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Skyline Query Processing

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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*

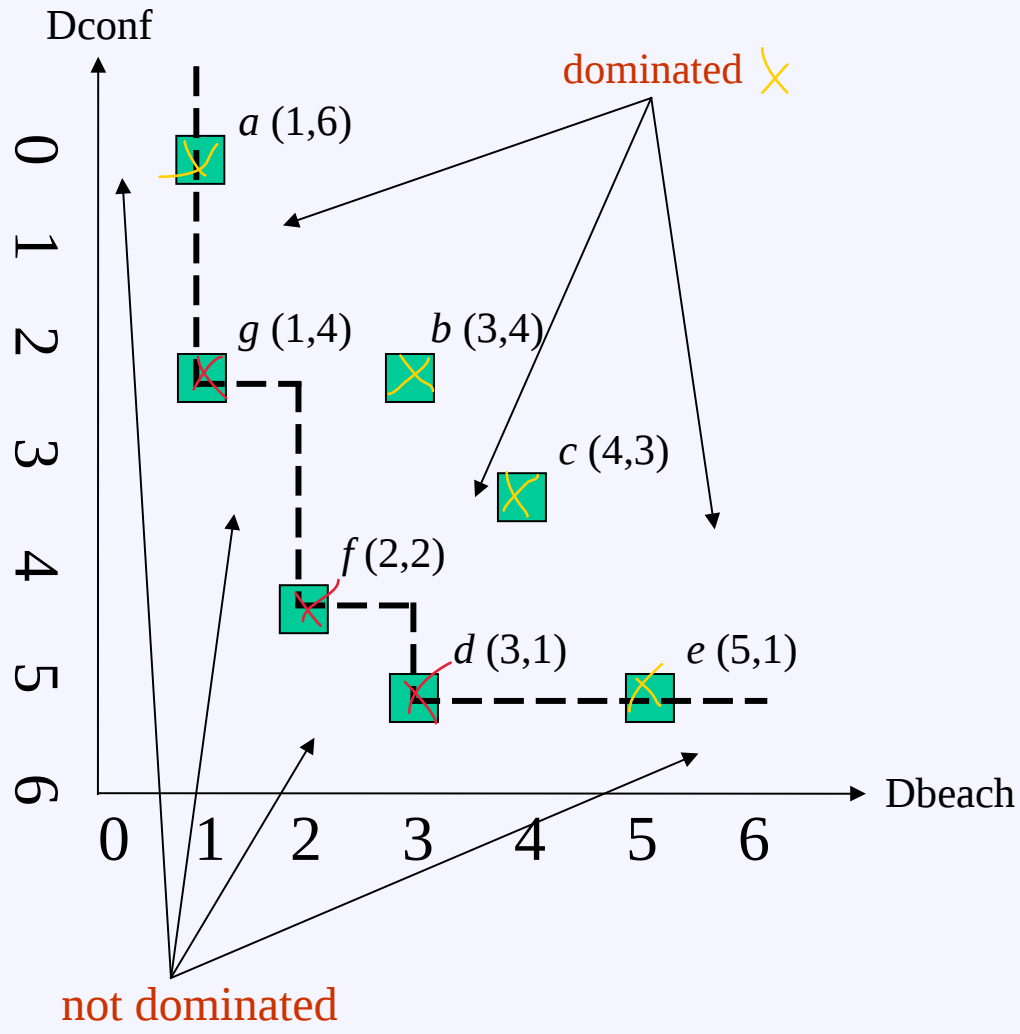
Introduction

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: { *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

id	score
a	0.9
c	0.7
b	0.6

google

i	score
b	0.8
d	0.7
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

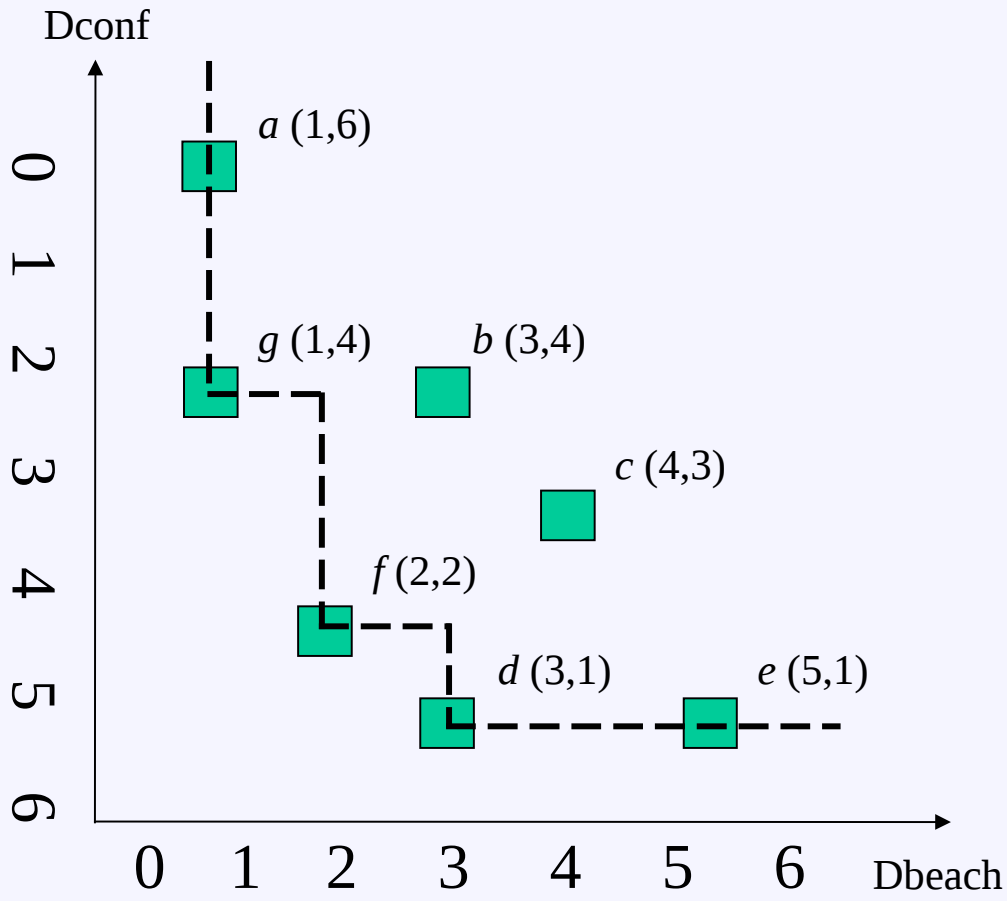
Skyline processing

- 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.

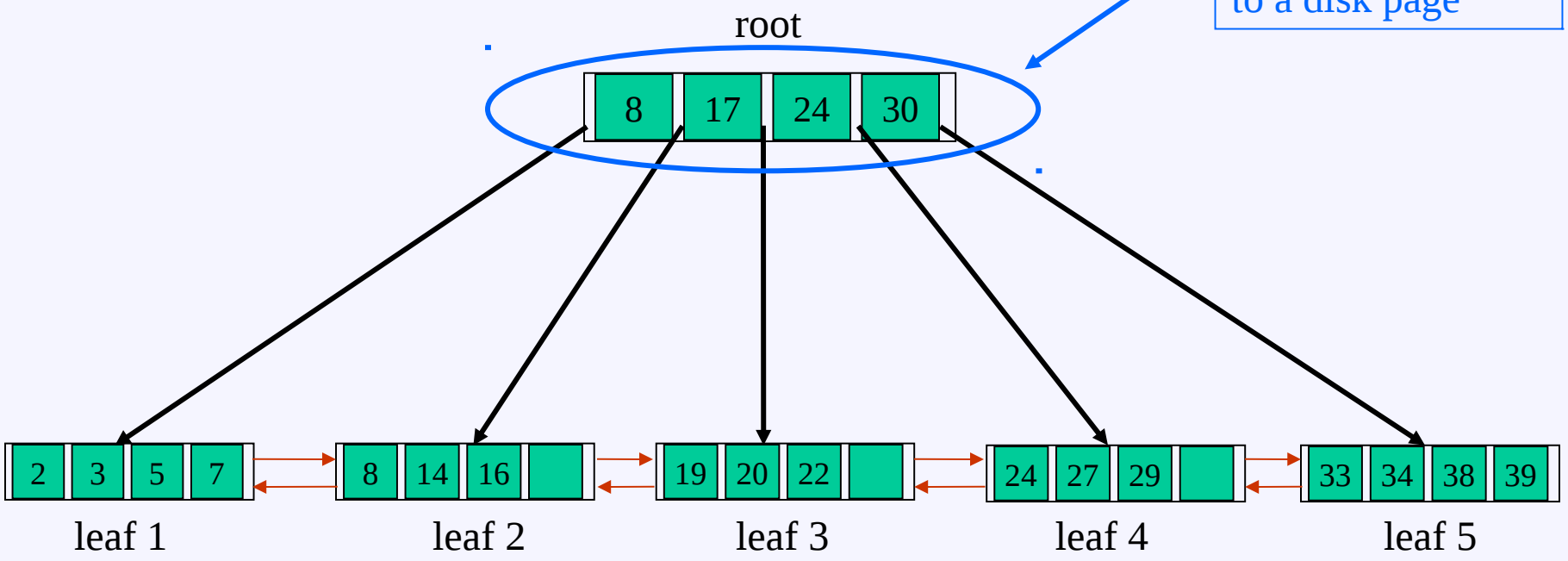
His work:
"R-trees: a dynamic index structure for spatial searching",
ACM SIGMOD Conference 1984

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*.

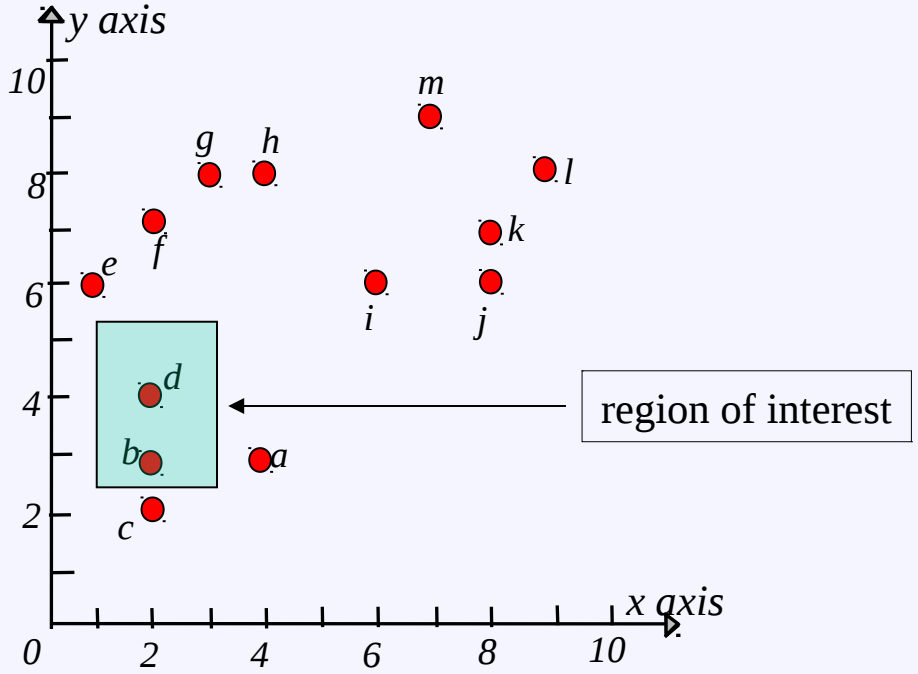
Introduction to R-trees

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

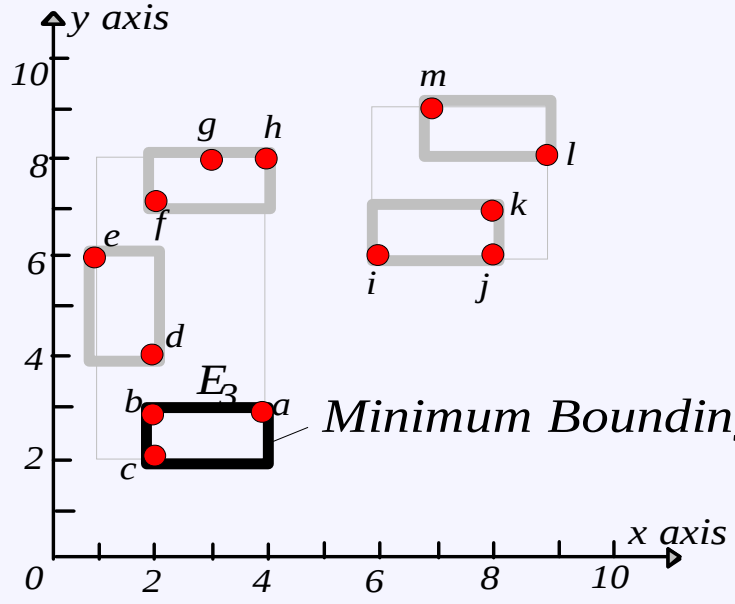
Example:
13 points in
2 dimensions



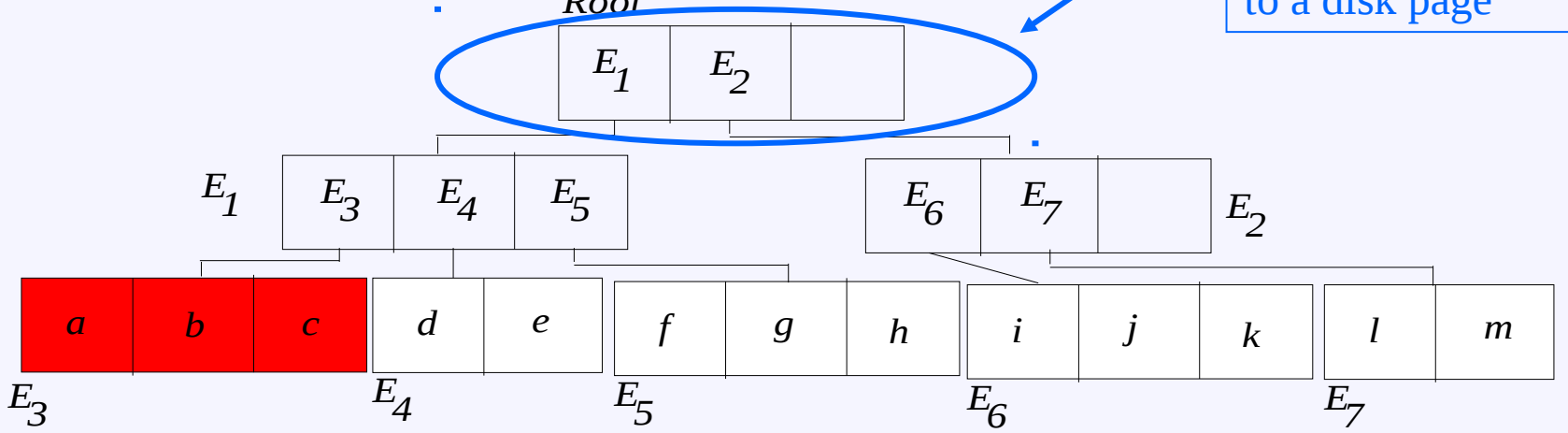
Range query example: *"find the objects in a given region"*.
E.g. find all hotels in Utrecht.

No index: scan through all objects. NOT EFFICIENT!

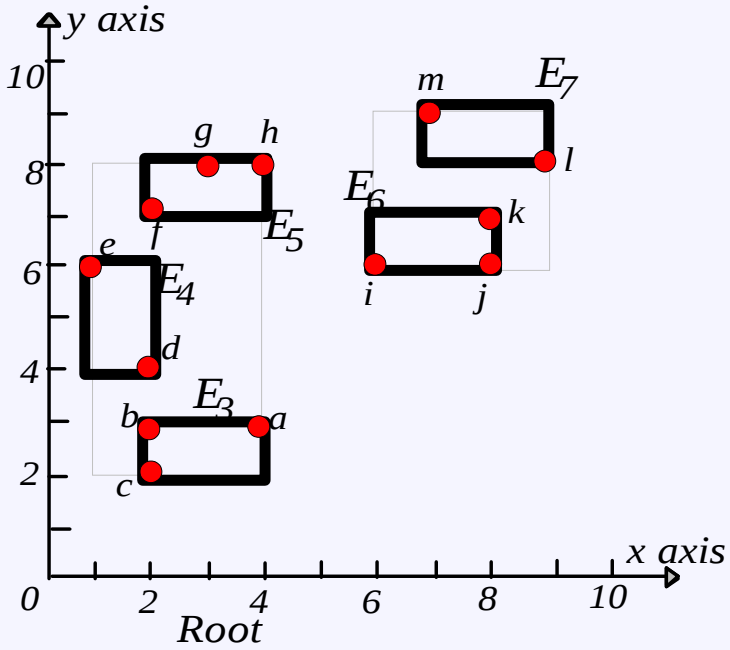
Introduction to R-trees – structure

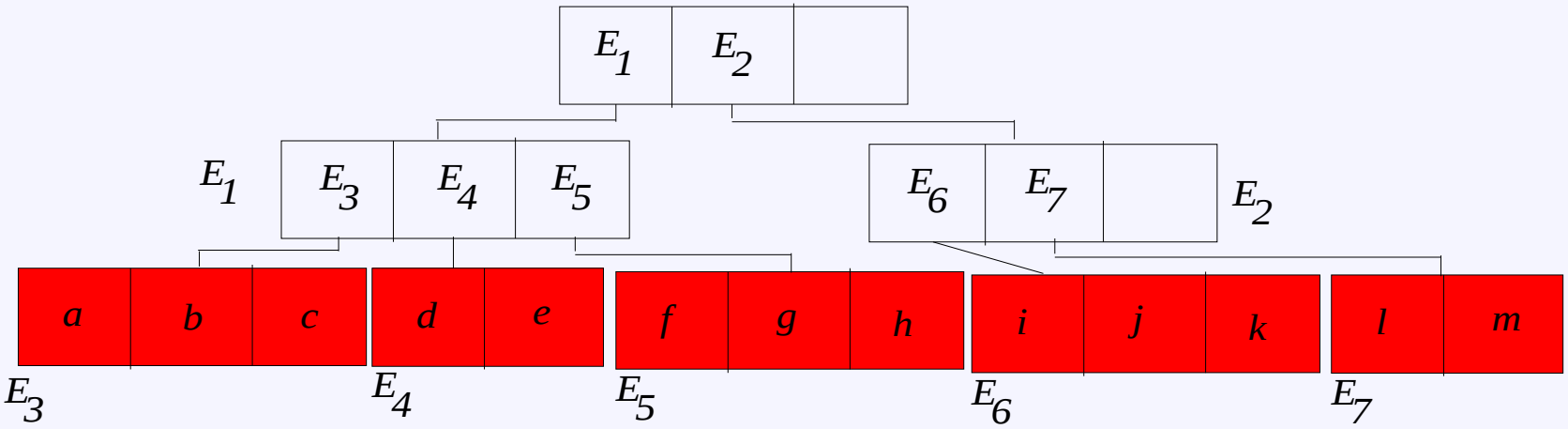


Each node corresponds to a disk page

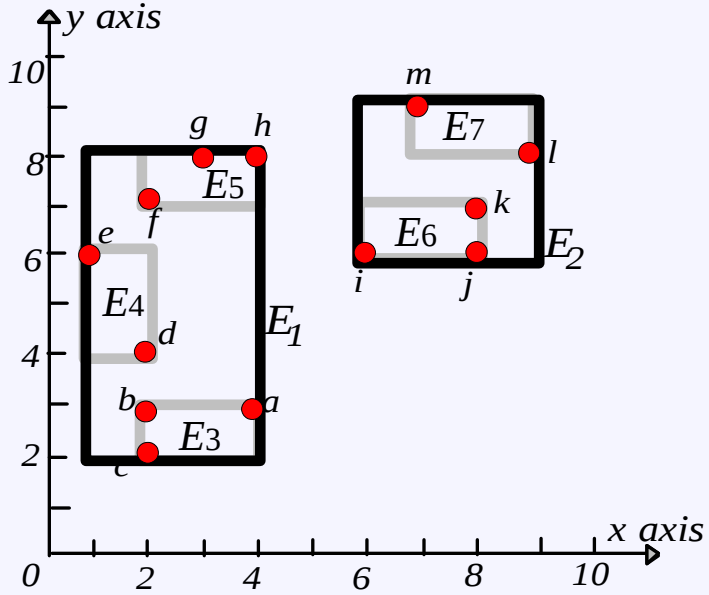


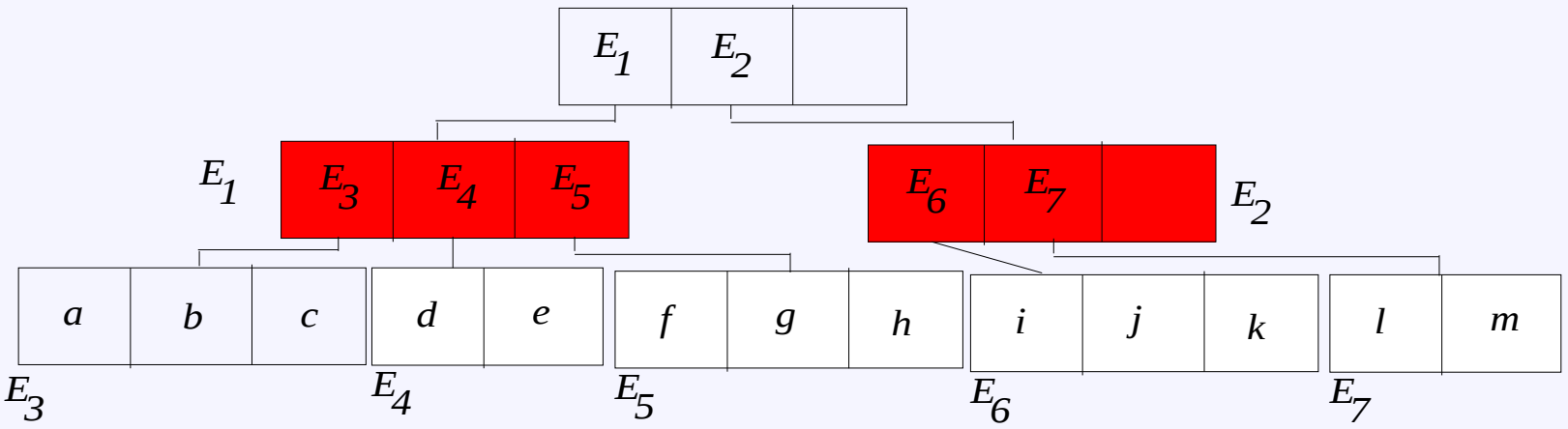
Introduction to R-trees – structure



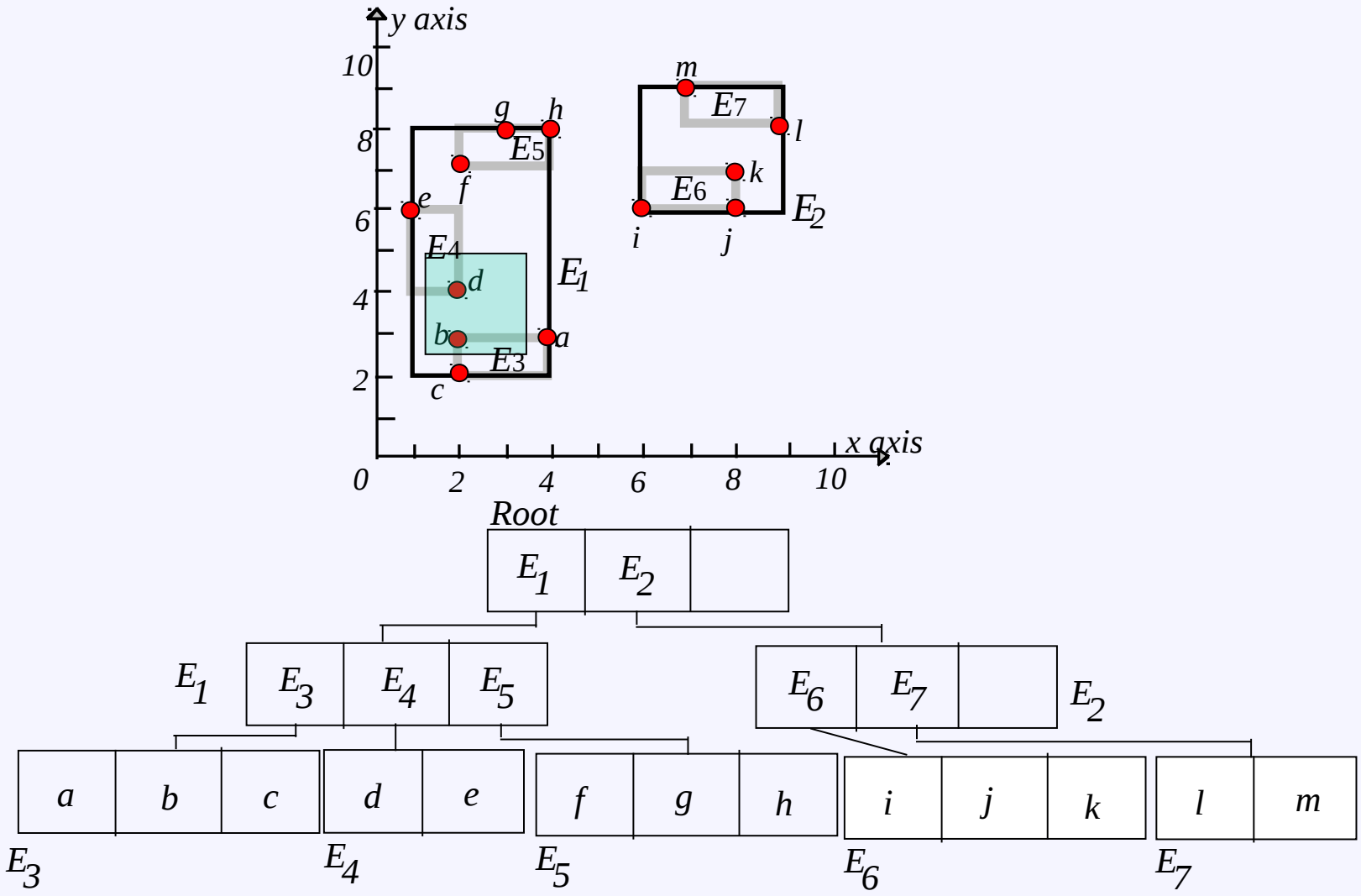


Introduction to R-trees – structure

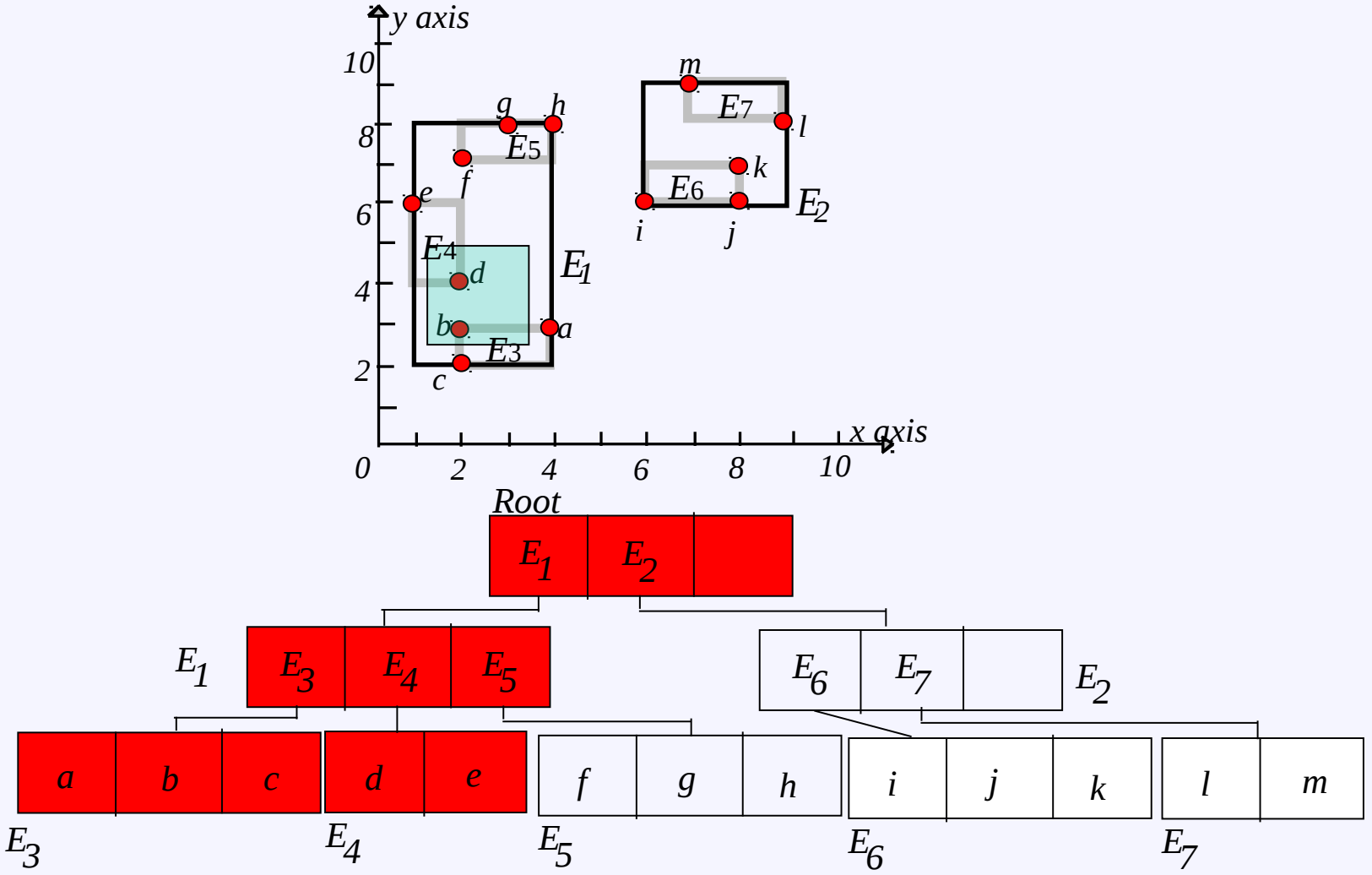




Introduction to R-trees – range query



Introduction to R-trees – range query



BBS Algorithm – Basic Properties

Any Branch-and-Bound method requires two decisions:

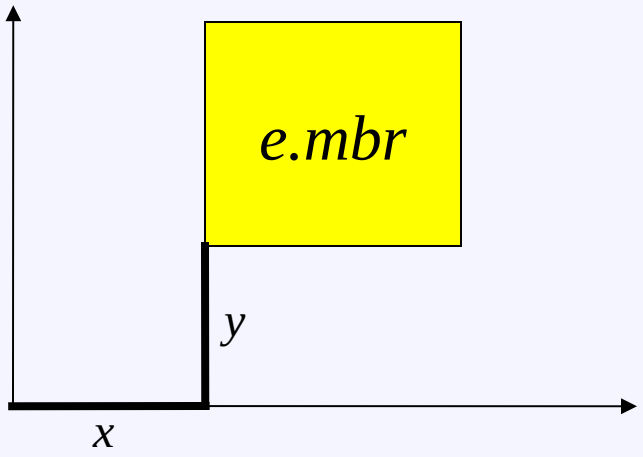
1. How to branch: which part of the space needs to be investigated next?

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:

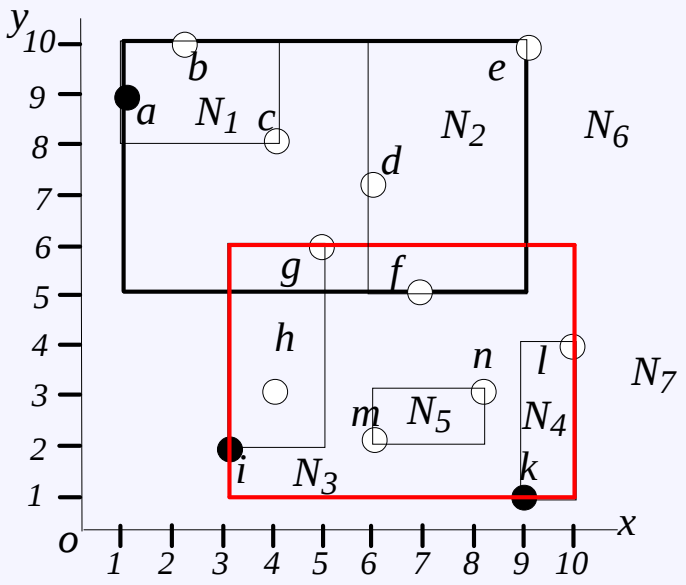


mindist(*e.mbr*) = x + y

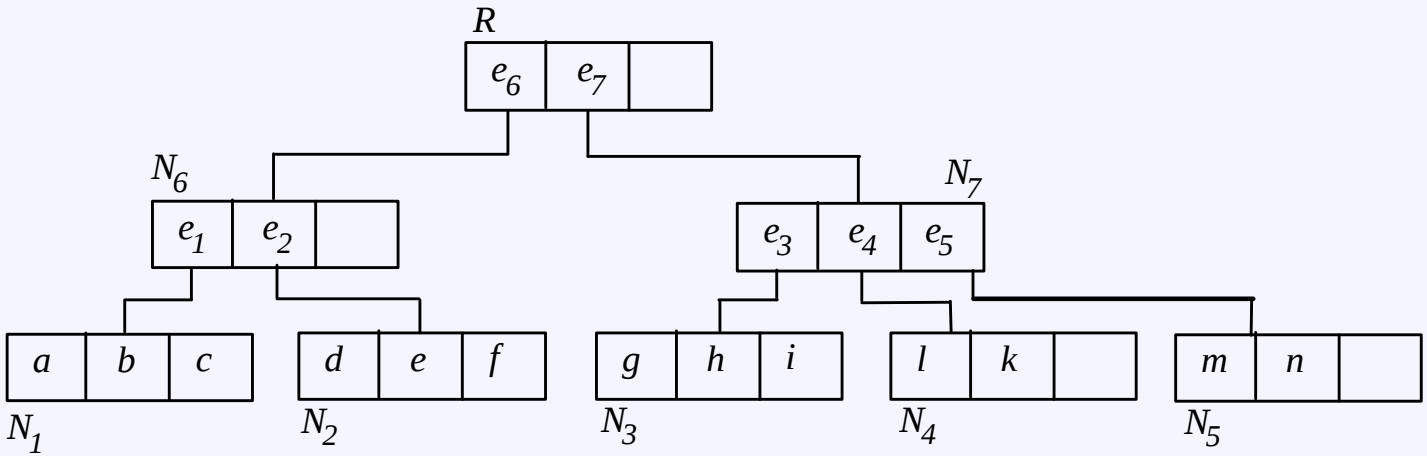
BBS Algorithm – basic properties

- 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*.

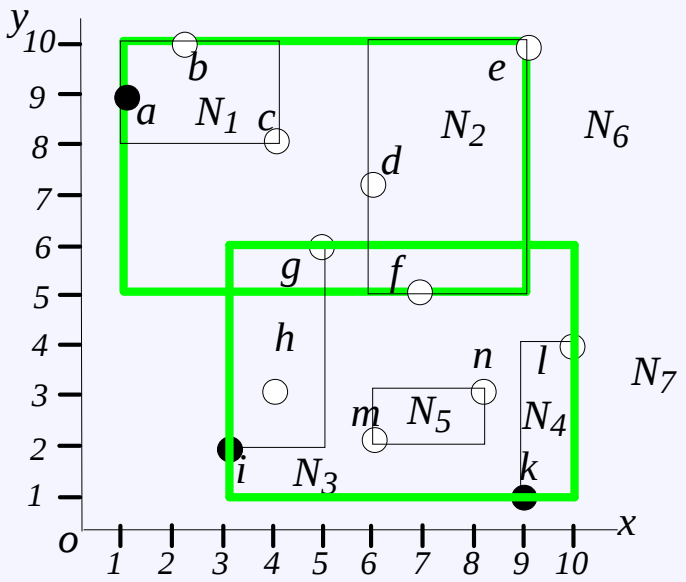
BBS Algorithm - example



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

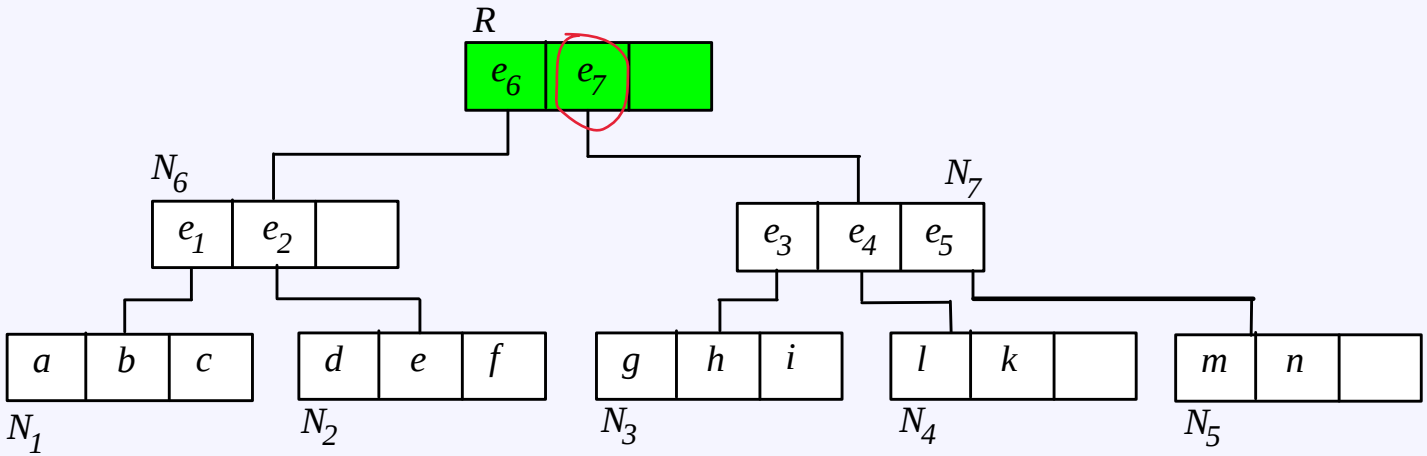


BBS Algorithm - example

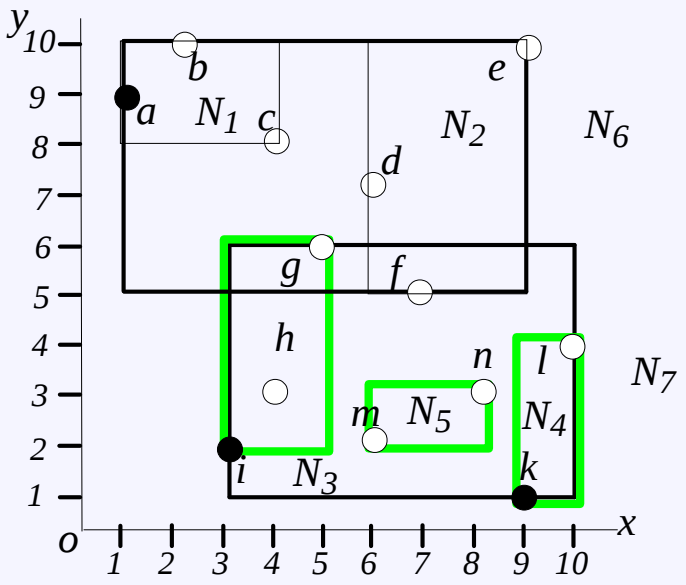


- Each heap entry keeps the mindist of the MBR.

action	heap contents	S
access root	<e_7,4><e_6,6>	⊘

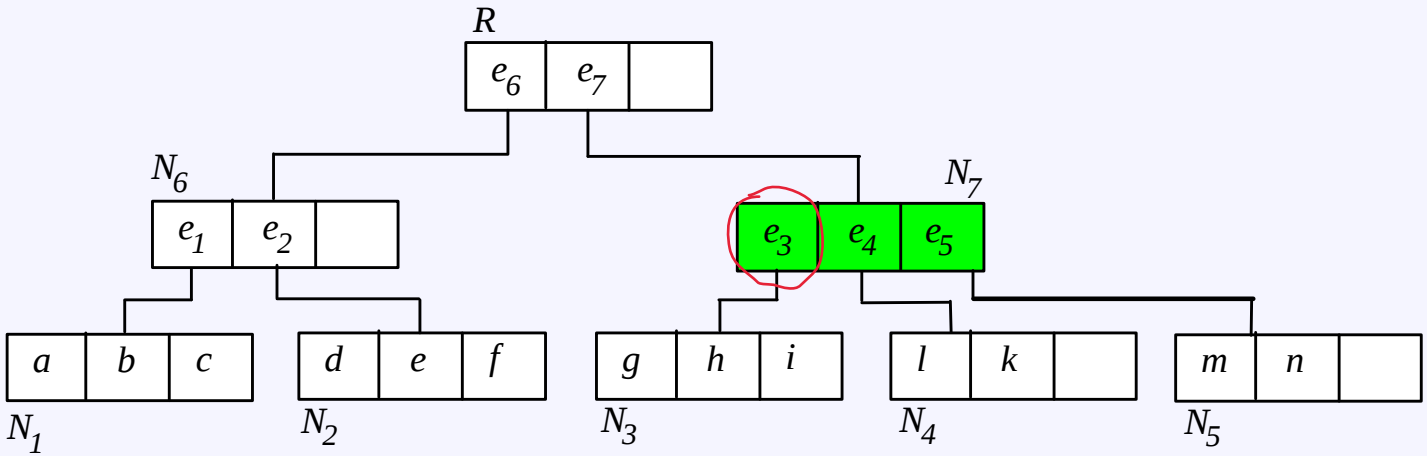


BBS Algorithm - example

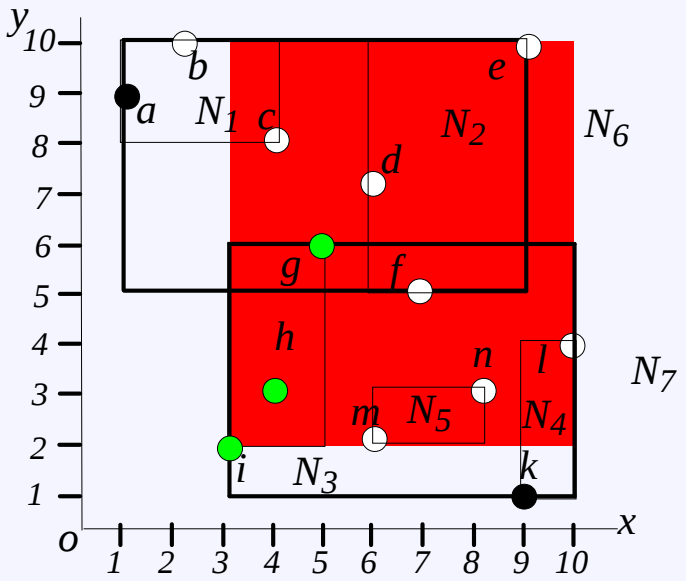


- Process entries in ascending order of their mindists.

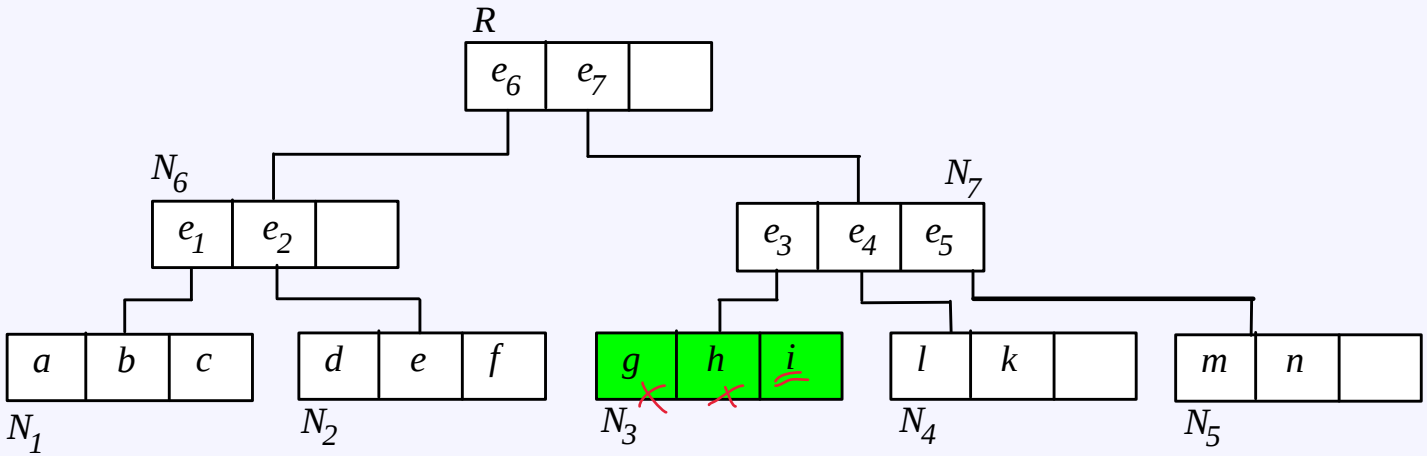
action	**heap contents**	***S***
access root	<e_7,4><e_6,6>	⊘
expand e_7	<e_3,5><e_6,6><e_5,8><e_4,10>	⊘



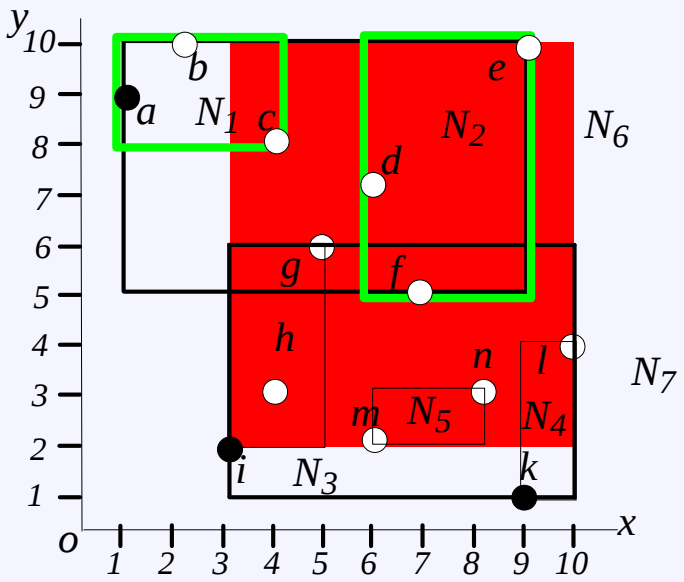
BBS Algorithm - example



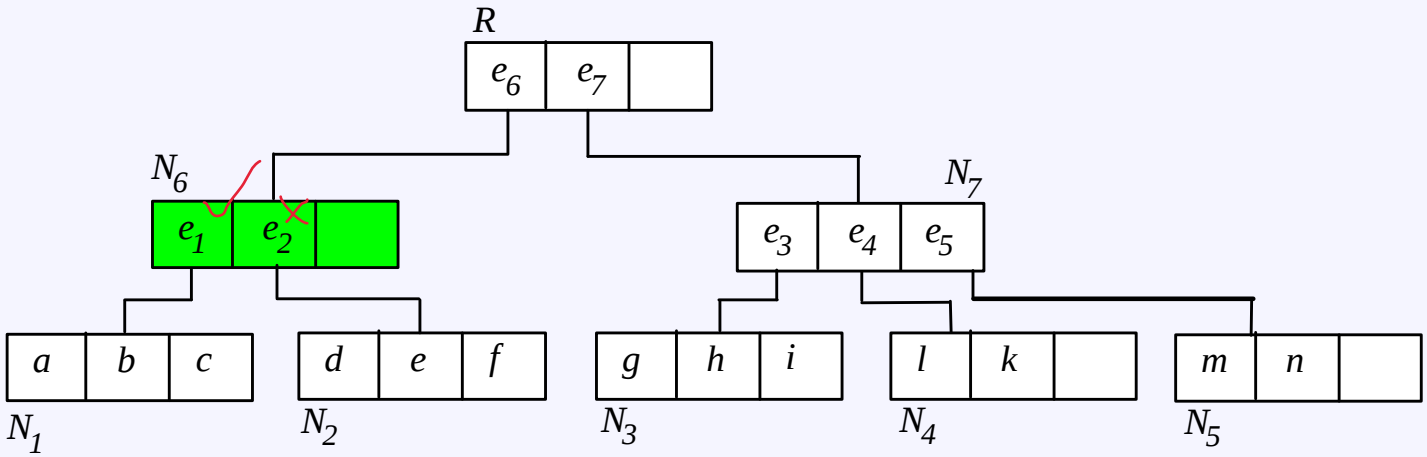
action	heap contents	S
access root	$<e_7,4><e_6,6>$	$\oslash$
expand e_7	$<e_3,5><e_6,6><e_5,8><e_4,10>$	$\oslash$
expand e_3	**<*i*,5>**$<e_6,6><e_5,8><e_4,10>$	$\{i\}$



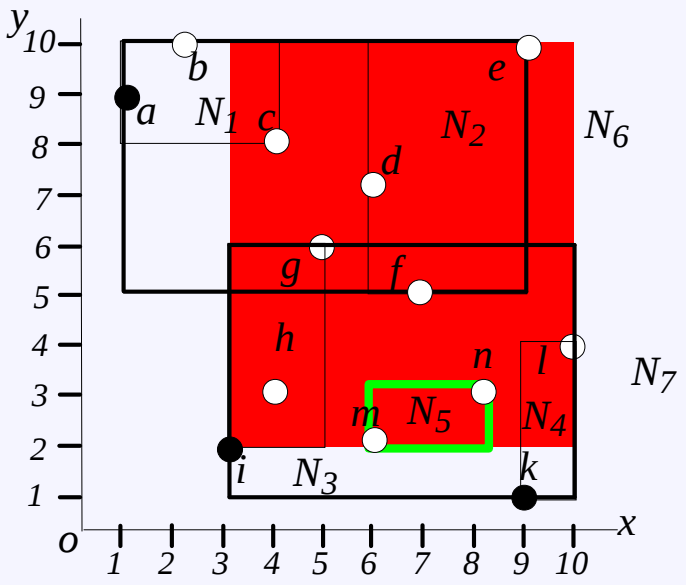
BBS Algorithm - example



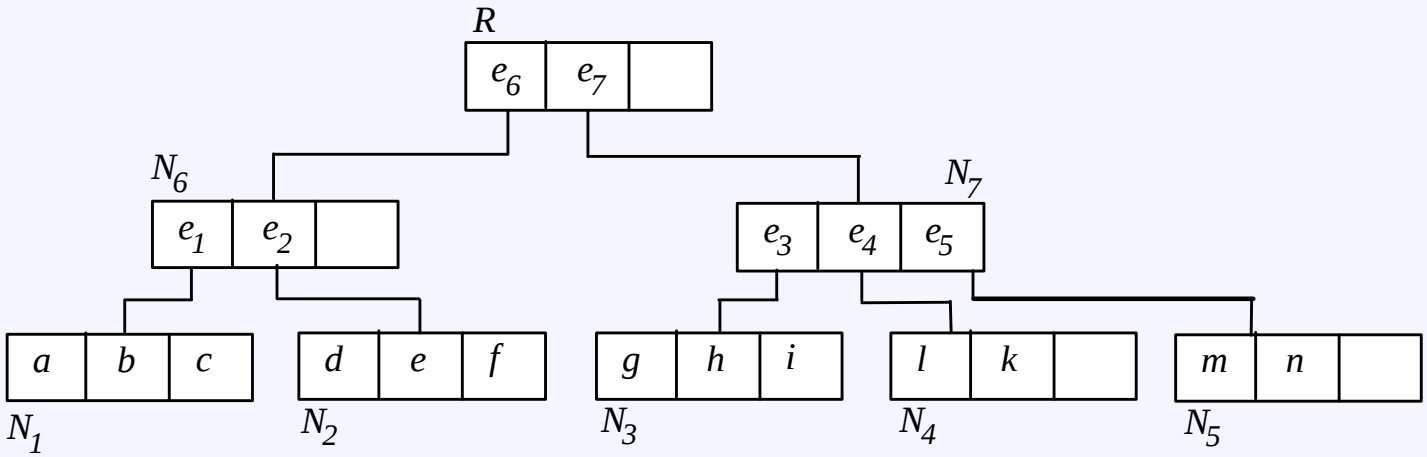
action	heap contents	S
access root	<e_7,4><e_6,6>	⊘
expand e_7	<e_3,5><e_6,6><e_5,8><e_4,10>	⊘
expand e_3	**<*i*,5>**<e_6,6><e_5,8> <e_4,10>	{*i*}
expand e_6	<e_5,8><e_1,9><e_4,10>	{*i*}



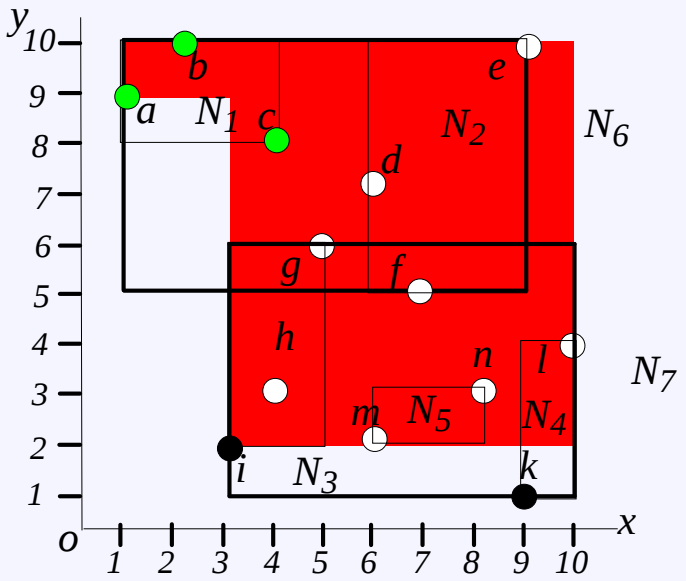
BBS Algorithm - example



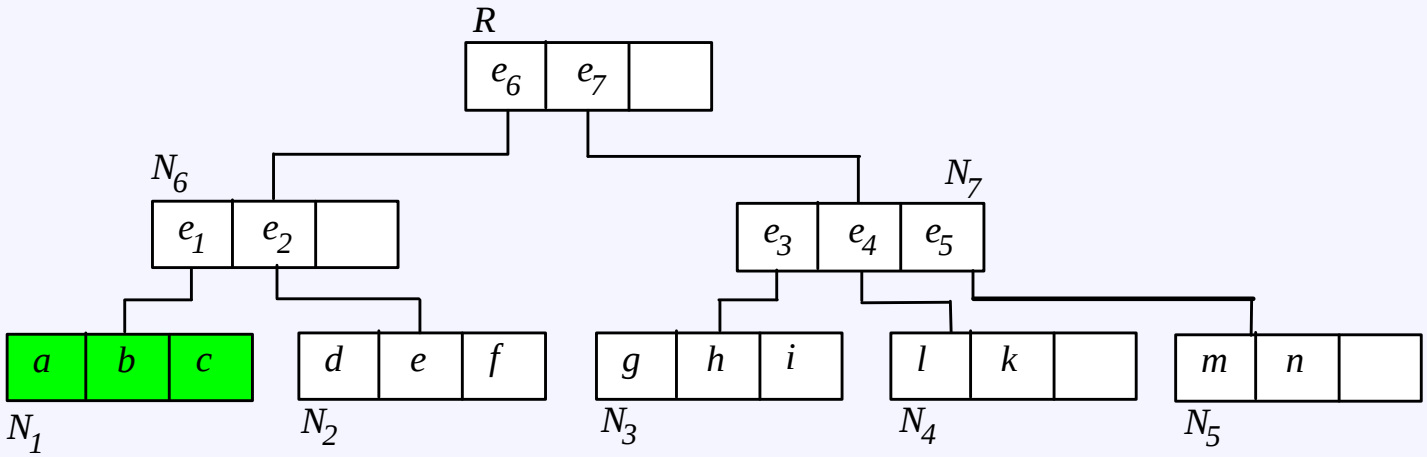
action	heap contents	S
access root	<e_7,4><e_6,6>	⊘
expand e_7	<e_3,5><e_6,6><e_5,8><e_4,10>	⊘
expand e_3	**<*i*,5>**<e_6,6><e_5,8> <e_4,10>	{*i*}
expand e_6	<e_5,8><e_1,9><e_4,10>	{*i*}
remove e_5	<e_1,9><e_4,10>	{*i*}



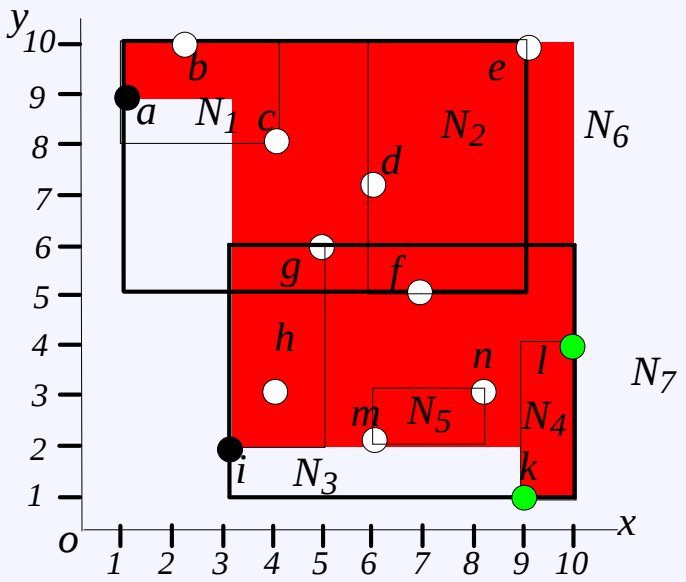
BBS Algorithm - example



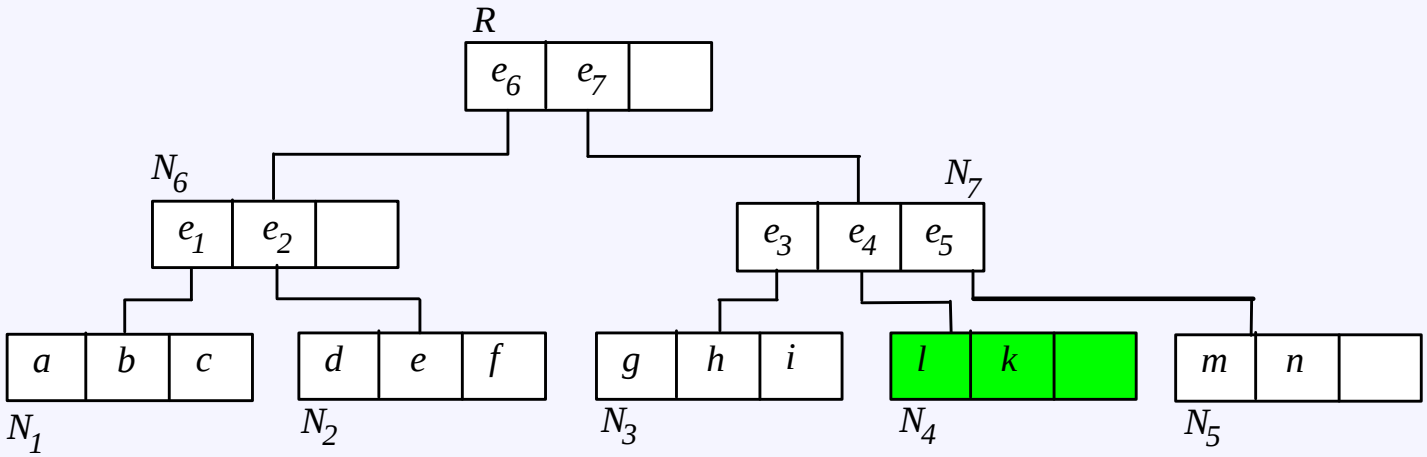
action	heap contents	S
access root	<e_7,4><e_6,6>	⊘
expand e_7	<e_3,5><e_6,6><e_5,8><e_4,10>	⊘
expand e_3	**<*i*,5>**<e_6,6><e_5,8> <e_4,10>	{*i*}
expand e_6	<e_5,8><e_1,9><e_4,10>	{*i*}
remove e_5	<e_1,9><e_4,10>	{*i*}
expand e_1	**<*a*,10>**<e_4,10>	{*i*,*a*}



BBS Algorithm - example

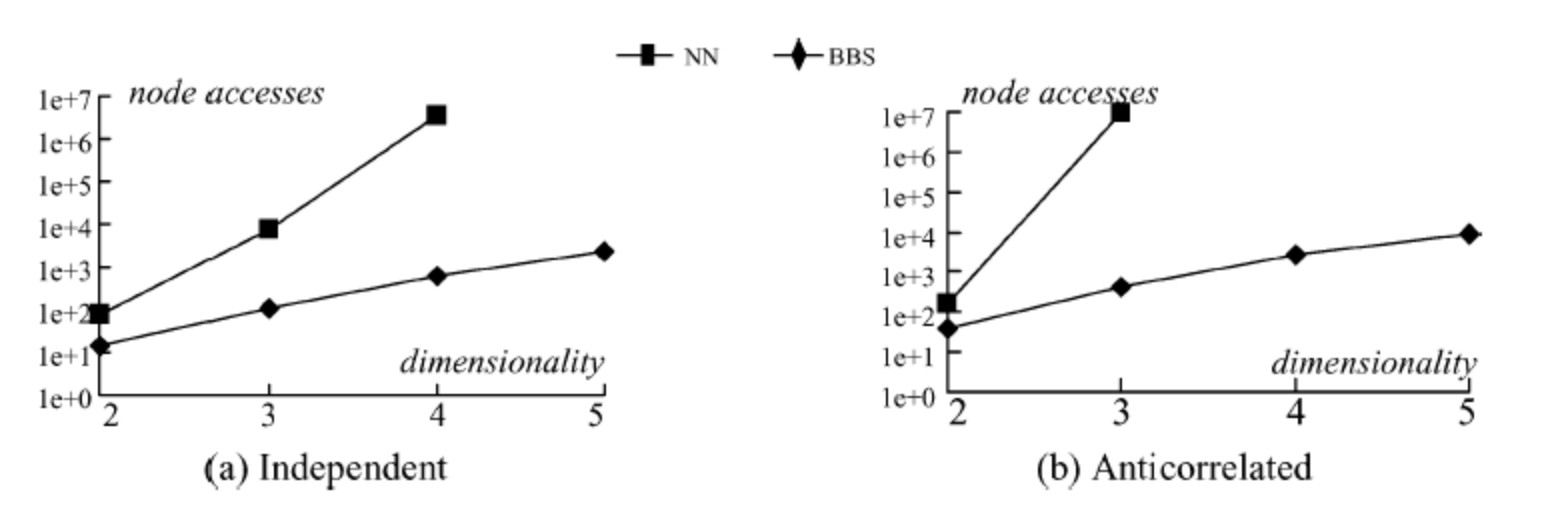


action	heap contents	S
access root	<e_7,4><e_6,6>	⊘
expand e_7	<e_3,5><e_6,6><e_5,8><e_4,10>	⊘
expand e_3	**<*i*,5>**<e_6,6><e_5,8> <e_4,10>	{*i*}
expand e_6	<e_5,8><e_1,9><e_4,10>	{*i*}
remove e_5	<e_1,9><e_4,10>	{*i*}
expand e_1	**<*a*,10>**<e_4,10>	{*i*,*a*}
expand e_4	**<*k*,10>**	{*i*,*a*,*k*}



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)

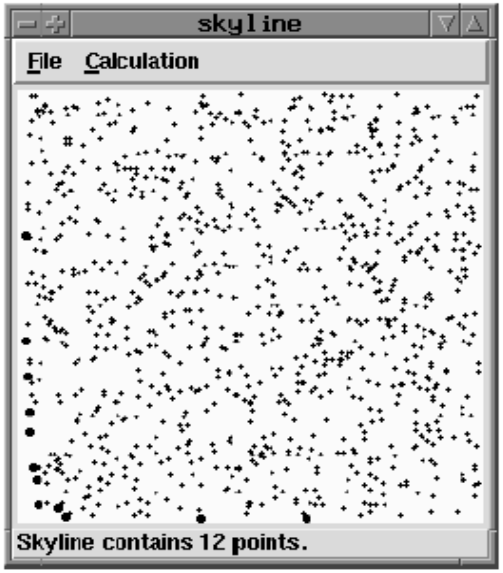
Skyline Computation - advanced topics I

Skylines in subspaces

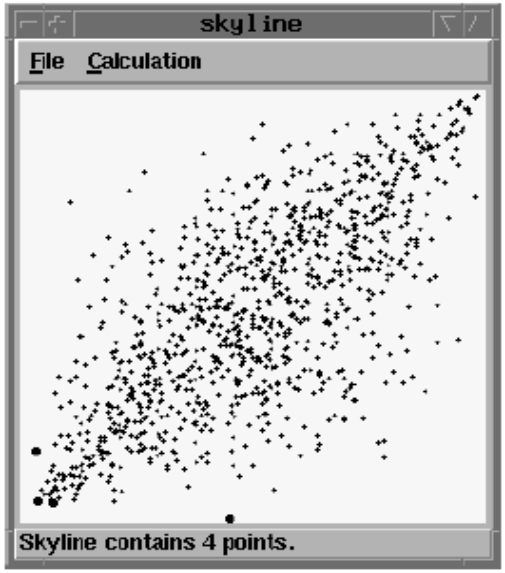
When the number of attributes (dimensions) increases, the number of points contained in the Skyline increases substantially. This happens because the probability that a point dominates another decreases.

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

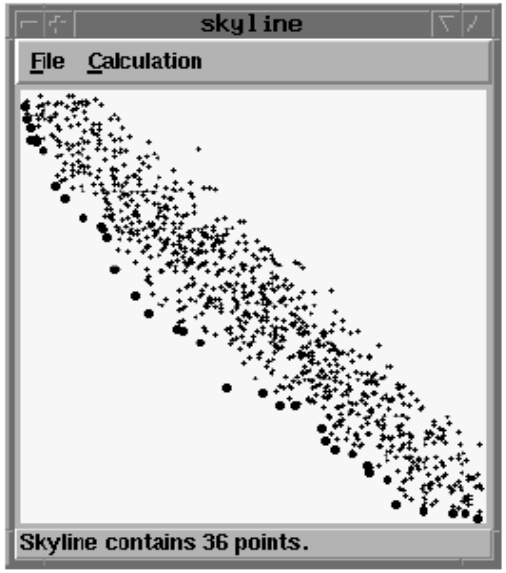
Skyline Computation - advanced topics I



independent



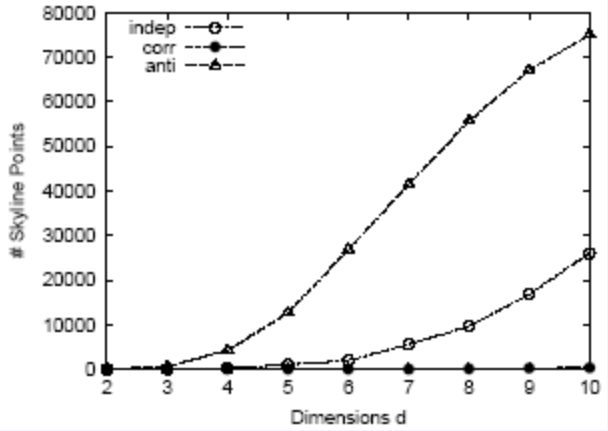
correlated



anticorrelated

100,000 points

d	*corr*	*indep*	*anti*
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: Borzonyi 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.

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