

Module 8: Data Structures for Multi-Dimensional Data

CS 240 - Data Structures and Data Management

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Based on lecture notes by many previous cs240 instructors

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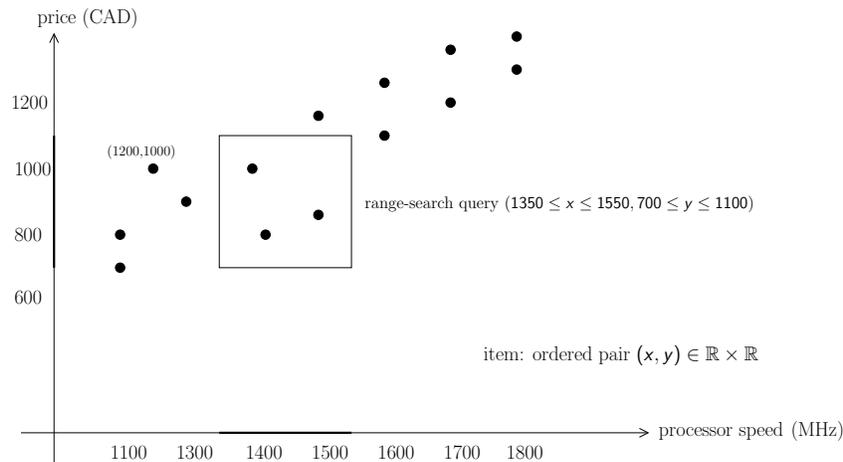
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Multi-Dimensional Data

- Various applications
 - ▶ Attributes of a product (laptop: price, screen size, processor speed, RAM, hard drive, ...)
 - ▶ Attributes of an employee (name, age, salary, ...)
- Dictionary for multi-dimensional data
 - A collection of d -dimensional items
 - Each item has d **aspects** (coordinates): $(x_0, x_1, \dots, x_{d-1})$
 - Operations: insert, delete, **range-search query**
- (Orthogonal) Range-search query: specify a range (interval) for certain aspects, and find all the items whose aspects fall within given ranges.
 - Example: laptops with screen size between 11 and 13 inches, RAM between 8 and 16 GB, price between 1,500 and 2,000 CAD

Multi-Dimensional Data

- Each item has d **aspects** (coordinates): $(x_0, x_1, \dots, x_{d-1})$
- Aspect values (x_i) are numbers
- Each item corresponds to a point in d -dimensional space
- We concentrate on $d = 2$, i.e., points in Euclidean plane



One-Dimensional Range Search

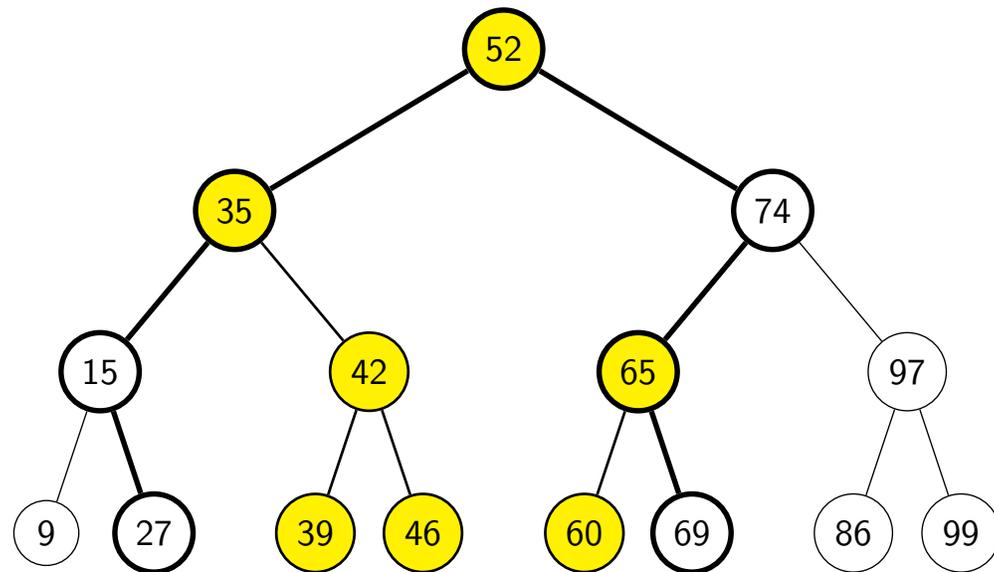
- **First solution:** ordered arrays
 - ▶ Running time:
 - ▶ Problem: does not generalize to higher dimensions
- **Second solution:** balanced BST (e.g., AVL tree)

```
BST-RangeSearch( $T, k_1, k_2$ )
 $T$ : A balanced search tree,  $k_1, k_2$ : search keys
Report keys in  $T$  that are in range  $[k_1, k_2]$ 
1.   if  $T = nil$  then return
2.   if  $key(T) < k_1$  then
3.       BST-RangeSearch( $T.right, k_1, k_2$ )
4.   if  $key(T) > k_2$  then
5.       BST-RangeSearch( $T.left, k_1, k_2$ )
6.   if  $k_1 \leq key(T) \leq k_2$  then
7.       BST-RangeSearch( $T.left, k_1, k_2$ )
8.       report  $key(T)$ 
9.       BST-RangeSearch( $T.right, k_1, k_2$ )
```

Range Search example

$BST\text{-}RangeSearch(T, 30, 65)$

Nodes either on boundary, inside, or outside.



Note: Not every boundary node is returned.

One-Dimensional Range Search

- P_1 : path from the root to a leaf that goes right if $k < k_1$ and left otherwise
- P_2 : path from the root to a leaf that goes left if $k > k_2$ and right otherwise
- Partition nodes of T into three groups:
 - ① **boundary nodes**: nodes in P_1 or P_2
 - ② **inside nodes**: non-boundary nodes that belong to either (a subtree rooted at a right child of a node of P_1) or (a subtree rooted at a left child of a node of P_2)
 - ③ **outside nodes**: non-boundary nodes that belong to either (a subtree rooted at a left child of a node of P_1) or (a subtree rooted at a right child of a node of P_2)
- k : number of reported items
- Nodes visited during the search:
 - ▶ $O(\log n)$ boundary nodes
 - ▶ $O(k)$ inside nodes
 - ▶ No outside nodes
- Running time $O(\log n + k)$

2-Dimensional Range Search

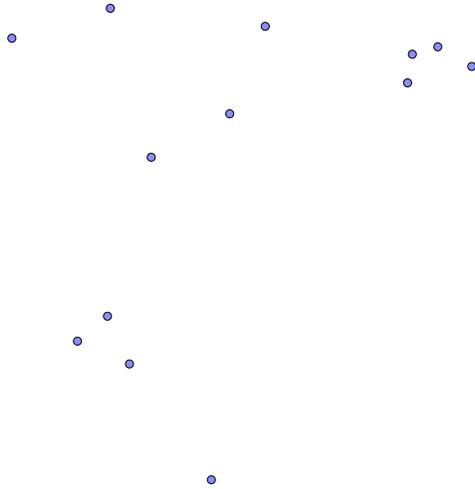
- Each item has 2 **aspects** (coordinates): (x_i, y_i)
- Each item corresponds to a point in Euclidean plane
- Options for implementing d -dimensional dictionaries:
 - ▶ Reduce to one-dimensional dictionary: combine the d -dimensional key into one key
Problem: Range search on one aspect is not straightforward
 - ▶ Use several dictionaries: one for each dimension
Problem: inefficient, wastes space
 - ▶ **Partition trees**
 - ★ A tree with n leaves, each leaf corresponds to an item
 - ★ Each internal node corresponds to a region
 - ★ **quadtrees, kd-trees**
 - ▶ multi-dimensional **range trees**

Quadtrees

- We have n points $P = \{(x_0, y_0), (x_1, y_1), \dots, (x_{n-1}, y_{n-1})\}$ in the plane
- How to **build** a quadtree on P :
 - ▶ Find a square R that contains all the points of P (We can compute minimum and maximum x and y values among n points)
 - ▶ Root of the quadtree corresponds to R
 - ▶ **Split**: Partition R into four equal subsquares (**quadrants**), each correspond to a child of R
 - ▶ Recursively repeat this process for any node that contains more than one point
 - ▶ Points on split lines belong to left/bottom side
 - ▶ Each leaf stores (at most) one point
 - ▶ We can delete a leaf that does not contain any point

Quadtrees

- Example: We have 13 points $P = \{(x_0, y_0), (x_1, y_1), \dots, (x_{12}, y_{12})\}$ in the plane



Quadtree Operations

- **Search:** Analogous to binary search trees
- **Insert:**
 - ▶ Search for the point
 - ▶ Split the leaf if there are two points
- **Delete:**
 - ▶ Search for the point
 - ▶ Remove the point
 - ▶ If its parent has only one child left, delete that child and continue the process toward the root.

Quadtree: Range Search

```
QTree-RangeSearch( $T, R$ )
 $T$ : A quadtree node,  $R$ : Query rectangle
1.   if ( $T$  is a leaf) then
2.       if ( $T.point \in R$ ) then
3.           report  $T.point$ 
4.   for each child  $C$  of  $T$  do
5.       if  $C.region \cap R \neq \emptyset$  then
6.           QTree-RangeSearch( $C, R$ )
```

- **spread factor** of points P : $\beta(P) = d_{max}/d_{min}$
- $d_{max}(d_{min})$: maximum (minimum) distance between two points in P
- **height** of quadtree: $h \in \Theta(\log_2 \frac{d_{max}}{d_{min}})$
- Complexity to build initial tree: $\Theta(nh)$
- Complexity of range search: $\Theta(nh)$ even if the answer is \emptyset

Quadtree Conclusion

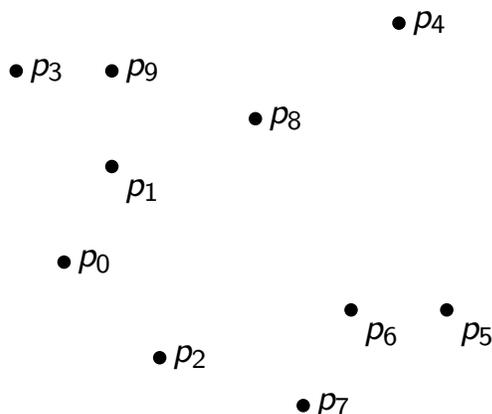
- Very easy to compute and handle
- No complicated arithmetic, only divisions by 2 (usually the boundary box is padded to get a power of two).
- Space wasteful
- Major drawback: can have very large height for certain nonuniform distributions of points
- Easily generalizes to higher dimensions (octrees, etc.).

kd-trees

- We have n points $P = \{(x_0, y_0), (x_1, y_1), \dots, (x_{n-1}, y_{n-1})\}$ in the plane
- Quadtrees split square into quadrants regardless of where points actually lie
- kd-tree idea: Split the points into two (roughly) equal subsets
- How to **build** a kd-tree on P :
 - ▶ Split P into two equal subsets using a vertical line
 - ▶ Split each of the two subsets into two equal pieces using horizontal lines
 - ▶ Continue splitting, alternating vertical and horizontal lines, until every point is in a separate region
- More details:
 - ▶ Initially, we sort the n points according to their x -coordinates.
 - ▶ The root of the tree is the point with median x coordinate (index $\lfloor n/2 \rfloor$ in the sorted list)
 - ▶ All other points with x coordinate less than or equal to this go into the left subtree; points with larger x -coordinate go in the right subtree.
 - ▶ At alternating levels, we sort and split according to y -coordinates instead.
- **Complexity:** $\Theta(n \log n)$, **height of the tree:** $\Theta(\log n)$

kd-trees

- kd-tree idea: Split the points into two (roughly) equal subsets
- A **balanced** binary tree



kd-tree: Range Search

```
kd-rangeSearch(T, R, split[← 'x'])
T: A kd-tree node, R: Query rectangle
1.  if T is empty then return
2.  if T.point ∈ R then
3.      report T.point
4.  for each child C of T do
5.      if C.region ∩ R ≠ ∅ then
6.          kd-rangeSearch(C, R)
7.  if split = 'x' then
8.      if T.point.x ≥ R.leftSide then
9.          kd-rangeSearch(T.left, R, 'y')
10.     if T.point.x < R.rightSide then
11.         kd-rangeSearch(T.right, R, 'y')
12.  if split = 'y' then
13.     if T.point.y ≥ R.bottomSide then
14.         kd-rangeSearch(T.left, R, 'x')
15.     if T.point.y < R.topSide then
16.         kd-rangeSearch(T.right, R, 'x')
```

kd-tree: Range Search Complexity

- The complexity is $O(k + U)$ where k is the number of keys **reported** and U is the number of regions we go to but **unsuccessfully**
- U corresponds to the number of regions which intersect but are not fully in R
- Those regions have to intersect one of the four sides of R
- $Q(n)$: Maximum number of regions in a kd-tree with n points that intersect a vertical (horizontal) line
- $Q(n)$ satisfies the following recurrence relation:

$$Q(n) = 2Q(n/4) + O(1)$$

- It solves to $Q(n) = O(\sqrt{n})$
- Therefore, the complexity of range search in kd-trees is $O(k + \sqrt{n})$

kd-tree: Higher Dimensions

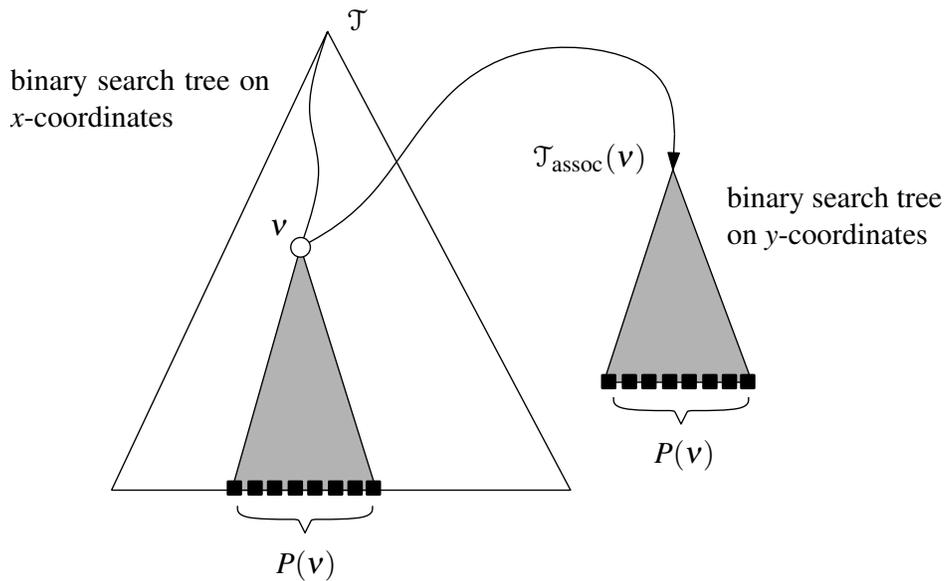
- kd-trees for d -dimensional space
 - ▶ At the root the point set is partitioned based on the first coordinate
 - ▶ At the children of the root the partition is based on the second coordinate
 - ▶ At depth $d - 1$ the partition is based on the last coordinate
 - ▶ At depth d we start all over again, partitioning on first coordinate
- **Storage:** $O(n)$
- **Construction time:** $O(n \log n)$
- **Range query time:** $O(n^{1-1/d} + k)$

(Note: d is considered to be a constant.)

Range Trees

- We have n points $P = \{(x_0, y_0), (x_1, y_1), \dots, (x_{n-1}, y_{n-1})\}$ in the plane
- A range tree is a **tree of trees** (a *multi-level* data structure)
- How to **build** a range tree on P :
 - ▶ Build a balanced binary search tree τ determined by the x -coordinates of the n points
 - ▶ For every node $v \in \tau$, build a balanced binary search tree $\tau_{\text{assoc}}(v)$ (**associated structure of τ**) determined by the y -coordinates of the nodes in the subtree of τ with root node v

Range Tree Structure



Range Trees: Operations

- **Search:** trivially as in a binary search tree
- **Insert:** insert point in τ by x -coordinate
- From inserted leaf, walk back up to the root and insert the point in all associated trees $\tau_{assoc}(v)$ of nodes v on path to the root
- **Delete:** analogous to insertion
- **Note:** re-balancing is a problem!

Range Trees: Range Search

- **A two stage process**
- To perform a range search query $R = [x_1, x_2] \times [y_1, y_2]$:
 - ▶ Perform a range search (on the x -coordinates) for the interval $[x_1, x_2]$ in τ ($BST\text{-}RangeSearch(\tau, x_1, x_2)$)
 - ▶ For every **outside node**, do nothing.
 - ▶ For every **“top” inside node** v , perform a range search (on the y -coordinates) for the interval $[y_1, y_2]$ in $\tau_{assoc}(v)$. During the range search of $\tau_{assoc}(v)$, do not check any x -coordinates (they are all within range).
 - ▶ For every **boundary node**, test to see if the corresponding point is within the region R .
- Running time: $O(k + \log^2 n)$
- Range tree space usage: $O(n \log n)$

Range Trees: Higher Dimensions

- Range trees for d -dimensional space
 - Space/time trade-off
 - ▶ **Storage:** $O(n(\log n)^{d-1})$
 - ▶ **Construction time:** $O(n(\log n)^{d-1})$
 - ▶ **Range query time:** $O((\log n)^d + k)$
- kd-trees: $O(n)$
kd-trees: $O(n \log n)$
kd-trees: $O(n^{1-1/d} + k)$

(Note: d is considered to be a constant.)

