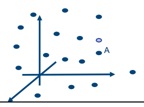
Challenge....

- Traditional data is one dimensional.
- Multimedia data is multi dimensional.
  - Ex. Maps are 2D
  - In general, if a given information has k features, it can be represented by a k-dimensional space



What kind of queries we can expect?

- Given a set of point in k-dimensional space
  - Exact match:
    - find if a given point is in the set or not
  - Nearest neihgbor:
    - find the closest point to a given point
  - Range search:
    - Given a region (rectangle or circle), find all the points in the given region

General approach

- Divide the space into regions
- Insert the new object into the corresponding region
- If the region is full, split the region
- retrieval: determine which regions are required to answer a given query and limit the search to these regions

Is there an alternative to multi-dimensional space decomposition?

- YES!
  - Convert a given k-D space to 1D space
  - We know how to handle 1D space!!
- Don't we loose information??
  - Yes, but if we are careful, we can minimize the information loss.

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Space filling curves

- Convert a k-D space into 1D space such that points that are close to each other in k-D space are also close to each other in 1-D space

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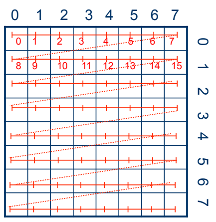
Row order/column order



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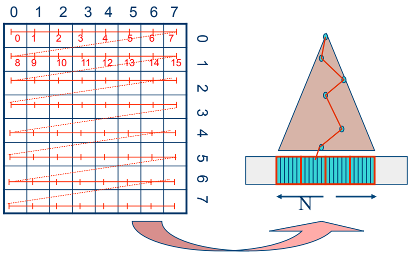
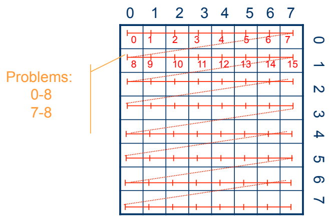
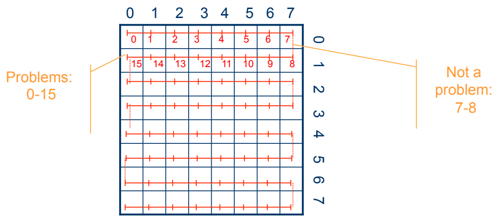
Row order/column order



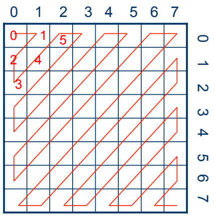
Row order/column order



Row prime order/column prime order



Cantor diagonal order



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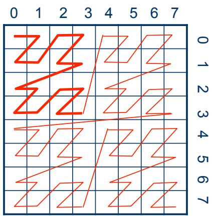
Z-order curve (hilbert curve)



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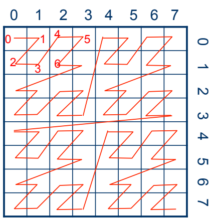
Z-order curve (hilbert curve)



Easy to compute (bit-shuffling): 1(001) X 2 (010) = 6 (000110)

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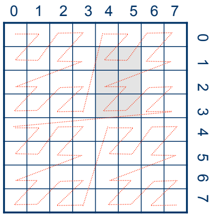
Z-order curve (hilbert curve)



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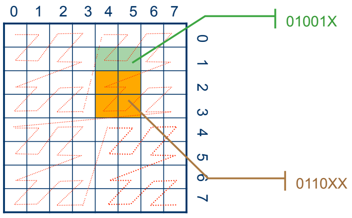
Z-order curve (hilbert curve)



Range search can be implemented using tries…

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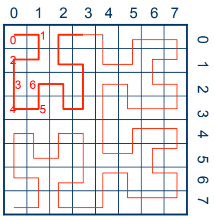
Peano-hilbert curve



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Indexing

- What are we indexing???
  - Text → tries
  - Numbers, text → B-trees, B+ trees, B*trees
  - Images→???????????
- Which feature are we going to index on?
  - Color? Texture? Time? (image series)
- What do we need to specify?
  - Lines? Points? Space?

How do we index points?

- Given
  - a space of N-dimensions
  - M points
  - a distance function between points
- we can use multidimensional index structures
  - k-d trees
  - point quadtrees
  - MX quadtrees
  - R-trees
  - TV-trees
  - X-trees

So…

- we can answer queries of the form
  - Given
    - a point X in N-dimensional space

    Find
    - all points Y that are in its proximity ($d(X,Y) < \varepsilon$)

…thus…

- If
  - we represent any feature as a point in N-dimensional space (color, texture, shape, etc.)
  - we define a distance function between those points
    - (larger distance→lower similarity)
- Then
  - we can find media object with similar properties.

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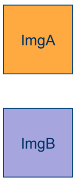
Populate database



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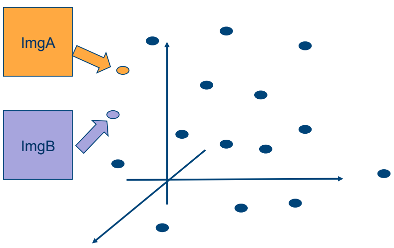
Populate database



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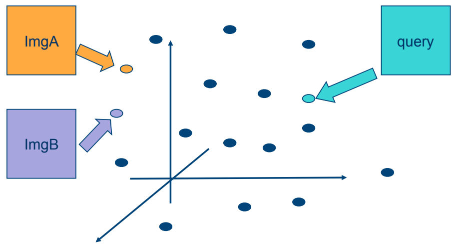
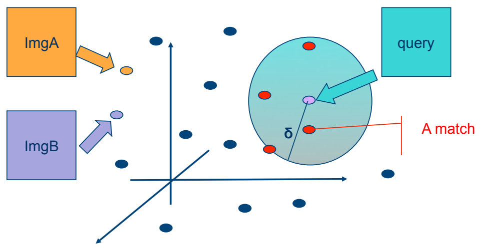
Map query image

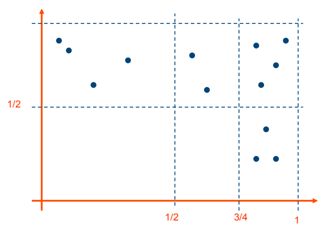


Range search



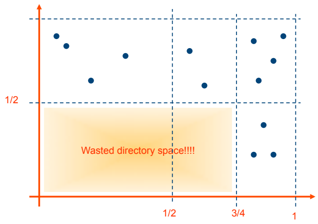
Grid File

- Every cell is one disk page



Grid File

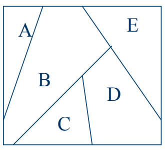
- Every cell is one disk page



Point Trees

How can we divide space?

- Let us assume that the space is 2-d
- There are many ways to divide the space
  - Fixed size squares
  - Triangles
  - Rectangles
  - Arbitrary space decomposition



- Each line divides the space into two
  - Line: $n_1x+n_2y = c$
  - Regions: $n_1x+n_2y >= c$
    $n_1x+n_2y < c$

Point quadtrees (Finkel and Bentley 74)

- Key features:
  - Every node in a point quadtree *implicitly* represents a rectangular region.
  - Each node contains an *explicit* point labeling it.
  - Root represents the whole region.
  - Each node's region is split into 4 parts ("quadrants") by drawing a vertical and a horizontal line through the point labeling the node.
  - Each node has 4 children corresponding to the 4 "quadrants" above.

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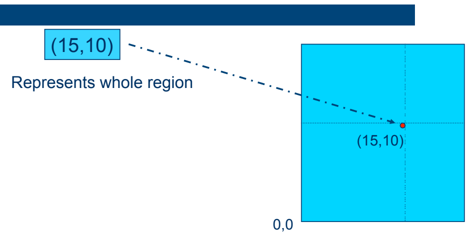
Point quadtrees: example



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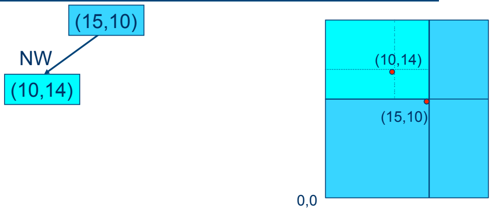
Point quadtrees: example



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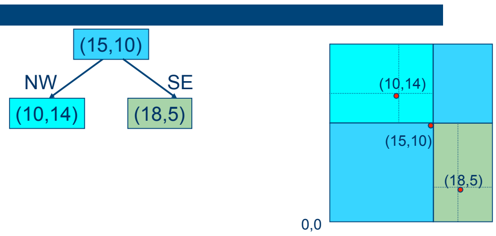
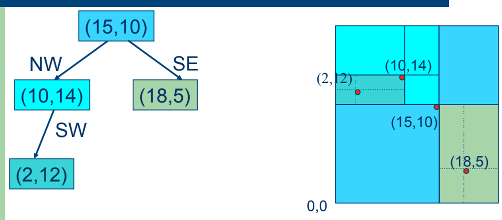
Point quadtrees: example



Point quadtrees: example



Observation

- The structure of the tree depends on the insertion order!!!!

- Exercise: try to insert nodes in the following order
  (18,5) (15,10), (2,12) (10,14)
  and compare the resulting tree with the previous one.

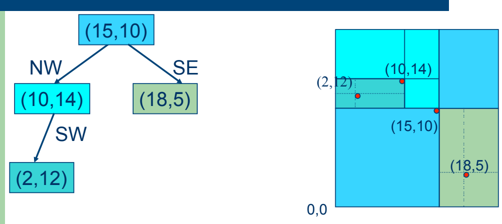
Key Points

- Suppose a point quadtree has N nodes in it.
- Worst case height = N.
- Worst case insertion time = N.
- Other operations are:
  - Deletion: delete a point
  - Range query: find all points within a given region
  - NN query: find the nearest neighbor (or M nearest neighbors) of a given point.

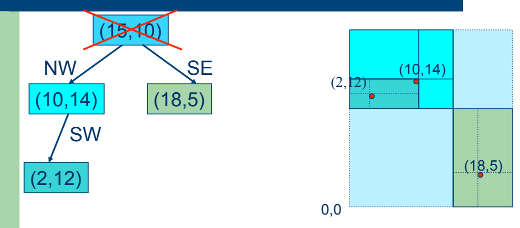
Deletion

- Suppose T is the root of a point quadtree and you want to delete (x,y).
- Steps:
  - Find (x,y) by doing a search.
  - If it is a leaf node, then simply set the appropriate link field of its parent to nil (and return the node to available storage).
  - What if it is not a leaf ?

Delete (15,10)



Delete (15,10)



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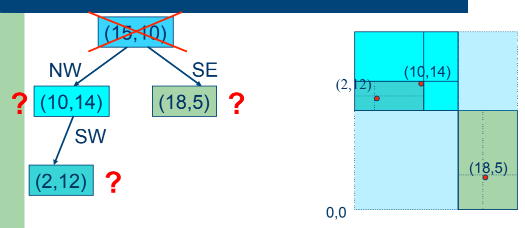
Delete (15,10)



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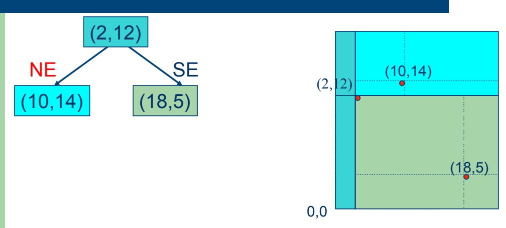
Let us choose (2,12)



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K-Nearest Neighbor Search

- This is the most important operation.
- Given a query point Q, find the K closest (to Q) points in the point quadtree.
- For simplicity, we will focus on K=1. Easy to generalize to K > 1.

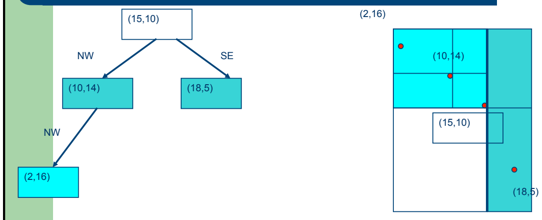
K-NN Search

- S – a set
- A metric d: S x S -> **N** is a mapping s.t.
  - d(x,x) = 0
  - d(x,y) = d(y,x)
  - d(x,y) + d(y,z) >= d(x,z)
- We extend d to a function from S x2^S -> **N** as follows:
  - d(x,R) = MIN{d(x,y) | y is in R }

K-NN Search

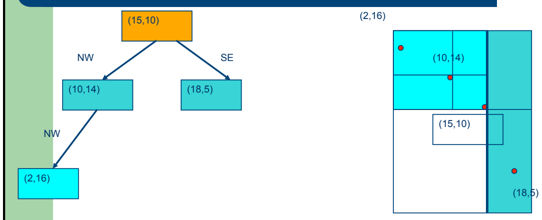
- Each node N *implicitly* represents a region N.reg.
- Algorithm for NN search works as follows.
  - Maintain variable bestdist (initialized to ∞)
  - Maintain variable bestSOL (initialized to NIL)
  - Algorithm visits nodes starting from root.
  - Everytime it visits a node N, it examines the point labeling that node. If d(Q,N.point) < bestdist, it updates bestdist and bestSol. Otherwise it continues.
  - Only nodes N such that d(Q,N.reg) < bestdist are visited. WHY?

NN Search example



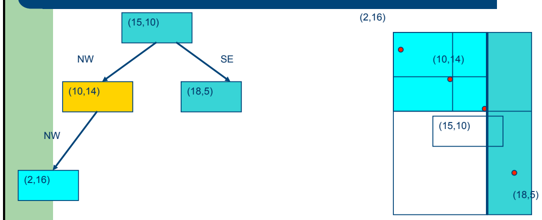
Q = (9,14) bestdist = ∞,   bestSOL = NIL

NN Search example



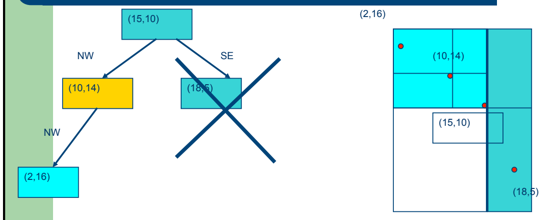
Q = (9,14) Visit root because d(Q,Root.reg) = 0 < bestDist
Set bestdist = SQRT(52), bestSOL = (15,10)

NN Search example



Q = (9,14). d(Q,Root.NW.Reg) = 0 < SQRT(52).

NN Search example



Q = (9,14). d(Q,Root.NW.Reg) = 0 < SQRT(52).
d(Q,Root.SE.Reg) is not less than SQRT(52) – so pruned away.

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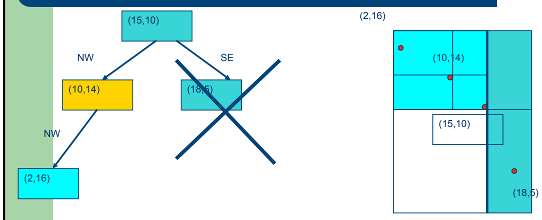
NN Search example



Q = (9,14). d(Q,(10,14)) = 1.
Bestdist = 1, bestsol = (10,14)

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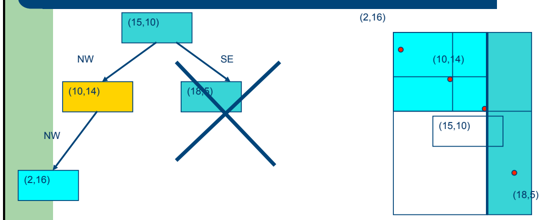
NN Search example



Q = (9,14). d(Q,Root.NW.NW.reg) = 0 < bestDist.

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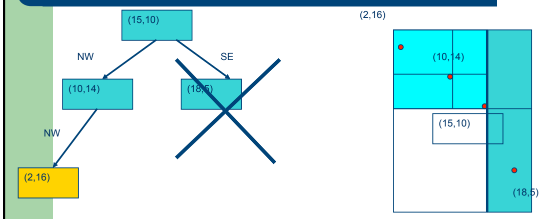
NN Search example



Q = (9,14). So must search. D(Q,(2,16)) > 1.
Algorithm terminates as no more nodes to search.

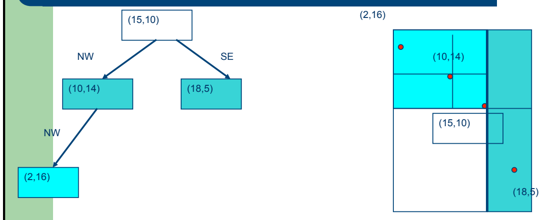
K-NN Search

- Want to find k-close points to Q.
- Maintain an array SOL[1,..,K] containing K points. Initialize all entries in array to NIL.
- SOL[1] is the closest point to Q found so far, SOL[2] is the second closest, etc.
- Let bestdist = dist(Q,SOL[K])).
- Can prune a node N if dist(Q,N.Reg) >= bestdist.

Range Search

- Done for the sake of completeness.
- Given query point Q and a distance R, find all points in the tree that are within R units of Q.
- The query defines a circular region, C(Q,R) of radius R centered at point Q.
- Prune node N if N.reg does not intersect C(Q,R).
- Sometimes, we modify the above to a weaker pruning condition: Prune node N if N.reg does not intersect bb(C(Q,R)) where bb is the bounding box operator.
- Second condition also yields correct answer, but may prune less.

Range Search example



Q = (9,14), R = 3, SOL = {}. Region of root intersects C(Q,R) so "visit" the root.

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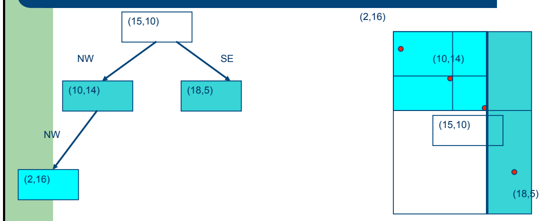
Range Search example



Q = (9,14), R = 3. D(Q,(15,10)) > 3. SOL stays {}.

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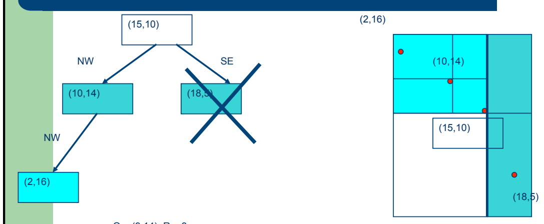
Range Search example



Q = (9,14), R = 3.
D(Q,Root.SE) > 3 so prune SE child.
D(Q,Root.NW) = 0. Visit NW child.

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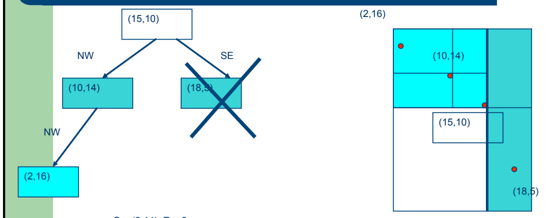
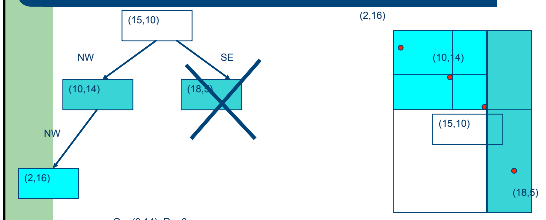
Range Search example



Q = (9,14), R = 3.
Visit NW child. D(Q,(10,14)) < 3. SOL = {(10,14)}
D(Q,Root.NW.NW) = 0. So visit NW child of (10,14)

Range Search example



Q = (9,14), R = 3.
Visit NW child. D(Q,(2,16)) > 3. SOL = {(10,14)}
No more nodes to visit so return SOL and halt.

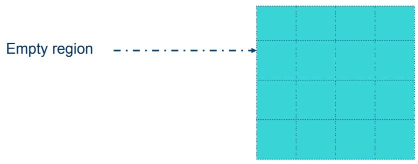
Problems with Point Quadtrees

- Deletion is slow.
- Tree can be highly unbalanced.
- Size of regions associated with nodes can vary dramatically.
- All these factors make the time taken to compute NN and range queries unpredictable.

MX quadtrees

- In point quadtrees, the region is split by drawing a vertical and a horizontal line through the point labeling node N.
- In MX-quadtrees,
  - the entire space is a $2^n \times 2^n$ matrix.
  - region is split by drawing a vertical and a horizontal line through the center of the region.

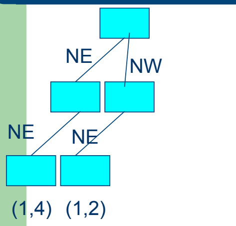
MX quadtrees: example

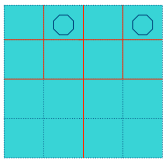


MX quadtrees: example

Insert (1,4)

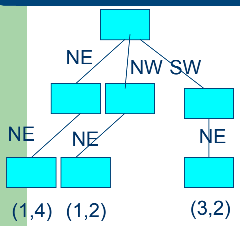
MX quadtrees: example

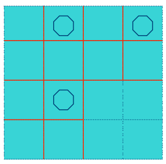




Insert (1,2)

MX quadtrees: example





Insert (3,2)

MX-quadtrees: salient features

- Each node represents a region.
- Root (level 0) represents 2^n x 2^n region.
- Nodes at level j represent 2^{n-j} x 2^{n-j} region.
- Points label leaf nodes (at level n).
- Insertion takes time O(n).
- So does search for a point.

MX-Quadtrees: deletion

- Very easy to delete a point.
- First search for the point (which must be a leaf) and delete the leaf.
- If the parent now has 4 empty child fields, then delete the parent. And repeat as long as possible. This process is termed "collapsing".

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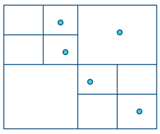
PR-quadtrees

- MX-quadtree works well if the data is discrete
  - otherwise, it may need to use buckets, which may increase search time
- PR-quadtree (point region quadtree) assumes a continous space.



Structure is independent of insertion order

Deletion is easy

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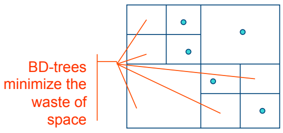

Structure is independent of insertion order

Deletion is easy

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KD-trees

- Deficiencies of quadtree:
  - each node requires k comparisons
  - each leaf contains k null pointers
  - node size gets larger as k increases

KD-trees

- Deficiencies of quadtree:
  - each node requires passk comparisons
  - each leaf contains k null pointers
  - node size gets larger as k increases
- Solution: KD-tree
  - the tree is binary whatever k is!!!
  - each node has two pointers only

K-d trees

- Used to store K-dimensional data, I.e. points of the form $(x_0,\ldots,x_{K-1})$
- Assuming the root is a level 0 node, each node at level i discriminates on $x_{i \bmod K}$.
- Always split region associated with a node into two parts.
- We now focus on K=2.

2-d-trees

- Structure of a node in a 2-d-tree
  - nodetype =record
    - INFO: infotype; (information content. It depends on the application domain)
    - xcoord:real; ycoord:real; (coordinates of the point associated to the node)
    - Llink: @nodetype;
    - Rlink: @nodetype;
  - end

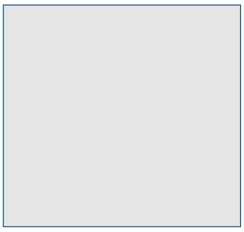
2-d-tree

- 2-d tree is a binary tree such that:
  - If N is a node such that level(N) is even , then for every node M in the subtree rooted at N.Llink, and for every node P in the subtree rooted in N.Rlink,
    - M.xcoord < N.xcoord P.xcoord>= N.xcoord
  - If N is a node such that level(N) is odd , then for every node M in the subtree rooted at N.Llink, and for every node P in the subtree rooted in N.Rlink,
    - M.ycoord < N.ycoord P.ycoord>= N.ycoord

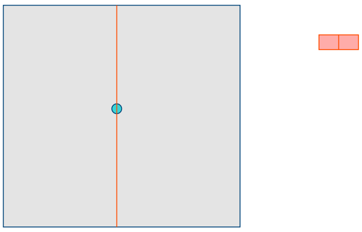
2-d-tree (notes)

- Every node partitions the space in 2 parts:
  - Nodes whose level is even, implicitly draw a vertical line, x=xcoord,
  - Nodes whose level is odd, implicitly draw a horizontal line, y=ycoord.

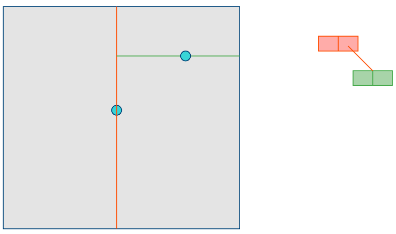
KD-trees



KD-trees



KD-trees



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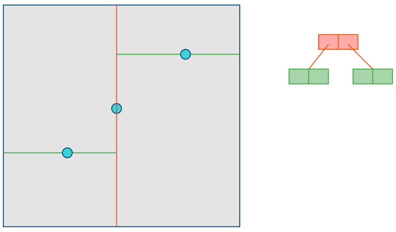

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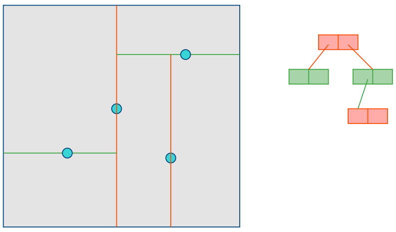
KD-trees



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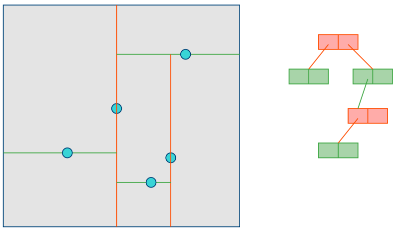

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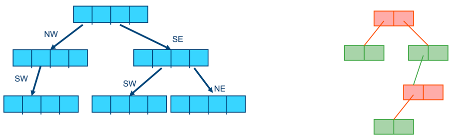
KD-trees



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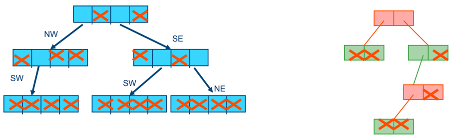
KD-trees



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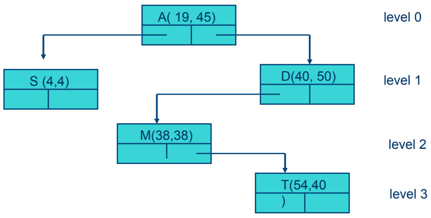
2-d-tree (example)



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range-queries

- Given a point (x_c, y_c) and a distance *d,* find the set of all points (x,y) such that (x,y) lies within distance *d* of (x_c, y_c).
  - Each node N implicitly represents a region R_N , constrained by N's coordinates and its parent's coordinates.
  - If the circle specified in the query has no intersection with R_N ,then there is no point searching the subtree rooted at N.
  - example: search for the circle with center (35,46)and radius 9.5 (returned: M(38, 38))

K-d-tree, k>2

- Extensions of 2-d trees, in which
  - Fields xcoord and ycoord in the definition of the node are replaced by a single field COORD, a vector of k elements.
    - For every node N, let i=level(N) mod k.
    - For every node M in N's left subtree:
      - M.VAL[i] < N.val[i]
    - For every node M in N's right subtree:
      - M.VAL[i] >= N.val[i]

…notes

- k-d trees are easy to implement
- A tree with *k* nodes can have height *k*
  - --> insertion and deletion can be expensive
- range searching costs, in the worst case, O(k $n^{1-1/k}$)

R-trees

- R-trees are used to store *two* dimensional rectangle data.
- They can be easily generalized to higher dimensions.
- R-trees themselves generalize the well known B-trees.

Node capacity

- Each node in a R-tree can contain upto N rectangles.
- But in addition, each node must contain *at least* N/2 rectangles.
- We will assume henceforth that N >= 4.

Node structure

- Each node has between N/2 and N rectangles.
- Like a B-tree:
  - All leaves are at the same level
  - Root has at least two children unless it's a leaf

Node properties

- Each node *implicitly* represents a region.
- Root represents the whole space.
- The region of a node N, N.reg, is the bounding box of the rectangles stored at that node.
- Unlike quadtrees, it is possible for regions of siblings to intersect.

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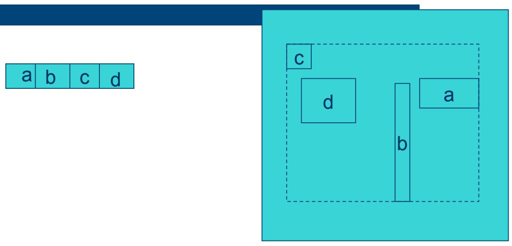
Example R-tree



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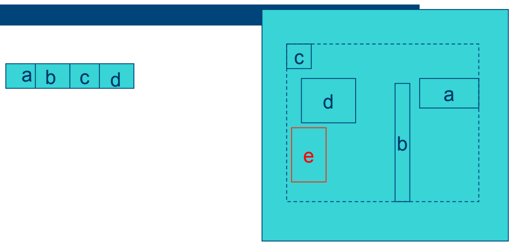
Example R-tree



No space in root ! Must split

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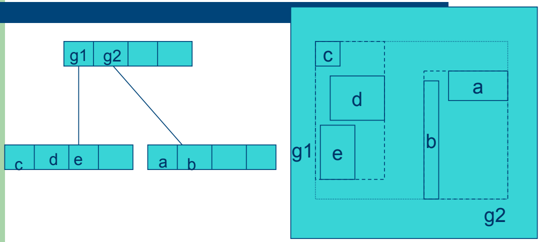
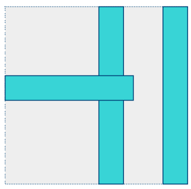
Example R-tree

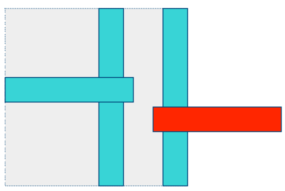


Minimize the sum of the areas of the two BRs.

Example: Let max size be 3



How do we split???



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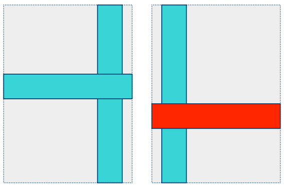

Minimize overlap of the BRs

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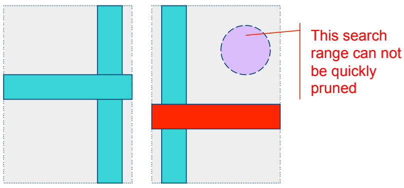

Minimize overlap of the BRs

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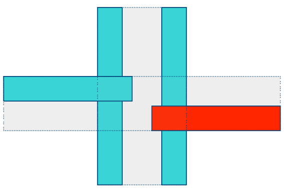

Minimize total area

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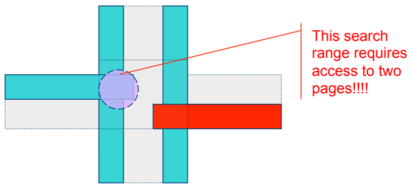
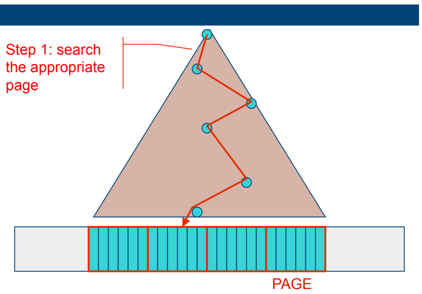


Minimize total area

Insertion (similar to B-trees)



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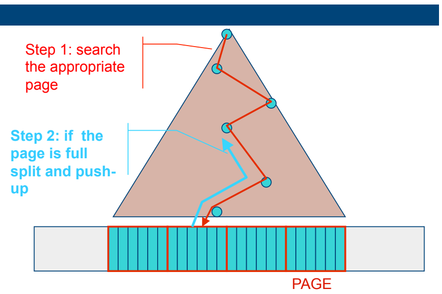

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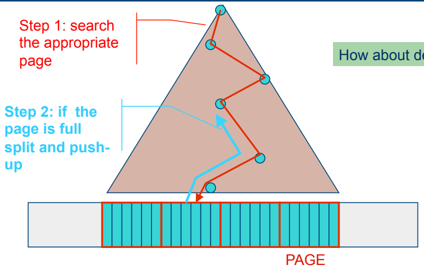
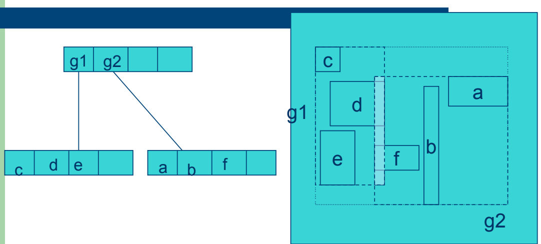


How about deletion??

R+-tree

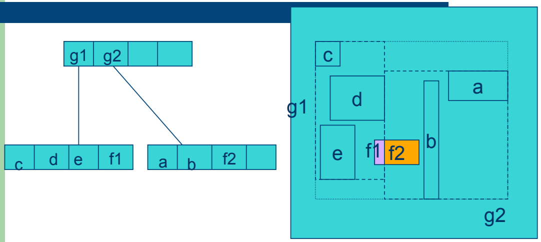
- Overlaps are bad…..
- ..so, let’s eliminate overlaps

Overlap in R-tree



The two BRs are overlapping.

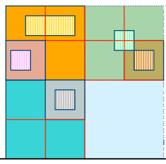
No-overlap in R+-tree



The two BRs are not-overlapping.

Other range/region index structures

- Range-tree, 2D-range tree
  - Precise, too much overhead
- MX-CIF quadtree
  - Regular division
  - Each rectangle is associated with the quadtree-page which covers it entirely



Nearest neighbor search

- ..no range given
  - first pick a (random) object $o \in D$ *and compute the distance dist(q, o)*….this is the first nearest neighbor candidate.
  - start a range search on the hierarchy using the range, *r = dist(q, o).*
  - whenever you find a data object *o* such that *dist(q, o) < r*, where *r* is the current nearest neighbor range, pick *o* is as the new nearest neighbor candidate
    - Set *dist(q, o)* as the new range, *r*

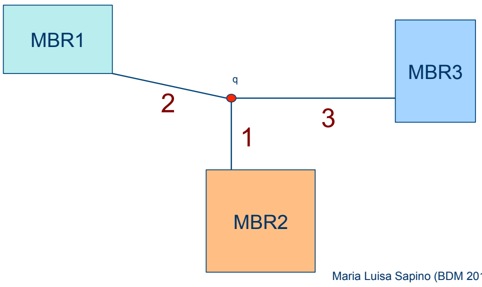
Nearest neighbor search

- ..great, but in which order do we visit the pages?
- ..how can we prune the pages that we have not visited yet most effectively??

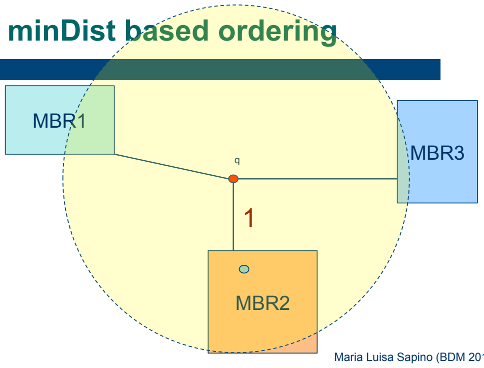
Nearest neighbor search

- Given q and MBR M
  - minDist(q,M)
  - minimum possible distance between the query and the objects contained within the MBR
  - minimum distance between q and any of the faces of M
- optimistic; yet minDist based ordering of the MBRs provides good pruning opportunities.

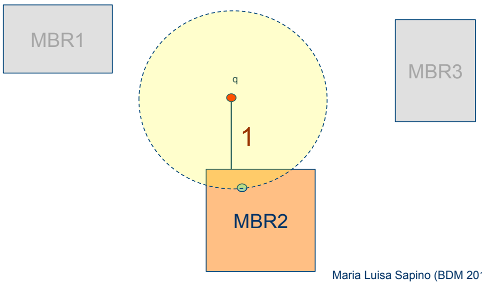
minDist based ordering



minDist based ordering



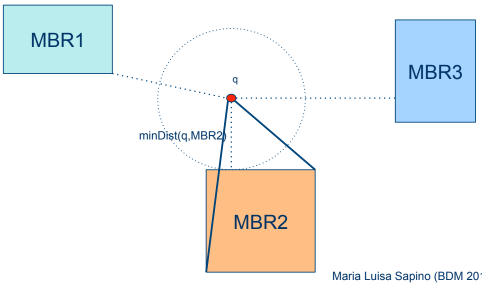
minDist based pruning



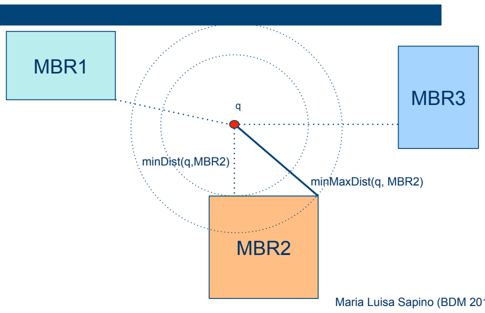
minMaxDist based pruning

- Given q and MBR M
  - minMaxDist(q,M)
  - upperbound on the distances
  - minimum among
    - maximum distances
      - on the closest faces of M on each dimension

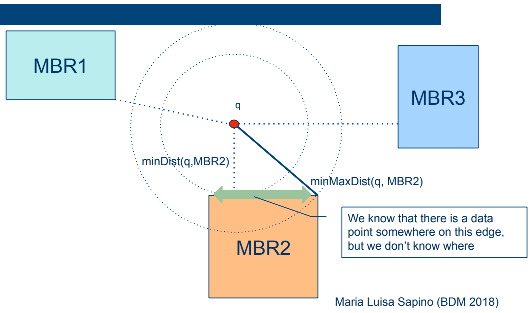
minMaxDist based pruning



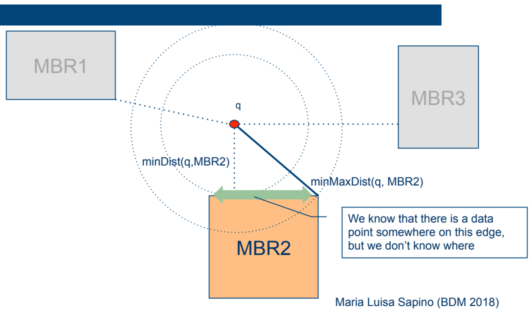
minMaxDist based pruning



minMaxDist based pruning



minMaxDist based pruning



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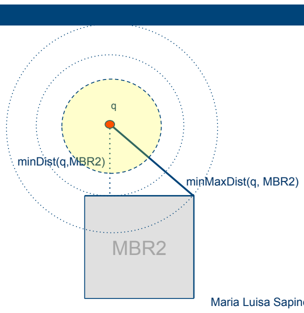
Case 1: r < minDist(q,M) ----- prune MBR



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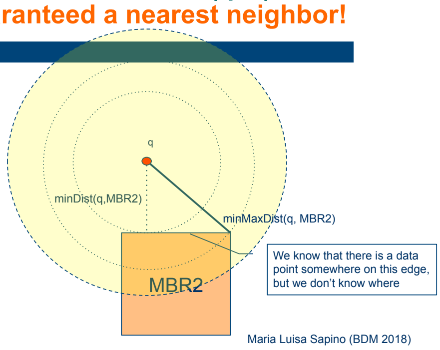
Case 2: r > minMaxDist(q,M) --- guaranteed a nearest neighbor!



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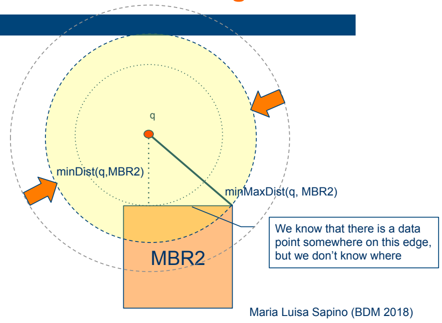
Case 2: r > minMaxDist(q,M) --- tighten the search range!



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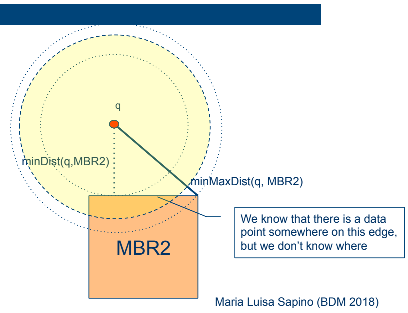
Case 3: minDist(q,M) <= r <= minMaxDist(q,M) maybe….we need to look into the MBR!



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Nearest neighbor search

- Cannot prune an MBR as long as
  minDist(q,M) <= r <= minMaxDist(q,M)
- downward pruning: discard M if there exists M' s.t.
  minDist(q,M) > minMaxDist(q,M')
- downward pruning: prune candidate object o if there exists M s.t.
  dist(q,o) =r > minMaxDist(q,M)
- upward pruning: M is discarded if the current candidate is s.t.
  minDist(q,M) > r = dist(q,o)

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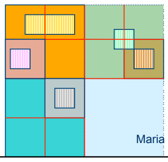
Nearest neighbor search

- What is we are looking for more than one, say *k*, nearest neighbors?
  - Maintain a list of *k* candidates in the memory
  - Always prune the search space using the current k^{th} best candidate
  - When you find an object better than the current k^{th} best candidate
    - Drop the current k^{th} best candidate
    - Include the new object in the list of *k* candidates
    - Identify the new k^{th} best candidate

Other range/region index structures

- Range-tree, 2D-range tree
  - Precise, too much overhead
- MX-CIF quadtree
  - Regular division
  - Each rectangle is associated with the quadtree-page which covers it entirely



X-tree

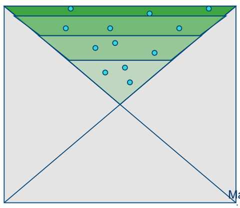
- Like R-trees, but
  - change the page size based on the depth to ensure that there is larger fanout higher in the tree structure
- A larger page size means multiple disk pages that are consecutively stored
  - so, no “page seek” penalty during disk access.

Dimensionality curse

- Exponential growth in the number of pointers needed, wasted storage,
- Exponential suqueries (quadtrees)
- Larger MBRs means smaller fanout in trees and this is bad

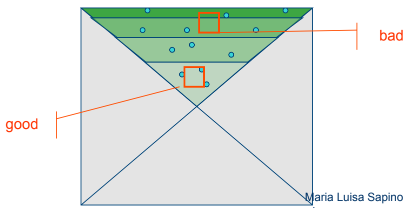
Pyramid tree

- If data is uniformly distributed, pages are likely to be of the same volume



Pyramid tree

- If data is uniformly distributed, queries likely to avoid thin pages, reducing the average access time

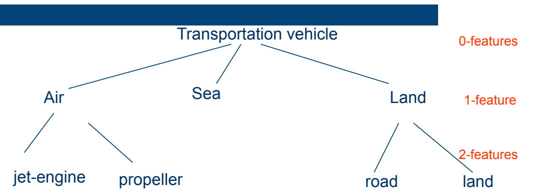


TV trees (telescopic vector trees)

(Lin, Jagadish, Faloutsos, VLDB Journal, 1994)

- Based on classification idea
- Dimensionality curse: R-trees do not work for large numbers of dimensions
- Idea:
  - not all features are equally important
  - order features based on importance (discrimination power)
  - use as little features as possible
  - "contract" and "extend" feature vectors based on need

Intuition



Classification requires less features at the higher levels than it uses at the lower levels

Cost of a dimension

- Every rectangle has to have values describing all its dimensions

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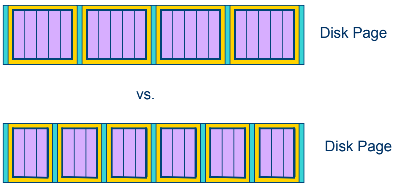
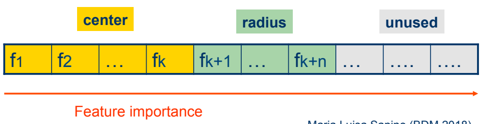


TV-trees

- Hierarchical
  - Leaves: objects (documents)
  - Internal nodes: Minimum Bounding Regions
    - Higher fan-out at the root
    - Lower fan-out at the leaves (or lower levels)

Node structure in TV-trees

- In R-trees, every node is a hyper-rectangle
- In TV-trees, every node has
  - a center (in k-dimensions)
  - a radius (defined in n-dimensions)



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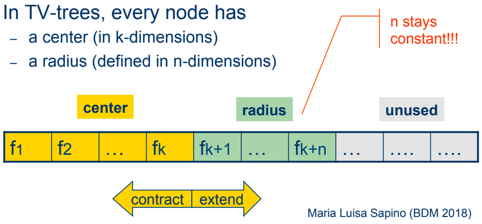
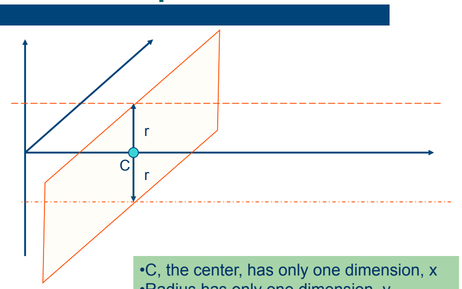
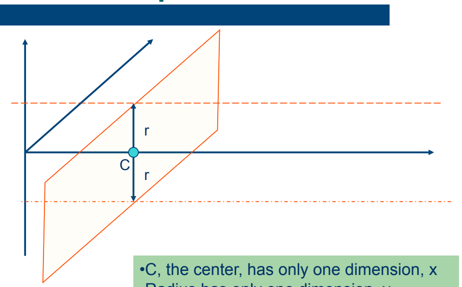


TV trees: example



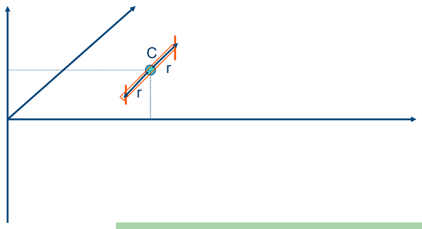
- C, the center, has only one dimension, x
- Radius has only one dimension, y

TV trees: example



- C, the center, has only one dimension, x
- Radius has only one dimension, y
- .....any z is okay

TV trees: extension example



•C, the center, has only two dimensions, x,y
•Radius has only one dimension, z

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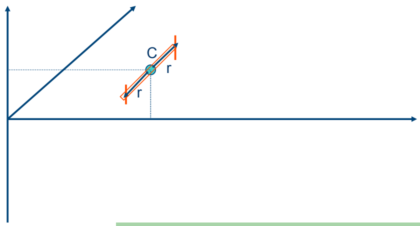
TV trees: extension example



•C, the center, has only two dimensions, x,y
•Radius has only one dimension, z
•....any z is not okay!!!!!

Drawback

- Information about the behaviour of single attributes, e.g., their selectivity, is required

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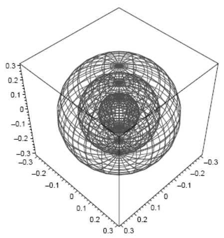
- …and…

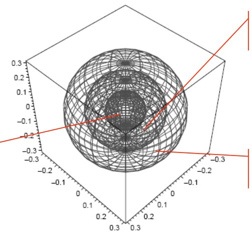
Dimensionality Curse

- Consider a query point and three alternative ranges:



Dimensionality Curse

- Consider a query point and three alternative ranges:



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Dimensionality Curse

- In n-dimensional space, if the number of points in the inner most sphere is *l*, then
  - number of points in the second slice is $O(2^{n-1}\, l)$
  - number of points in the third slice is $O(3^{n-1}\, l)$
  - number of points in the fourth slice is $O(4^{n-1}\, l)$
- This means that most of the points lie in the outermost slice!!!!

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Pyramid trees (Berchtold, Bohm, Kriegel, SIGMOD98)

- Motivation: drawbacks of already existing multidimensional index structures
  - Querying and indexing techniques which provide good results on
    - low-dimensional data do not perform sufficiently well on multi-dimensional data (curse of dimensionality)
  - high cost for insert/delete operations
  - Poor support for concurrency control/recovery

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Pyramid tree

- Space-filling curves were using B-trees
- Pyramid trees also do the same..without space filling curves

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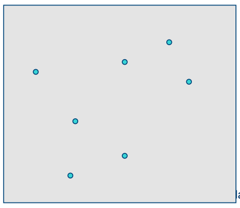

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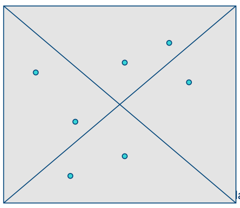

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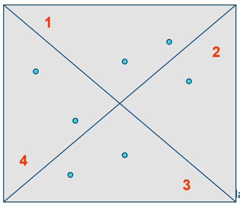

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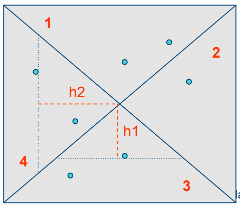

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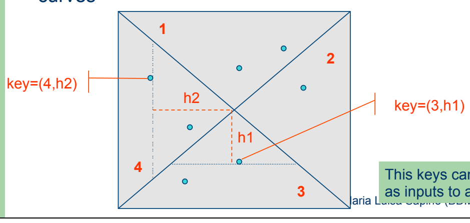

This keys can be used as inputs to a B-tree!!!

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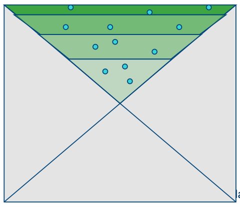
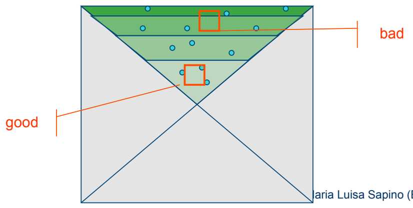
Pyramid tree

- If data is uniformly distributed, pages are likely to be of the same volume



Pyramid tree

- If data is uniformly distributed, queries likely to avoid thin pages, reducing the average access time



Other index structures

- Grids
- VA-files
  - extension of the grid idea..
- SR-, SS-trees
  - like R-trees
  - use spheres instead of rectangles
- X-trees
  - like R-trees
  - change the page size based on the depth