Learning Multi-dimensional Indexes

Vikram Nathan*, **Jialin Ding***, Mohammad Alizadeh, Tim Kraska

CSAIL

ML for Systems

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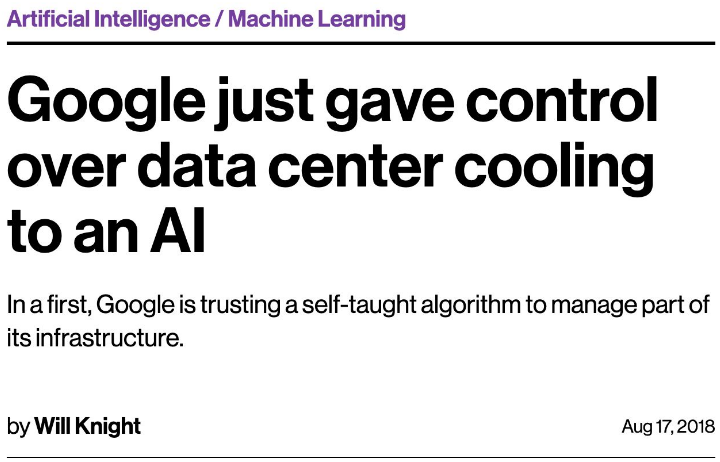
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by **Will Knight** Aug 17, 2018

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  - Want 10X, not 10%
  - Implication: favor creative uses of simple models

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Outline

1. **Completed work: Flood (SIGMOD 2020)**
2. Future work: column correlations, query skew, categorical attributes

Motivation: scanning and filtering in analytics

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Lower scan overhead generally leads to lower query time

Single-dimensional indexes

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Query	**Scan Overhead**
SELECT COUNT(*) FROM table WHERE Price >= 10 AND Price < 100	1

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Query	**Scan Overhead**
SELECT COUNT(*) FROM table WHERE Price >= 10 AND Price < 100	1
SELECT COUNT(*) FROM table WHERE Price >= 10 AND Price < 100 AND Quantity = 1	

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SELECT COUNT(*) FROM table WHERE Price >= 10 AND Price < 100 AND Quantity = 1	2

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SELECT COUNT(*) FROM table WHERE Price >= 10 AND Price < 100	1
SELECT COUNT(*) FROM table WHERE Price >= 10 AND Price < 100 AND Quantity = 1	2
SELECT COUNT(*) FROM table WHERE Quantity > 2	

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Query	**Scan Overhead**
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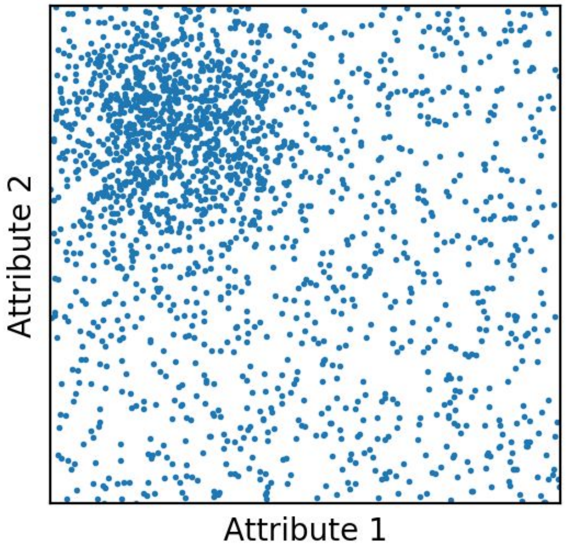
SELECT COUNT(*) FROM table WHERE Price >= 10 AND Price < 100 AND Quantity = 1	2
SELECT COUNT(*) FROM table WHERE Quantity > 2	8

Multi-dimensional indexes



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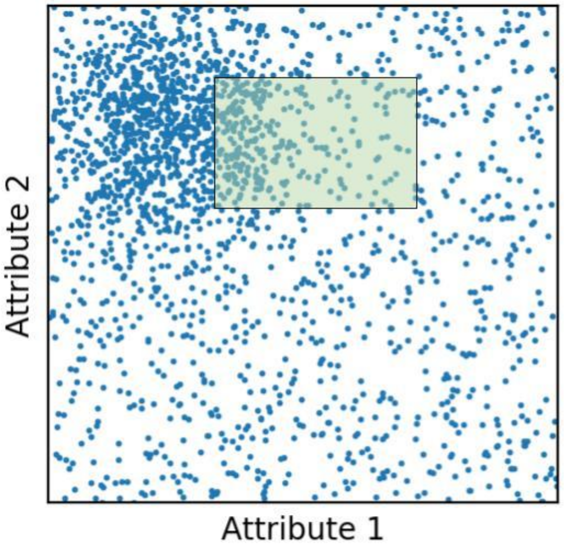
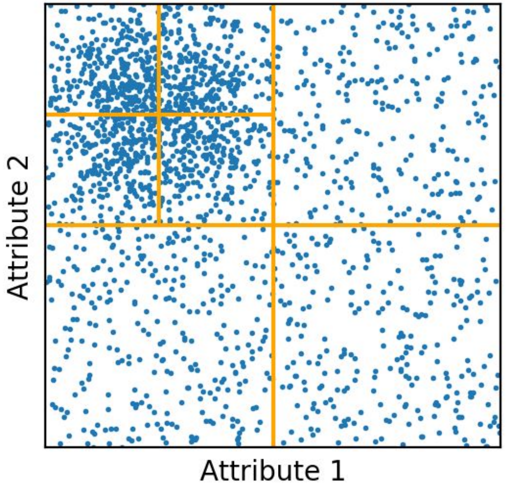


Query

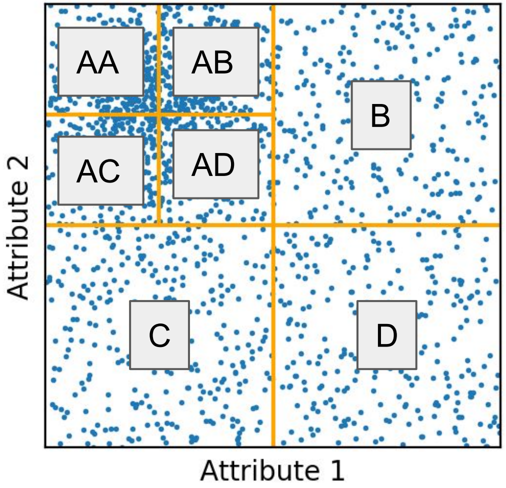
SELECT COUNT(*)
FROM table
WHERE Attribute 1 >= A
AND Attribute 1 <= B
AND Attribute 2 >= C
AND Attribute 2 <= D

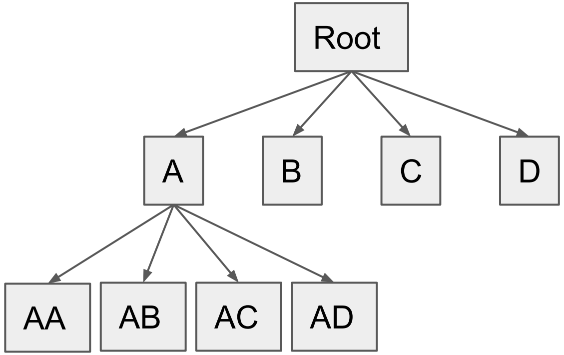
Existing multi-dimensional indexes



- Quadtree (hyper-octree in higher dimensions)

Existing multi-dimensional indexes





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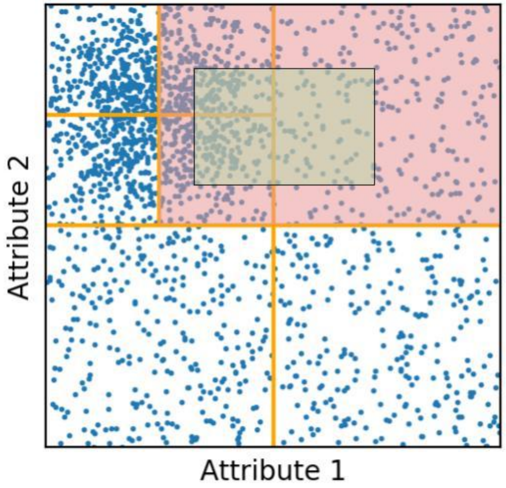

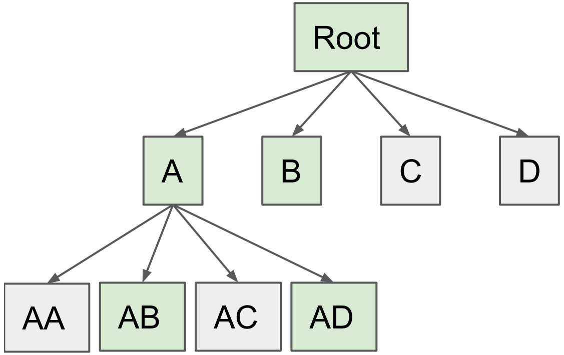

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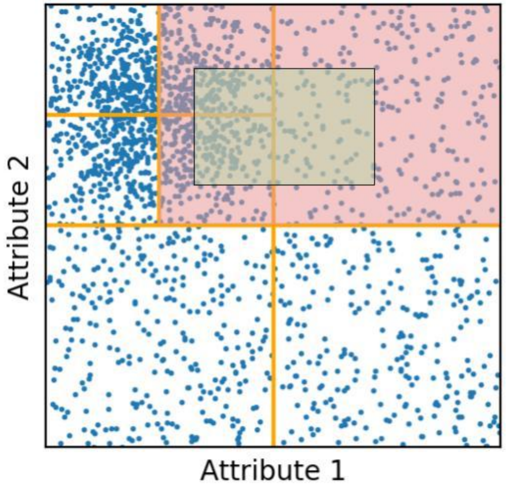

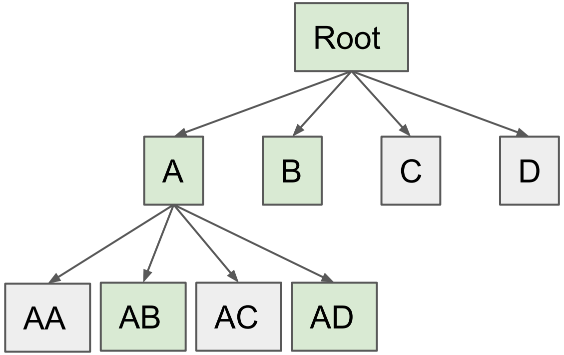

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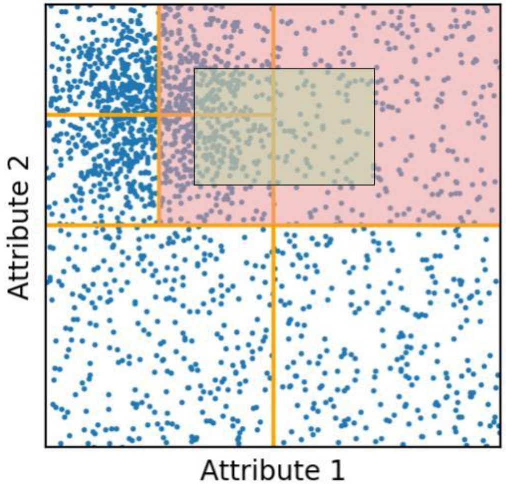
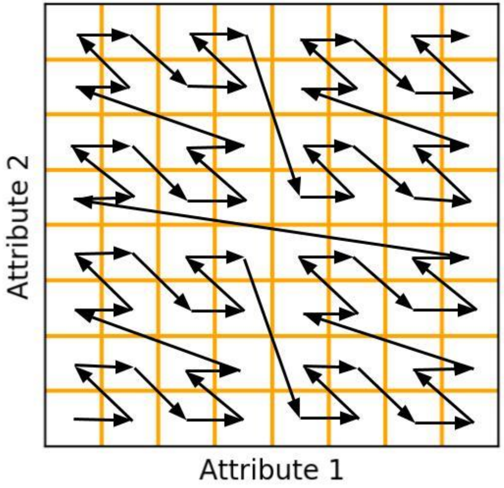
- Other tree-based indexes: R-tree, k-d tree
- Geospatial databases

Existing multi-dimensional indexes





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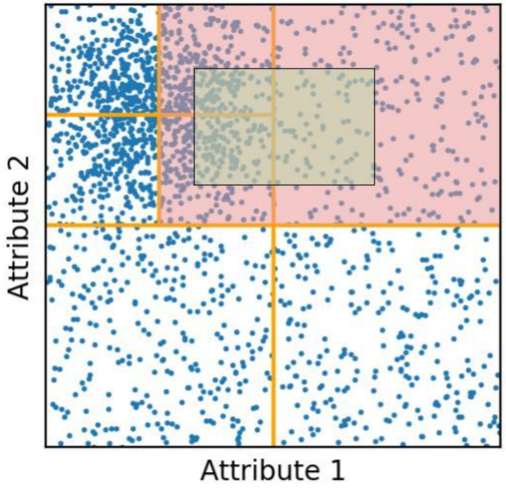

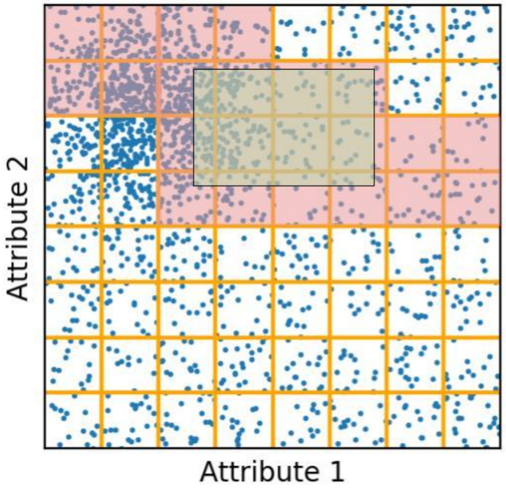

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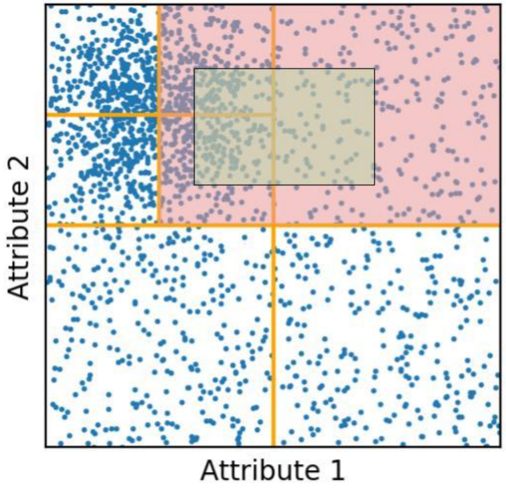

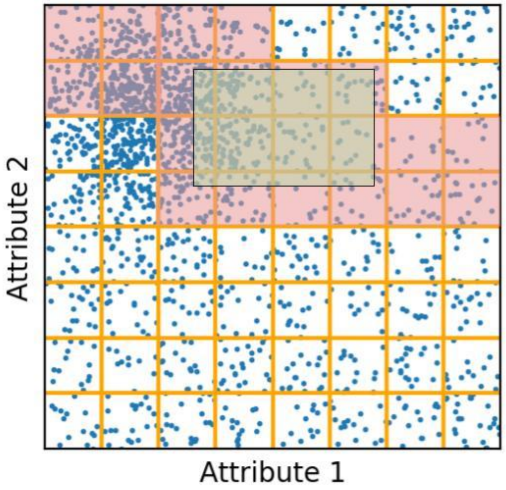

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- Other sort-order-based indexes: UB-tree
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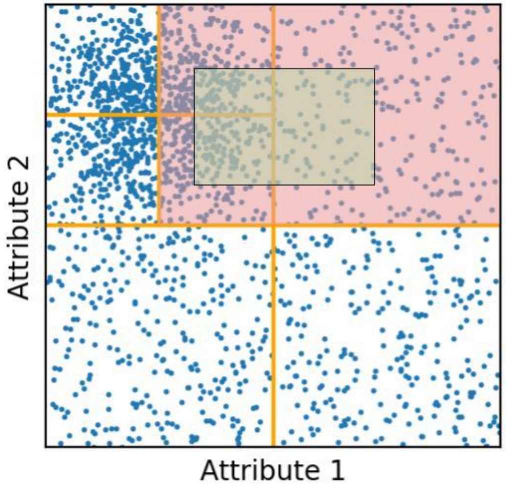

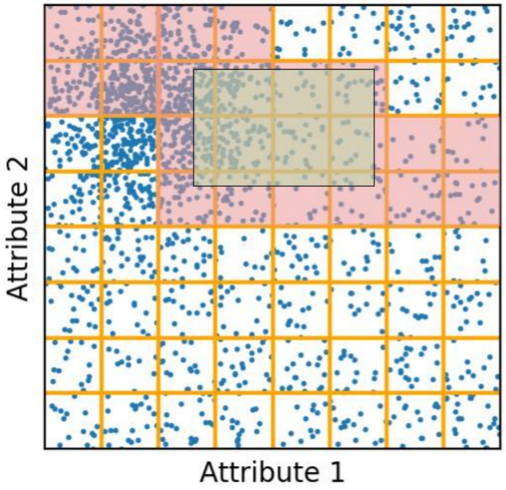

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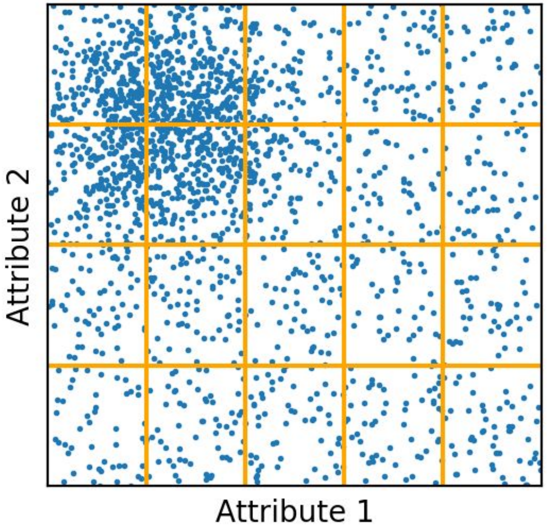
Drawbacks

- Difficult to create and maintain, requires DBA
- No index dominates all others
- Does not allow fined-grained customization

Our new index: *Flood*

- Multi-dimensional in-memory read-optimized index
- Grid-based layout



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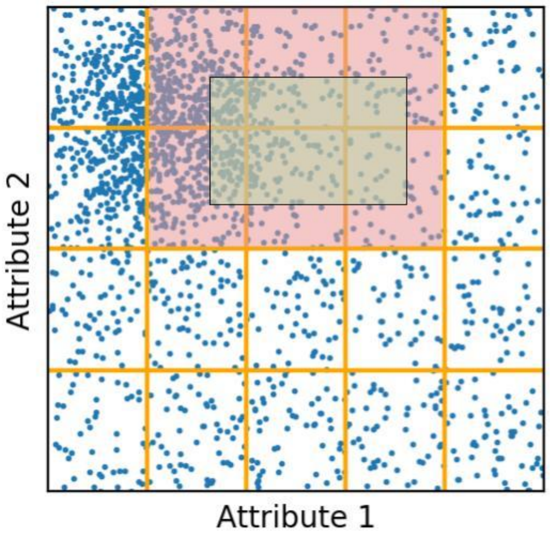

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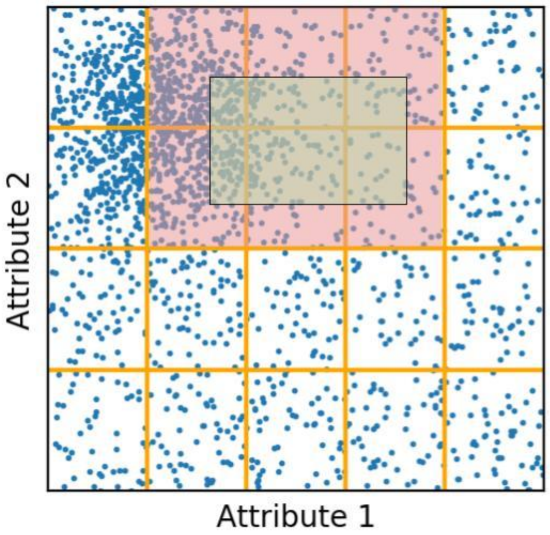

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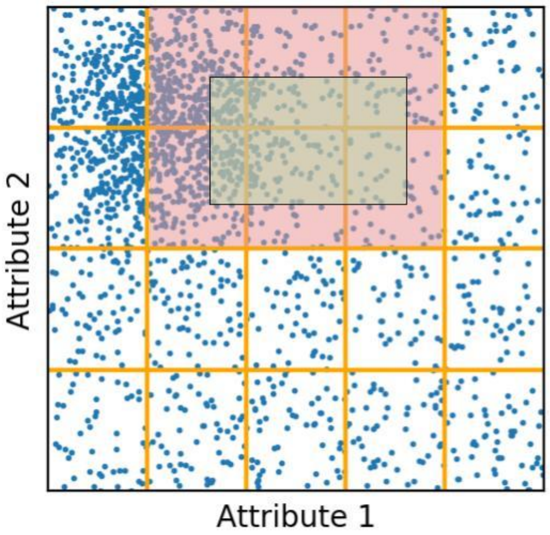
- Multi-dimensional in-memory read-optimized index
- Grid-based layout
  - Low index time (vs. tree-based index)
  - Has good number of tunable parameters
- Key idea: learning-based approach to jointly optimize the index structure and layout
  - Learn from data
  - Learn from queries



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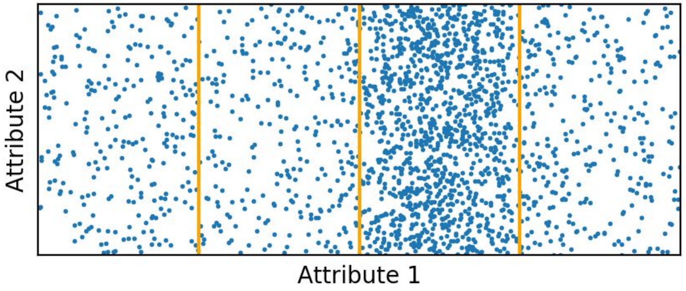

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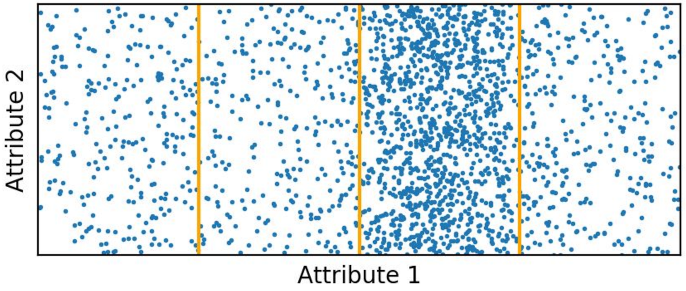
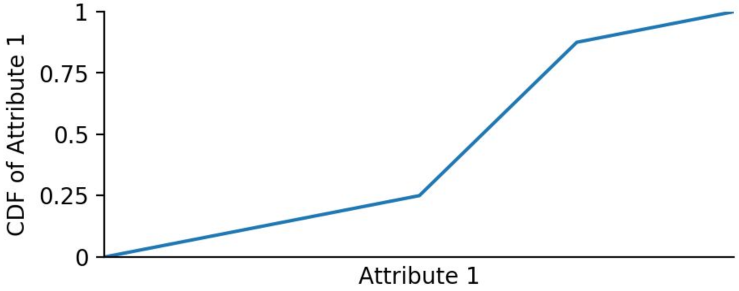
- Key idea: model the CDF of each dimension





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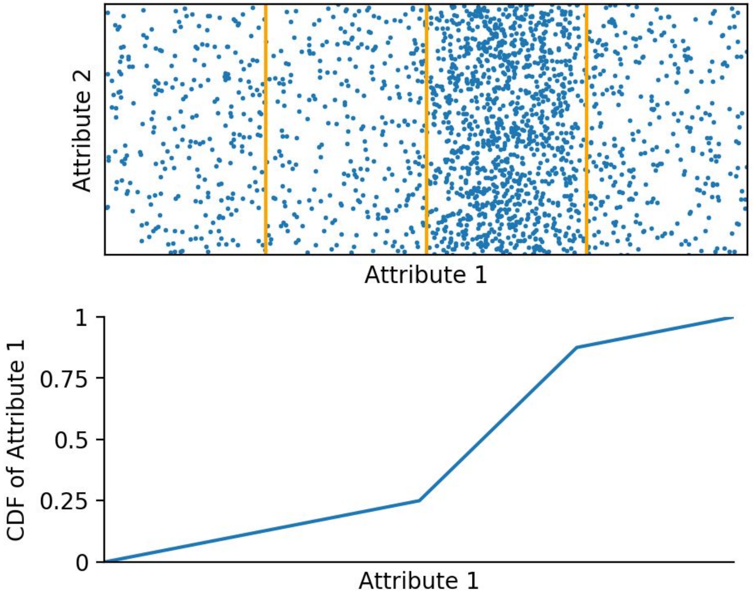
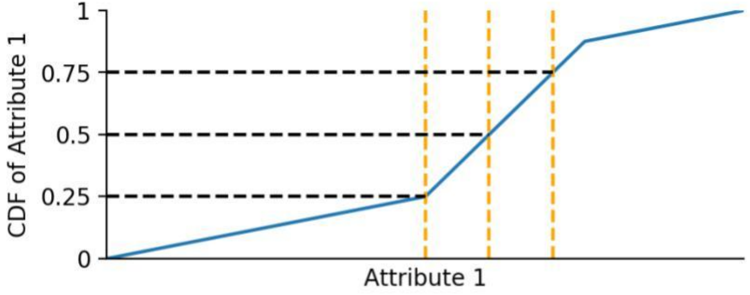
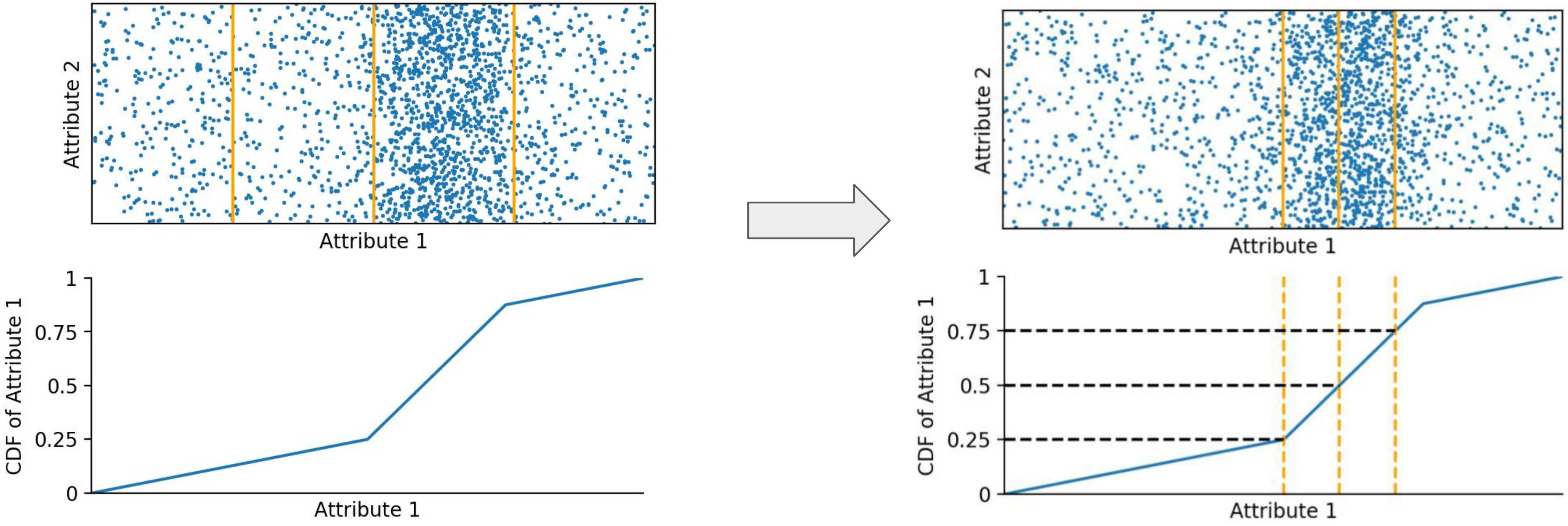




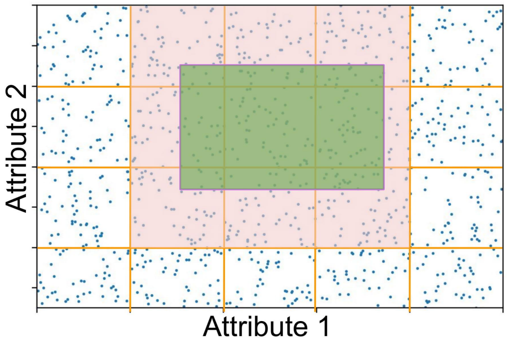
(1) Learning from the data: “flattening”

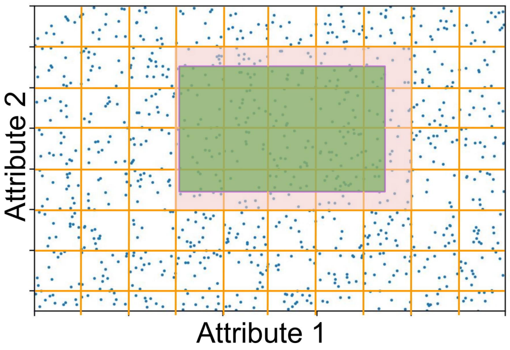
- Goal: uniform number of points per cell
- Key idea: model the CDF of each dimension



(2) Learning from the queries: optimizing layout

- Goal: find optimal number of partitions in each dimension





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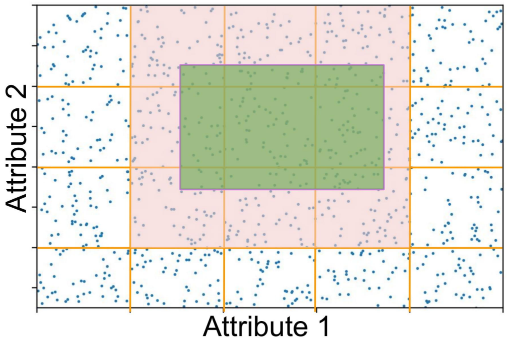

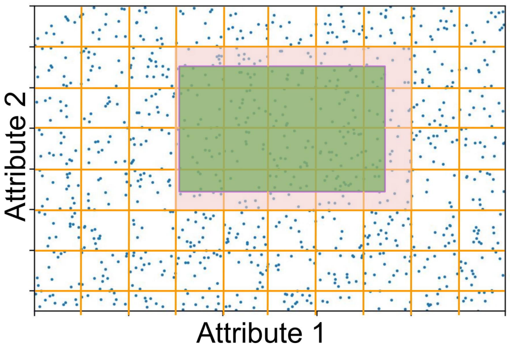

- Pro: Lower scan overhead
- Con: More cells

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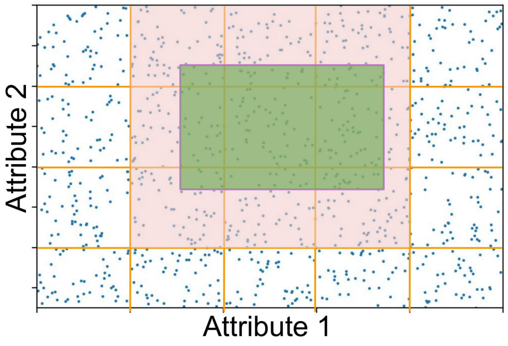
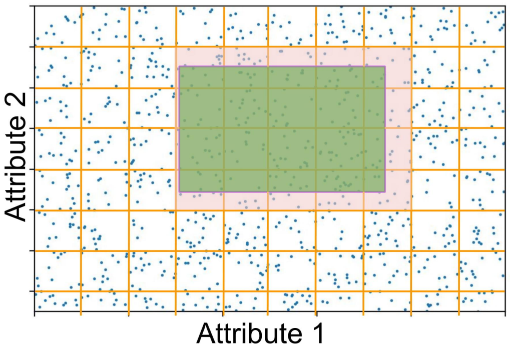


- Pro: Fewer cells
- Con: Higher scan overhead



- Pro: Lower scan overhead
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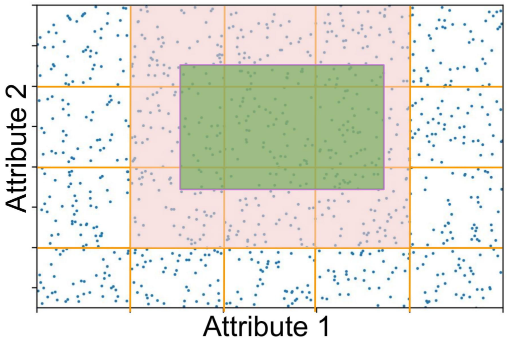
(2) Learning from the queries: optimizing layout

- Goal: find optimal number of partitions in each dimension
- Key idea: use cost model to predict query time

$$Time(D, q, L) = w_c N_c + w_s N_s$$

\# cells   # scanned points



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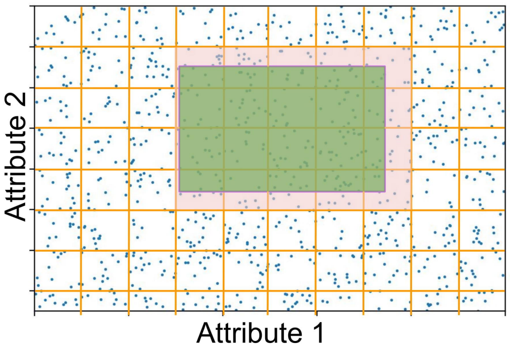

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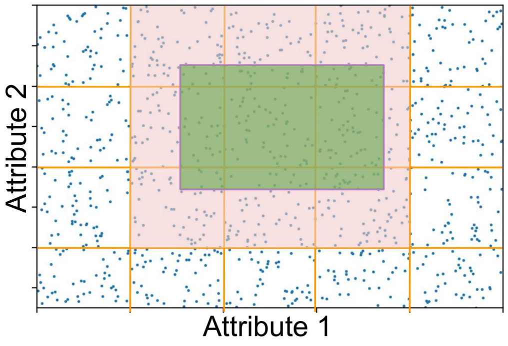
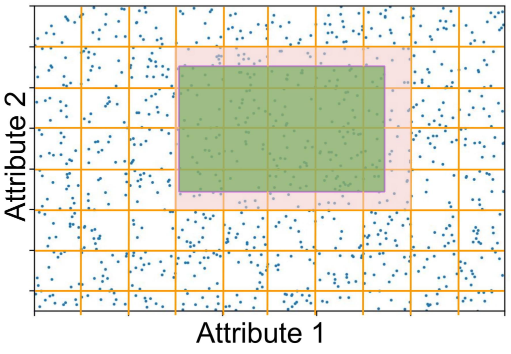
N_c: # cells N_s: # scanned points





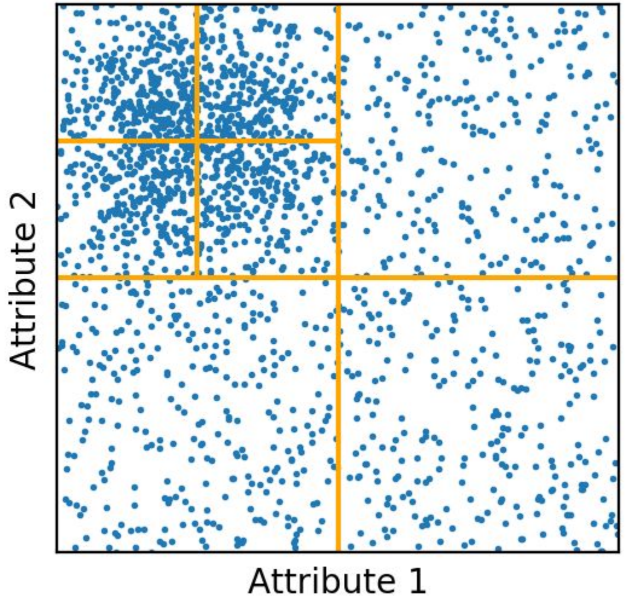
- Solve for layout with lowest average query time using gradient descent

- Pro: Fewer cells
- Con: Higher scan overhead

- Pro: Lower scan overhead
- Con: More cells

(2) Learning from the queries: optimizing layout

Quadtree



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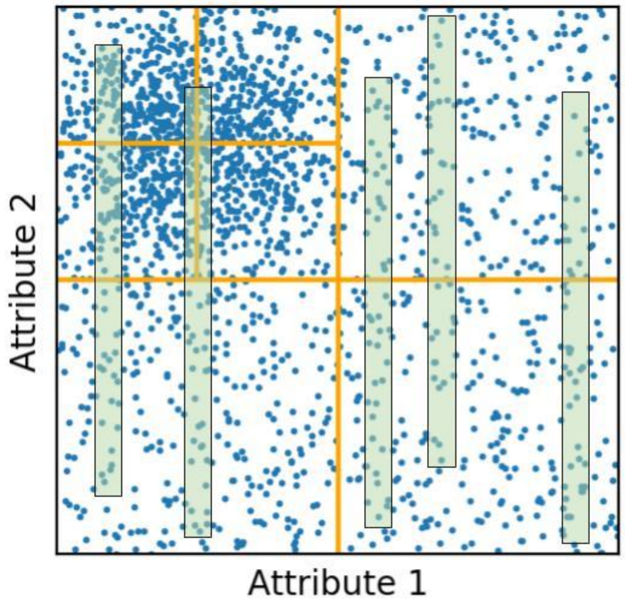

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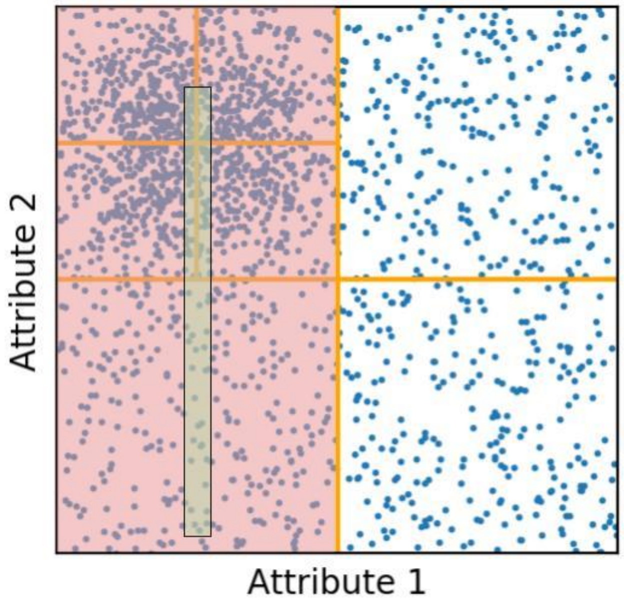
Quadtree



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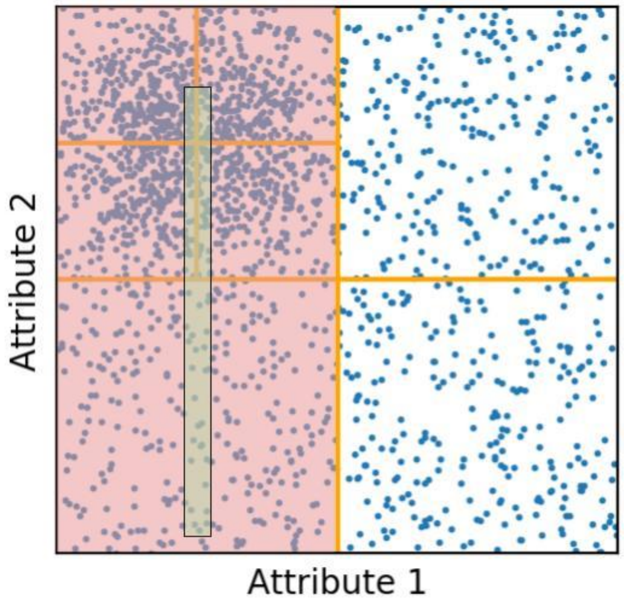
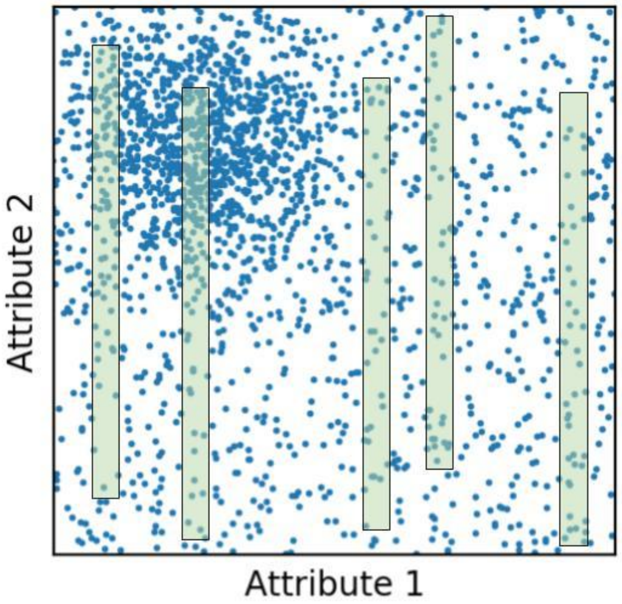


Flood



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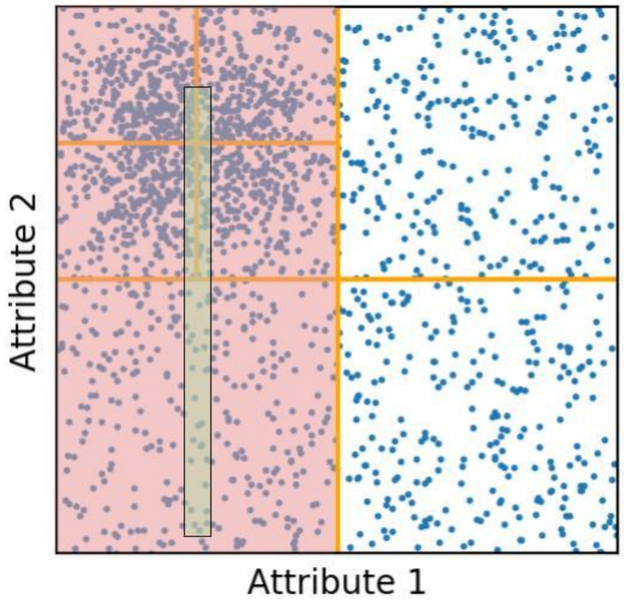
Quadtree



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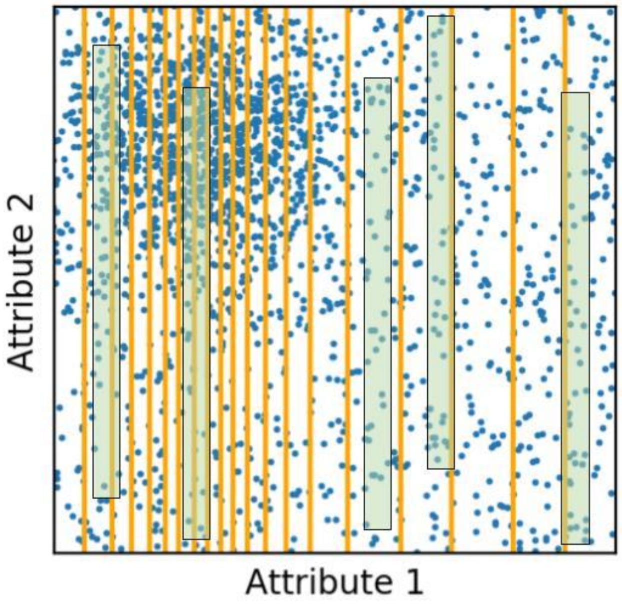

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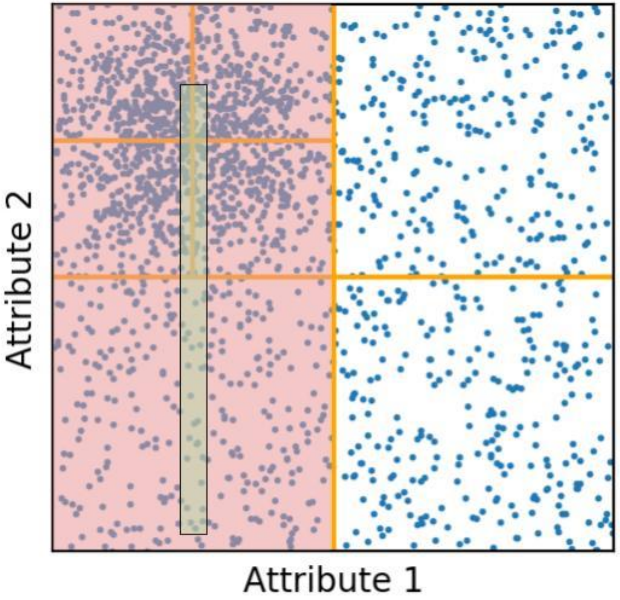
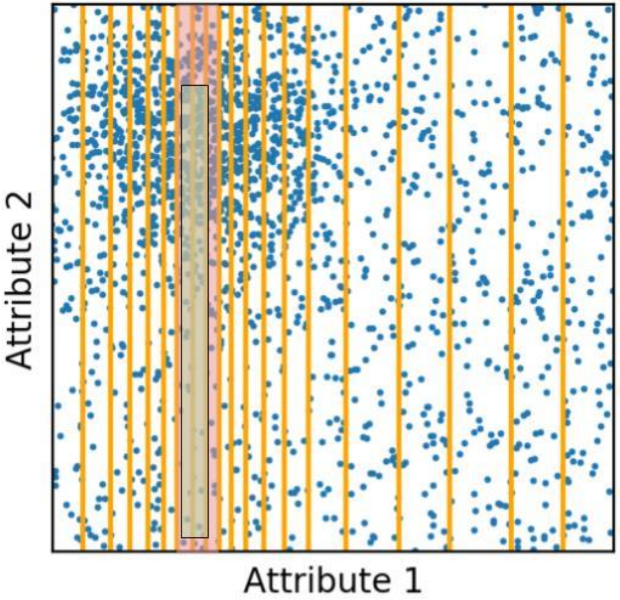


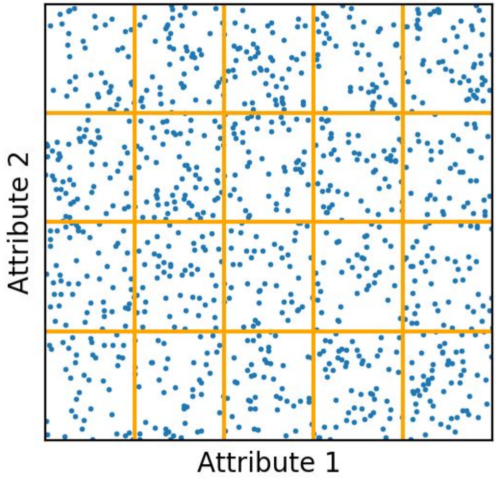
Flood



(3) Optimization: the “sort dimension”

<u>“Naive” grid</u>

- Grid over d dimensions
- Cells are ordered
- Within each cell, points are unsorted



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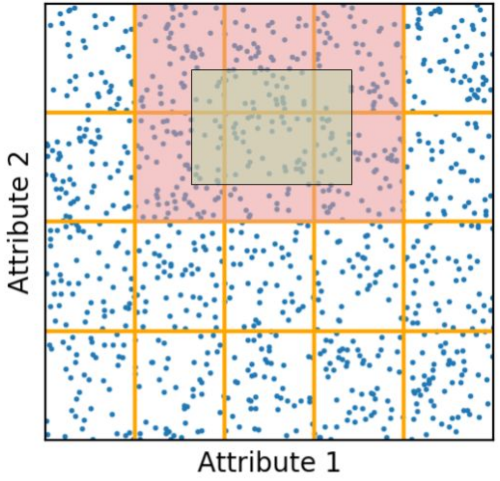

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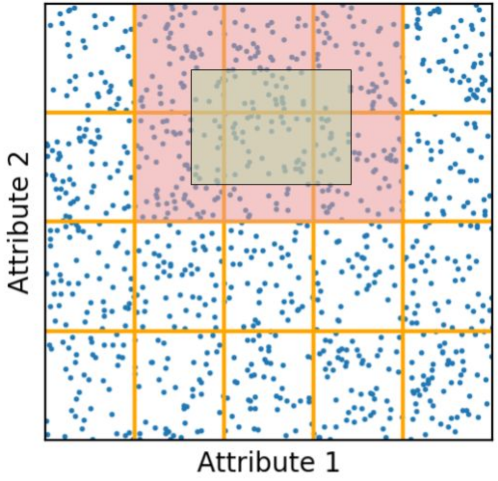
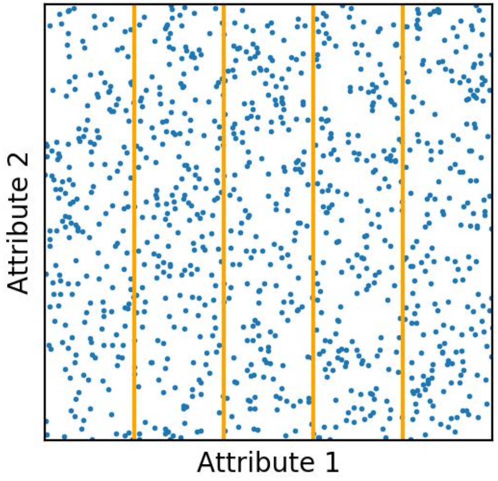


<u>Flood’s grid</u>

- Grid over d-1 dimensions
- Cells are ordered
- Within each cell, points are sorted by d-th dimension



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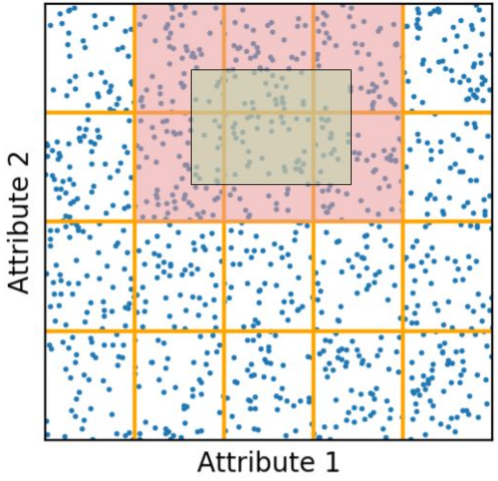

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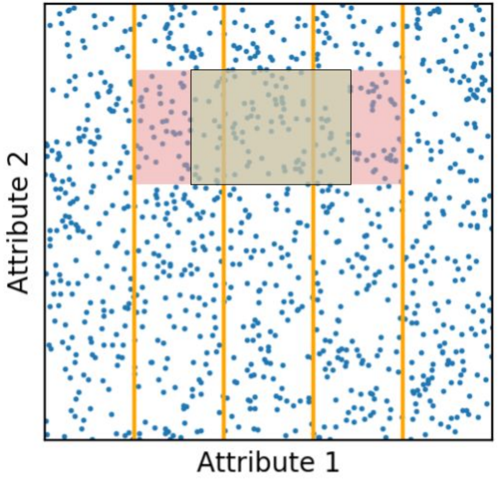

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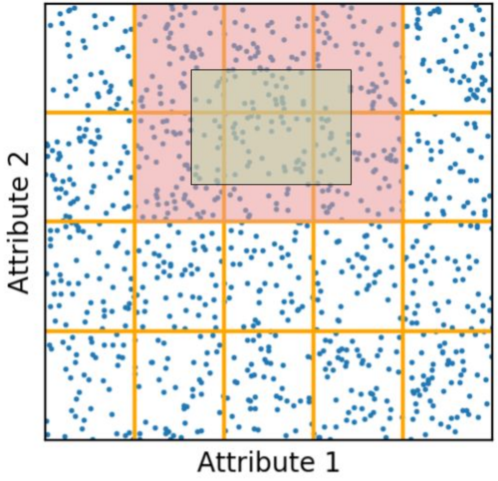

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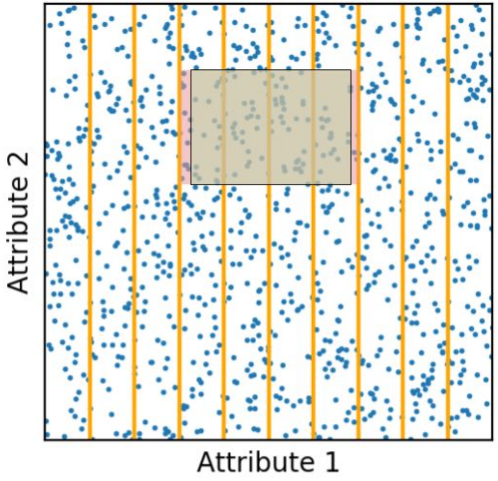
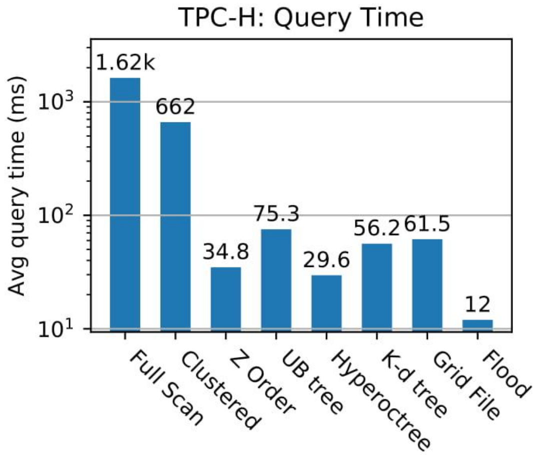
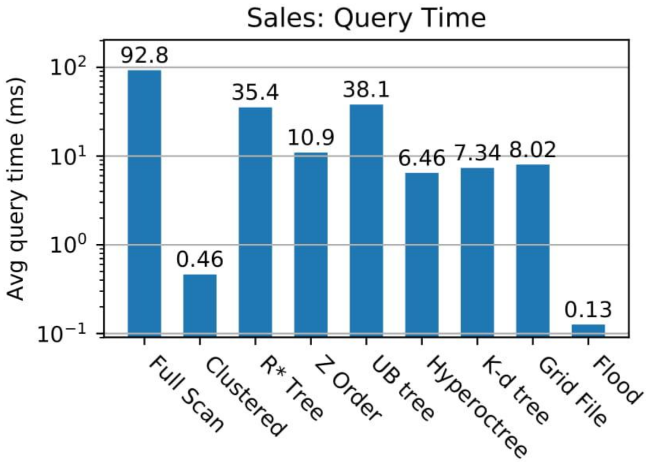


Results

- How does Flood compare to other indexes?
  - Faster than every other index





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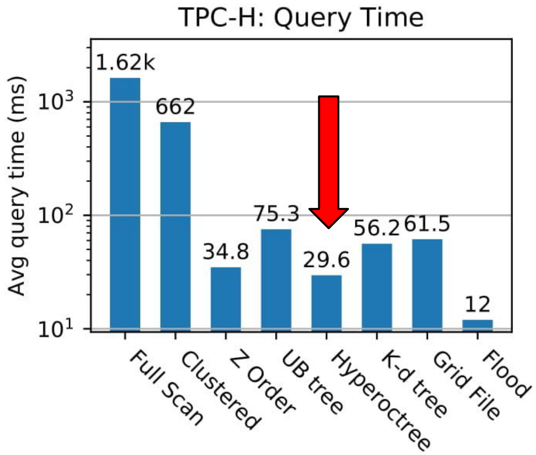
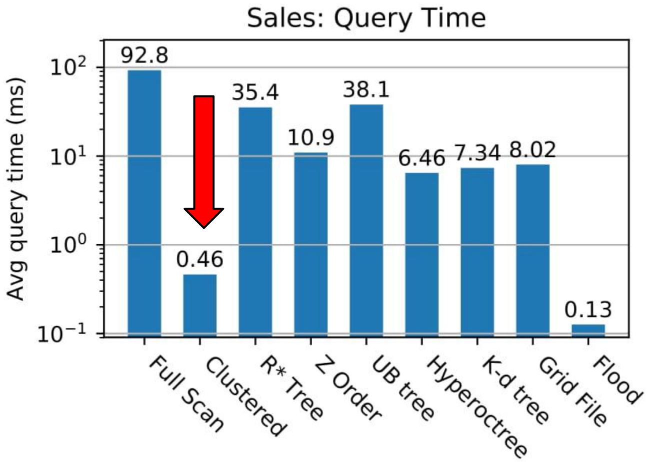
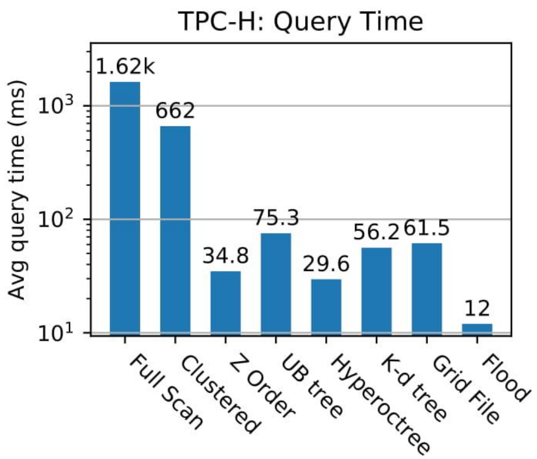




Results

- How does Flood compare to other indexes?
  - Faster than every other index
- Where does Flood's advantage come from?
  - Low scan overhead



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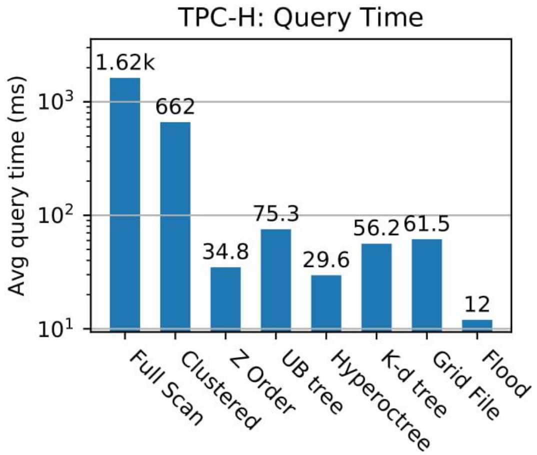
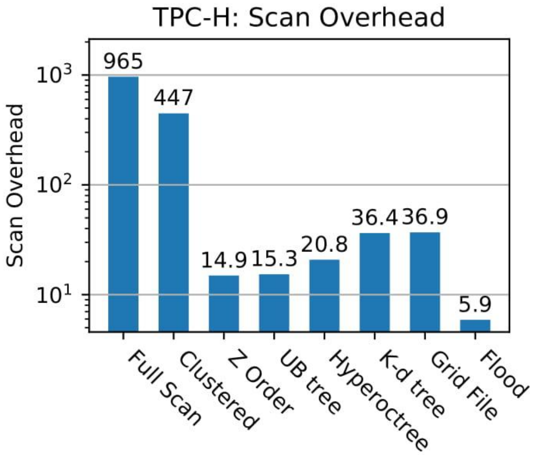
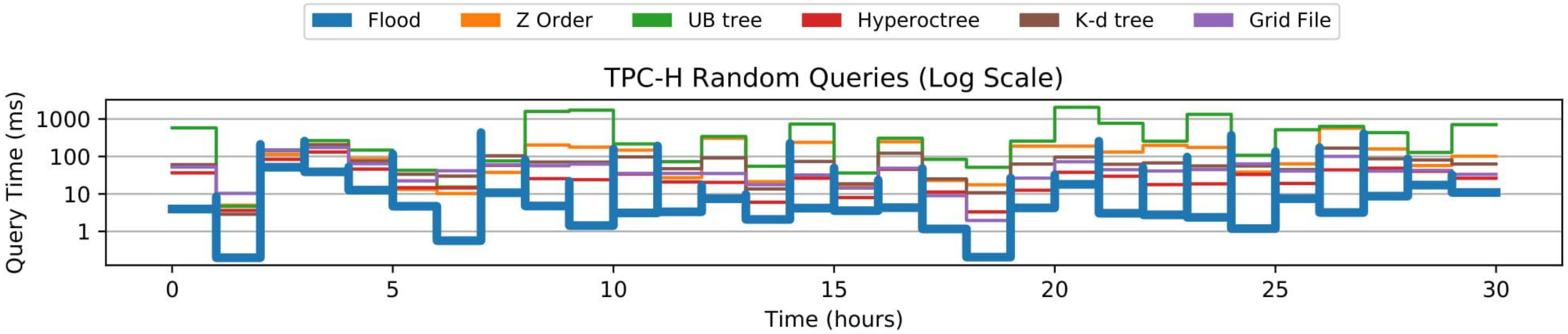




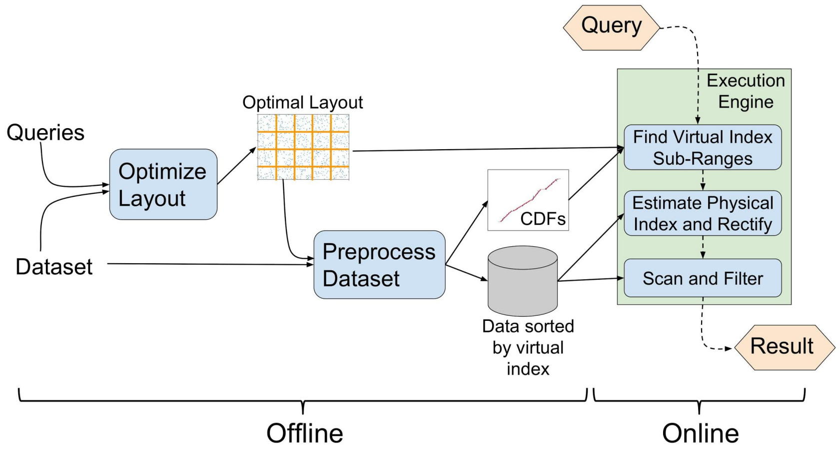
Results

- How does Flood compare to other indexes?
  - Faster than every other index
- Where does Flood's advantage come from?
  - Low scan overhead
- What if the query workload changes?
  - Flood can adapt



Summary of Flood

- Multi-dimensional in-memory read-optimized index
- Automatically learned based on data distribution and query workload
- Outperforms all other indexes by achieving lower scan overhead



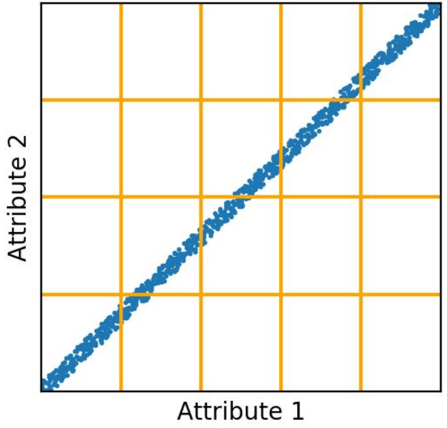
Outline

1. Completed work: Flood (SIGMOD 2020)
2. **Future work: column correlations, query skew, categorical attributes**

(1) Column correlations

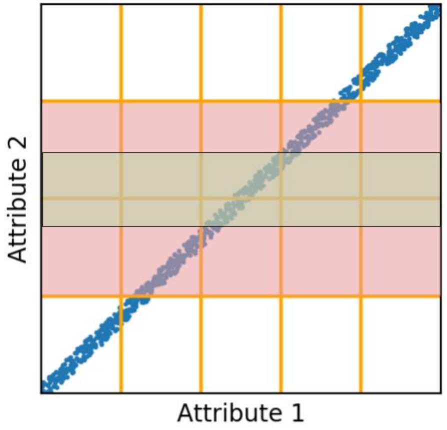
(1) Column correlations

Monotonic correlations



(1) Column correlations

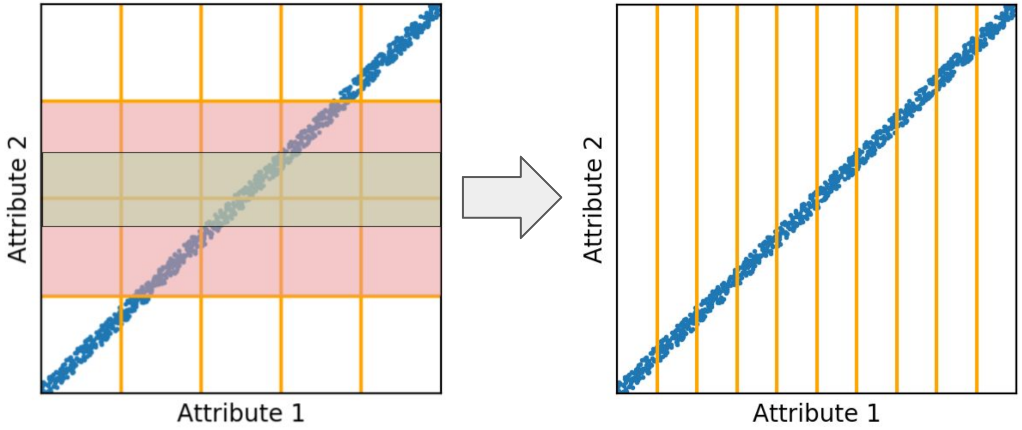
Monotonic correlations



(1) Column correlations

Monotonic correlations

- Possible solution: function-based mapping



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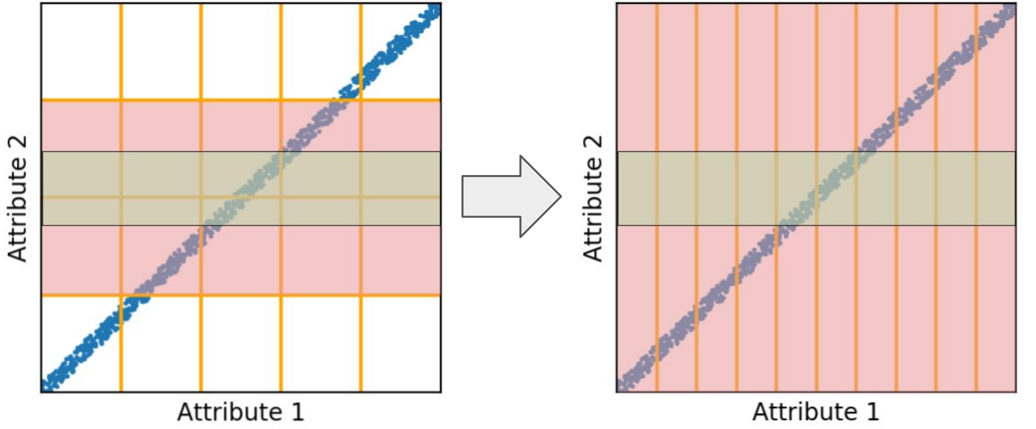

(1) Column correlations

Monotonic correlations

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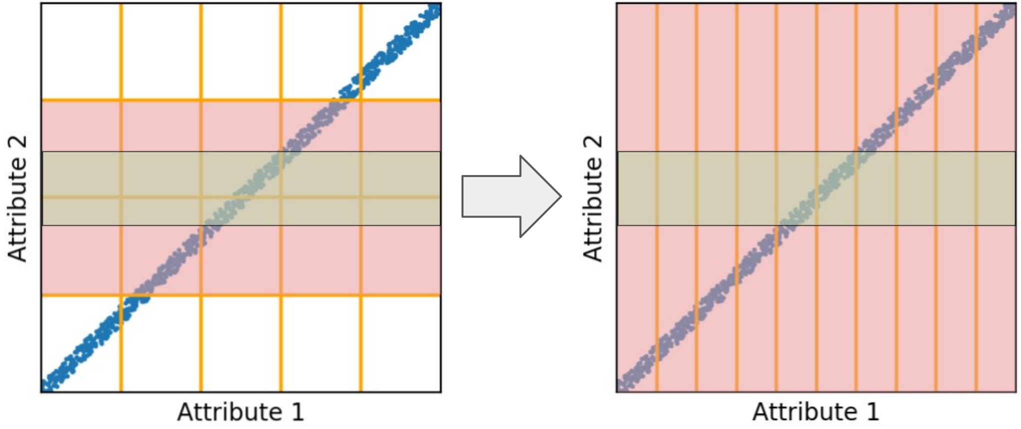
[A_min, A_max] = Fn([B_min, B_max]) + error



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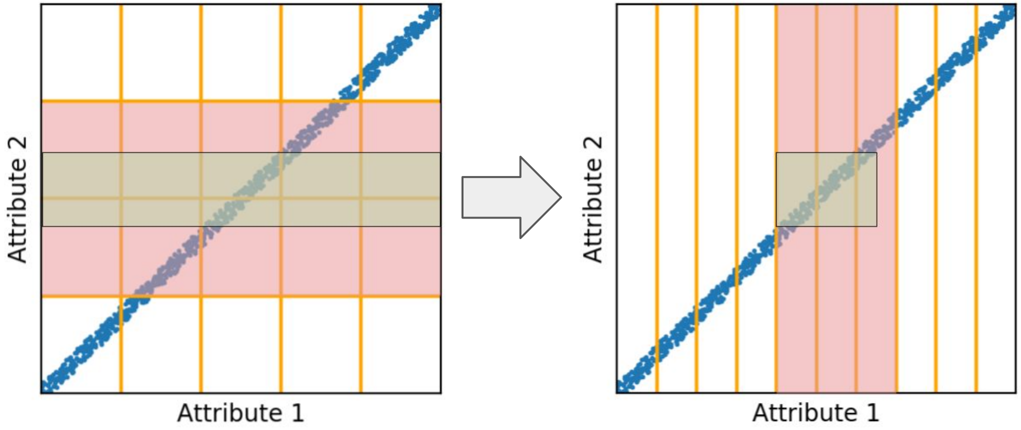

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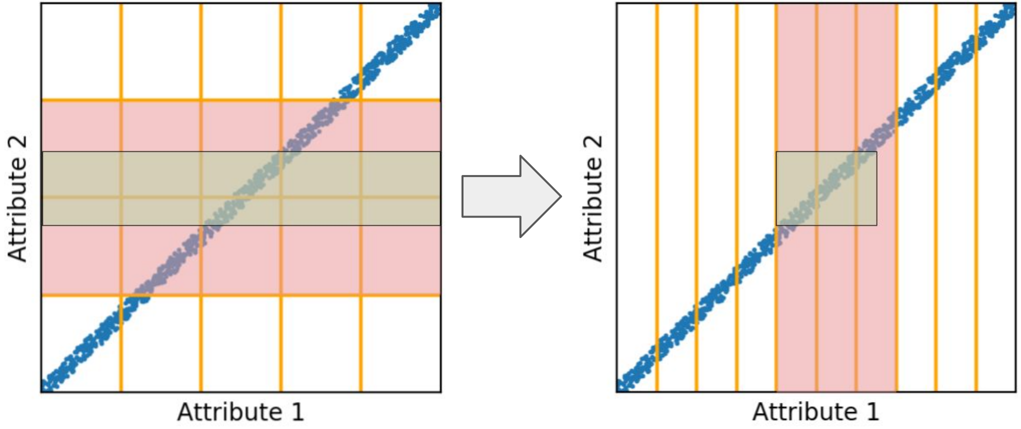
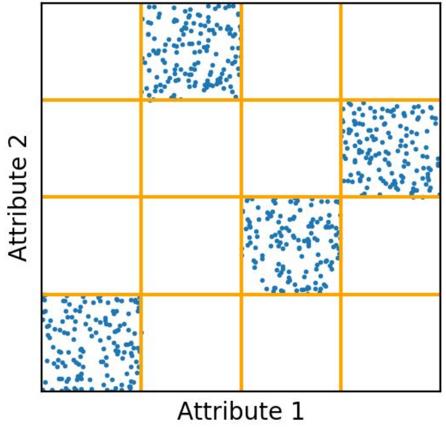


Hotspots



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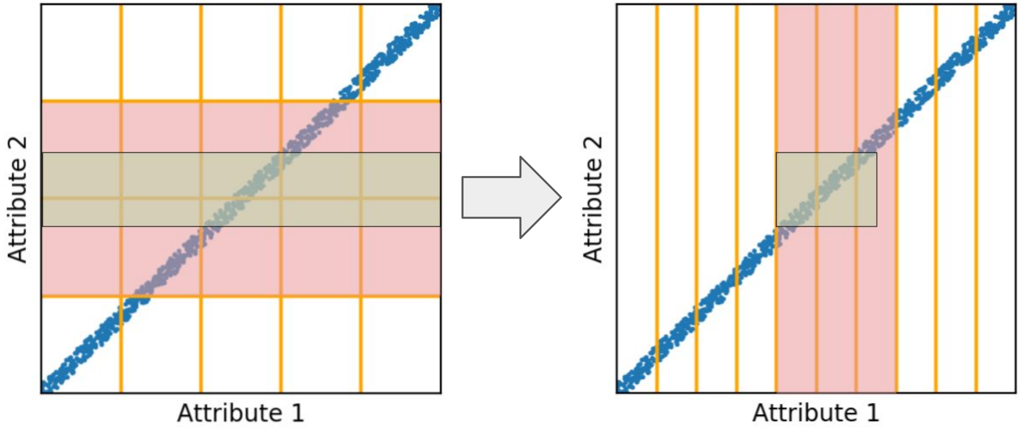
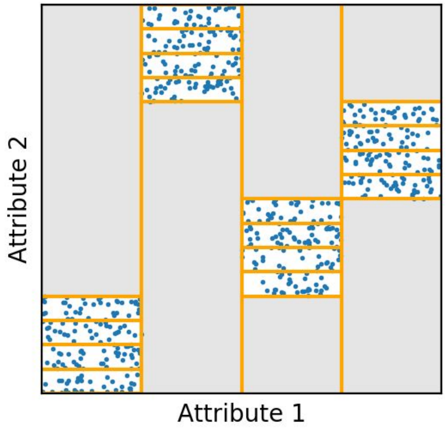


Hotspots

- Possible solution: “non-uniform grid”



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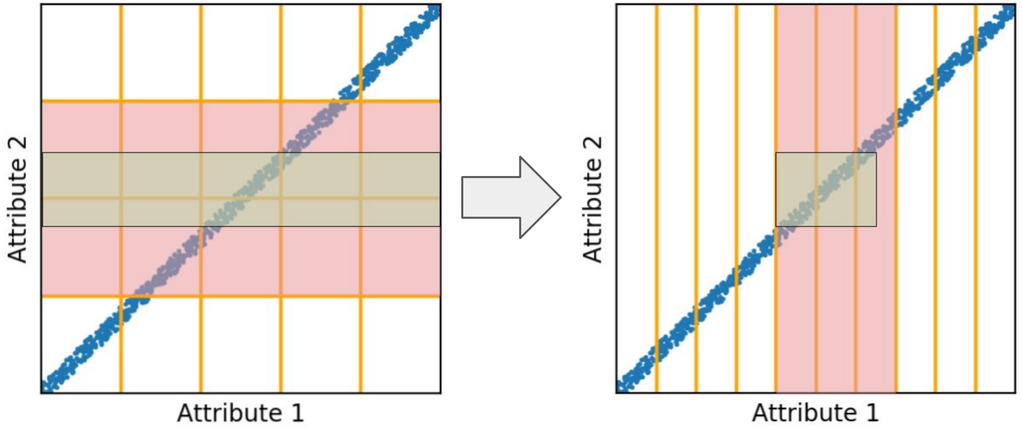

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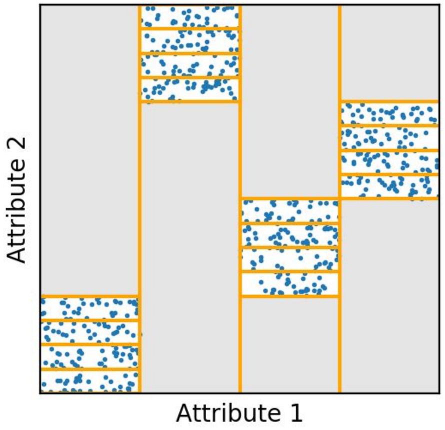

***Challenge**: combinatorial explosion of possible layouts*

(2) Query skew

- Queries “look different” in different regions
  - Selectivity
  - Frequency

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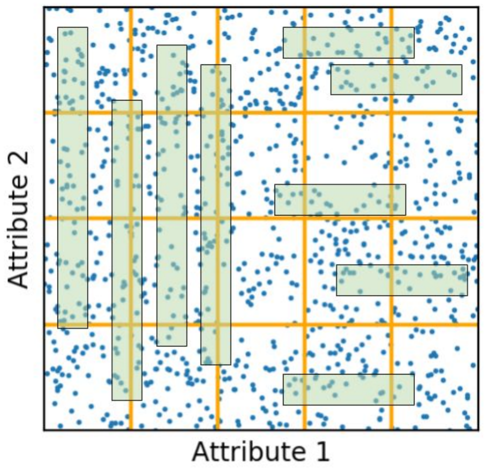

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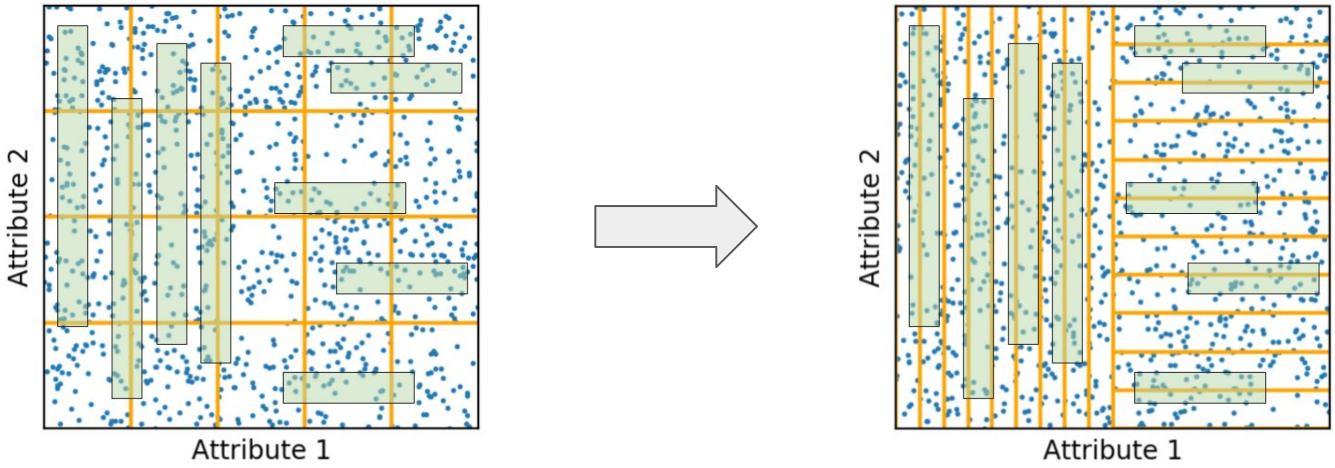
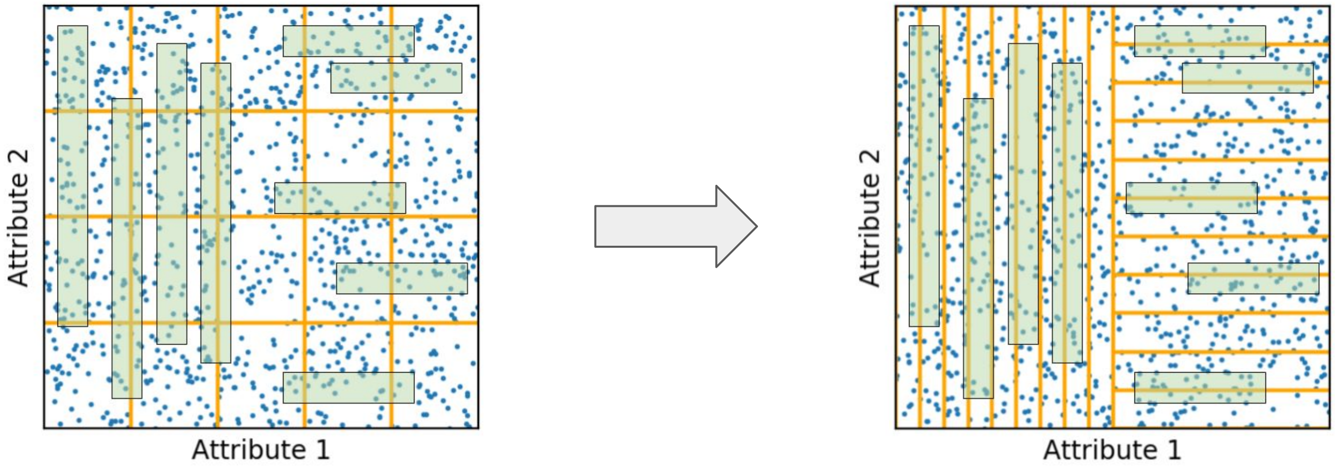


(2) Query skew

- Queries “look different” in different regions
  - Selectivity
  - Frequency
- Possible solution: “Flood tree”
  - Lightweight decision tree
  - Each leaf node is an instance of Flood



(3) Categorical attributes

- Opportunity 1: No semantic sort order
  - Order based on co-access frequency

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  - Direct mapping

rid	***State***	**City**	**...**
0	IL	Springfield	...
1	MA	Salem	...
2	MA	Springfield	...
3	MA	Salem	...
4	MO	Springfield	...
5	OR	Salem	...

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Secondary index

City	rid
Salem	1
Salem	3
Salem	5
Springfield	0
Springfield	2
Springfield	4

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City	rid
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Direct Mapping

City	State
Salem	{MA, OR}
Springfield	{IL, MA, MO}

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Direct Mapping

City	State
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Springfield	{IL, MA, MO}

Pro: smaller space

Con: higher scan overhead?

Summary of Future Work

- Column correlations
  - Solution: function-based mapping, non-uniform grid
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  - Solution: Flood tree
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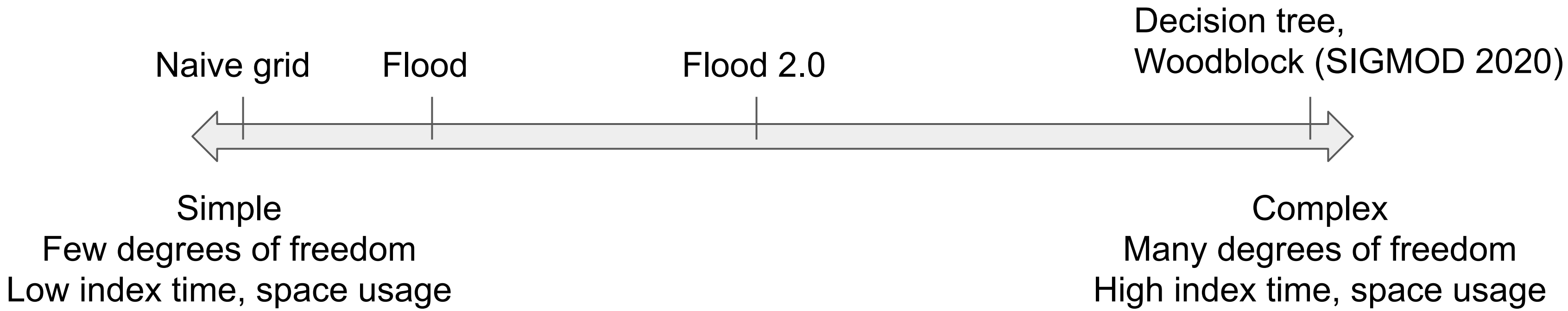

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