Architecture and Implementation of Database Systems (Winter 2015/16)

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Part IV

Multi-Dimensional Indexing

More Dimensions. . .

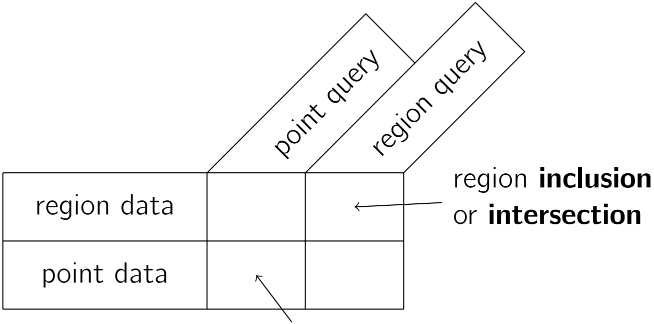
```
SELECT  *
  FROM  CUSTOMERS
 WHERE  ZIPCODE BETWEEN 8000 AND 8999
   AND  REVENUE BETWEEN 3500 AND 6000
```

This query involves a **range predicate** in **two** dimensions.

Typical use cases with **multi-dimensional data** include

- **geographical data** (GIS: Geographical Information Systems),
- **multimedia retrieval** (*e.g.*, image or video search),
- **OLAP** (Online Analytical Processing).

Queries **and** data can be **points** or **regions**.

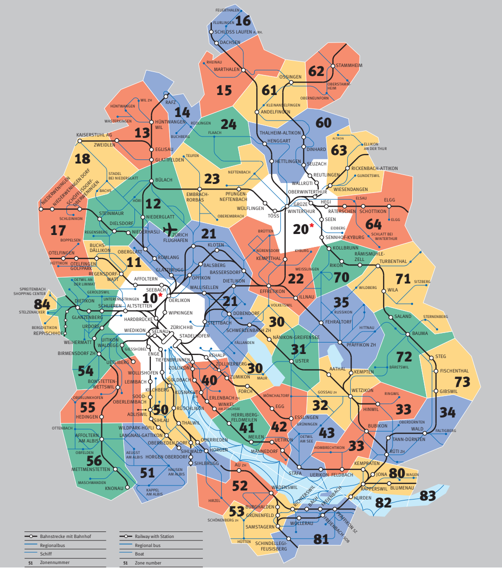


most interesting: k-**nearest-neighbor search** (k-NN)

. . . and you can come up with many more meaningful types of queries over multi-dimensional data.

Note: All equality searches can be reduced to one-dimensional queries.

Points, Lines, and Regions



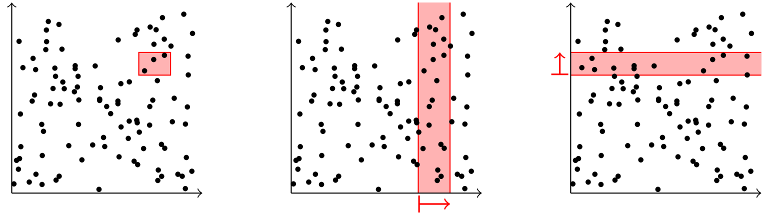
. . . More Solutions

- Quad Tree [Finkel 1974]
- R-tree [Guttman 1984]
- R^+-tree [Sellis 1987]
- R*-tree [Geckmann 1990]
- Vp-tree [Chiueh 1994]
- UB-tree [Bayer 1996]
- SS-tree [White 1996]
- M-tree [Ciaccia 1996]
- Pyramid [Berchtold 1998]
- DABS-tree [Böhm 1999]
- Slim-tree [Faloutsos 2000]
- P-Sphere-tree [Goldstein 2000]
- K-D-B-Tree [Robinson 1981]
- Grid File [Nievergelt 1984]
- LSD-tree [Henrich 1989]
- hB-tree [Lomet 1990]
- TV-tree [Lin 1994]
- hB-$^\Pi$-tree [Evangelidis 1995]
- X-tree [Berchtold 1996]
- SR-tree [Katayama 1997]
- Hybrid-tree [Chakrabarti 1999]
- IQ-tree [Böhm 2000]
- landmark file [Böhm 2000]
- A-tree [Sakurai 2000]

Note that none of these is a "fits all" solution.

Can't We Just Use a B^+-tree?

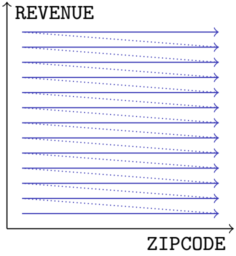
- Maybe two B^+-trees, over `ZIPCODE` and `REVENUE` each?



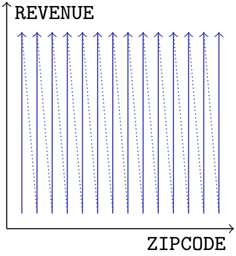
- Can only scan along **either** index at once, and both of them produce many **false hits**.

- If all you have are these two indices, you can do **index intersection**: perform both scans in separation to obtain the rids of candidate tuples. Then compute the (expensive!) intersection between the two rid lists (DB2: `IXAND`).

Hmm, . . . Maybe With a Composite Key?



⟨REVENUE, ZIPCODE⟩ index



⟨ZIPCODE, REVENUE⟩ index

- **Exactly the same thing!**
  Indices over composite keys are **not symmetric**: The major attribute dominates the organization of the B$^+$-tree.

- Again, you can use the index if you really need to. Since the second argument is also stored in the index, you can discard non-qualifying tuples **before** fetching them from the data pages.

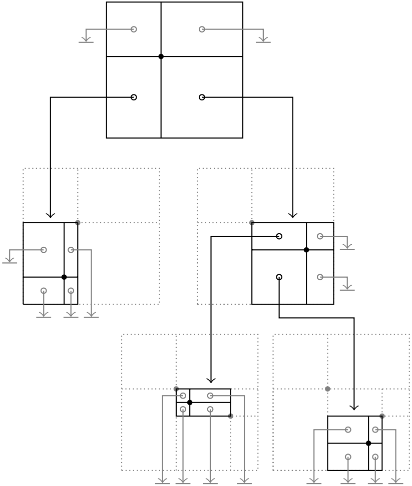
Multi-Dimensional Indices

- B^+-trees can answer **one-dimensional** queries **only**.[7]
- We'd like to have a **multi-dimensional** index structure that
  - is **symmetric** in its dimensions,
  - **clusters** data in a space-aware fashion,
  - is **dynamic** with respect to updates, and
  - provides good support for useful queries.
- We'll start with data structures that have been designed for **in-memory** use, then tweak them into **disk-aware** database indices.

[7] Toward the end of this chapter, we'll see UB-trees, a nifty trick that uses B^+-trees to support some multi-dimensional queries.

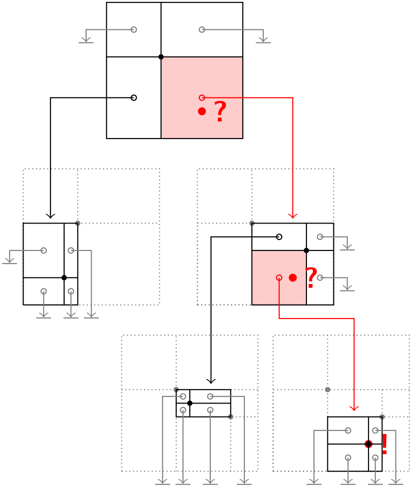
“Binary” Search Tree

In k dimensions, a **“binary tree”** becomes a 2^k**-ary tree**.



- Each data point **partitions** the data space into 2^k **disjoint regions**.
- In each node, a region points to another node (representing a refined partitioning) or to a special **null** value.
- This data structure is a **point quad tree**.

  ↗ Finkel and Bentley. Quad Trees: A Data Structure for Retrieval on Composite Keys. *Acta Informatica*, vol. 4, 1974.



Function: `p_search` (q, *node*)

if q matches data point in *node* **then**
    return data point ;

else
    $P \leftarrow$ partition containing q ;
    if P points to **null then**
        return not found ;
    else
        node$'$ $\leftarrow$ node pointed to by P ;
        return `p_search` (q, *node*$'$) ;

Function: `pointsearch` (q)

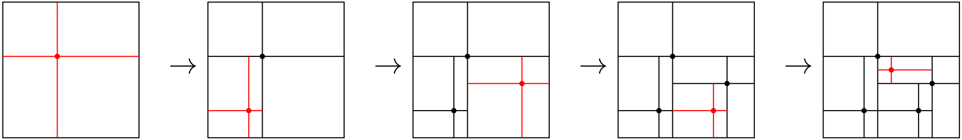
return `p_search` (q, *root*) ;

Inserting into a Point Quad Tree

Inserting a point q_{new} into a quad tree happens analogously to an insertion into a binary tree:

1. **Traverse** the tree just like during a search for q_{new} until you encounter a partition P with a **null** pointer.
2. Create a **new node** n' that spans the same area as P and is partitioned by q_{new}, with all partitions pointing to **null**.
3. Let P point to n'.

Note that this procedure does **not** keep the tree **balanced**.



Range Queries

To evaluate a **range query**[8], we may need to follow **several** children of a quad tree node *node*:

```
Function: r_search (Q, node)
if data point in node is in Q then
    append data point to result ;
foreach partition P in node that intersects with Q do
    node′ ← node pointed to by P ;
    r_search (Q, node′) ;
```

```
Function: regionsearch (Q)
return r_search (Q, root) ;
```

[8]We consider **rectangular** regions only; other shapes may be answered by querying for the **bounding rectangle** and post-processing the output.

Point Quad Trees—Discussion

Point quad trees

- ✔ are **symmetric** with respect to all dimensions and
- ✔ can answer **point queries** and **region queries**.

But

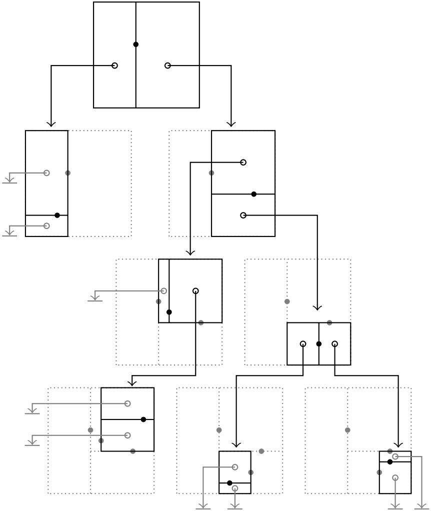
- ✗ the shape of a quad tree depends on the **insertion order** of its content, in the worst case **degenerates** into a **linked list**,
- ✗ **null** pointers are **space inefficient** (particularly for large k).

In addition,

- ☹ they can only store **point data**.

Also remember that quad trees are designed for **main memory**.

k-d Trees



- Index k-dimensional data, but keep the tree **binary**.
- For each **tree level** l use a different **discriminator dimension** d_l along which to **partition**.
  - Typically: **round robin**
- This is a **k-d tree**.

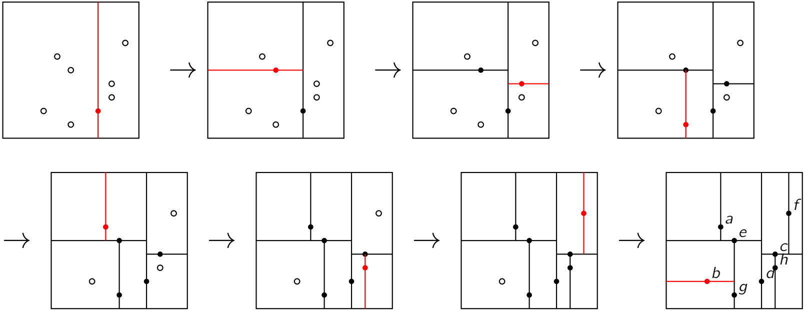
  ↗ Bentley. Multidimensional Binary Search Trees Used for Associative Searching. *Comm. ACM*, vol. 18, no. 9, Sept. 1975.

k-d trees inherit the positive properties of the point quad trees, but improve on **space efficiency**.

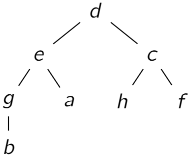
For a given point set, we can also construct a **balanced** *k*-d tree:[9]

```
Function: kdtree (pointset, level)
if pointset is empty then
    return null ;
else
    p ← median from pointset (along d_level) ;
    points_left ← {v ∈ pointset where v_{d_level} < p_{d_level}};
    points_right ← {v ∈ pointset where v_{d_level} ≥ p_{d_level}};
    n ← new k-d tree node, with data point p ;
    n.left ← kdtree (points_left, level + 1) ;
    n.right ← kdtree (points_right, level + 1) ;
    return n ;
```

[9] v_i: coordinate i of point v.



Resulting tree shape:



K-D-B-Trees

k-d trees improve on some of the deficiencies of point quad trees:

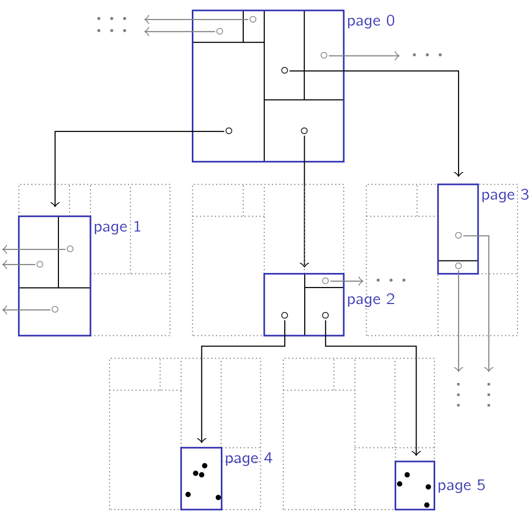
- ✔ We can **balance** a *k*-d tree by **re-building** it.
  (For a limited number of points and in-memory processing, this may be sufficient.)
- ✔ We're no longer wasting big amounts of **space**.
- ✗ *k*-d trees are not really symmetric with respect to space dimensions.

It's time to bring *k*-d trees to the disk. The **K-D-B-Tree**

- uses **pages** as an organizational unit
  (*e.g.*, each node in the K-D-B-tree fills a page) and
- uses a ***k*-d tree-like layout** to organize each page.

↗ John T. Robinson. The K-D-B-Tree: A Search Structure for Large Multidimensional Dynamic Indexes. *SIGMOD 1981*.

K-D-B-Tree Idea



region pages:

- contain entries $\langle \mathit{region}, \mathit{pageID} \rangle$
- no **null** pointers
- form a **balanced** tree
- all regions **disjoint** and **rectangular**

point pages:

- contain entries $\langle \mathit{point}, \mathit{rid} \rangle$
- $\rightsquigarrow$ B^+-tree leaf nodes

K-D-B-Tree Operations

- **Searching** a K-D-B-Tree works straightforwardly:
  - Within each page determine all regions R_i that contain the query point q (intersect with the query region Q).
  - For each of the R_i, consult the page it points to and recurse.
  - On point pages, fetch and return the corresponding record for each matching data point p_i.
- When **inserting** data, we keep the K-D-B-Tree **balanced**, much like we did in the **B$^+$-tree**:
  - Simply insert a $\langle \mathit{region}, \mathit{pageID} \rangle$ ($\langle \mathit{point}, \mathit{rid} \rangle$) entry into a region page (point page) if there's **sufficient space**.
  - **Otherwise**, **split** the page.

Splitting a Point Page

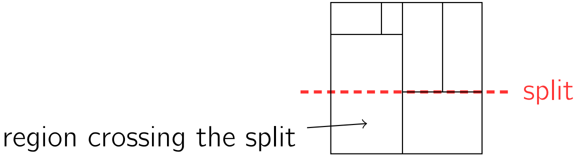
Splitting a point page p:

1. **Choose a dimension** i and an i-coordinate x_i along which to split, such that the split will result in two pages that are not overfull.
2. **Move** data points p with $p_i < x_i$ and $p_i \geq x_i$ to new pages p_{left} and p_{right} (respectively).
3. Replace $\langle \mathit{region}, p \rangle$ in the **parent** of p with $\langle \mathit{left\ region}, p_{\text{left}} \rangle$ $\langle \mathit{right\ region}, p_{\text{right}} \rangle$.

Step 3 may cause an **overflow** in p's parent and, hence, lead to a **split** of a **region page**.

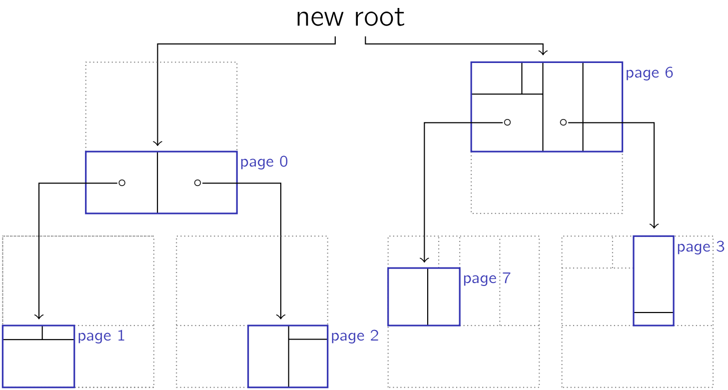
Splitting a Region Page

- Splitting a **point page** and moving its data **points** to the resulting pages is straightforward.
- In case of a **region page split**, by contrast, some **regions** may intersect with **both** sides of the split (*e.g.*, page 0 on slide 131).



- Such regions need to be **split**, too.
- This can cause a **recursive** splitting **downward** (!) the tree.

Example: Page 0 Split in Tree on Slide 131



- Root page 0 → pages 0 and 6 (⇝ creation of new root).
- Region page 1 → pages 1 and 7 (point pages not shown).

K-D-B-Trees—Discussion

K-D-B-Trees

- ✔ are **symmetric** with respect to all dimensions,[10]
- ✔ **cluster** data in a space-aware and page-oriented fashion,
- ✔ are **dynamic** with respect to updates, and
- ✔ can answer **point queries** and **region queries**.

However,

- ☹ we still don't have support for **region data** and
- ☹ K-D-B-Trees (like *k*-d trees) won't handle **deletes** dynamically.

This is because we always partitioned the data space such that

- every region is **rectangular** and
- regions never **intersect**.

[10] However, split dimensions must be chosen, which re-introduces asymmetry.

R-Trees

R-trees do not have the disjointness requirement.

- R-tree inner or leaf nodes contain $\langle \textit{region}, \textit{pageID} \rangle$ or $\langle \textit{region}, \textit{rid} \rangle$ entries (respectively). *region* is the **minimum bounding rectangle** that spans all data items reachable by the respective pointer.
- Every node contains between d and $2d$ entries ($\rightsquigarrow$ B$^+$-tree).[11]
- **Insertion** and **deletion** algorithms keep an R-tree **balanced** at all times.

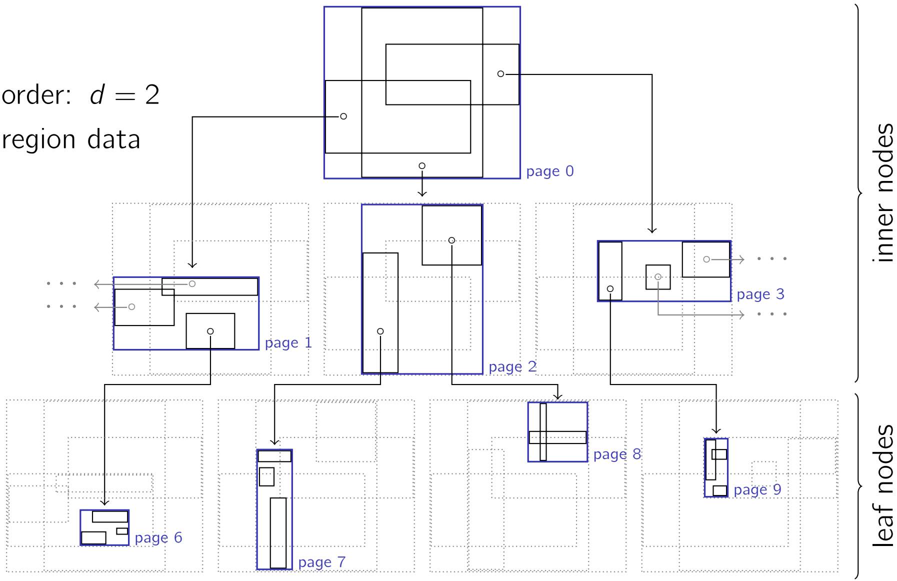
R-trees allow the storage of **point and region data**.

↗ Antonin Guttman. R-Trees: A Dynamic Index Structure for Spatial Searching. *SIGMOD 1984*.

[11] except the root node

R-Tree: Example

- order: $d = 2$
- region data



R-Tree: Searching and Inserting

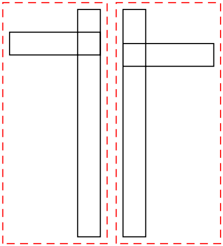
While **searching** an R-tree, we may have to descend into more than one child node for point **and** region queries (↗ range search in point quad trees, slide 125).

Inserting into an R-tree very much resembles B^+-tree insertion:

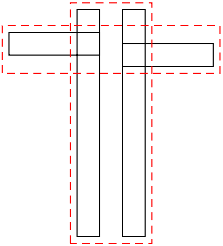
1. **Choose** a leaf node n to insert the new entry.
   - Try to minimize the necessary region enlargement(s).
2. If n is **full**, **split** it (resulting in n and n') and distribute old and new entries evenly across n and n'.
   - Splits may propagate bottom-up and eventually reach the root (↗ B^+-tree).
3. After the insertion, some regions in the ancestor nodes of n may need to be **adjusted** to cover the new entry.

Splitting an R-Tree Node

To **split** an R-tree node, we have more than one alternative.



bad split*



good split*

*according to Guttman

Heuristic: Minimize the totally covered area.

- **Exhaustive** search for the best split infeasible.
- Guttman proposes two ways to **approximate** the search.
- Follow-up papers (*e.g.*, the R*-tree) aim at improving the quality of node splits.

R-Tree: Deletes

All R-tree invariants (slide 137) are maintained during **deletions**.

1. If an R-tree node n **underflows** (*i.e.*, less than d entries are left after a deletion), the whole node is **deleted**.
2. Then, all entries that existed in n are **re-inserted** into the R-tree (as discussed before).

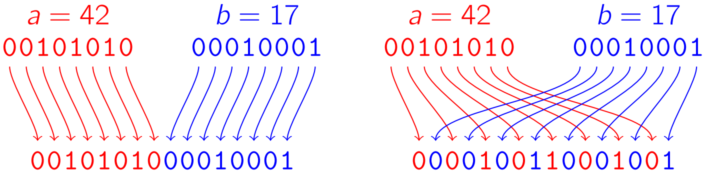
Note that Step 1 may lead to a recursive deletion of n's parent.

- Deletion, therefore, is a rather **expensive** task in an R-tree.

Spacial indexing in mainstream database implementations.

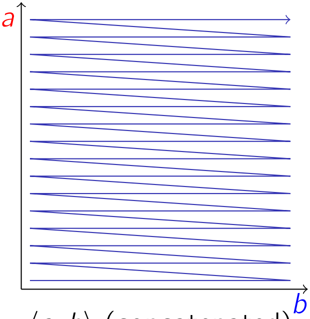
- Indexing in commodity systems is typically based on **R-trees**.
- Yet, only few systems implement them out of the box (*e.g.*, PostgreSQL).

- We saw earlier that a B$^+$-tree over **concatenated** fields $\langle a, b\rangle$ doesn't help our case, because of the **asymmetry** between the role of a and b in the index.
- What happens if we **interleave** the bits of a and b (hence, make the B$^+$-tree "more symmetric")?

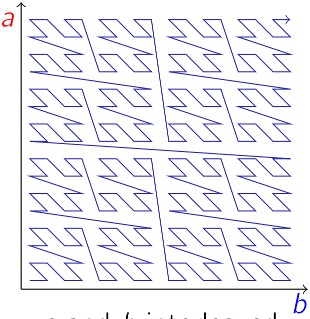


$\langle a, b\rangle$ (concatenation) a and b interleaved

Z-Ordering



$\langle a, b \rangle$ (concatenated)



a and *b* interleaved

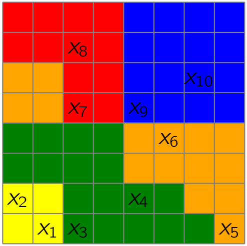
- Both approaches **linearize** all coordinates in the value space according to some **order**.

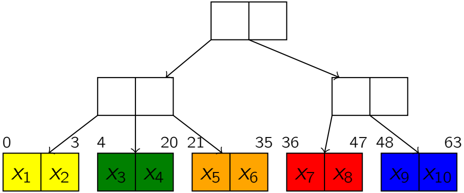
↗ see also slide 120

- Bit interleaving leads to what is called the **Z-order**.
- The Z-order (largely) preserves spacial **clustering**.

B^+-trees Over Z-Codes

- Use a **B^+-tree** to index Z-codes of multi-dimensional data.
- Each leaf in the B^+-tree describes an **interval** in the **Z-space**.
- Each interval in the Z-space describes a **region** in the multi-dimensional data space.

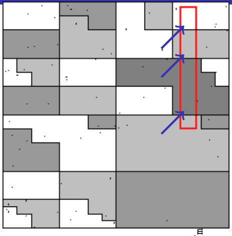




- To retrieve all data points in a query region Q, try to touch only those leave pages that **intersect** with Q.

UB-Tree Range Queries

After each page processed, perform an **index re-scan** (↗) to fetch the next leaf page that intersects with Q.



Example by Volker Markl and Rudolf Bayer, taken from http://m

Function: `ub_range` (Q)
$cur \leftarrow z(Q_{\text{bottom,left}})$;
while true **do**
    // search B$^+$-tree page containing *cur* (↗ slide 70)
    page ← `search` (*cur*);
    foreach data point p on *page* **do**
        if p is in Q **then**
            append p to result ;
    if region in *page* reaches beyond $Q_{\text{top,right}}$ **then**
        break ;
    // compute next Z-address using Q and data on current page
    cur ← `get_next_z_address` (Q, *page*);

UB-Trees—Discussion

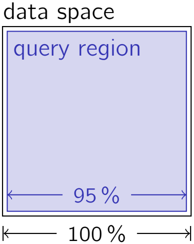
- The cost of a region query is **linear** in the **size of the result** Q and **logarithmic** with respect to the stored data volume N ($\frac{4 \cdot Q}{2d} \cdot \mathcal{O}(\log_d N)$).
- UB-trees are **fully dynamic**, a property inherited from the underlying B^+-trees.
- The use of other **space-filling curves** to linearize the data space is discussed in the literature, too. *E.g.*, **Hilbert curves**.

UB-trees have been commercialized in the Transbase® database system.

Spaces with High Dimensionality

For large k, all the techniques we discussed become **ineffective**:

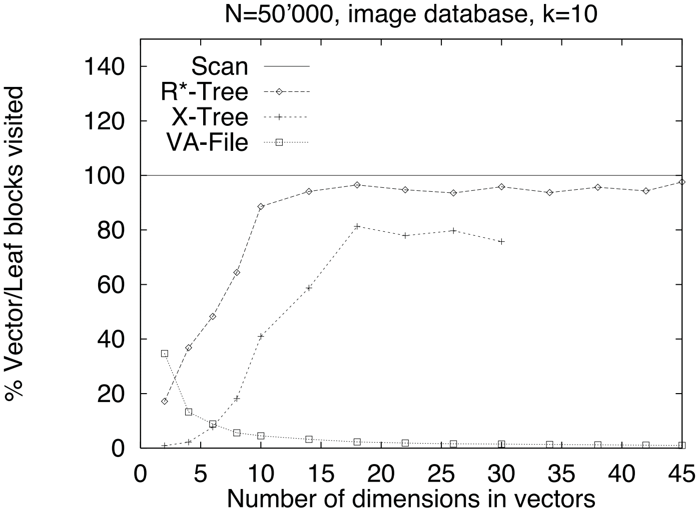
- *E.g.*, for $k = 100$, we'd get $2^{100} \approx 10^{30}$ partitions per node in a **point quad tree**. Even with billions of data points, **almost all** of these are empty.
- Consider a **really big** search region, cube-sized covering 95 % of the range along **each** dimension:



For $k = 100$, the probability of a point being in this region is still only $0.95^{100} \approx 0.59\,\%$.

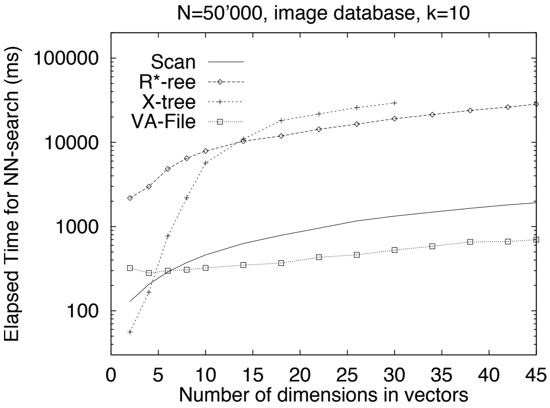
- We experience the **curse of dimensionality** here.

Page Selectivty for *k*-NN Search



Data: Stephen Bloch. What's Wrong with High-Dimensionality Search. *VLDB 2008*.

Query Performance in High Dimensions



- VA-File: **vector approximation file** ($|\text{VA-File}| \ll |\text{data file}|$)
- **Scan** VA-File and use it as a **filter** for actual disk pages.

Wrap-Up

Point Quad Tree

k-dimensional analogy to binary trees; main memory only.

k-d Tree, K-D-B-Tree

k-d tree: partition space one dimension at a time (round-robin); K-D-B-Tree: B^+-tree-like organization with pages as nodes, nodes use a k-d-like structure internally.

R-Tree

regions within a node may overlap; fully dynamic; for point and region data.

UB-Tree

use space-filling curve (Z-order) to linearize k-dimensional data, then use B^+-tree.

Curse Of Dimensionality

most indexing structures become ineffective for large k; fall back to seq. scanning and approximation/compression.