,394	9	11,901	78,800
Static: 5-5-5	41.560	3,090,405	.540	5,722,922	3,145
Static: 6-6-3	42.924	617,555	.163	3,788,680	33,554
Static: 7-8	45.630	36,710	.028	1,377,630	576,575

Thank you for listening

Questions?