
Department of Informatics
Aristotle University of Thessaloniki

Skyline Query Processing

A. Papadopoulos
Associate Professor

Outline of Presentation

- Introduction
- Skyline computation
 - Introduction to R-trees
 - Algorithm BBS (branch-and-bound skyline)
 - Advanced topics
- Conclusions
- Bibliography

Introduction

Skyline queries have been proposed as an alternative to satisfy user preferences.

The Skyline query

- does not require a ranking function
- does not need the integer k

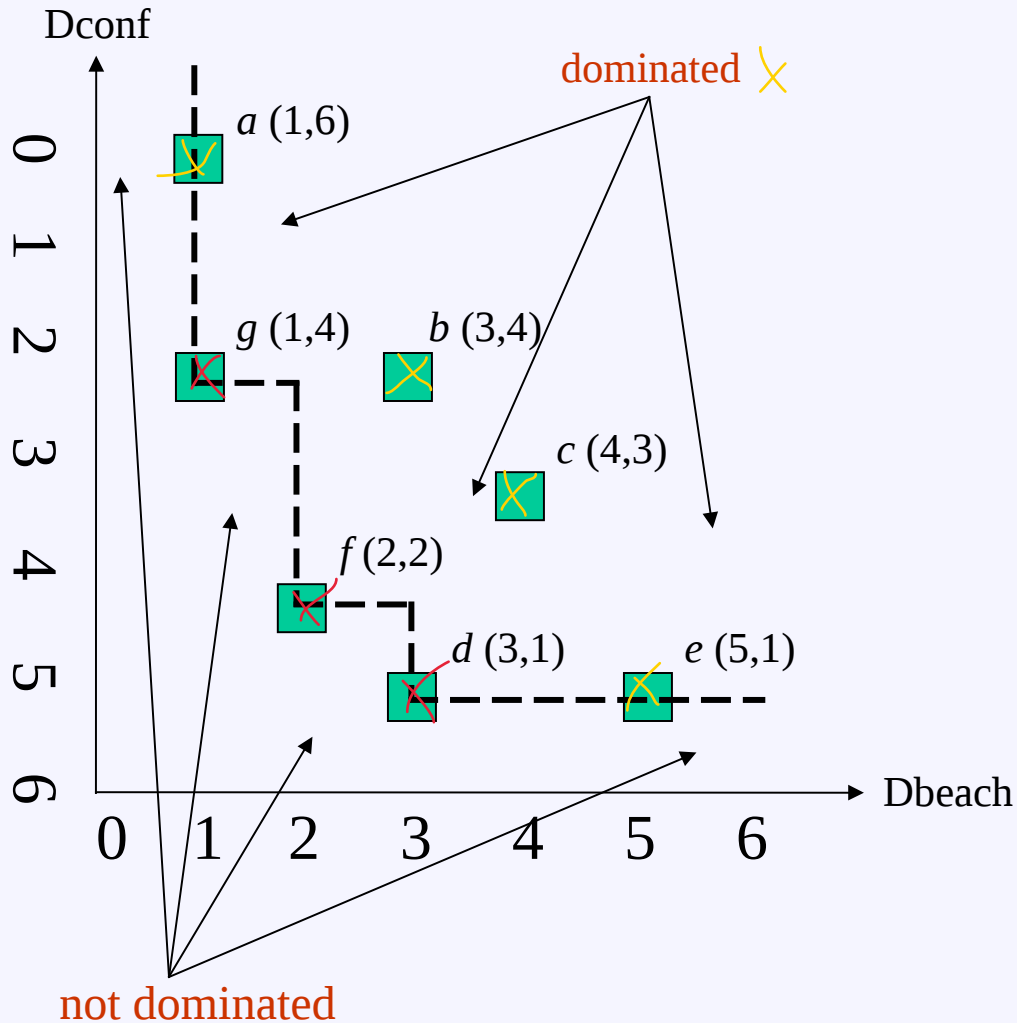
Introduction

The Skyline of a set of objects (records) comprises all records that are **not dominated** by any other record.

A record x **dominates** another record y if x is as good as y in all attributes and strictly **better** in at least one attribute.

Again, in some cases we are interested in **minimizing** attribute values (e.g., price) and in other cases **maximizing** them (e.g., floor number)

Introduction



Domination examples:

g dominates b because $1 < 3$ and $4 = 4$

f dominates c because $2 < 4$ and $2 < 3$

d dominates e because $3 < 5$ and $1 = 1$

The Skyline is the set: $\{ \underline{g, f, d} \}$

These objects **are not dominated** by any other object.

Introduction - applications

E-commerce

“I want to buy a PDA which is as cheap as possible, has large memory capacity and it is light-weighted”

For Top- k queries we should also provide the number k (how many PDAs we want in the answer) and the ranking function.

Introduction - applications

Multimedia Databases

“Give me the 3 images that have the highest resolution, they are red and depict flowers”

Introduction - applications

Web Information Retrieval

Let M be a **meta search engine** which uses yahoo and google. Both search engines return a set of results ranked by relevance.

yahoo

google

id	score	i	score
a	0.9	b	0.8
c	0.7	d	0.7
b	0.6	a	0.6

The challenge is to **combine** the results of all search engines in order to give a **total ranking** of the documents.

Introduction – naïve methods

Skyline processing

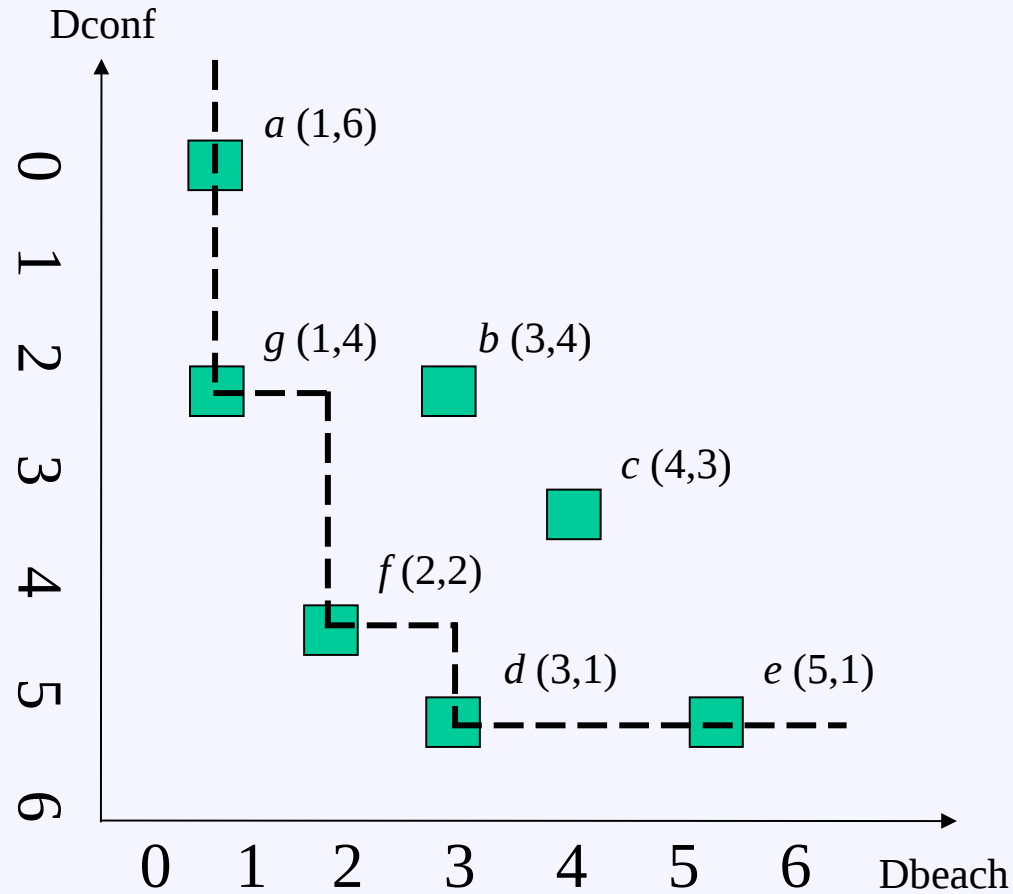
- For each object, check if it is dominated by any other object
- Return the objects that are not dominated

Disadvantages:

Requires scanning the whole database for each object.

Complexity $O(n^2)$. This is not convenient in systems with large volumes of data.

Skyline Computation



Skyline objects: g, f, d

Skyline Computation

Some techniques:

- **Nested Block Loop** (NBL): perform a nested loop over all blocks of the data.
- **Divide and Conquer** (DC): partition the space in subspaces, solve the problem in the subspaces and then synthesize the solution in the whole space.
- **Nearest-Neighbor based** (NN): uses an R-tree index and performs a sequence of nearest-neighbor queries until all Skyline objects have been found.

Introduction to R-trees

- Many real-life applications require the organization and management of **multidimensional data** (e.g., each image is represented as a point in the 5-dimensional space).
- To enable efficient query processing, data should be organized by means of an **indexing scheme** which is used to speed-up processing.
- The index helps in **reducing the number of inspected objects** significantly, avoiding the **sequential scan** of the whole database.
- Indexing schemes for multidimensional data work in a similar manner to access methods for simple numeric data (e.g., **B-trees** and **Hashing**).

Introduction to R-trees

One of the most important contributions in the area of multidimensional indexing is due to Antonin Guttman which invented the [R-tree](#).



His work:

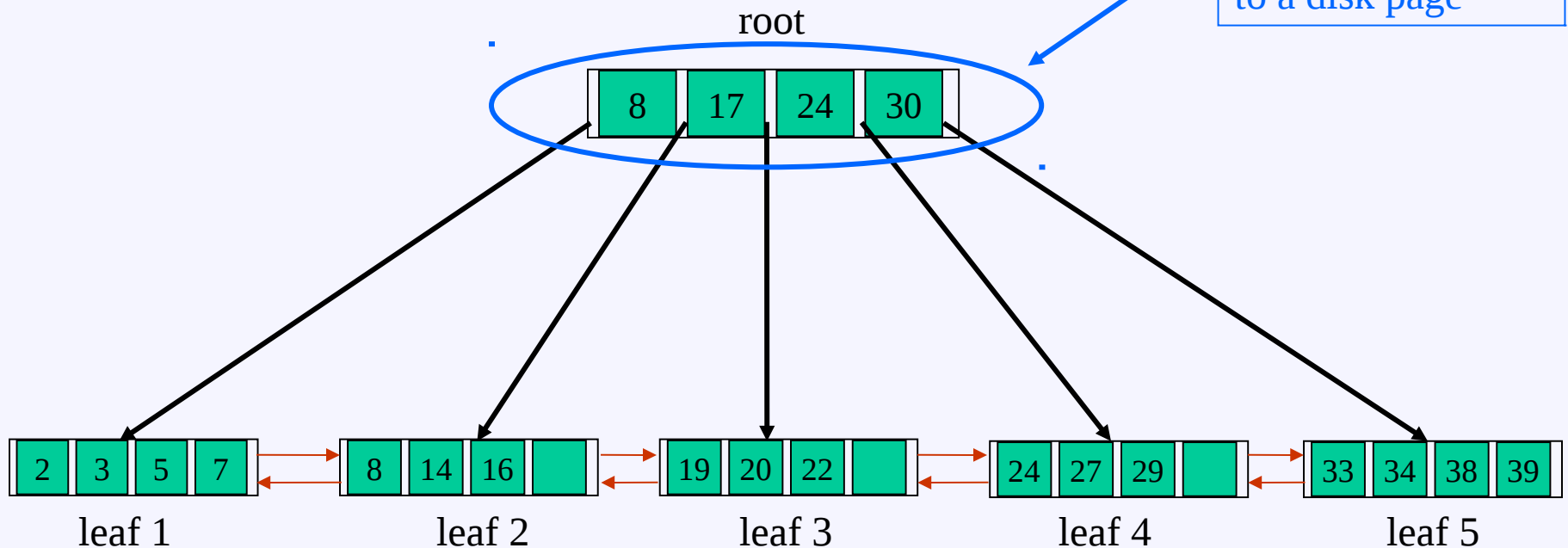
“R-trees: a dynamic index structure for spatial searching”,
ACM SIGMOD Conference 1984

has received [more than 2,900 citations](#)
(source google scholar)

Introduction to R-trees

The R-tree can be viewed as an extension of the B+-tree to handle multiple dimensions. Recall that, a B+-tree is used to organize numeric data in one dimension only.

B+ tree example with 6 nodes:



Introduction to R-trees

R-trees have been extensively used in spatial databases to organize points and rectangles. They show excellent performance in processing interesting queries such as:

Range query: return the points that are contained in a specified region.

K-nearest-neighbor: given a point p and an integer k return the k objects closer to p .

Introduction to R-trees



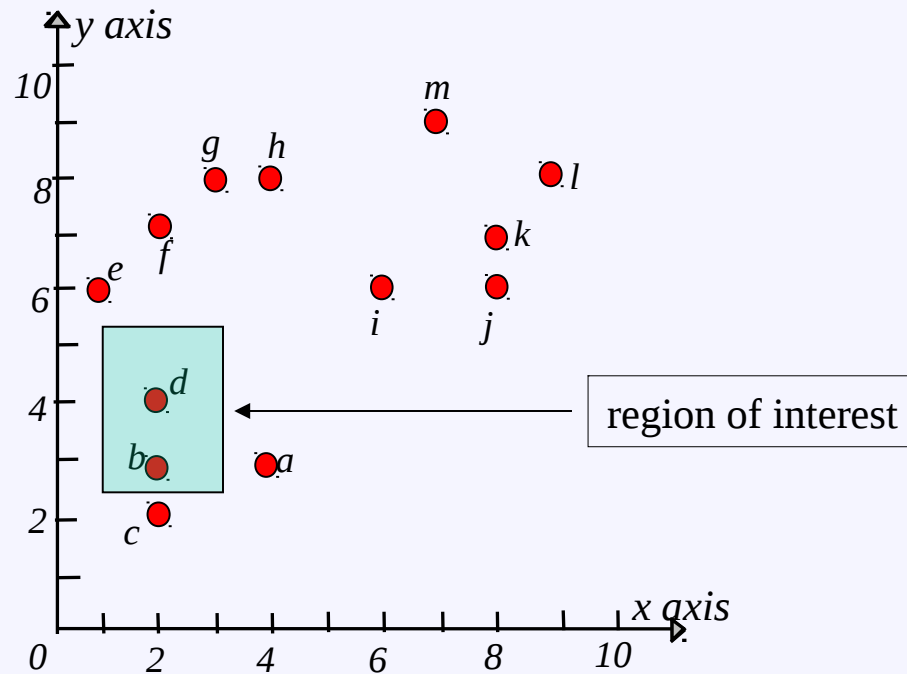
range query example:
which cities are within distance R from Amsterdam



k -NN query example:
Find the 3 cities closer to Utrecht ($k = 3$)

Introduction to R-trees

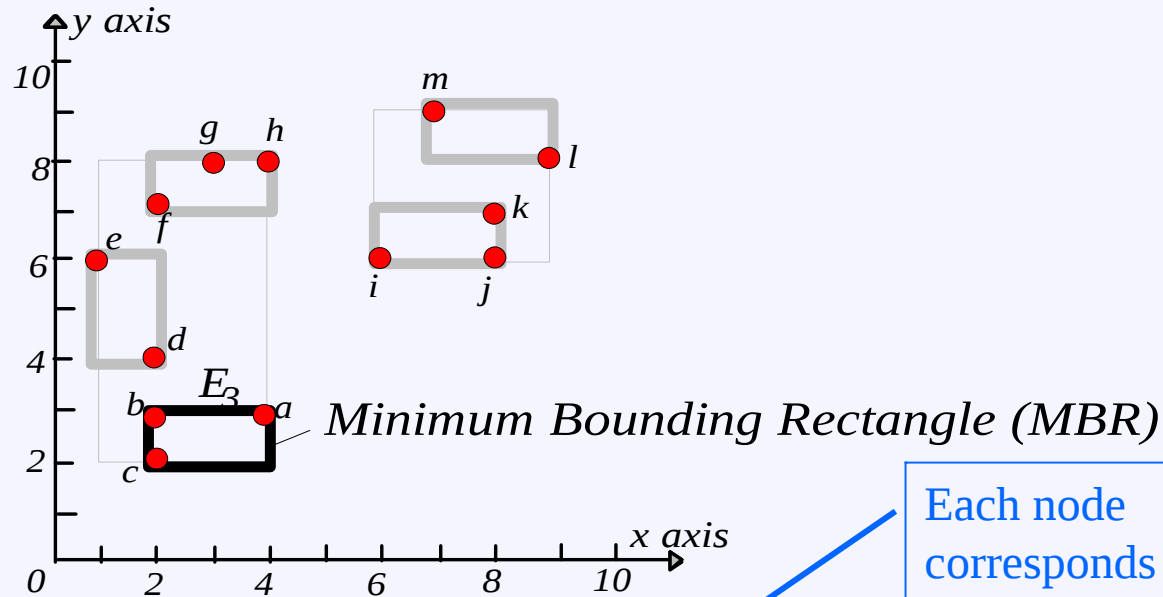
Example:
13 points in
2 dimensions



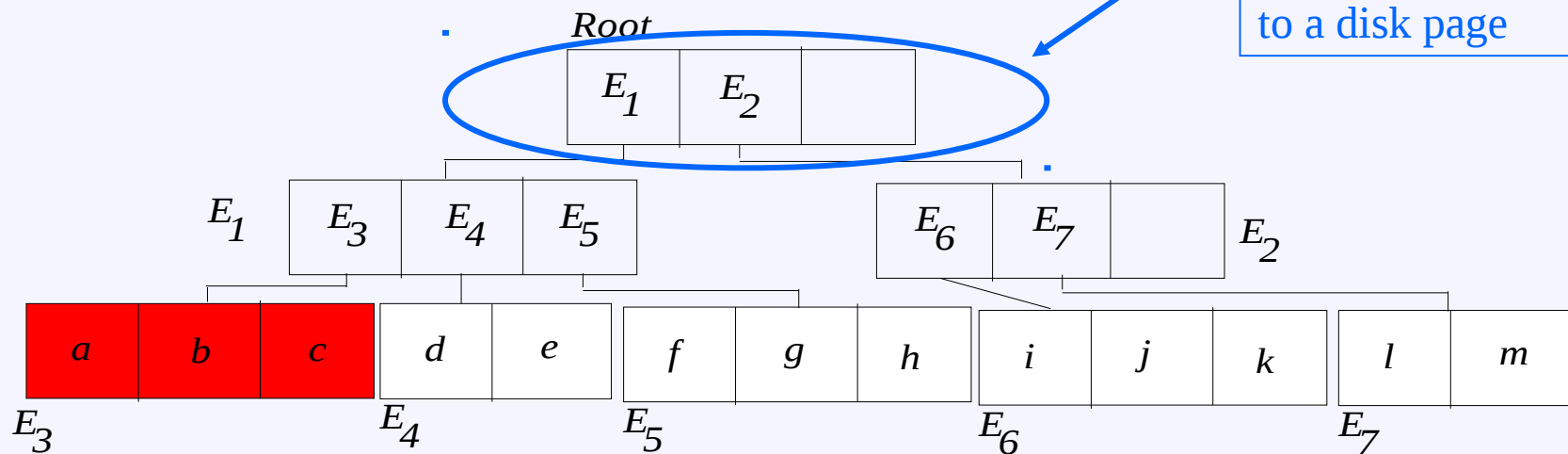
Range query example: “*find the objects in a given region*”.
E.g. find all hotels in Utrecht.

No index: scan through all objects. **NOT EFFICIENT!**

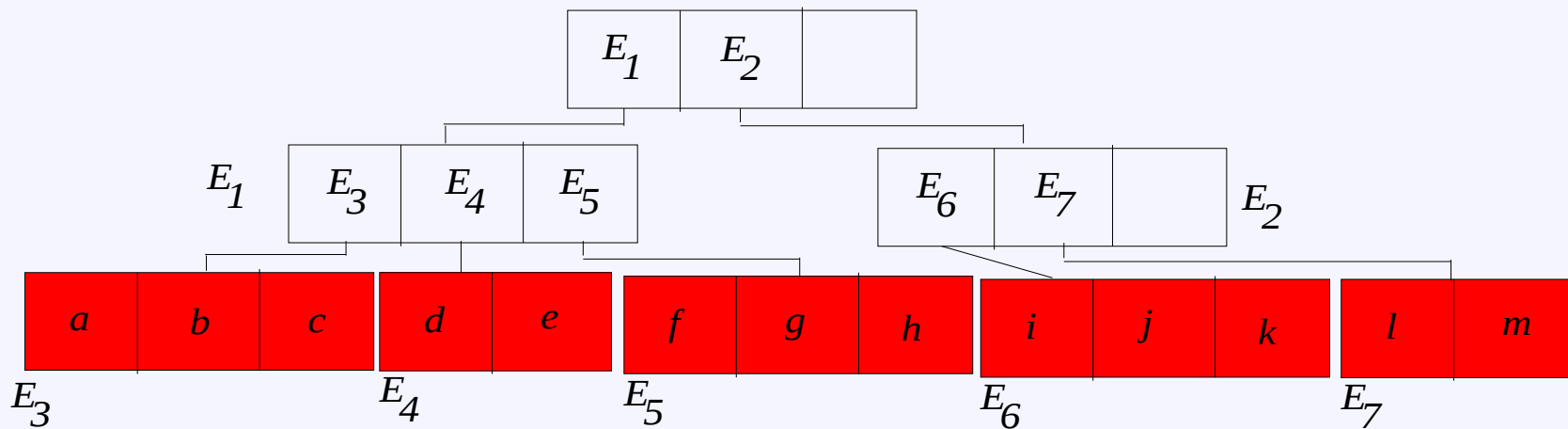
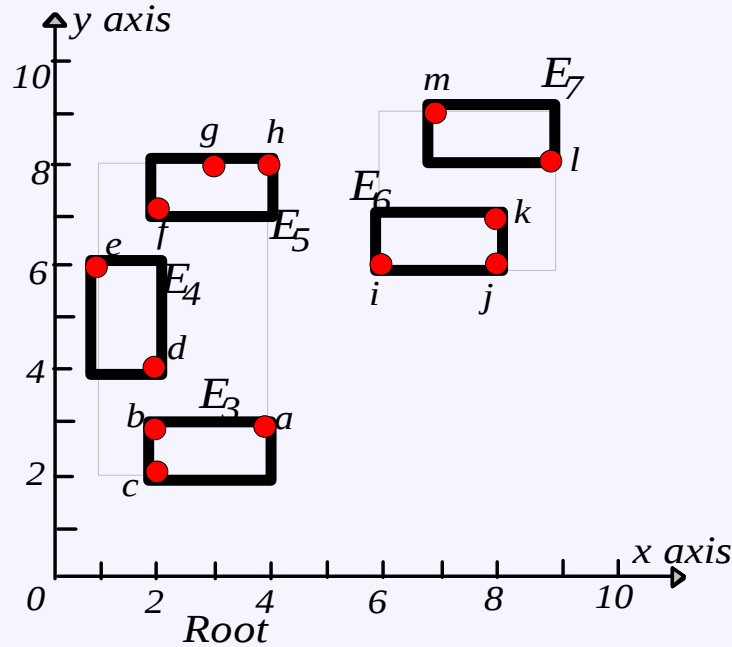
Introduction to R-trees – structure



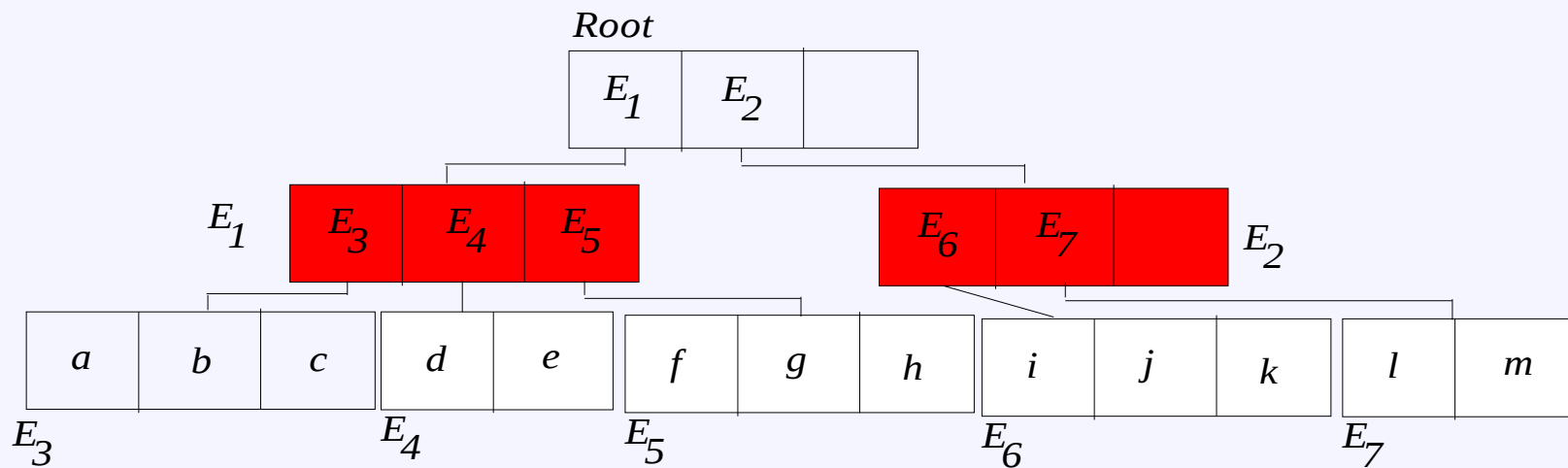
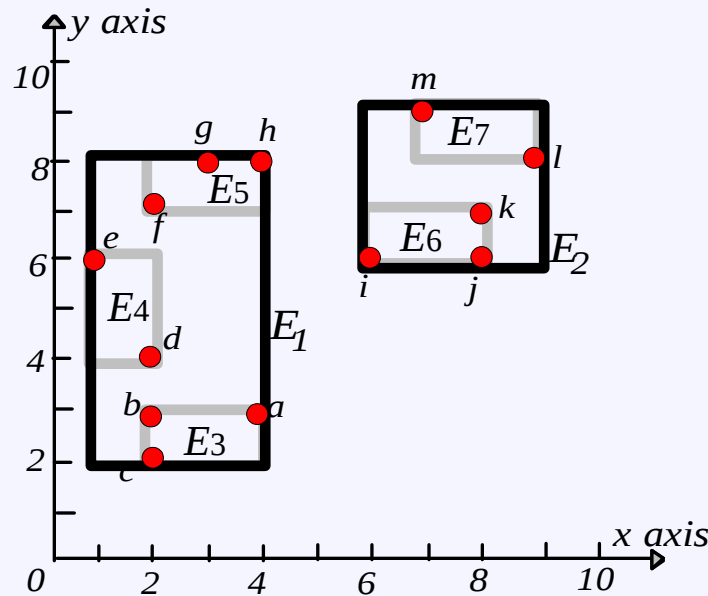
Each node corresponds to a disk page



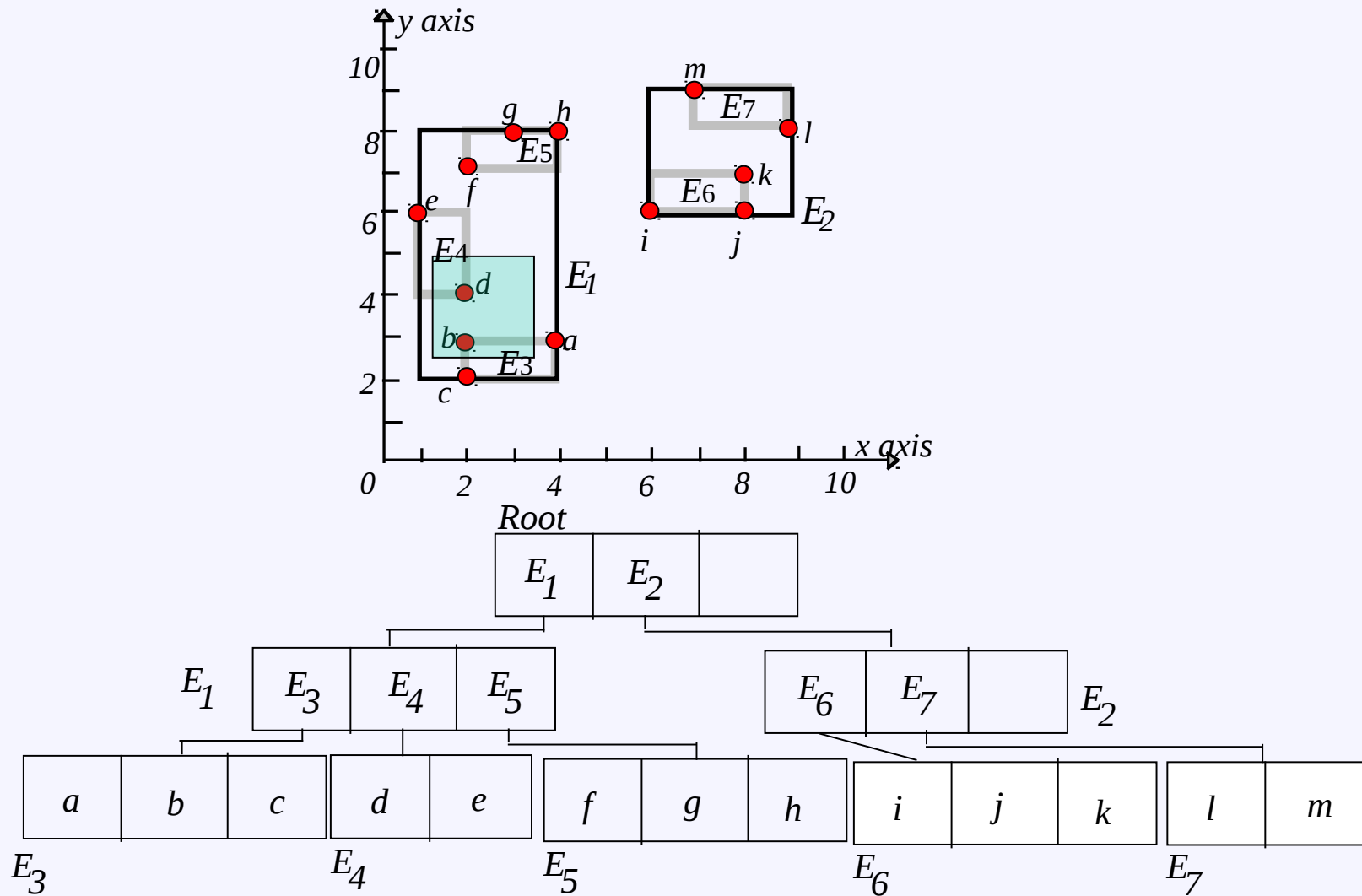
Introduction to R-trees – structure



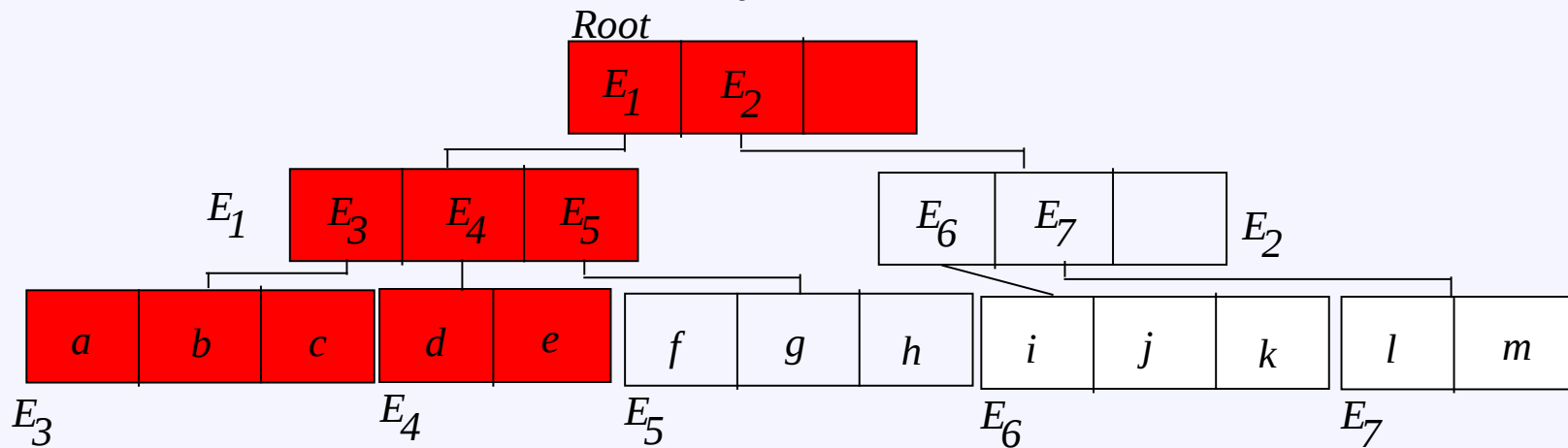
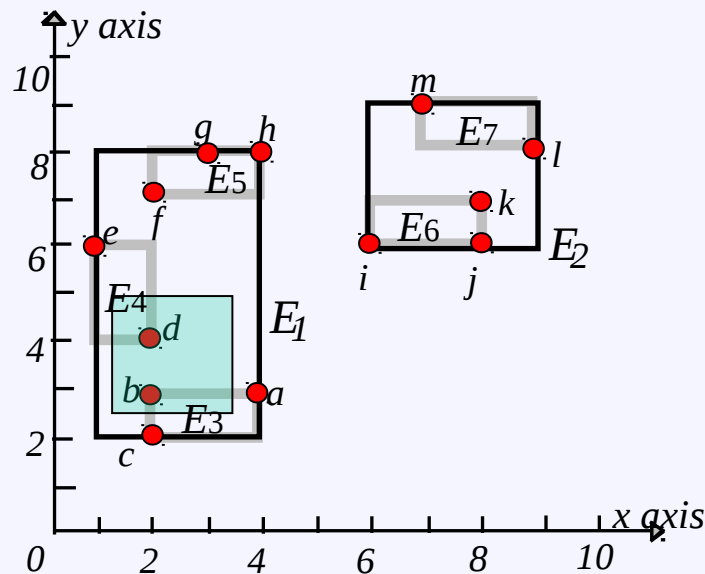
Introduction to R-trees – structure



Introduction to R-trees – range query



Introduction to R-trees – range query



BBS Algorithm – Basic Properties

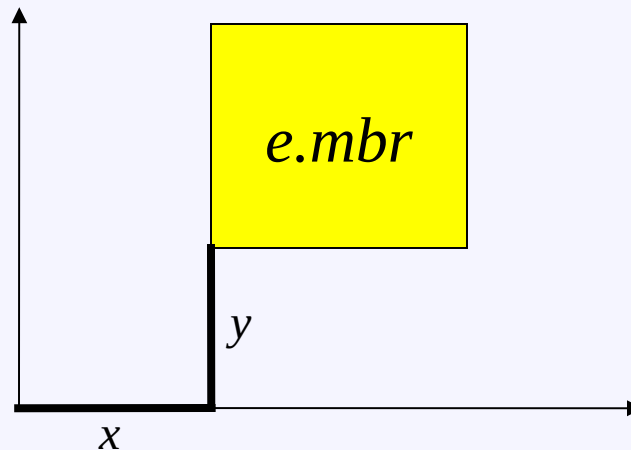
Any Branch-and-Bound method requires two decisions:

1. **How to branch**: which part of the space needs to be investigated next?
2. **How to bound**: which parts of the search space can be safely eliminated.

BBS Algorithm – basic properties

The algorithm uses a priority queue, where R-tree entries are prioritized by the **mindist** value. The mindist value of an entry e , is the **cityblock** (L_1) distance of its MBR's ($e.mbr$) lower-left corner to the origin.

For example:

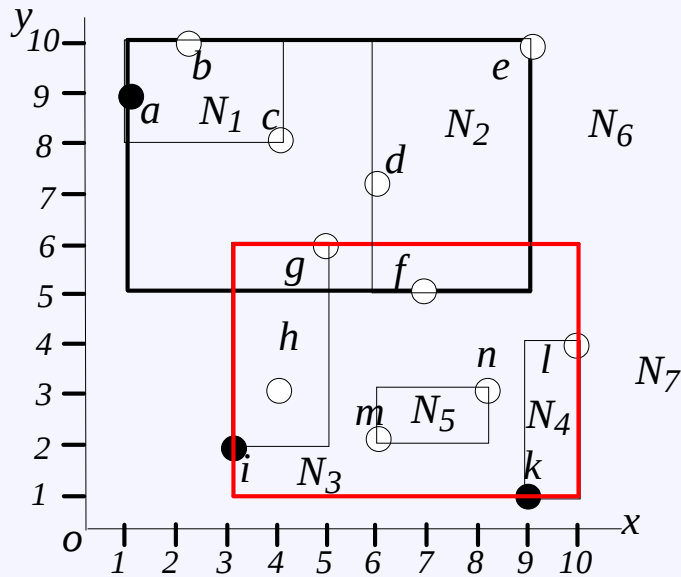


$$\text{mindist}(e.mbr) = x + y$$

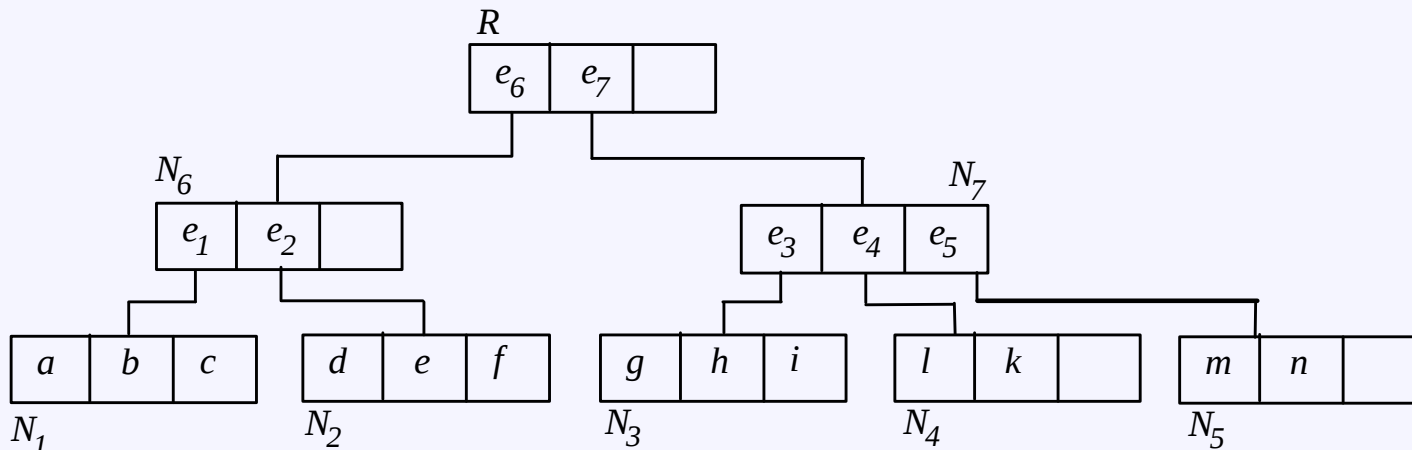
BBS Algorithm – basic properties

- The algorithm in every step chooses the **best** R-tree entry to check, according to the mindist measure. Upon visiting a node, the mindist of its entries is calculated and entries are inserted into the priority queue.
- The algorithm keeps the discovered skyline points in the **set S** .
- If the top of the queue is a data point, it is tested if it is dominated by any point in S . If yes it is rejected, otherwise it is inserted into S .

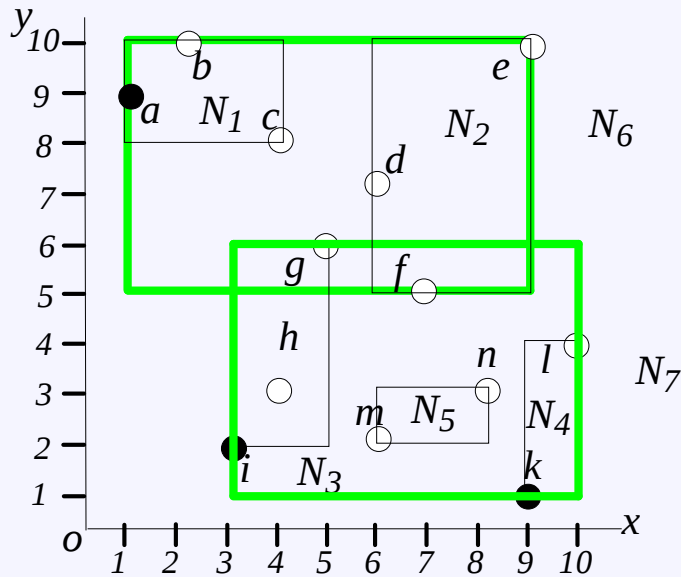
BBS Algorithm - example



- Assume all points are indexed in an R-tree.
- $\text{mindist}(\text{MBR}) = \text{the } L_1 \text{ distance between its lower-left corner and the origin.}$



BBS Algorithm - example

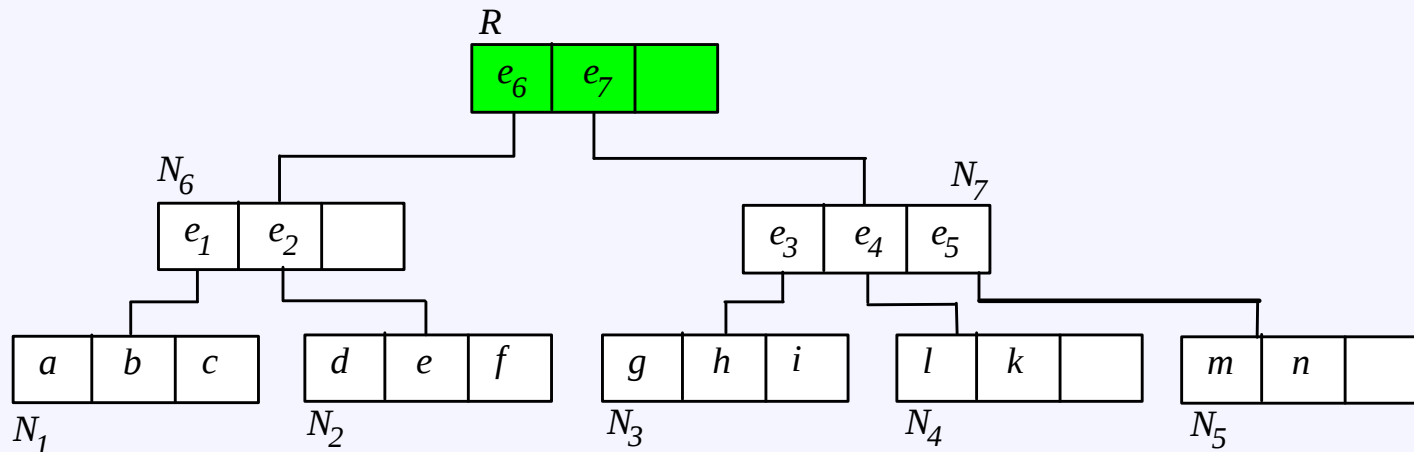


- Each heap entry keeps the **mindist** of the MBR.

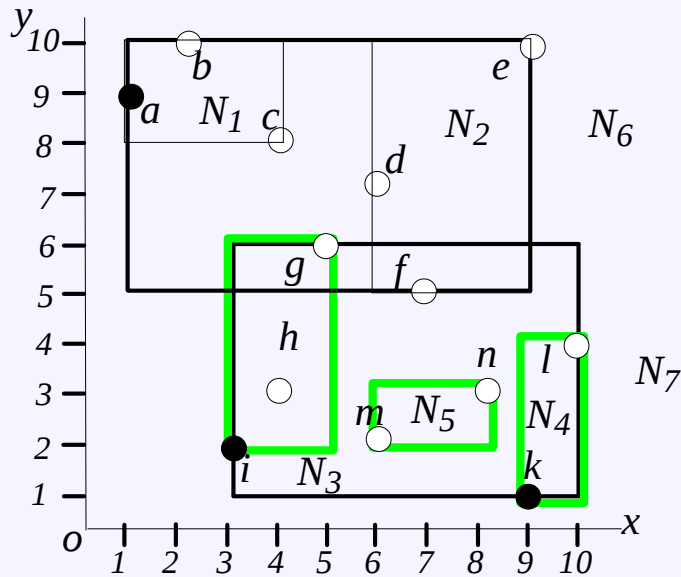
action
access root

heap contents
<e₇,4><e₆,6>

S
∅



BBS Algorithm - example

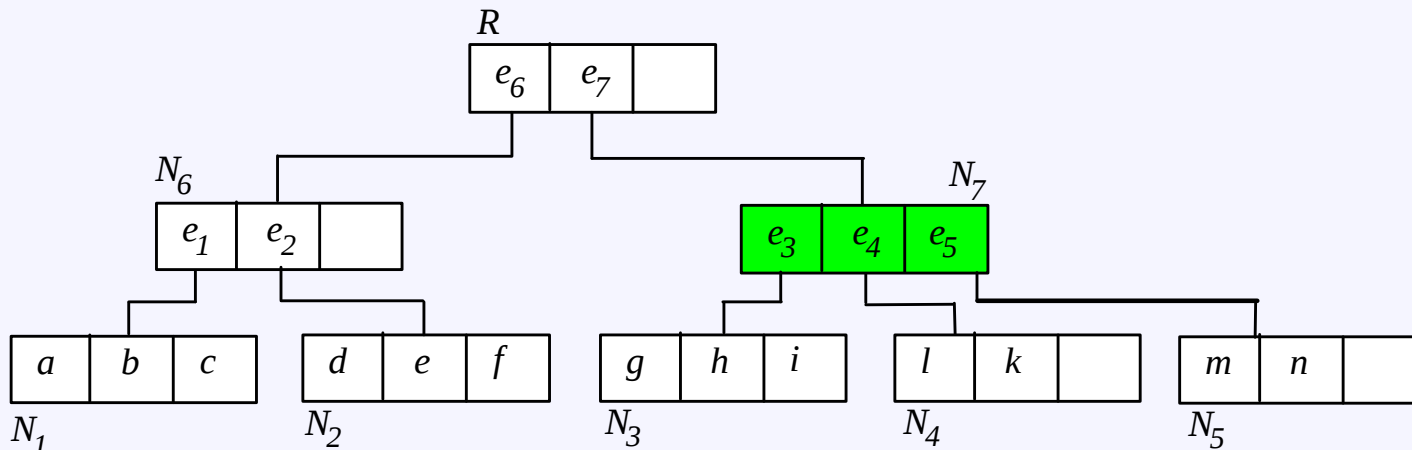


- Process entries in ascending order of their mindists.

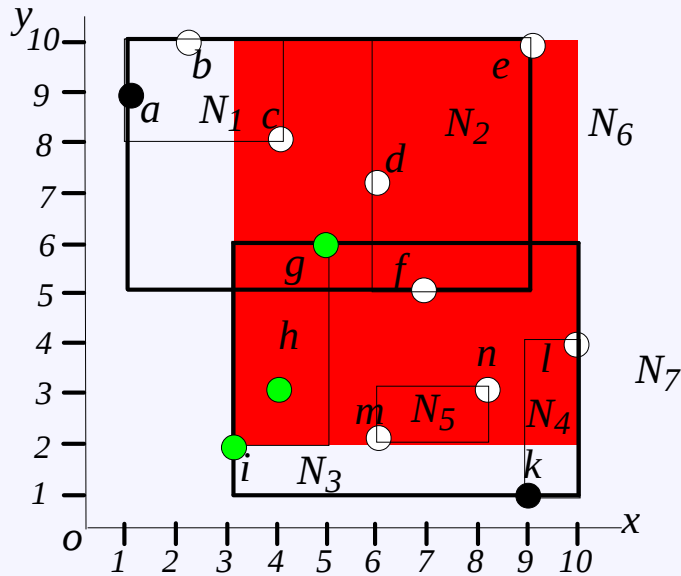
action
access root
expand e_7

heap contents
 $\langle e_7, 4 \rangle \langle e_6, 6 \rangle$
 $\langle e_3, 5 \rangle \langle e_6, 6 \rangle \langle e_5, 8 \rangle \langle e_4, 10 \rangle$

S
 \emptyset
 \emptyset



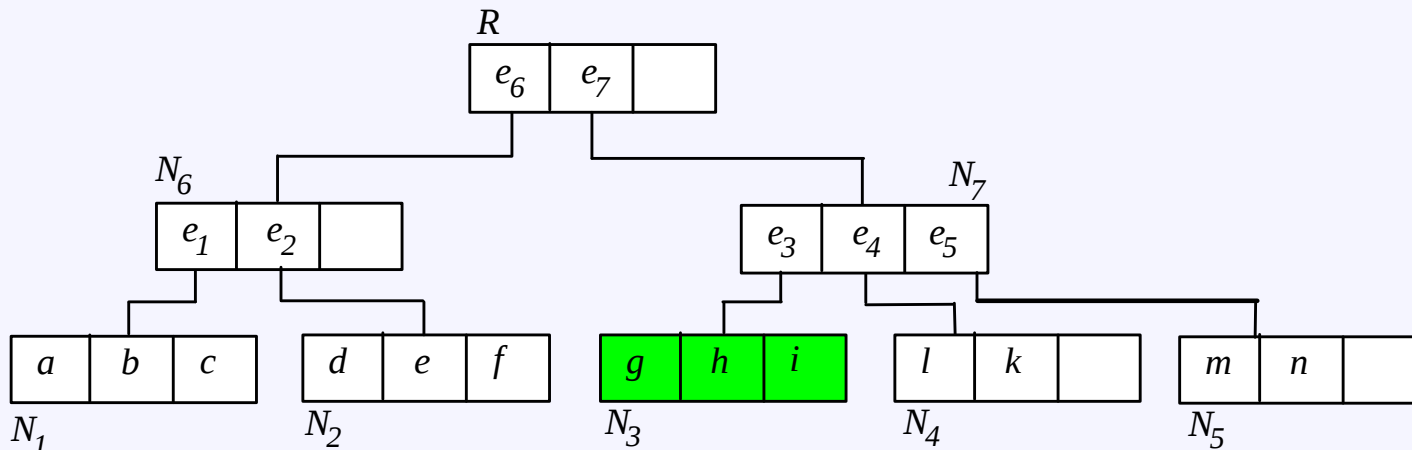
BBS Algorithm - example



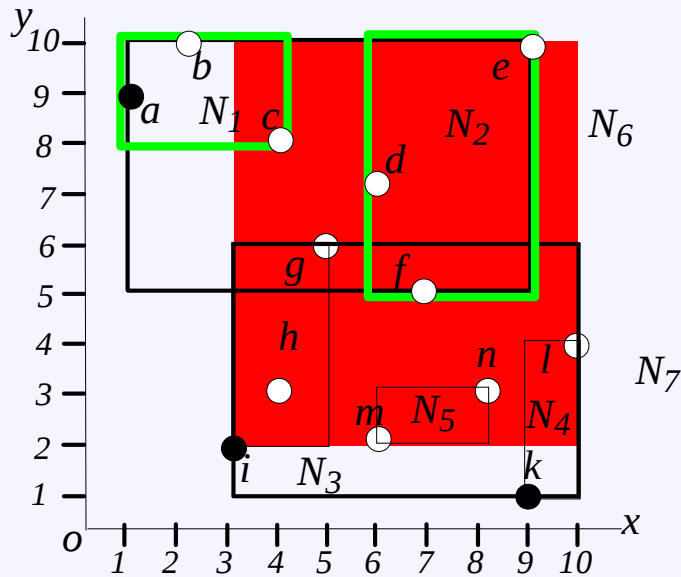
action
 access root
 expand e_7
 expand e_3

heap contents
 $\langle e_7, 4 \rangle \langle e_6, 6 \rangle$
 $\langle e_3, 5 \rangle \langle e_6, 6 \rangle \langle e_5, 8 \rangle \langle e_4, 10 \rangle$
 $\langle i, 5 \rangle \langle e_6, 6 \rangle \langle e_5, 8 \rangle \langle e_4, 10 \rangle$

S
 \emptyset
 \emptyset
 $\{i\}$



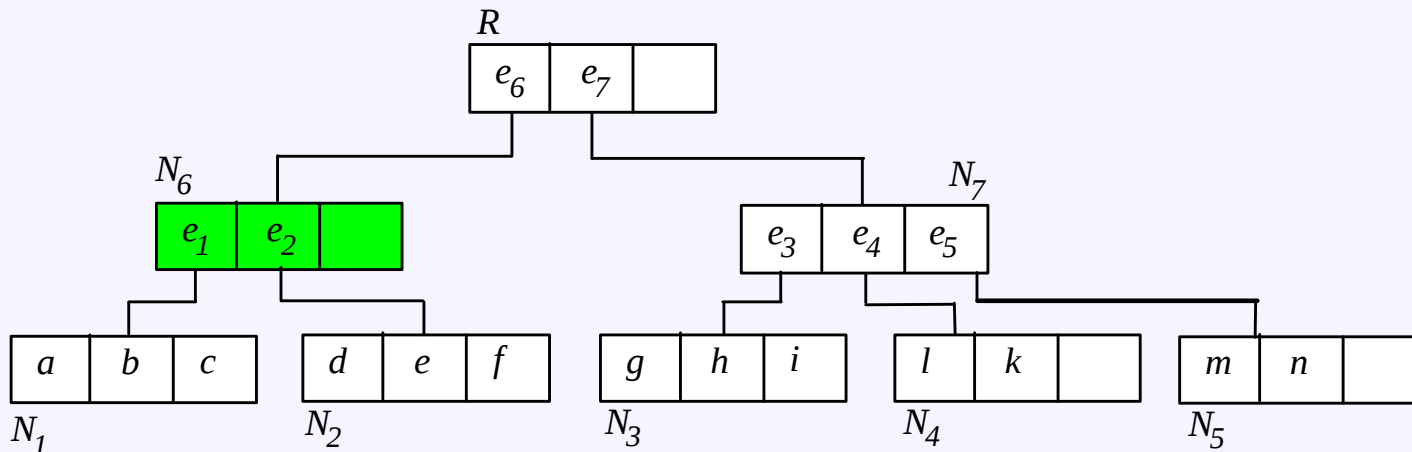
BBS Algorithm - example



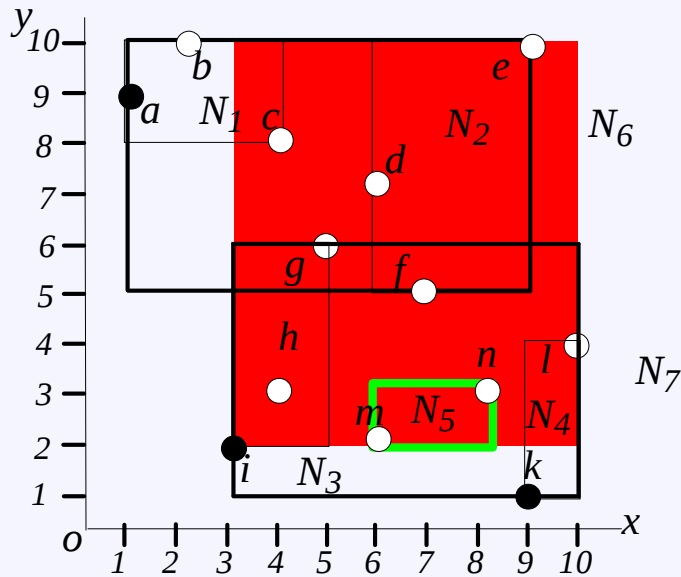
action
 access root
 expand e_7
 expand e_3
 expand e_6

heap contents
 $\langle e_7, 4 \rangle \langle e_6, 6 \rangle$
 $\langle e_3, 5 \rangle \langle e_6, 6 \rangle \langle e_5, 8 \rangle \langle e_4, 10 \rangle$
 $\langle i, 5 \rangle \langle e_6, 6 \rangle \langle e_5, 8 \rangle \langle e_4, 10 \rangle$
 $\langle e_5, 8 \rangle \langle e_1, 9 \rangle \langle e_4, 10 \rangle$

S
 \emptyset
 \emptyset
 $\{i\}$
 $\{i\}$



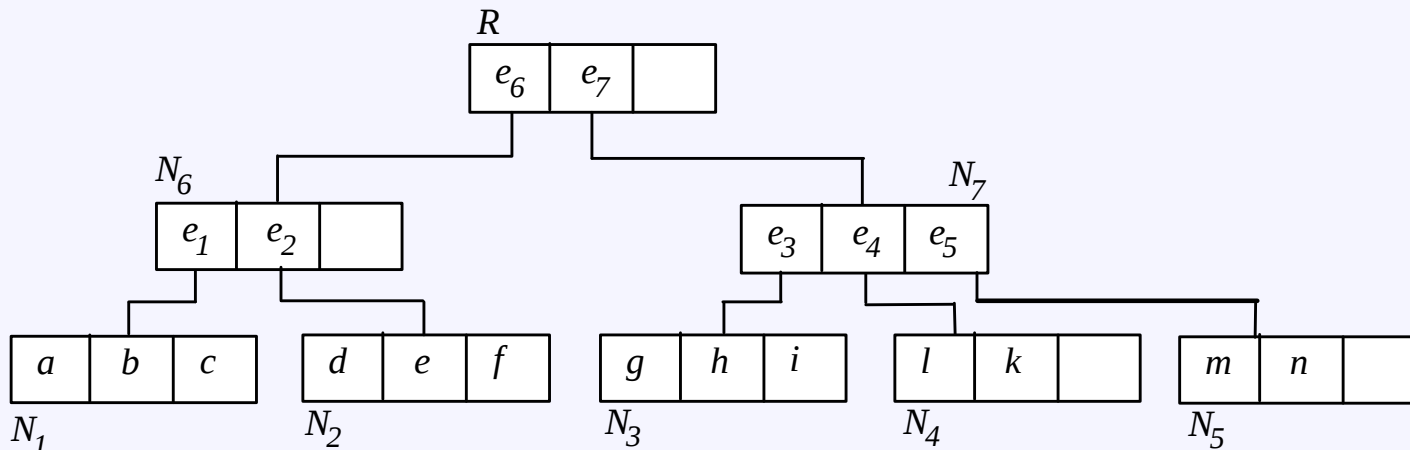
BBS Algorithm - example



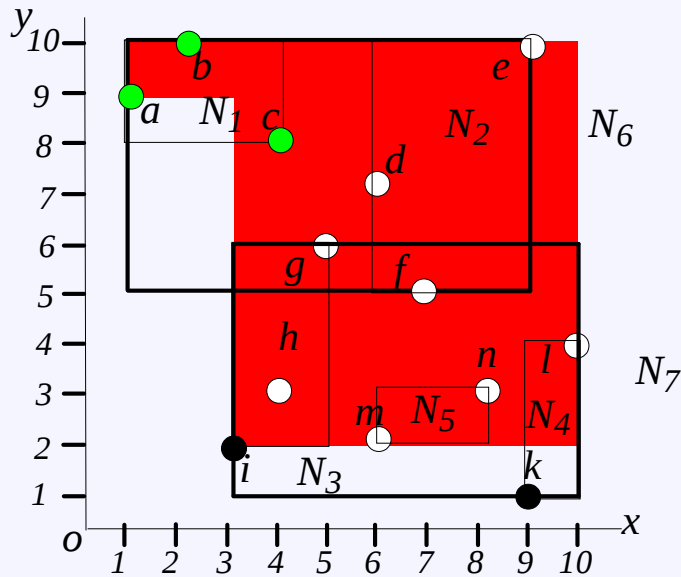
action
 access root
 expand e_7
 expand e_3
 expand e_6
 remove e_5

heap contents
 $\langle e_7, 4 \rangle \langle e_6, 6 \rangle$
 $\langle e_3, 5 \rangle \langle e_6, 6 \rangle \langle e_5, 8 \rangle \langle e_4, 10 \rangle$
 $\langle i, 5 \rangle \langle e_6, 6 \rangle \langle e_5, 8 \rangle \langle e_4, 10 \rangle$
 $\langle e_5, 8 \rangle \langle e_1, 9 \rangle \langle e_4, 10 \rangle$
 $\langle e_1, 9 \rangle \langle e_4, 10 \rangle$

S
 \emptyset
 \emptyset
 $\{i\}$
 $\{i\}$
 $\{i\}$



BBS Algorithm - example

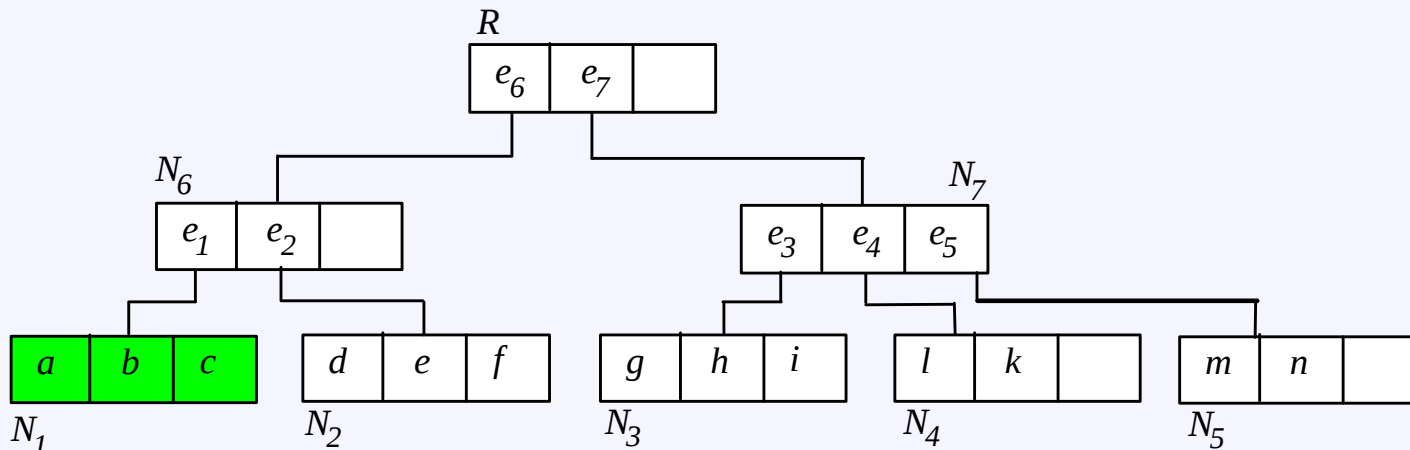


action
 access root
 expand e_7
 expand e_3
 expand e_6
 remove e_5
 expand e_1

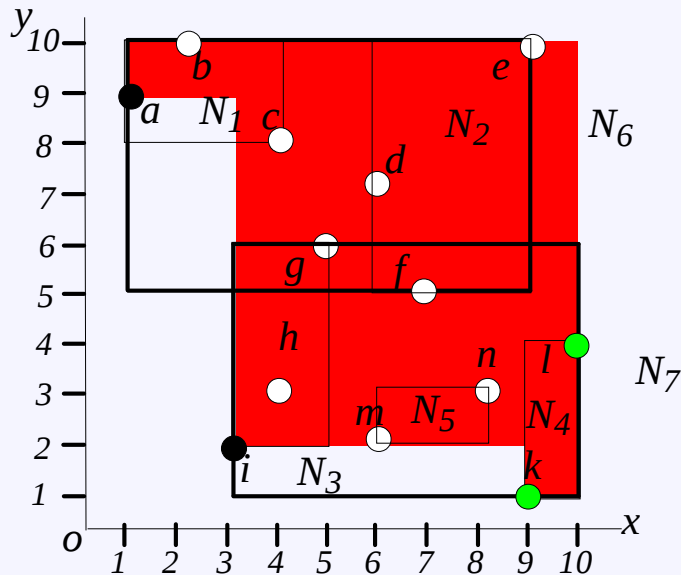
heap contents

$\langle e_7, 4 \rangle \langle e_6, 6 \rangle$
 $\langle e_3, 5 \rangle \langle e_6, 6 \rangle \langle e_5, 8 \rangle \langle e_4, 10 \rangle$
 $\langle i, 5 \rangle \langle e_6, 6 \rangle \langle e_5, 8 \rangle \langle e_4, 10 \rangle$
 $\langle e_5, 8 \rangle \langle e_1, 9 \rangle \langle e_4, 10 \rangle$
 $\langle e_1, 9 \rangle \langle e_4, 10 \rangle$
 $\langle a, 10 \rangle \langle e_4, 10 \rangle$

S
 \emptyset
 \emptyset
 $\{i\}$
 $\{i\}$
 $\{i\}$
 $\{i, a\}$



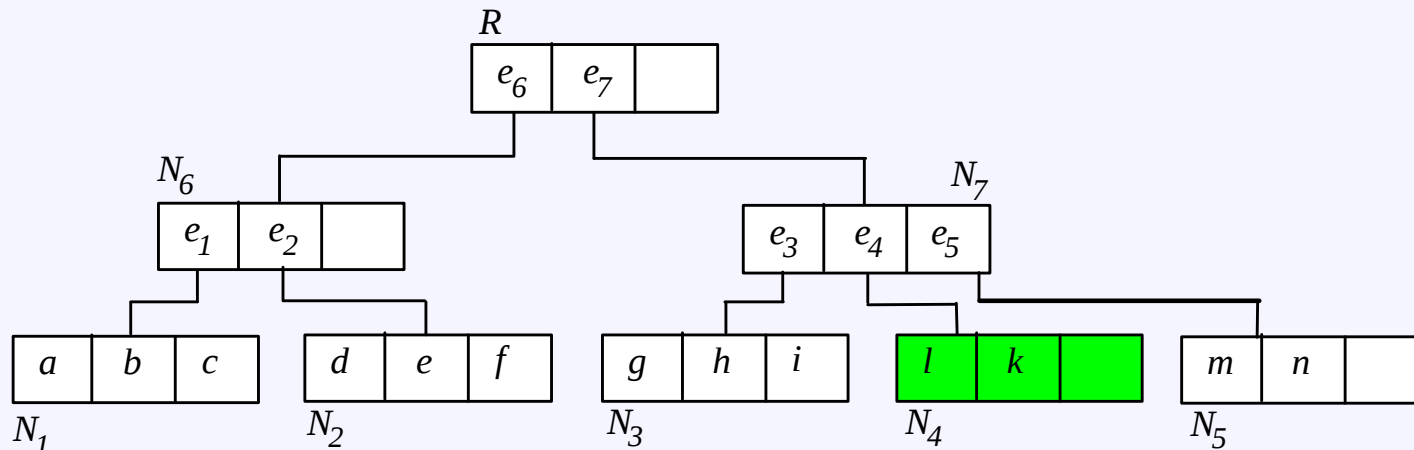
BBS Algorithm - example



action
 access root
 expand e_7
 expand e_3
 expand e_6
 remove e_5
 expand e_1
 expand e_4

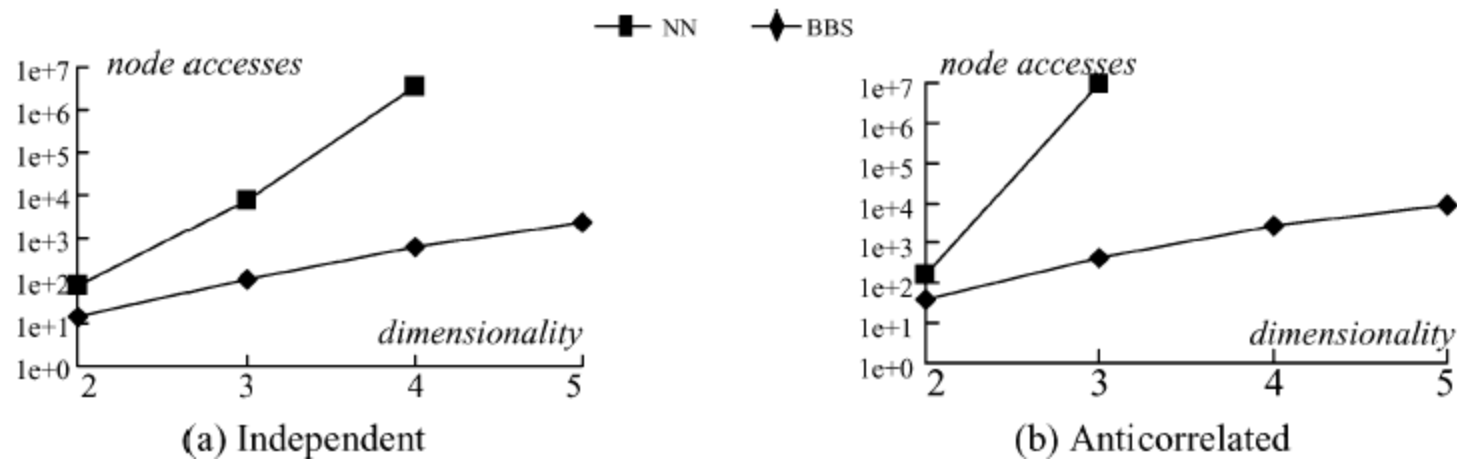
heap contents
 $\langle e_7, 4 \rangle \langle e_6, 6 \rangle$
 $\langle e_3, 5 \rangle \langle e_6, 6 \rangle \langle e_5, 8 \rangle \langle e_4, 10 \rangle$
 $\langle i, 5 \rangle \langle e_6, 6 \rangle \langle e_5, 8 \rangle \langle e_4, 10 \rangle$
 $\langle e_5, 8 \rangle \langle e_1, 9 \rangle \langle e_4, 10 \rangle$
 $\langle e_1, 9 \rangle \langle e_4, 10 \rangle$
 $\langle a, 10 \rangle \langle e_4, 10 \rangle$
 $\langle k, 10 \rangle$

S
 \emptyset
 \emptyset
 $\{i\}$
 $\{i\}$
 $\{i\}$
 $\{i, a\}$
 $\{i, a, k\}$



BBS Algorithm - performance

BBS performs better than previously proposed Skyline algorithms, regarding **CPU time** and **I/O time**.



Number of R-tree node accesses vs dimensionality

(source: Papadias et al TODS 2005)

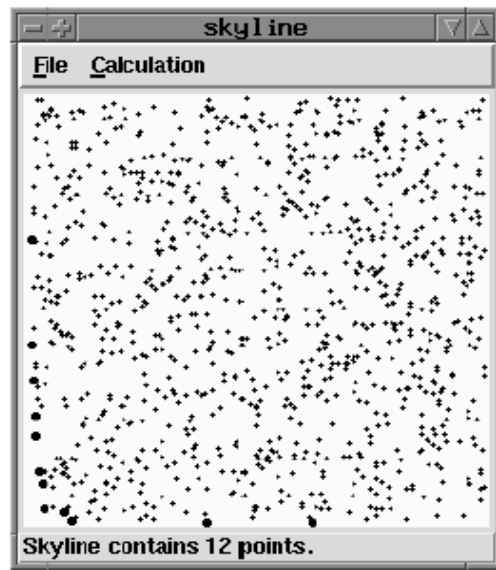
Skyline Computation - advanced topics I

Skylines in subspaces

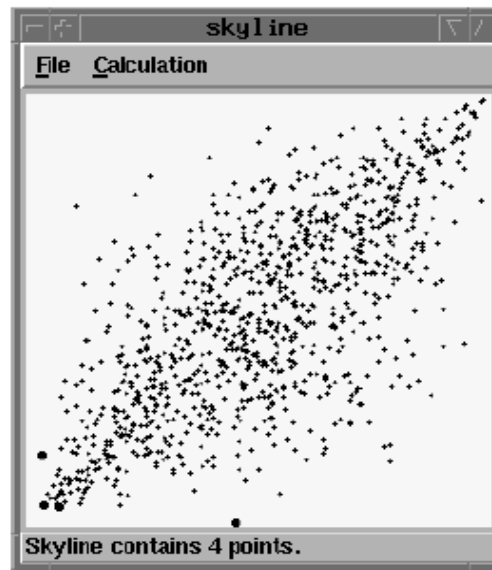
When the number of attributes (dimensions) **increases**, the number of points contained in the Skyline **increases** substantially. This happens because the probability that a point dominates another **decreases**.

Solution: find the Skyline on a **subset** of the attributes instead of using the whole set of attributes.

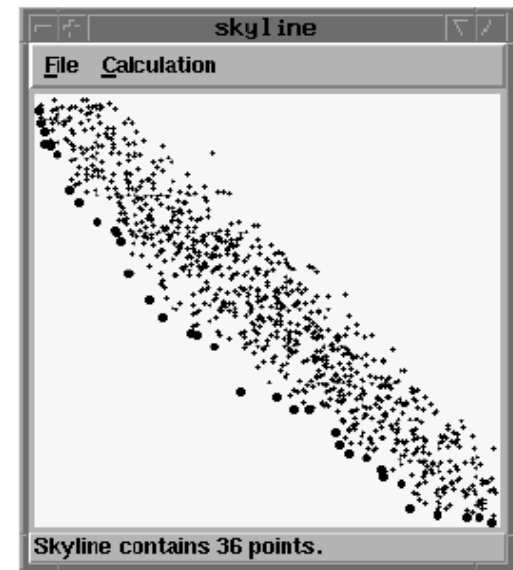
Skyline Computation - advanced topics I



independent



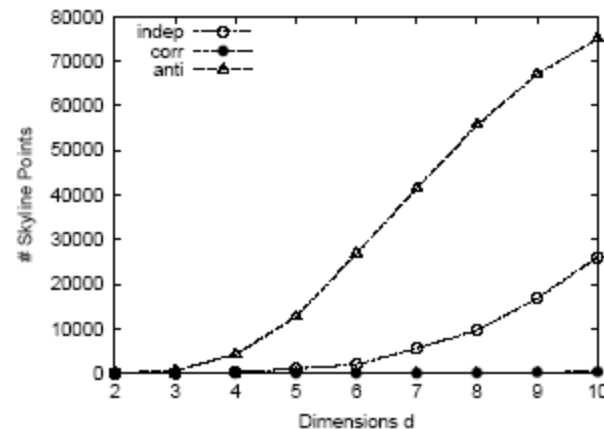
correlated



anticorrelated

100,000 points

<i>d</i>	<i>corr</i>	<i>indep</i>	<i>anti</i>
2	1	12	49
3	3	69	632
4	11	267	4239
5	17	1032	12615
6	21	1986	26843
7	43	5560	41484
8	121	9662	55691
9	243	16847	67101
10	378	26047	75028



(source: Borzanyi et al ICDE 2001)

Skyline Computation - advanced topics II

Distributed Skylines

In several applications, data are distributed across different sites (e.g., web applications, P2P). A number of research contributions deal with efficient processing of Skyline queries in such an environment.

Skyline Computation - advanced topics III

Most important Skyline objects

The number of Skyline points may be large in some cases. The challenge is to rank the Skyline points according to a score. For example, each Skyline point may be ranked according to the number of points it dominates. The highly-ranked points are presented to the user.

Bibliography

S. Borzsonyi, D. Kossmann, K. Stocker. “[The Skyline Operator](#)”. *Proceedings of the International Conference on Data Engineering*, pp.421-430, 2001.

A. Guttman. “[R-trees: A Dynamic Index Structure for Spatial Searching](#)”, *Proceedings of the ACM SIGMOD Conference*, 1984.

D. Papadias, Y. Tao, G. Fu, B. Seeger. “[Progressive Skyline Computation in Database Systems](#)”, *ACM Transactions on Database Systems*, Vol.30, No.1, pp.41-82, 2005.