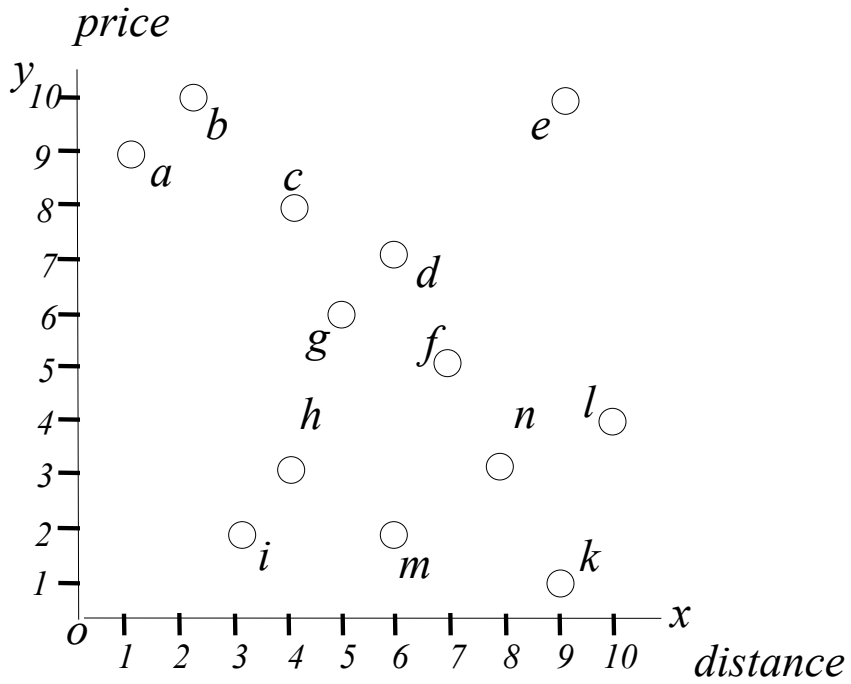
An Optimal and Progressive Algorithm for Skyline Queries

Instructor: Cyrus Shahabi

Outline

- *Introduction*
  - *Skyline queries*
  - *Existing solutions*
  - *Motivation*
- *Algorithms BBS*
- *Other discussions*
- *Experiments*
- *Conclusion*

Finding the Cheapest & Closest Hotels



Which one is better?

i and *h*?

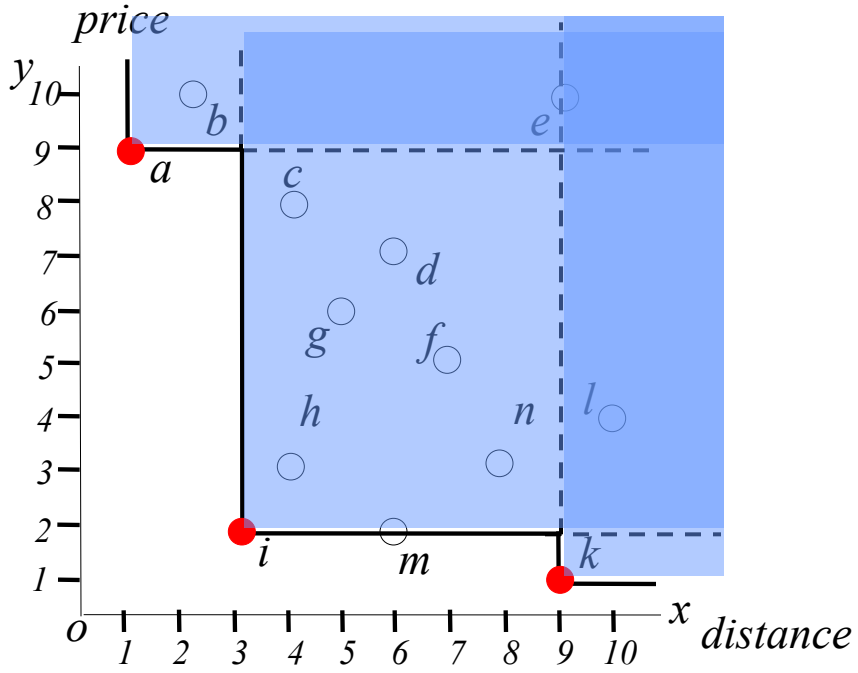
i, because its price and distance *dominate* those of *h*.

i and *k*?

We do not know.

Skyline Objects

- A set of objects *not dominated* by any other object.



- Dominance region

Existing Solutions

- Block Nested Loop (BNL)
- Divide-and-Conquer (D&C)

Elementary skyline algorithms

- Bitmap method
- Index method
- Nearest Neighbor (NN)

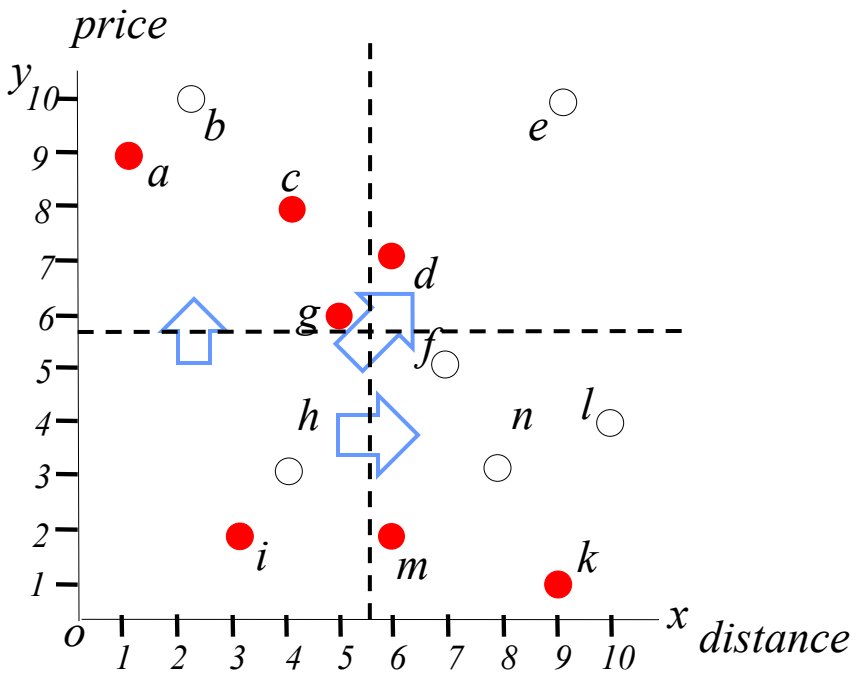
Progressive skyline algorithms

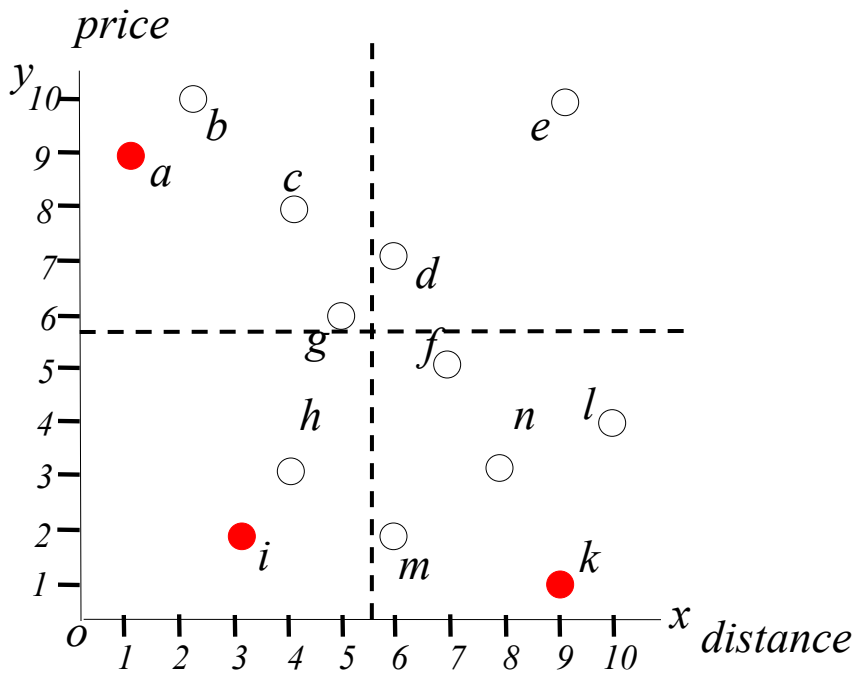
Existing Solutions

- Block Nested Loop (BNL)
  - Scan the dataset and keep a list of candidate skyline points.
  - Compare a point *p* with every other point in the list.
- Advantages
  - Applicable for any dimensionality
  - Does not need sorting or indexing of data file
- Disadvantages
  - Numerous comparisons
  - Inadequacy for on-line processing

Existing Solutions

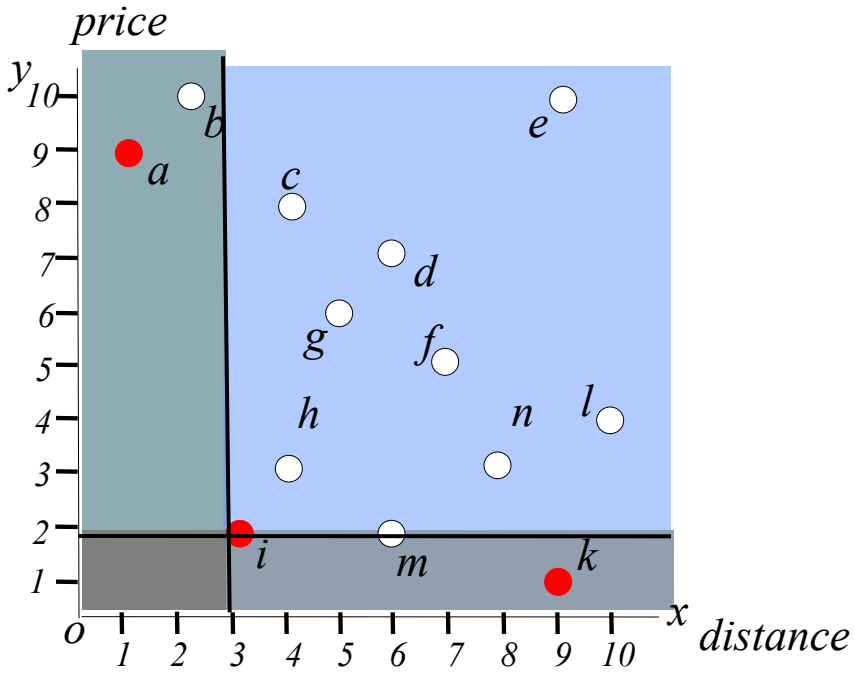
- Divide-and-Conquer (D&C)
  - Divide the dataset into several partitions.
  - Compute partial skylines in each partition.
  - Compute global skylines by merging them.

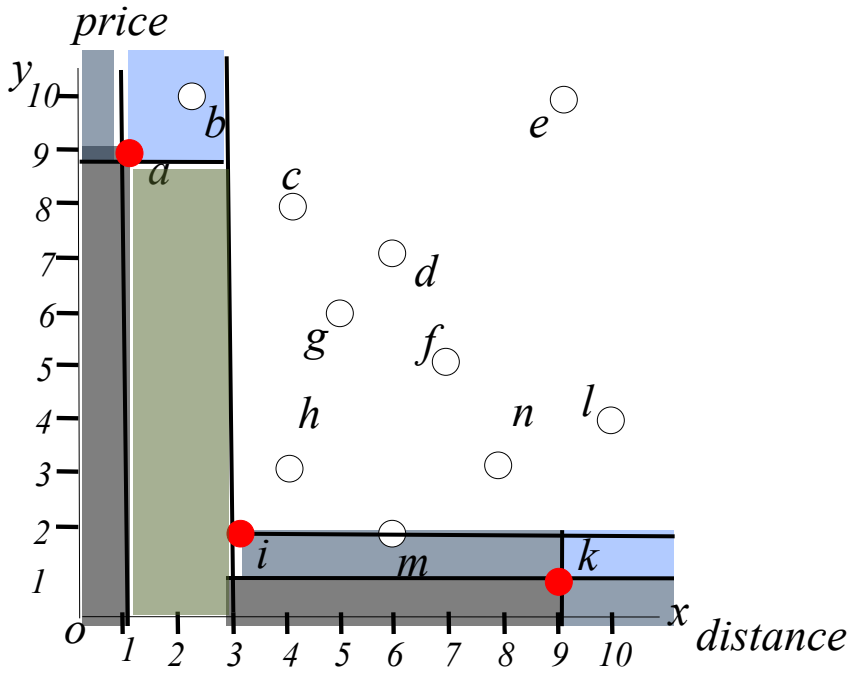




Existing Solutions

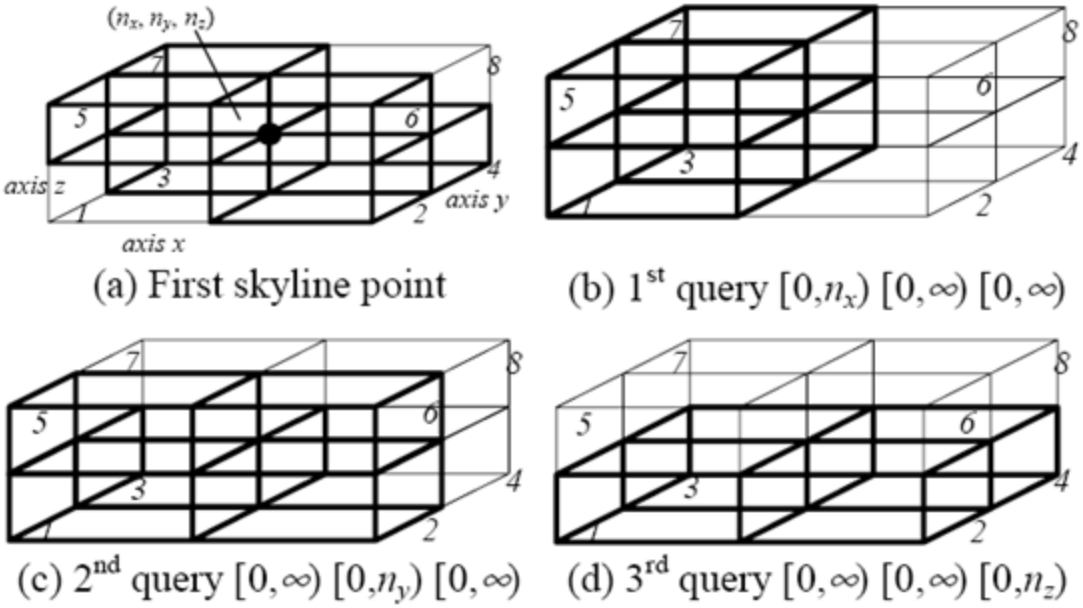
- Nearest Neighbor (NN)
  - Find nearest neighbor point -> skyline
  - Prune all the points in the dominance region of this point
  - Divide the space by the nearest neighbor point -> *to-do lists*
  - Compute recursively until empty space.





Existing Solutions

- NN over three or more dimensions
  - Has overlapped partitions in divided subspaces.
  - Needs duplicate elimination.



NN partitions for 3 dimensions

Motivation

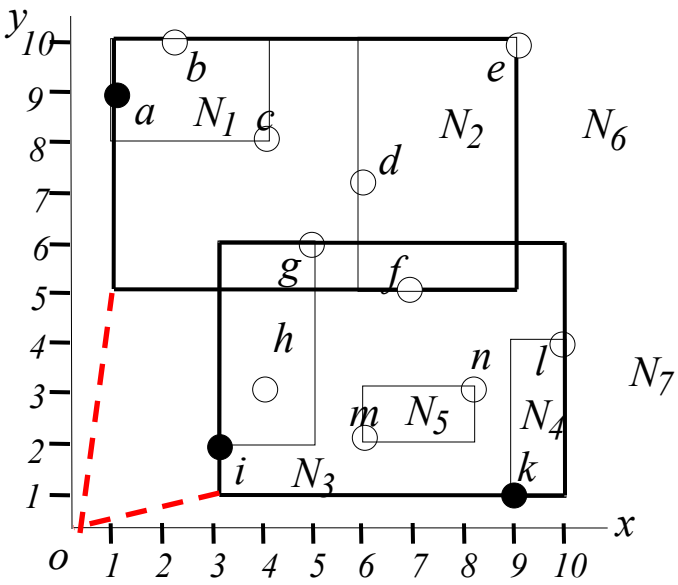
- Advantages of *NN* algorithm
  - Fast running time to finding the first result
  - Progressiveness

- Disadvantages of *NN* algorithm
  - Redundant I/O computation
    - Gets worse as dimensionality increases
  - Explosive to-do list size

Contents

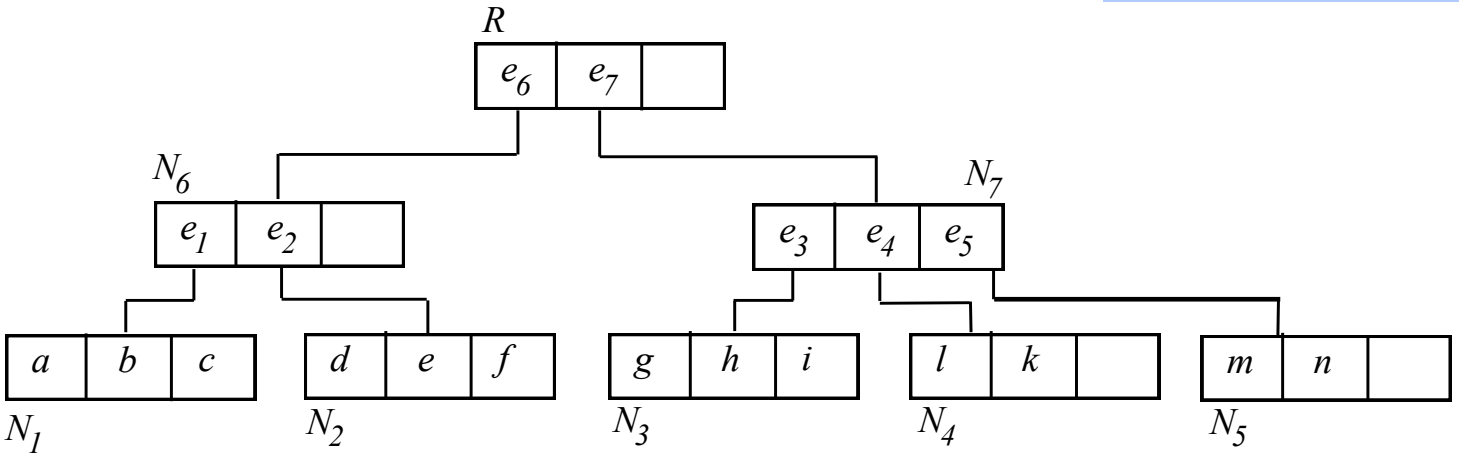
- *Introduction*
- *Algorithms BBS*
  - *Preliminary: R-Tree*
  - *How BBS works*
  - *Example*
- *Other Discussions*
- *Experiments*
- *Conclusion*

Branched and Bound Skyline (BBS)



- Assume all points are indexed in an R-tree.
- *Top-down Approach*
- *mindist* = the L_1 distance between its lower-left corner and the origin.

f(x, y) = x + y

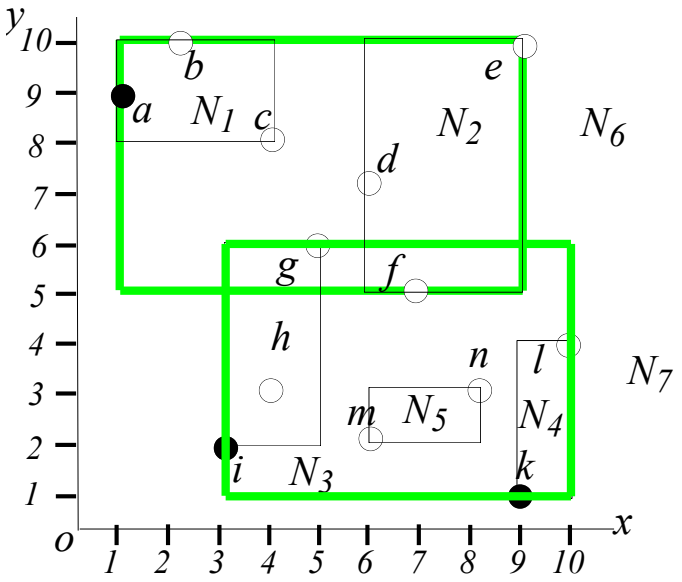


Branched and Bound Skyline (BBS)

- Data structure
  - *Heap* sorted by min distance
  - *List* to maintain the current skyline
- Dominance check condition
  - Before expanding, compare to current skylines.
  - Before inserting an object, also check for internal objects.
- Stop condition: empty heap

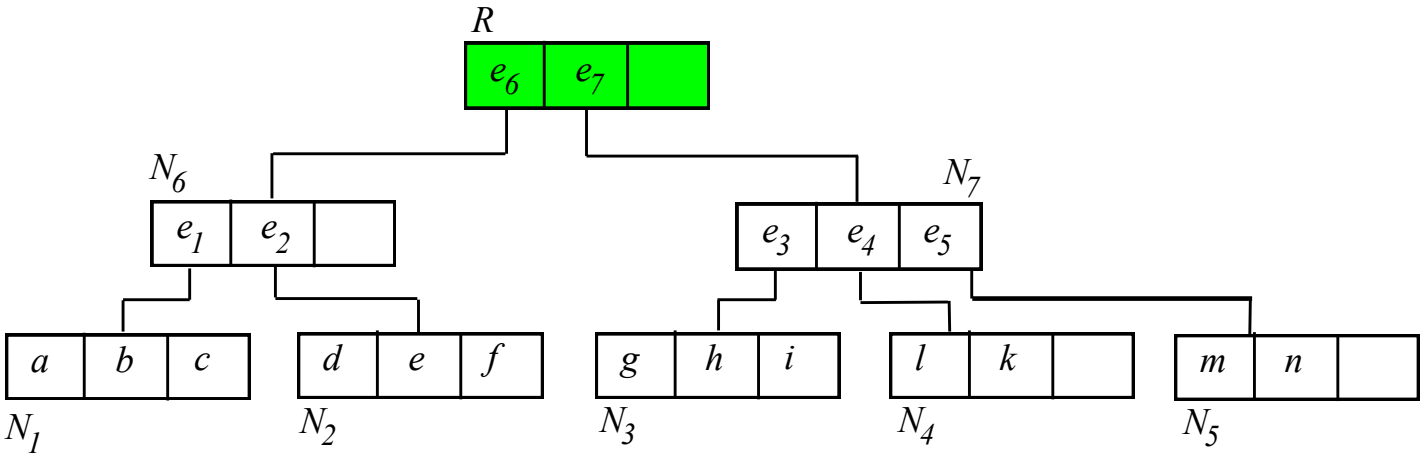
```
Algorithm BBS (R-tree R)
1. S=∅ // list of skyline points
2. insert all entries of the root R in the heap
3. while heap not empty
4.  remove top entry e
5.  if e is dominated by some point in S discard e
6.     else // e is not dominated
7.             if e is an intermediate entry
8.                for each child e_i of e
9.                      if e_i is not dominated by some point in S
10.                        insert e_i into heap
11.            else // e is a data point
12.                   insert e_i into S
13. end while
End BNN
```

Example of BBS

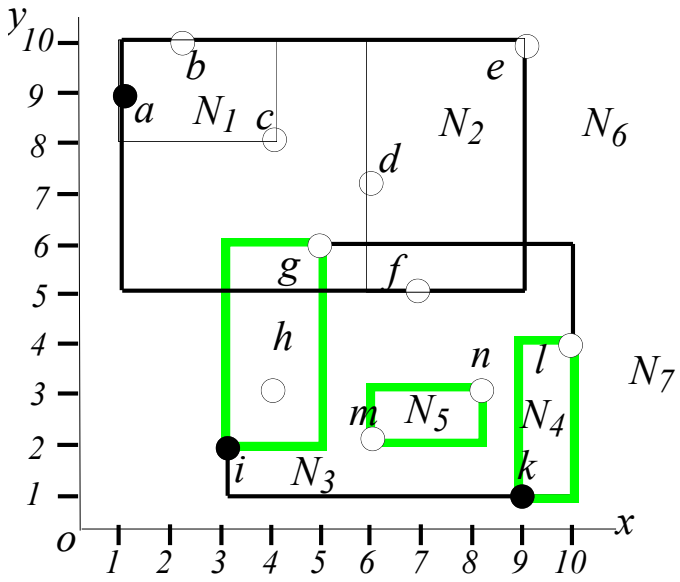


- Each heap entry keeps the mindist of the MBR.

action	heap contents	S
access root	$\langle e_7,4\rangle\langle e_6,6\rangle$	∅

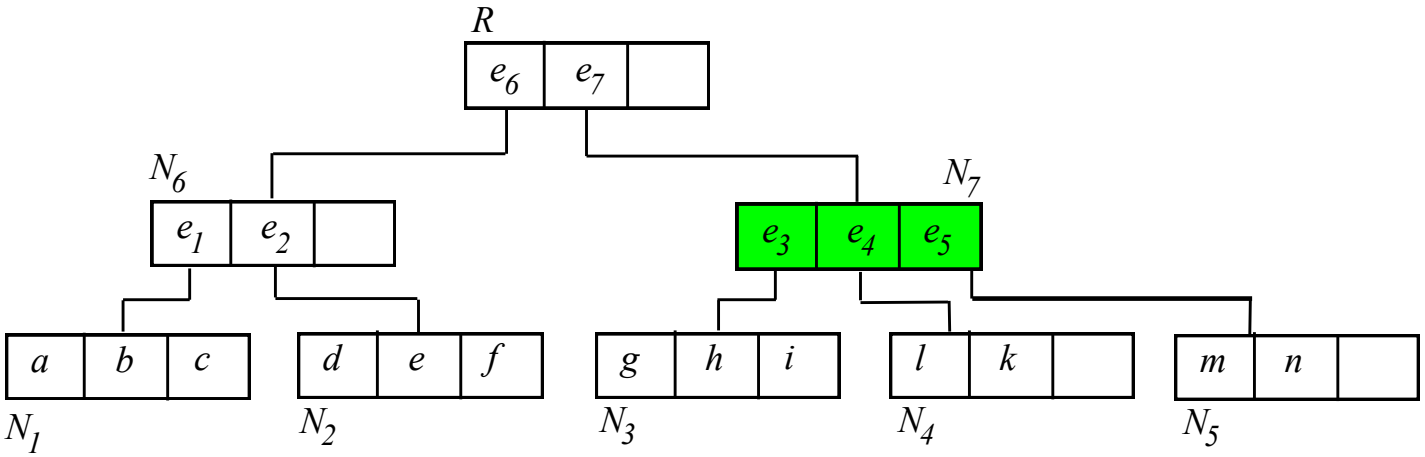


Example of BBS

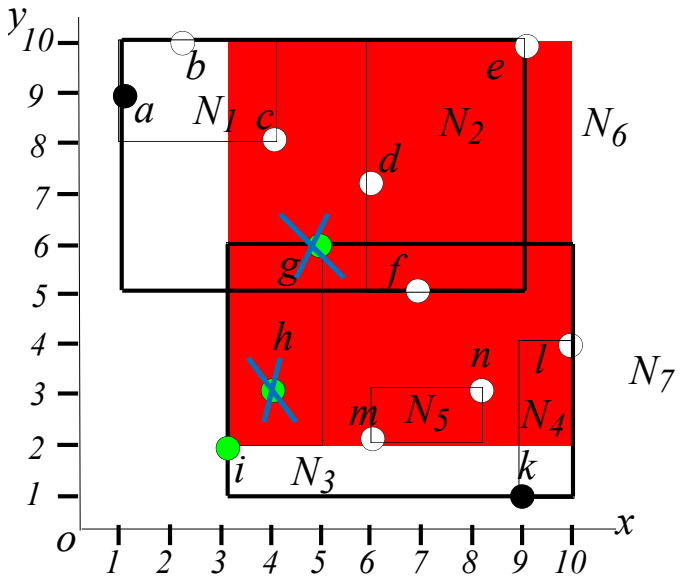


- Process entries in ascending order of their mindists.

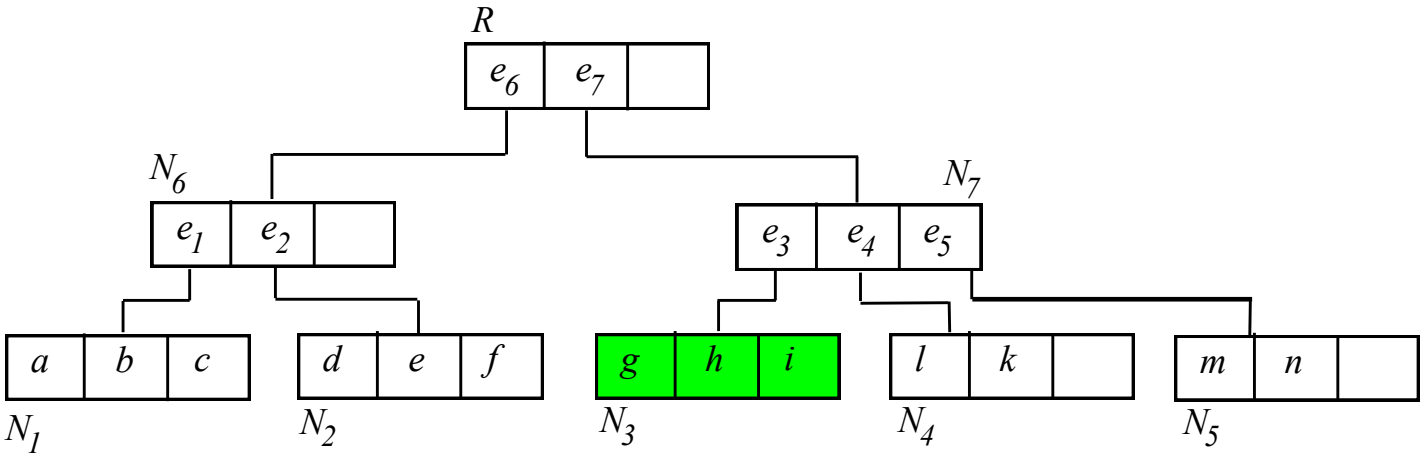
action	heap contents	S
access root	$\langle e_7,4\rangle\langle e_6,6\rangle$	∅
expand e7	$\langle e_3,5\rangle\langle e_6,6\rangle\langle e_5,8\rangle\langle e_4,10\rangle$	∅



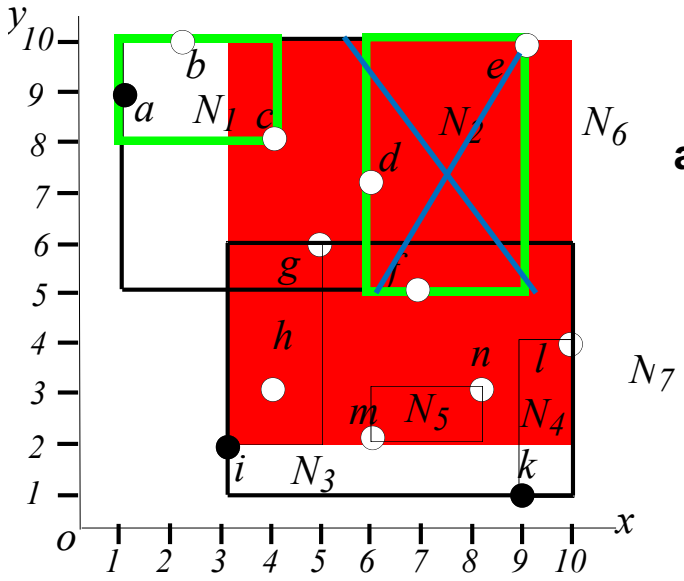
Example of BBS



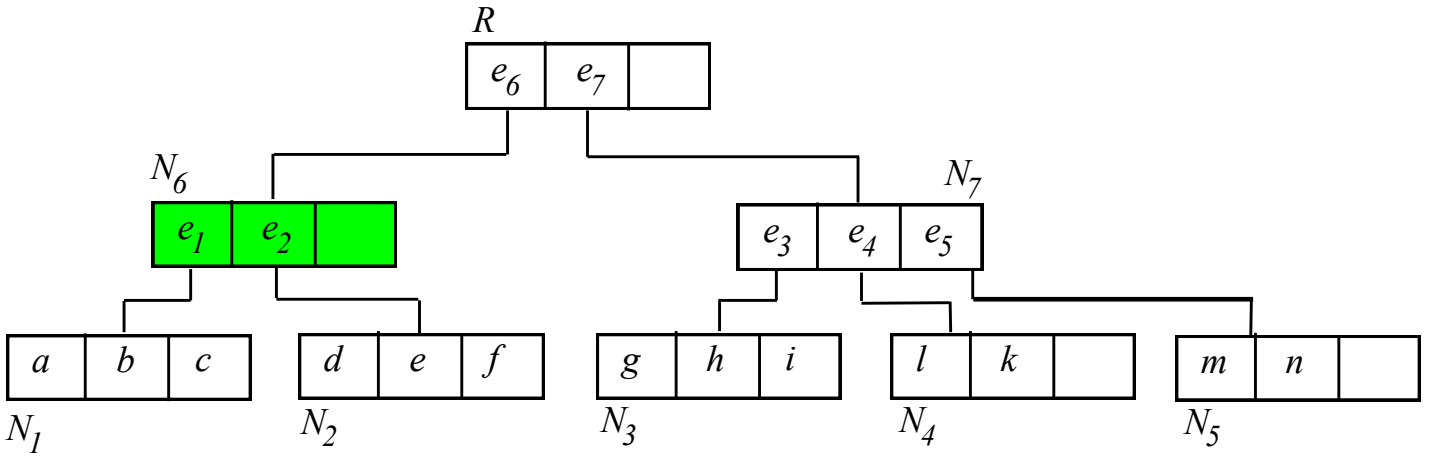
action	heap contents	S
access root	$\langle e_7,4\rangle\langle e_6,6\rangle$	∅
expand e7	$\langle e_3,5\rangle\langle e_6,6\rangle\langle e_5,8\rangle\langle e_4,10\rangle$	∅
expand e3	$\langle i,5\rangle\langle e_6,6\rangle\langle e_5,8\rangle\langle e_4,10\rangle$	{i}



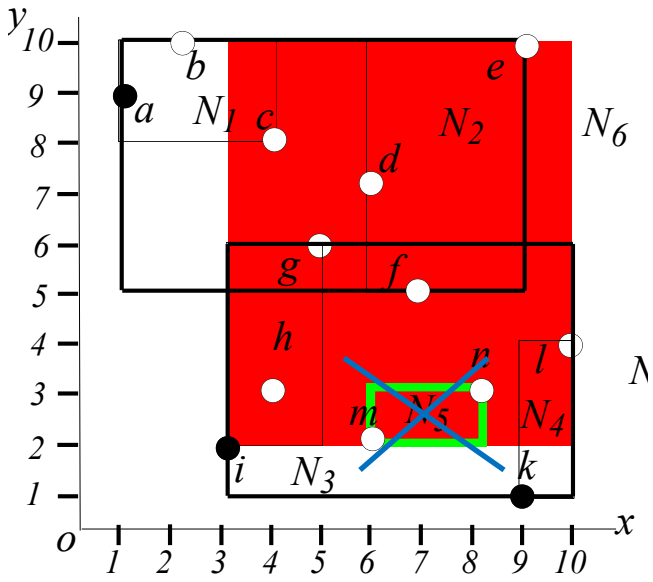
Example of BBS



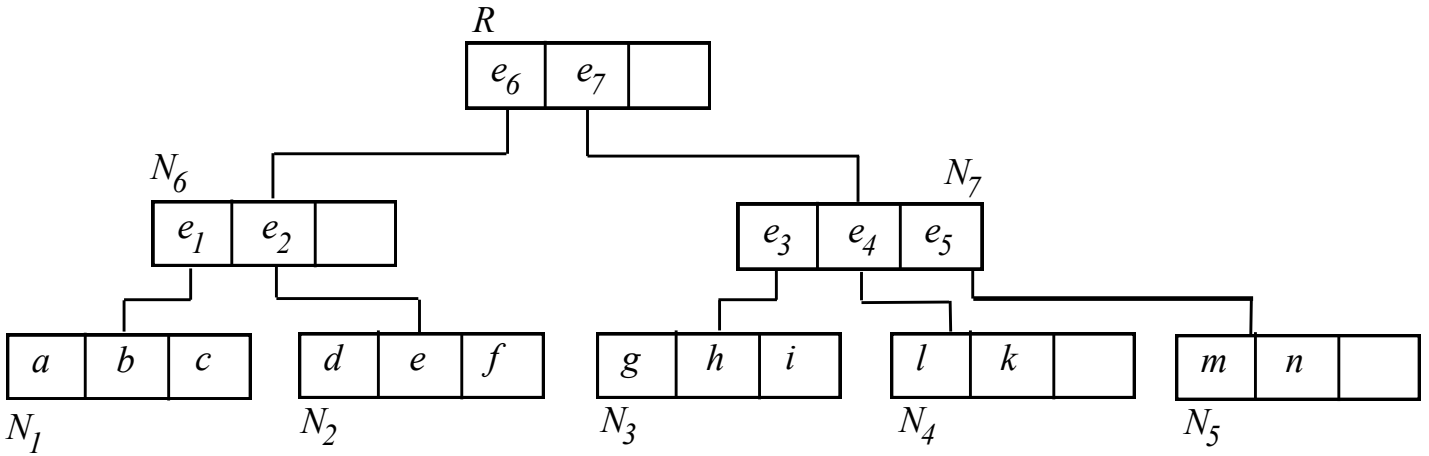
action	heap contents	S
access root	$<e_7,4><e_6,6>$	$\varnothing$
expand e7	$<e_3,5><e_6,6><e_5,8><e_4,10>$	$\varnothing$
expand e3	$\mathbf{<i,5>}<e_6,6><e_5,8><e_4,10>$	$\{i\}$
No-insert e2	$<e_5,8><e_1,9><e_4,10>$	$\{i\}$



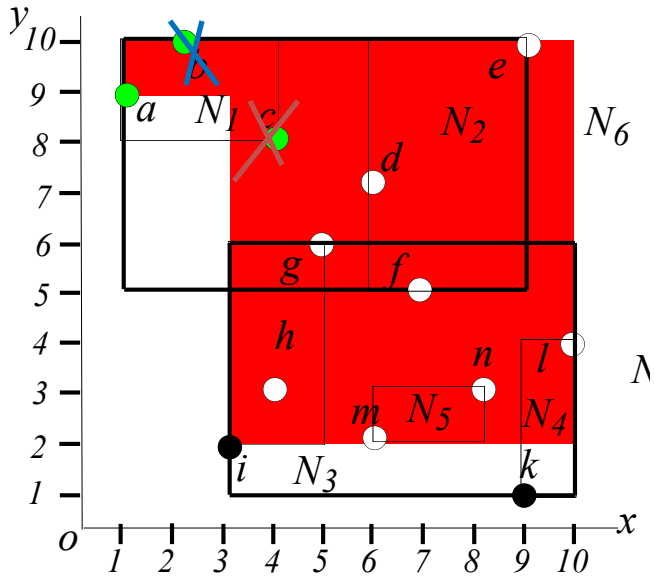
Example of BBS



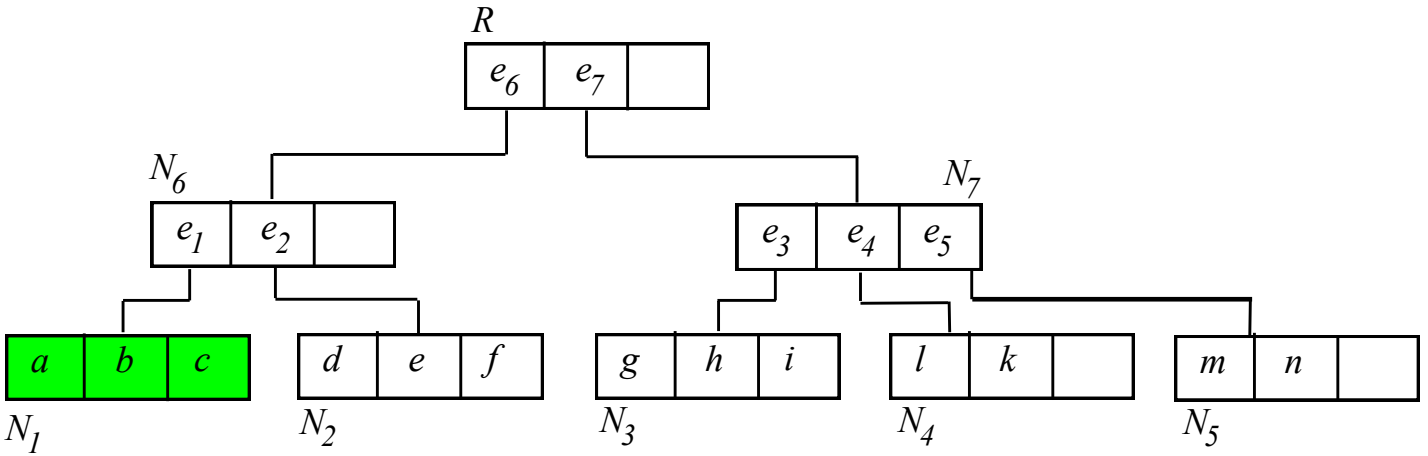
action	heap contents	S
access root	$<e_7,4><e_6,6>$	$\varnothing$
expand e7	$<e_3,5><e_6,6><e_5,8><e_4,10>$	$\varnothing$
expand e3	$\mathbf{<i,5>}<e_6,6><e_5,8><e_4,10>$	$\{i\}$
expand e6	$<e_5,8><e_1,9><e_4,10>$	$\{i\}$
remove e5	$<e_1,9><e_4,10>$	$\{i\}$



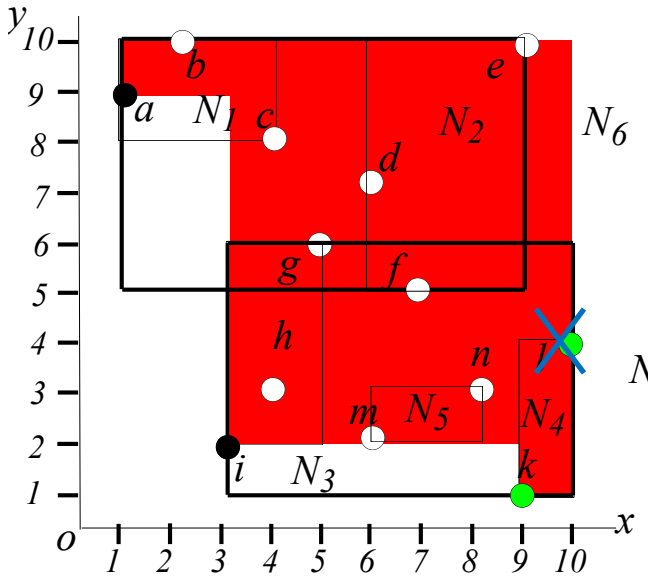
Example of BBS



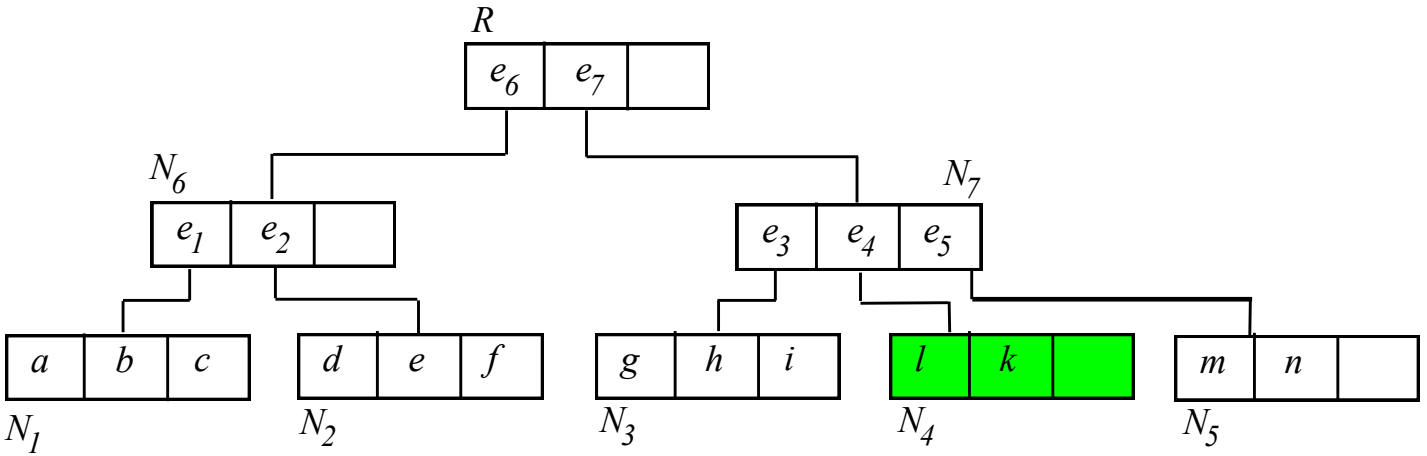
action	heap contents	S
access root	$<e_7,4><e_6,6>$	$\varnothing$
expand e7	$<e_3,5><e_6,6><e_5,8><e_4,10>$	$\varnothing$
expand e3	$\mathbf{<i,5>}<e_6,6><e_5,8><e_4,10>$	$\{i\}$
expand e6	$<e_5,8><e_1,9><e_4,10>$	$\{i\}$
remove e5	$<e_1,9><e_4,10>$	$\{i\}$
expand e1	$\mathbf{<a,10>}<e_4,10>$	$\{i,a\}$



Example of BBS



action	heap contents	S
access root	$<e_7,4><e_6,6>$	$\varnothing$
expand e7	$<e_3,5><e_6,6><e_5,8><e_4,10>$	$\varnothing$
expand e3	**$<i,5>$**$<e_6,6><e_5,8><e_4,10>$	$\{i\}$
remove e6	$<e_5,8><e_1,9><e_4,10>$	$\{i\}$
remove e5	$<e_1,9><e_4,10>$	$\{i\}$
expand e1	**$<a,10>$**$<e_4,10>$	$\{i,a\}$
expand e4	**$<k,10>$**	$\{i,a,k\}$



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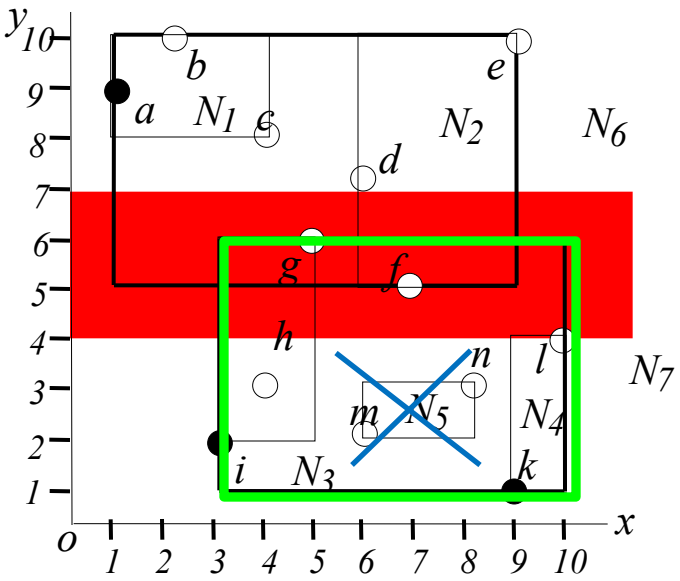
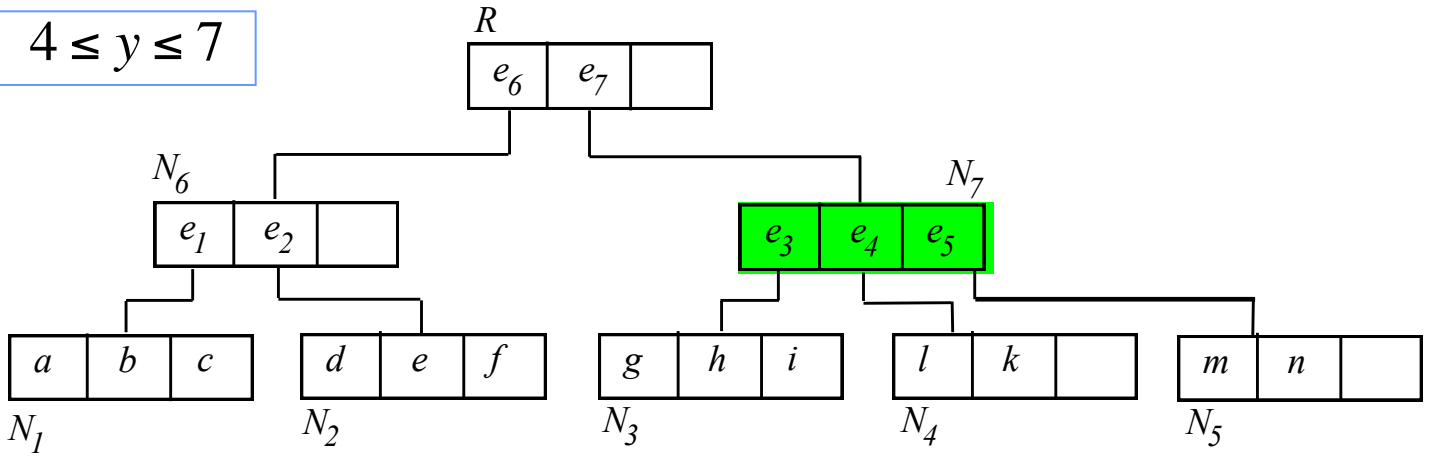
Constrained Skyline Queries

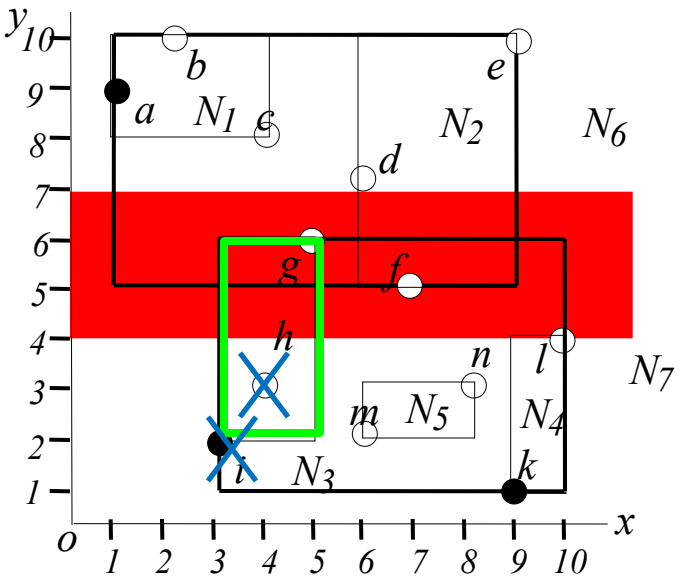


action	*heap contents*	*S*
access root	*<e7, 4>, <e6, 6>*	∅
expand e7	*<e3, 5>, <e6, 6>, <e4, 10>*	∅

constrain : $4 \le y \le 7$

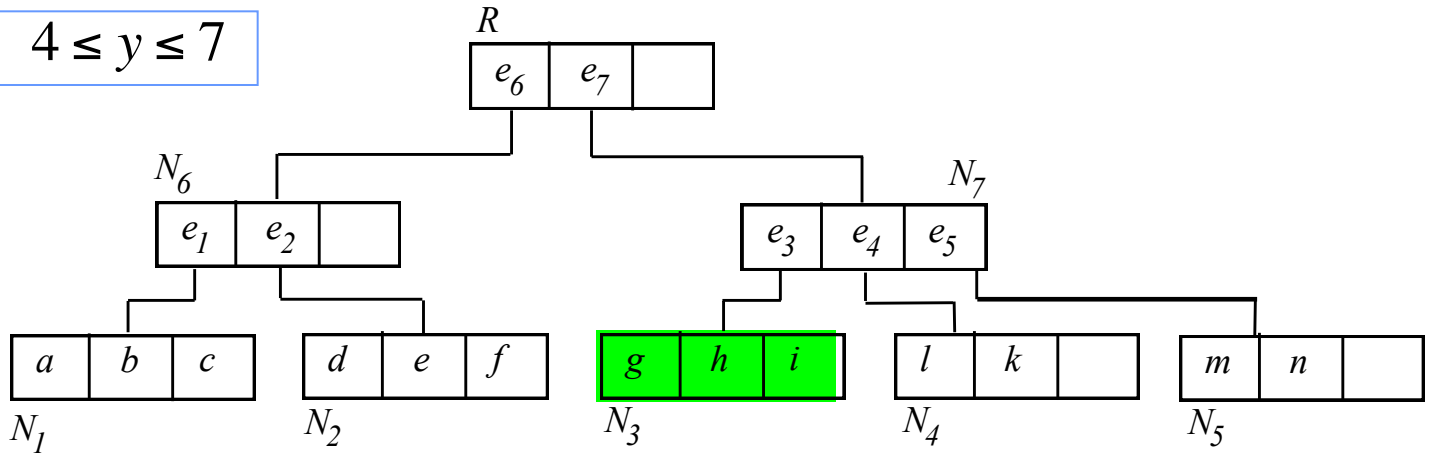


Constrained Skyline Queries

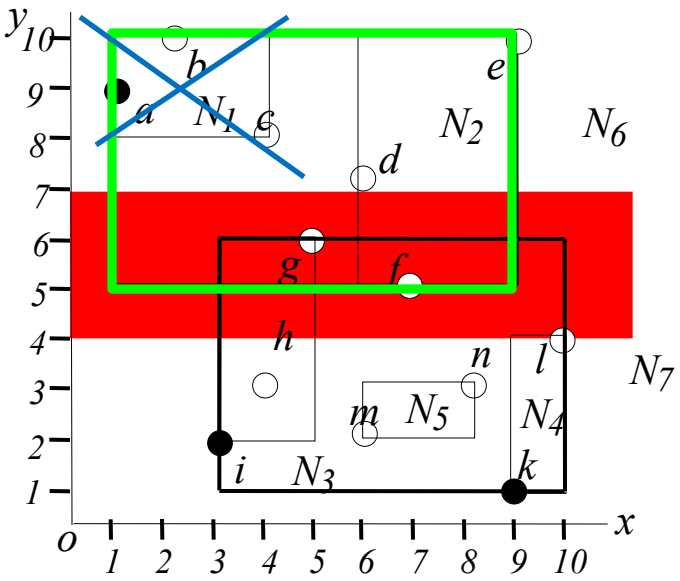


action	*heap contents*	*S*
access root	*<e7, 4>, <e6, 6>*	∅
expand e7	*<e3, 5>, <e6, 6>, <e4, 10>*	∅
expand e3	*<e6, 6>, <e4, 10>, <g, 11>*	∅

constrain : $4 \le y \le 7$

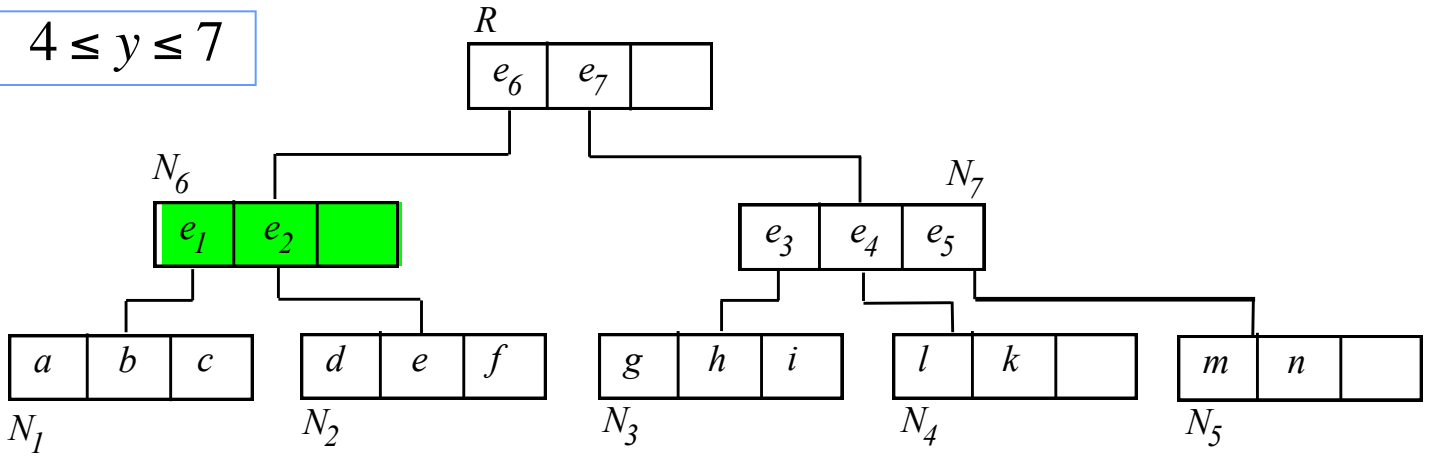


Constrained Skyline Queries

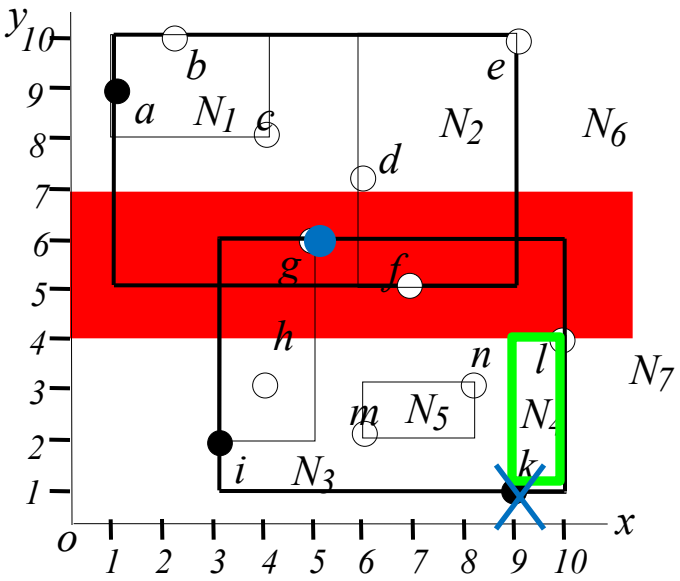


action	*heap contents*	*S*
access root	*<e7, 4>, <e6, 6>*	∅
expand e7	*<e3, 5>, <e6, 6>, <e4, 10>*	∅
expand e3	*<e6, 6>, <e4, 10>, <g, 11>*	∅
expand e6	*<e4, 10>, <g, 11>, <e2, 11>*	∅

constrain : $4 \le y \le 7$

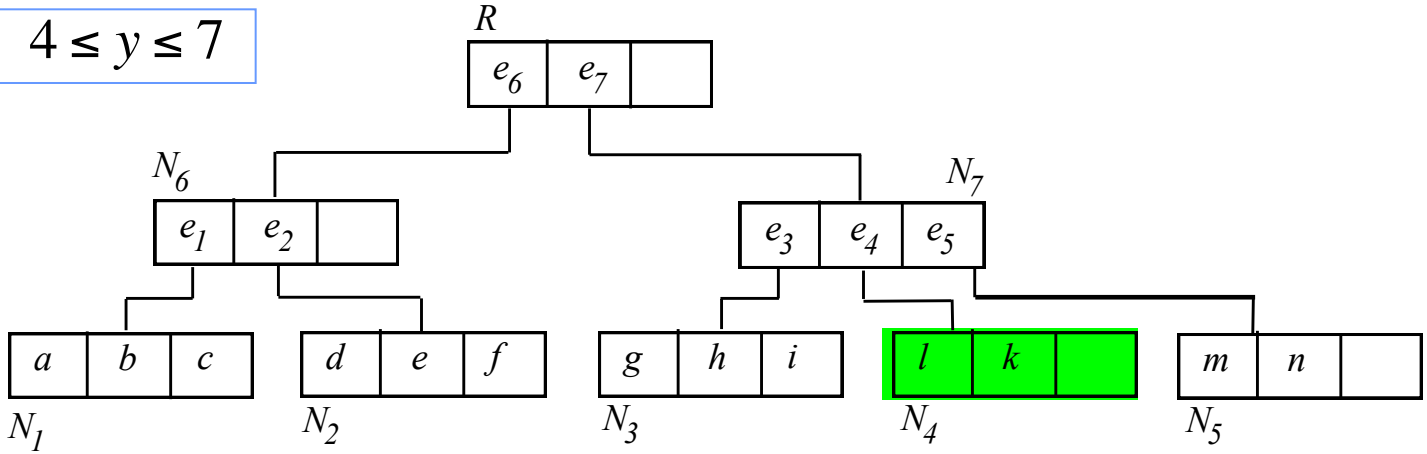


Constrained Skyline Queries

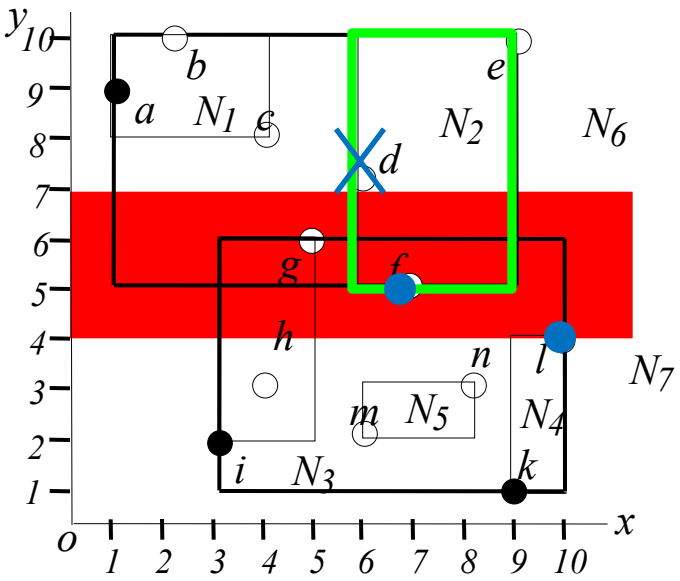


action	*heap contents*	*S*
access root	*<e7, 4>, <e6, 6>*	∅
expand e7	*<e3, 5>, <e6, 6>, <e4, 10>*	∅
expand e3	*<e6, 6>, <e4, 10>, <g, 11>*	∅
expand e6	*<e4, 10>, <g, 11>, <e2, 11>*	∅
expand e4	*<g, 11>, <e2, 11>, <l, 14>*	*{g}*

constrain : $4 \le y \le 7$

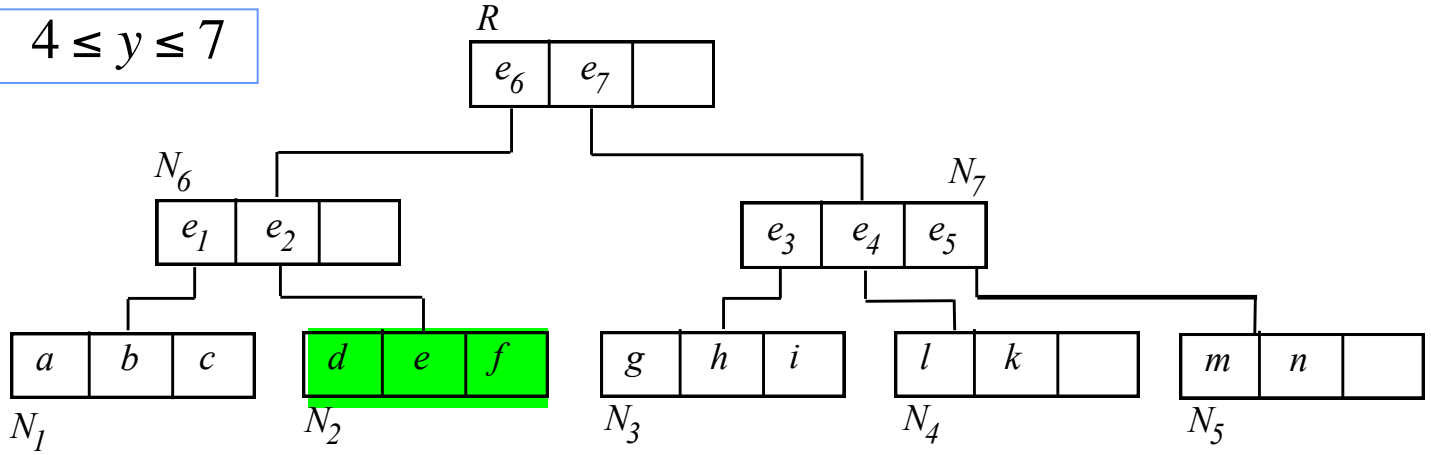


Constrained Skyline Queries



action	*heap contents*	*S*
access root	*<e7, 4>, <e6, 6>*	*∅*
expand e7	*<e3, 5>, <e6, 6>, <e4, 10>*	*∅*
expand e3	*<e6, 6>, <e4, 10>, <g, 11>*	*∅*
expand e6	*<e4, 10>, <g, 11>, <e2, 11>*	*∅*
expand e4	*<g, 11>, <e2, 11>, <l, 14>*	*{g}*
expand e2	*<f, 12>, ~~<d, 13>~~, <l, 14>*	*{g, f, l}*

constrain : $4 \le y \le 7$

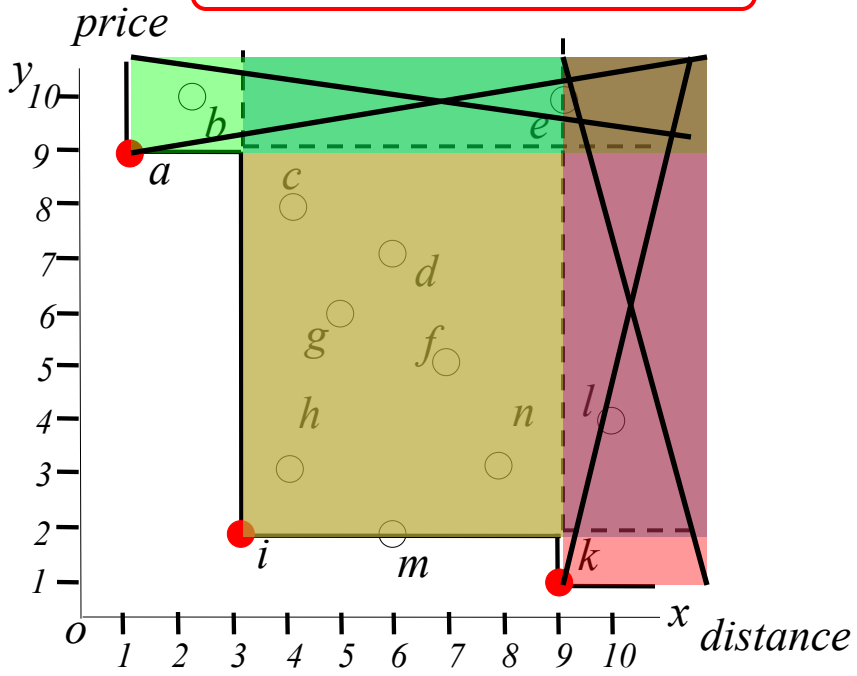


K-dominating Queries

- Retrieve 3 points that dominate the largest number of other points.

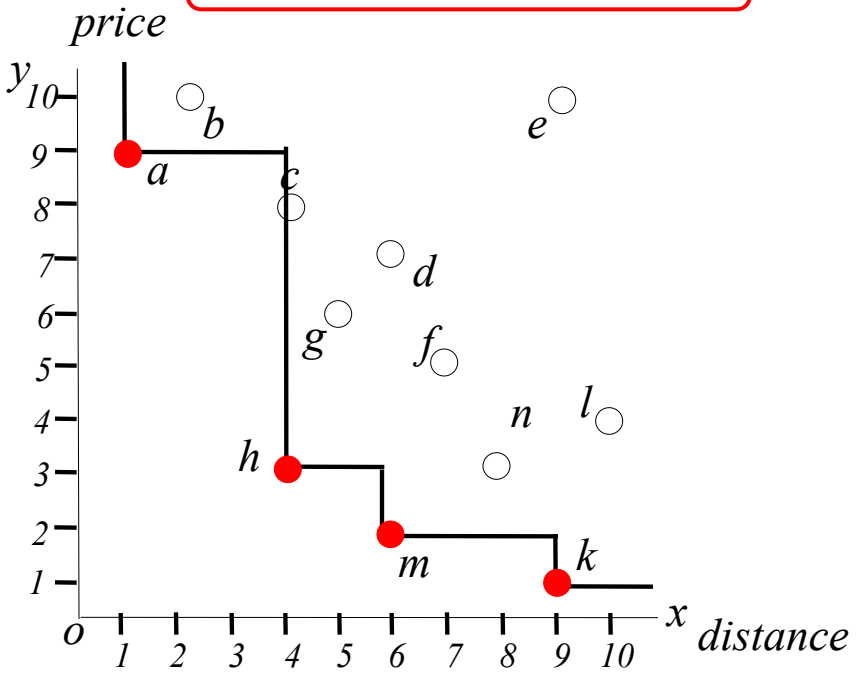
num(i)= 9, num(a)=2, num(k)=2

1-dominating result: {i}



h and m may dominate at most 7 points. (num(i) – 2)

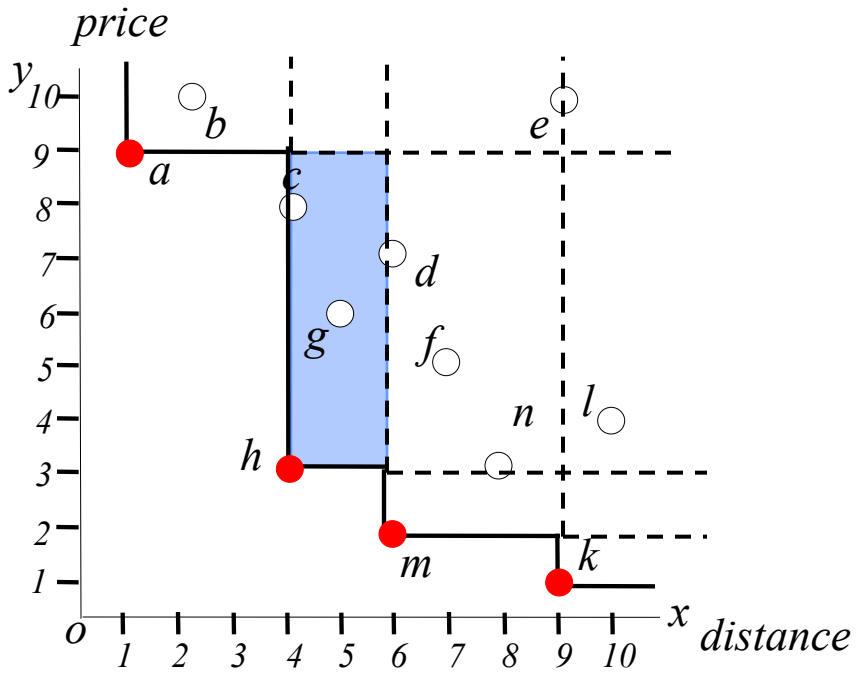
1-dominating result: {i}



K-dominating Queries

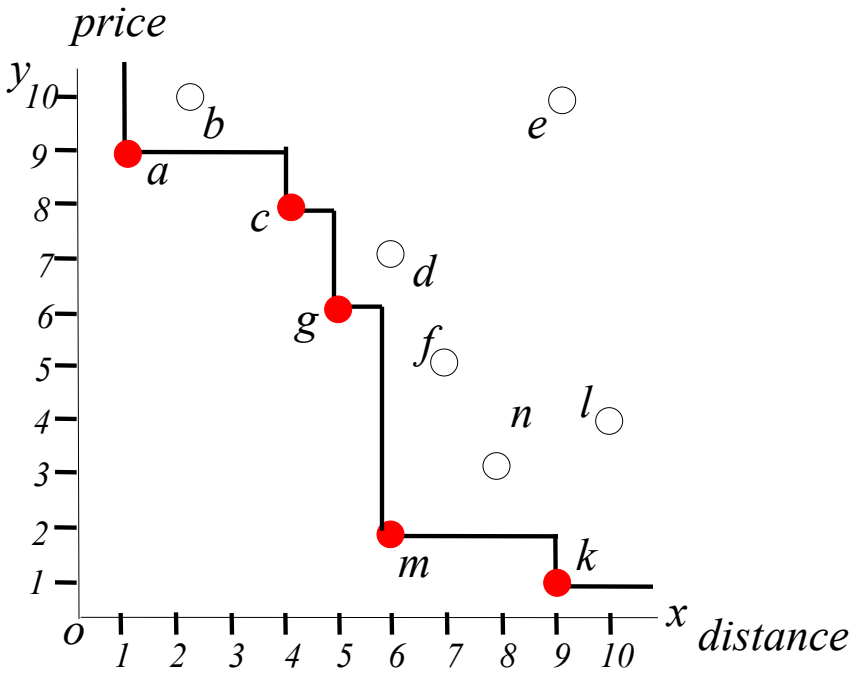
num(h)= 7, num(m)=5, num(a)=2, num(k)=2

2-dominating result: {i, h}



c and g may dominate at most 5 points. (num(h) – 2)

3-dominating result: {i, h, m}



Contents

Experiments (Comparing BBS with NN)

- Datasets:
  - Independent (uniform),anti-correlated
- Dimensionality:
  - In range [2,5]
- Cardinality:
  - In range [100k,10M]
- Machine:
  - Pentium 4 CPU
  - 2.4 GHz
  - 512MB Ram

EXP 1: Effect of dimensionality

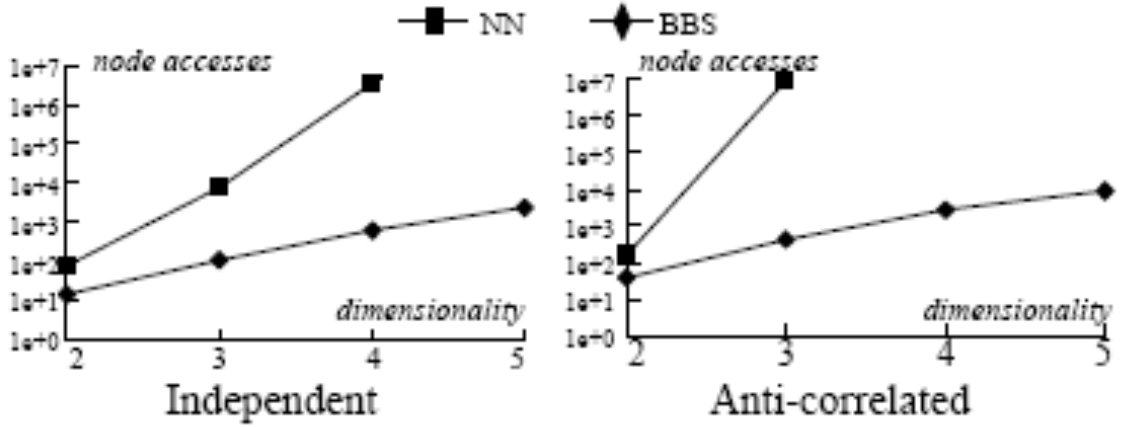


Figure 5.1: Node accesses vs. d (N=1M)

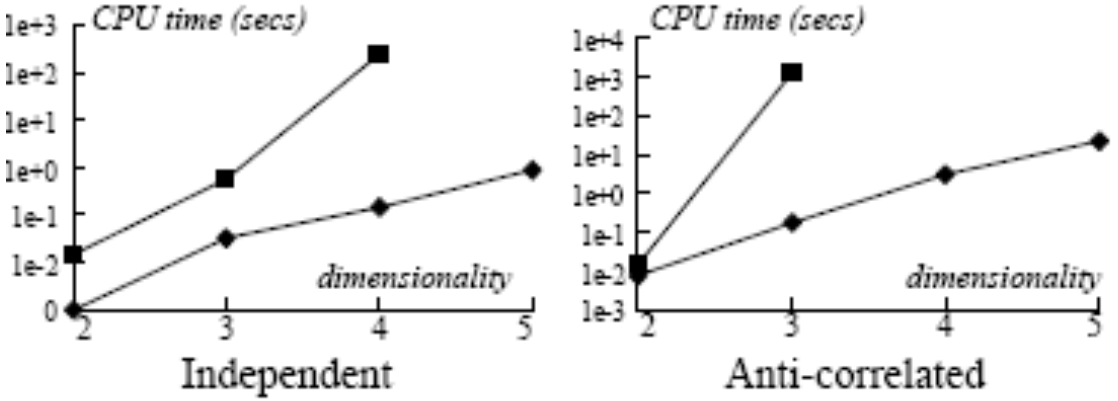


Figure 5.2: CPU-time vs. d (N=1M)

EXP 1: Observations

- NN could not terminate successfully for d > 4 (independent), d > 3 (anti-correlated)
  - Due to prohibitive size of the *to-do* lists
- Degradation of NN is caused mainly by
  - Growth of the number of partitions
  - Growth of number of duplicates
- Degradation of BBS is due to
  - Growth of skyline points
  - Poor performance of R-tree in higher dimensions

EXP 2: Effect of cardinality

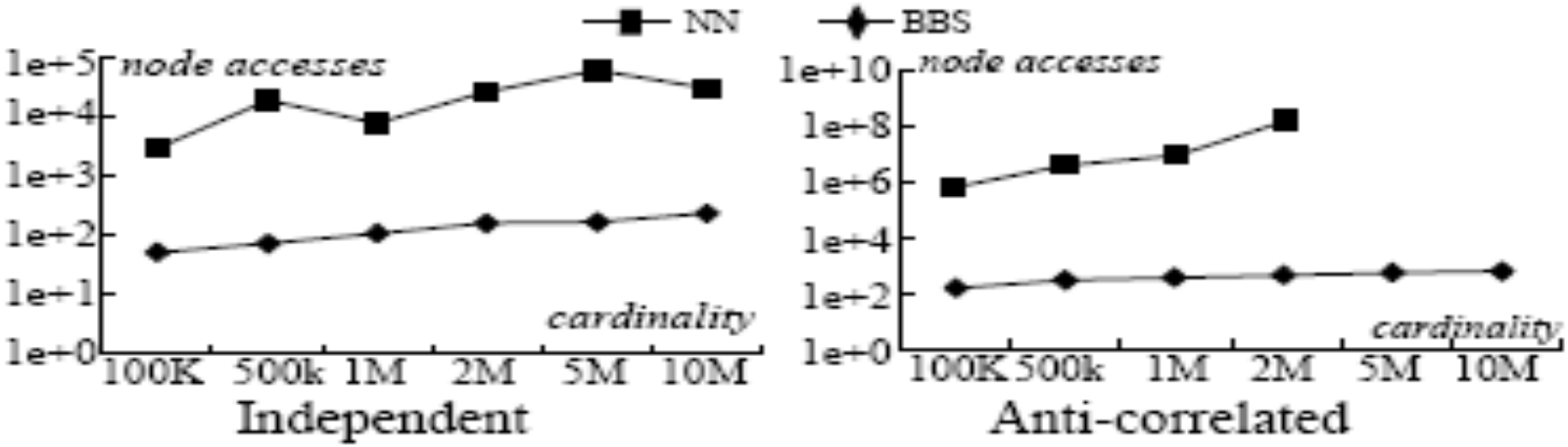


Figure 5.5: Node accesses vs. N (d=3)

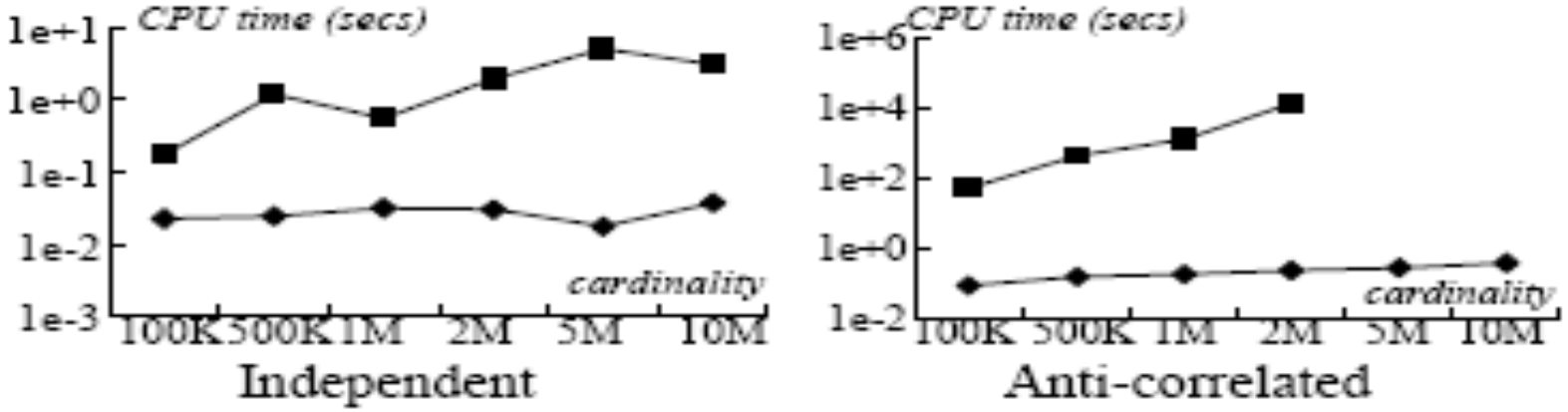


Figure 5.6: CPU-time vs. N (d=3)

EXP 3: Progressive behavior

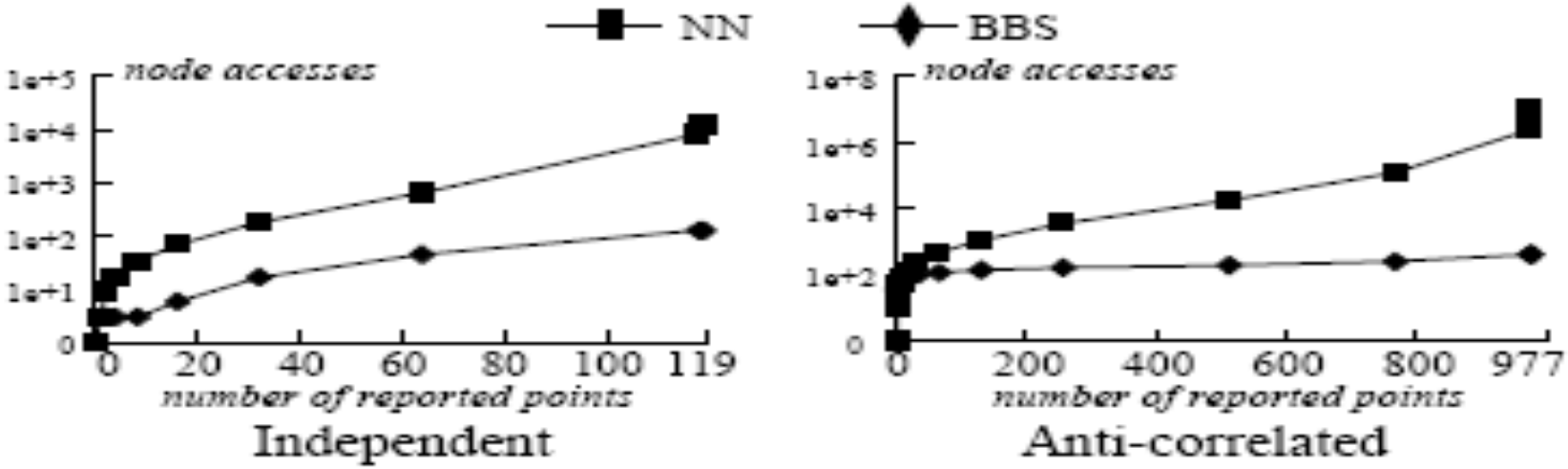


Figure 5.7: Node accesses vs. # points returned (N=1M, d=3)

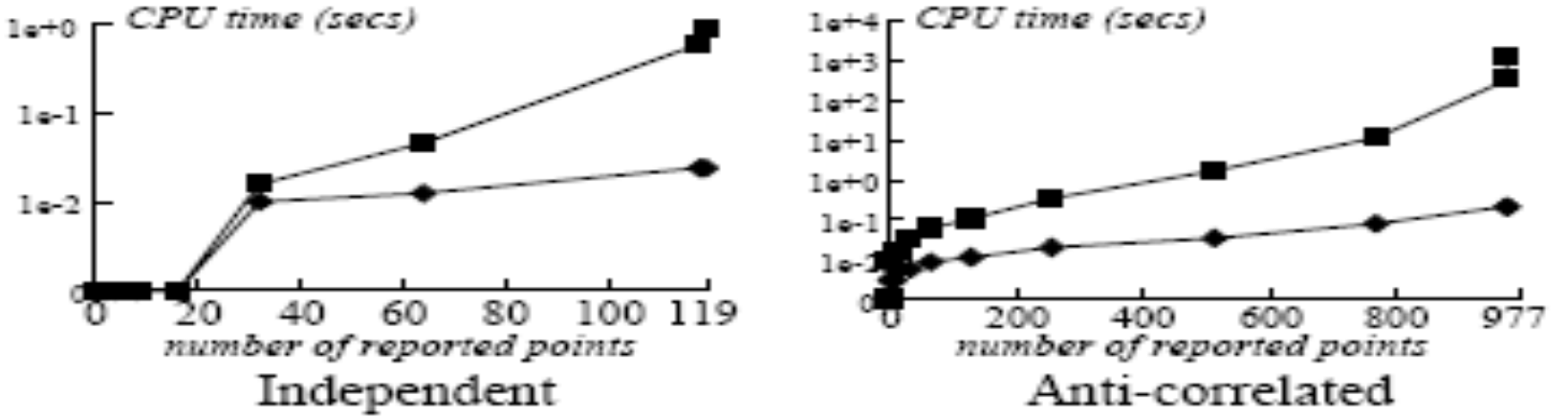


Figure 5.8: CPU-time vs. # points returned (N=1M, d=3)

Experiments - Key Notes

- In General BBS outperforms NN significantly
- For dimensionality
  - NN does not terminate when d increases due to explosive to do list
- For cardinality
  - NN does not terminate here as well if N>=5M due to to do list
- For Progressive behavior
  - NN requires more node access and CPU time to return number of reported points

Contents

Conclusion and Future Work

- All existing database algorithms for skyline computation have several deficiencies.
- BBS overcomes all these deficiencies
  - it is efficient for both progressive and complete skyline computation, independently of the data characteristics
  - it can easily handle numerous alternative skyline queries (e.g. constrained, k-dominating)
  - it can be used for any subset of the dimensions
  - it has limited main memory requirements
- Future work
  - Investigate alternatives for high dimensional spaces where R-Trees are inefficient.
  - Approximate skyline queries

References

1. Papadias, D.; Tao, Y.; Fu, G. & Seeger, B. An Optimal and Progressive Algorithm for Skyline Queries . SIGMOD Conference, 2003, 467-478.
2. A presentation by Ali Khodaei in csci587 Fall'2010