Finding Similar Items III

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Review of the previous lectures

- Mining of massive datasets.
- Evolution of database systems.
- Dimensional modeling.
- ETL and OLAP systems.
- Processing of massive datasets.
- Spark: MapReduce in practice.
- Approximate query processing.
- Finding similar items:
  - Minhash signatures
  - LSH

Outline

1. Motivation
2. Hash Structures for Multidimensional data
3. Tree Structures for Multidimensional Data
4. The curse of dimensionality
5. Summary

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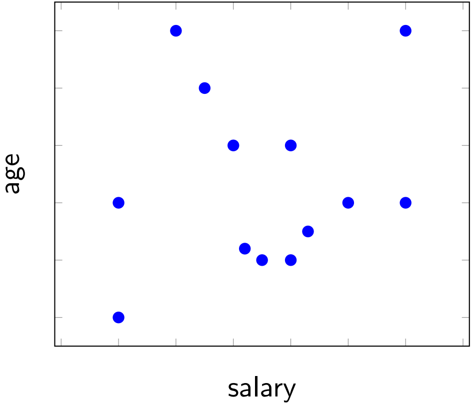
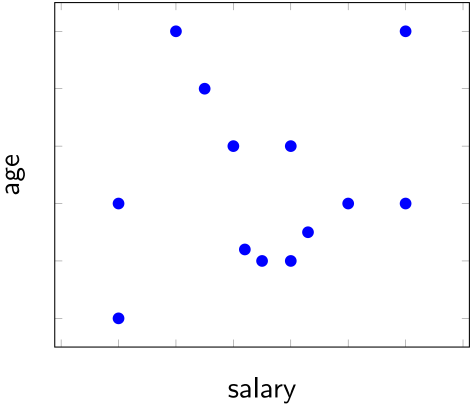
Multi-dimensional structures

- To speed up the **exact** search of **nearest neighbors** we need additional data structures.



Multi-dimensional structures

- To speed up the **exact** search of **nearest neighbors** we need additional data structures.
- Conventional index structures are one dimensional and are not suitable for multi-dimensional search queries.



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    where salary between 3500 and 5000
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  - **Where-am-I queries**: for a given point, where this point is located (in which shape).

Multi-dimensional queries with conventional indexes

- Consider a range query:

```
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  and age between 25 and 35
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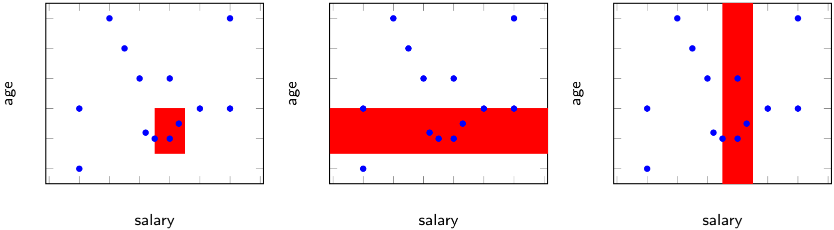

- To answer the query:
  - Scan along either index at once,
  - Intersect the elements returned by indexes
- This approach produces many false hits on each index!

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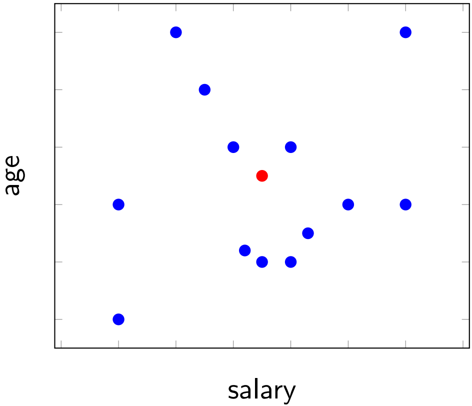

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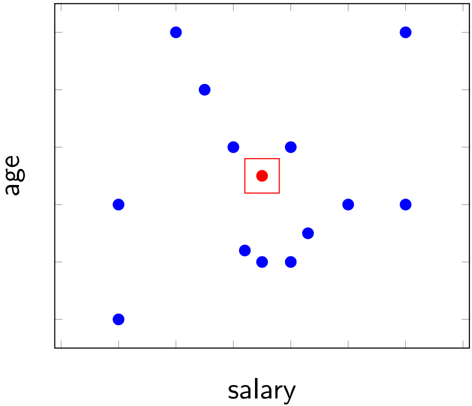

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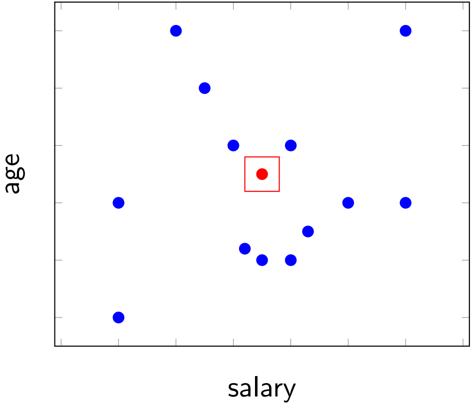

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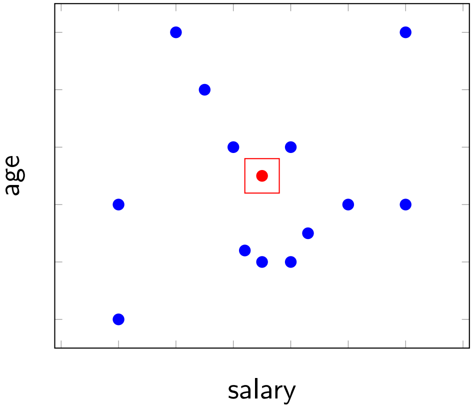

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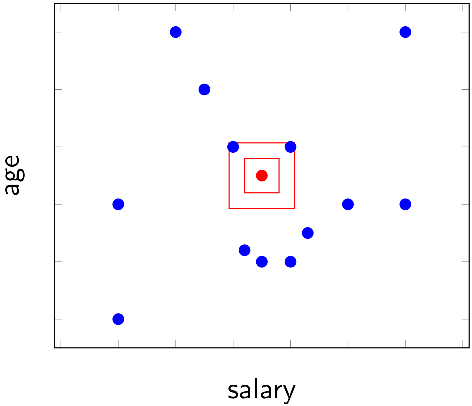

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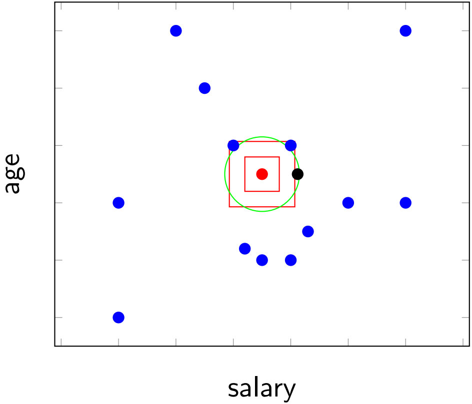

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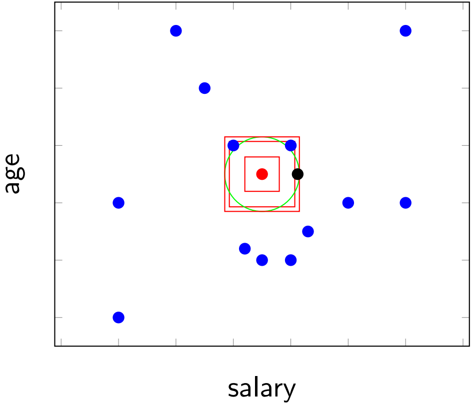

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  - If no points are found within that range, repeat with a larger range, until at least one point will be found.
  - Consider, whether there is the possibility that a closer point exists outside the range used. If so, increase appropriately the range once more and retrieve all points in the larger range to check.

Multidimensional index structures

- Hash-table-like approaches
- Tree-like approaches

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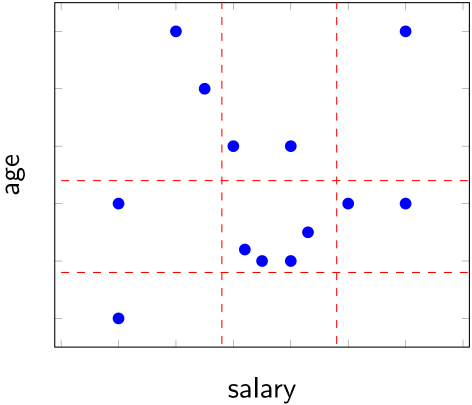
Grid files

- The space of points partitioned in a grid.



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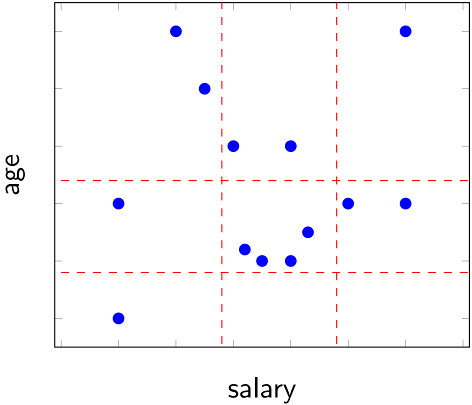

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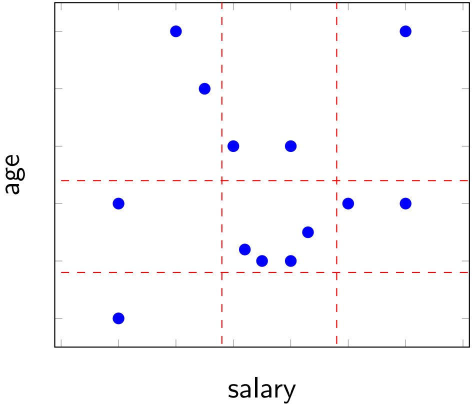

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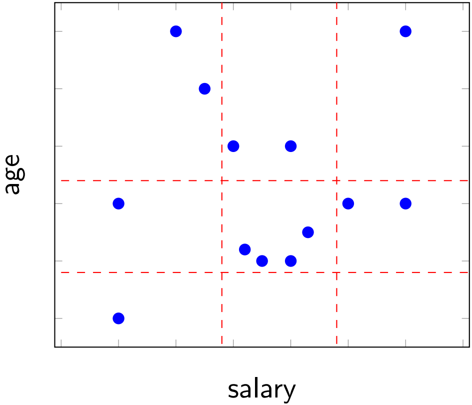

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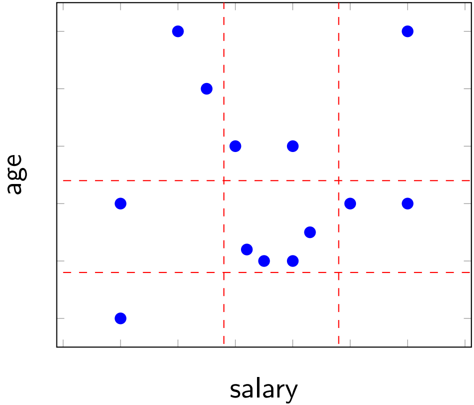
- Each region corresponds to a bucket.



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        - Reorganize the structure by adding or moving the grid lines.

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- If the matrix is sparse treat it as a relation whose attributes are corners of the nonempty buckets and a final attribute representing the pointer to the bucket.

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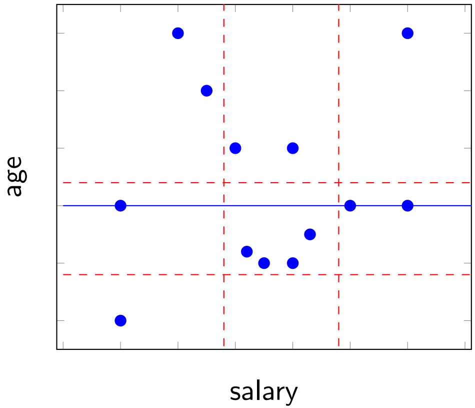
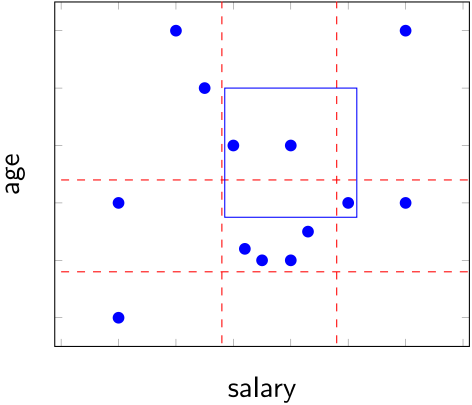
- Partial-match queries: We need to look at all the buckets in dimension not specified in the query



Grid files

- Range queries: We need to look at all the buckets that cover the rectangular region defined by the query



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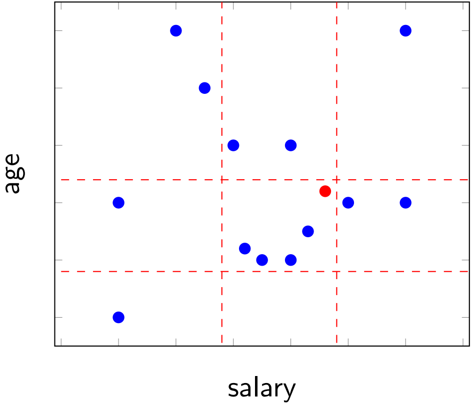

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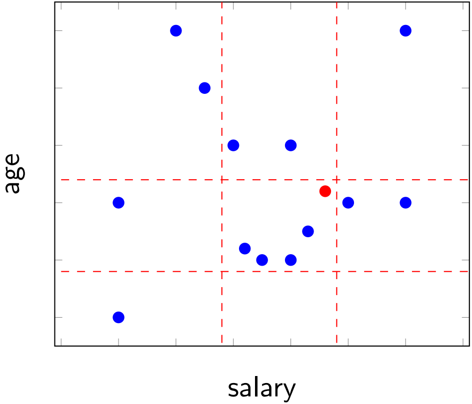

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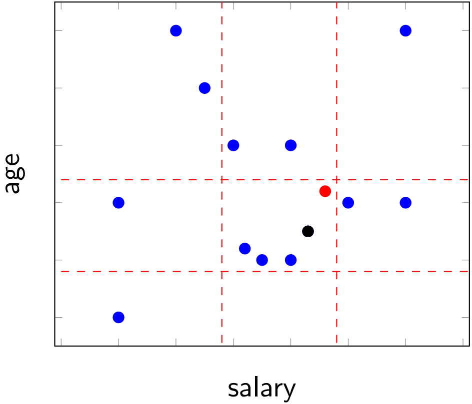

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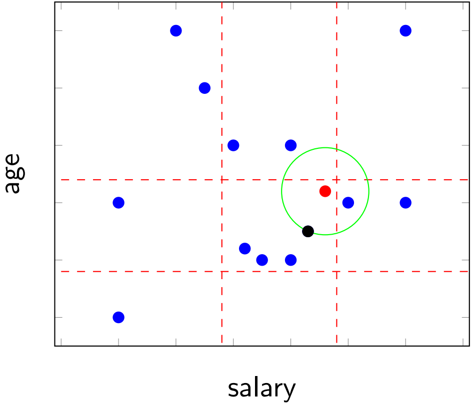
  - Check points in the adjacent buckets if the distance between the query point and the border of its bucket is less than the distance from the candidate.



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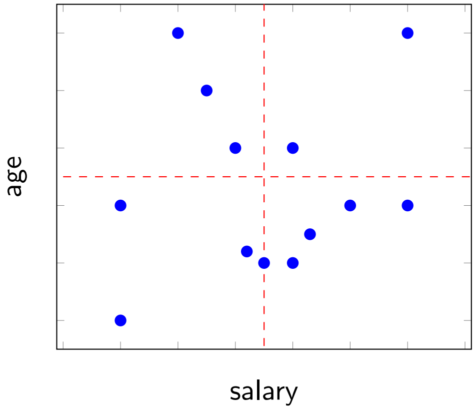
  - A query `SELECT SUM(B) FROM R WHERE A=5` is covered by the index.
  - But for a query `SELECT SUM(A) FROM R WHERE B=5` records with $B = 5$ are scattered throughout index.

Quad trees

- Quad tree splits the space into 2^d equal sub-squares (cubes), where d is number of attributes.



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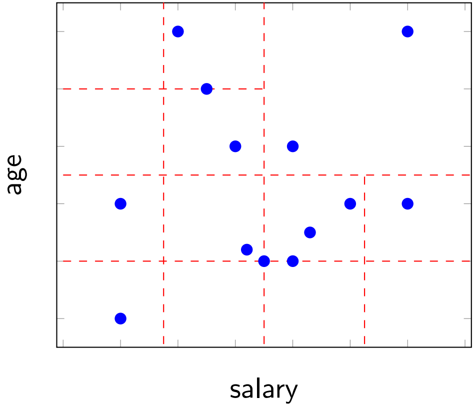
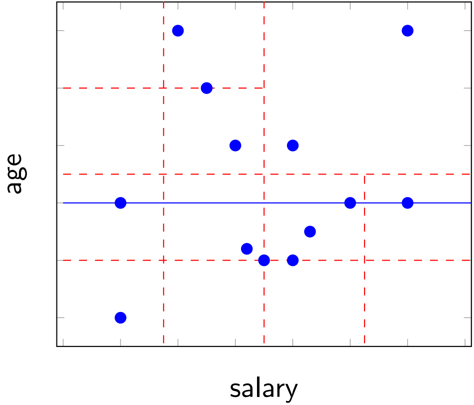
- Repeat the partition until: only one pixel left; only one point left; only a few points left.



Quad trees

- Partial-match queries: We need to look at all cubes that intersect the condition of queries.



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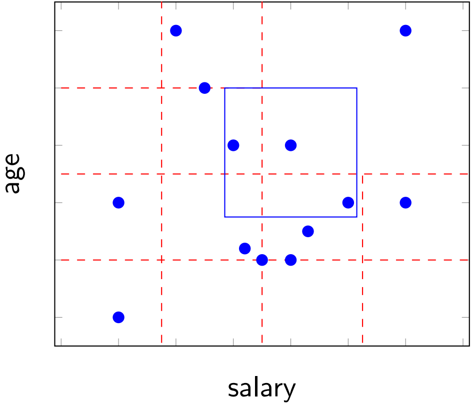
- Range queries: We need to look at all cubes that cover the region defined by the query



Quad trees

- Nearest neighbor search for point q:

```
Put  the root on the priority queue with the min distance = 0
Repeat {
    Pop the next node T from the priority queue
        if (min distance > r ) {
            the candidate is the nearest neighbor;
            break;
        }
        if (T is leaf) {
            examine point(s) in T and find the candidate;
            update r to be distance between q and the candidate;
        }
        else {
            for each child C of T {
                if( C intersects with the ball of radius r around q) {
                    compute the min distance from q to any point in C;
                    add C to the priority queue with the min distance;
                }
            }
    }
}
```

- Start search with $r = \infty$.
- Whenever a candidate point is found, update r.
- Only investigate nodes with respect to current r.

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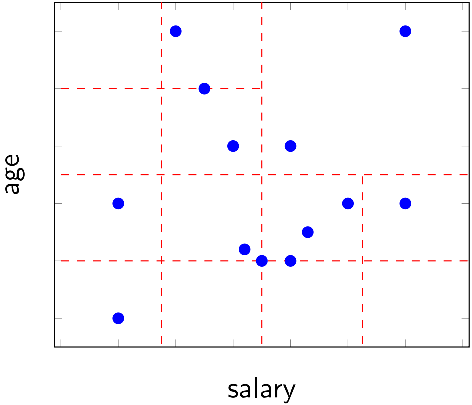

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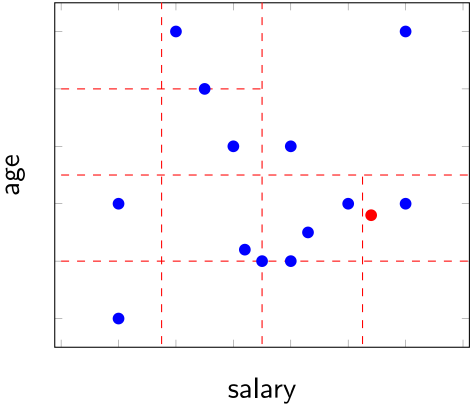

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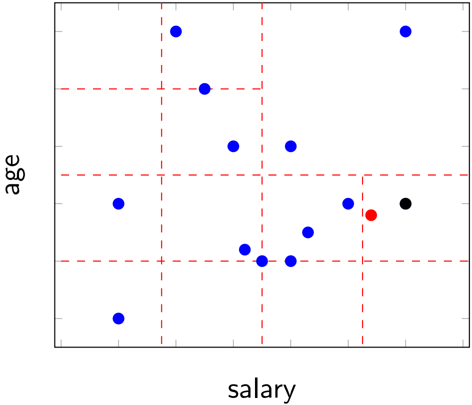

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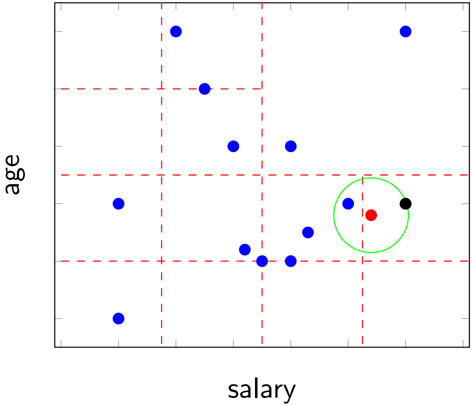

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- Similar operations as for quad trees.
- Advantages: no (or less) empty spaces, only linear space.

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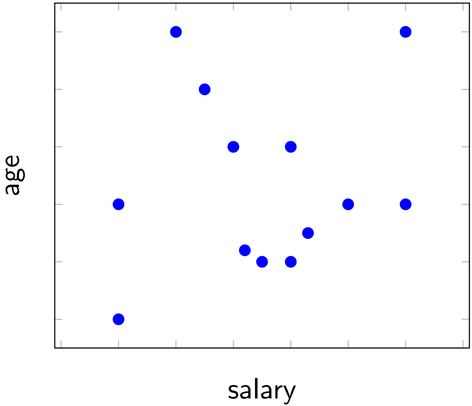

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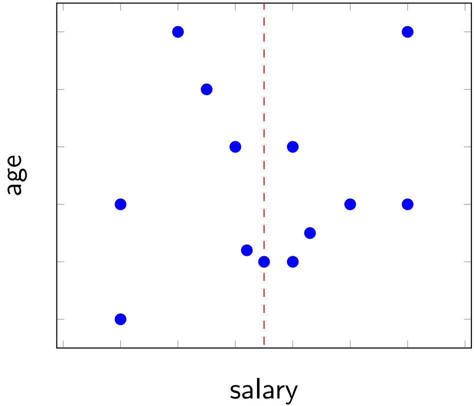
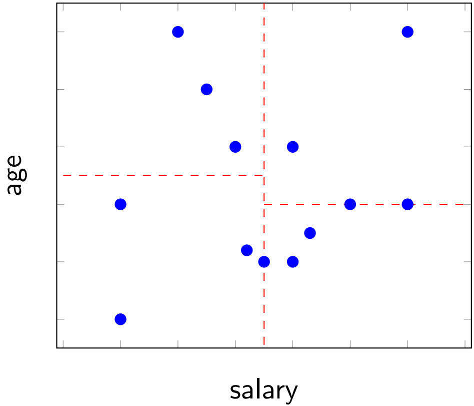
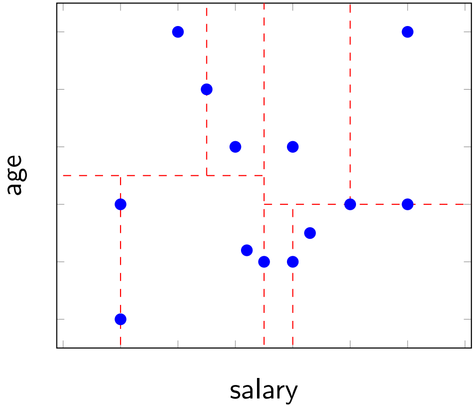


kd-trees



kd-trees



Additional aspects of multidimensional indexes

- Adaptation to secondary storage.
- Balancing of the tree structures.
- Storing data only in leaves or in internal nodes and leaves.
- Many variations of the structures presented.

Outline

1 Motivation

2 Hash Structures for Multidimensional data

3 Tree Structures for Multidimensional Data

4 The curse of dimensionality

5 Summary

Problems with nearest neighbor search

- Exponential query time
  - The query time is from $\log n$ to $\mathcal{O}(n)$, but can be exponential in d.
  - Tree structures are good when $n \gg 2^d$.
  - The curse of dimensionality.
- Solution: Approximate nearest neighbor search.

The curse of dimensionality

- In high-dimensional spaces almost all pairs of points are equally far away from one another.
- In other words, the neighborhood becomes very large
- **Example**:
  - Task: Find the 5-nearest neighbor in the unit hypercube.
  - There are 5000 points uniformly distributed.
  - The query point: The origin of the space.
  - For 1-dimensional hypercube (line), the average distance to capture all 5 nearest neighbors is $5/5000 = 0.001$.
  - For 2 dimensional hypercube, we must go $\sqrt{0.001}$ in each direction to get a square that contains 0.001 of the volume.
  - In general, for d dimensions, we must go $(0.001)^{\frac{1}{d}}$.
  - For instance, for $d = 20$, it is 0.707, and for $d = 200$, it is 0.966.

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Summary

- Multi-dimensional index structures:
  - Applications: partial match queries, range queries, where-am-I-queries, nearest-neighbor search.
  - Approaches: hash table-based, tree-like structures.
  - Work good for low-dimensional problems – curse of dimensionality.

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