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VoR-Tree: R-trees with Voronoi Diagrams for Efficient Processing of Spatial Nearest Neighbor Queries

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Outline

- Introduction
  - Motivation: I/O-efficient spatial query processing
- Our Index Structure: VoR-tree
  - Voronoi Diagram
  - R-tree
  - VoR-tree
- Query Processing Using VoR-tree
  - Related works
  - k Nearest Neighbor Query
  - k Aggregate Nearest Neighbor Query
  - Reverse k Nearest Neighbor Query
- Performance Evaluation
- Summary and Future Directions

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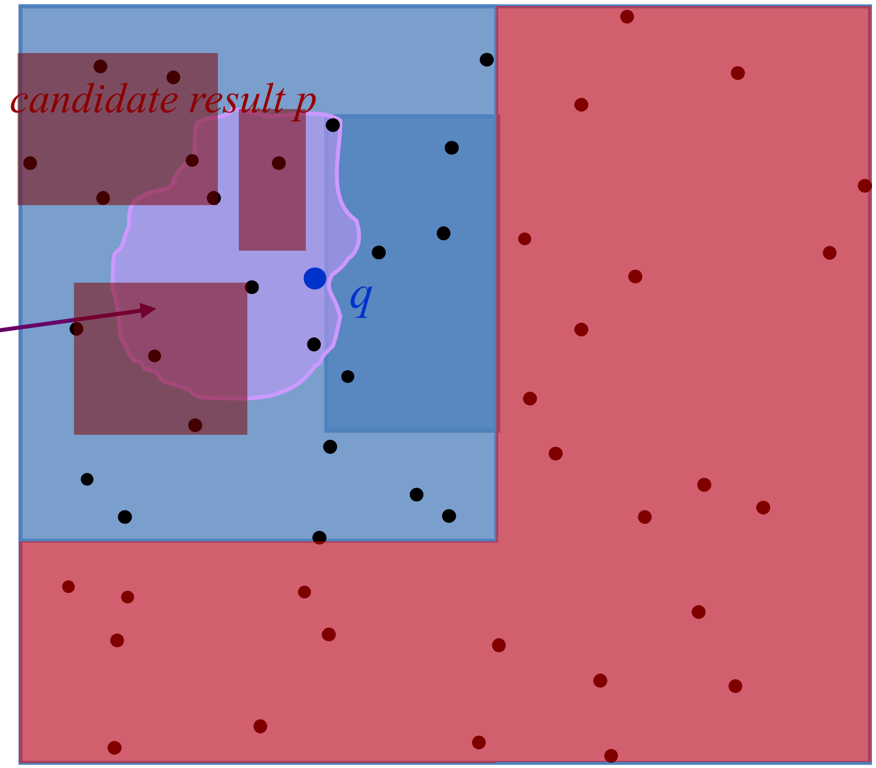
Motivation

- Index-based processing of Nearest Neighbor queries
  - Spatial index provides fast access by hierarchical grouping
  - Algorithms utilize aggregate information to *minimize I/O* operations

Search Region of p: a possible better result must be inside this region



- **Step 1:**

  Filtering through iterative pruning

  R-trees

- **Step 2:**

  Refinement through exploration

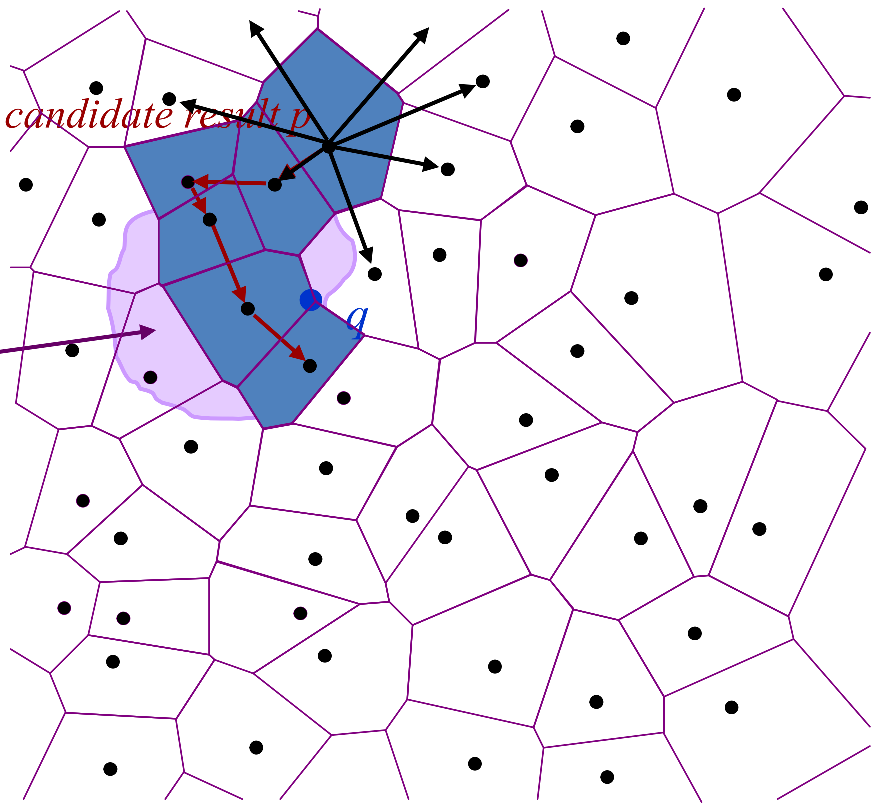
  R-trees

Motivation

- Index-based processing of Nearest Neighbor queries

Traverse along edges of Delaunay graph to minimize/maximize a function f …

Search Region of p: a possible better result must be inside this region



- **Step 1:**
  Filtering through iterative pruning
  - R-trees
- **Step 2:**
  Refinement through exploration
  - Voronoi diagrams

Voronoi Diagrams

- Given a set of spatial objects, a Voronoi diagram *uniquely* partitions the space into disjoint regions (cells).
- The region including object p includes all locations which are closer to p than to any other object p'.

Ordinary Voronoi Diagram

Dataset:

Points

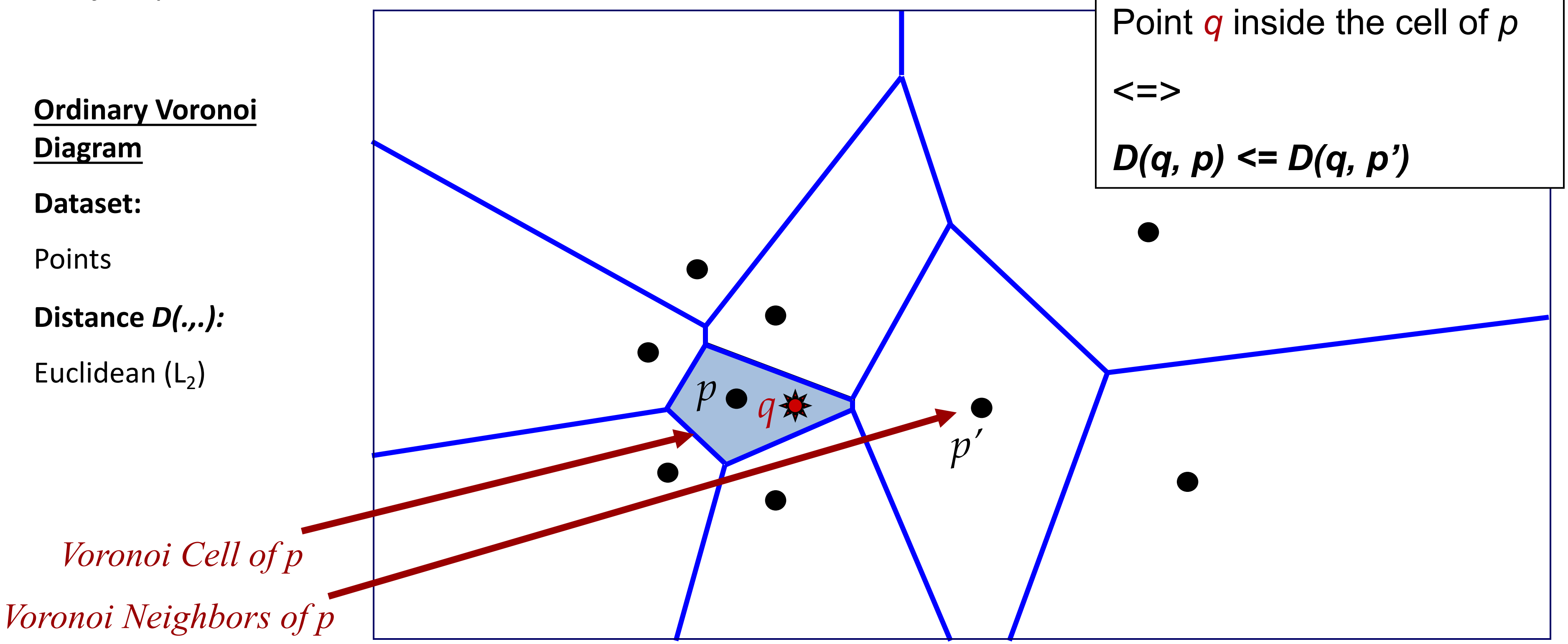
Distance *D(.,.)*:

Euclidean (L_2)

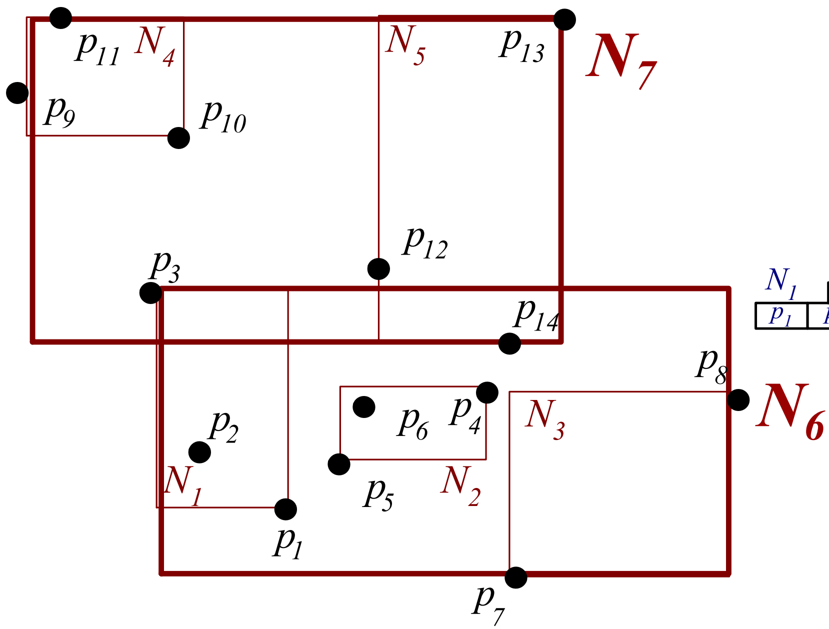
Point *q* inside the cell of *p*

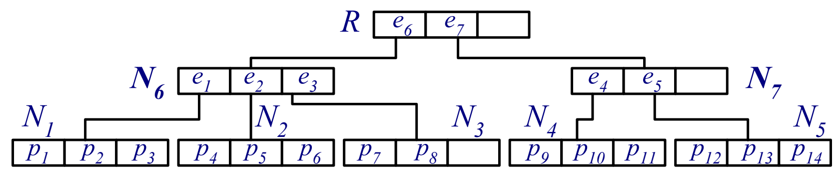
<=>

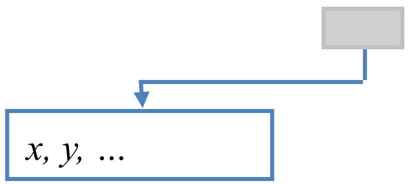
D(q, p) <= D(q, p')



R-tree: Classic Spatial Index Structure







Data Record of p_1

- Hierarchical grouping of objects into MBRs
- The best NN query processing algorithms utilize R-tree
- Algorithms utilize mindist()

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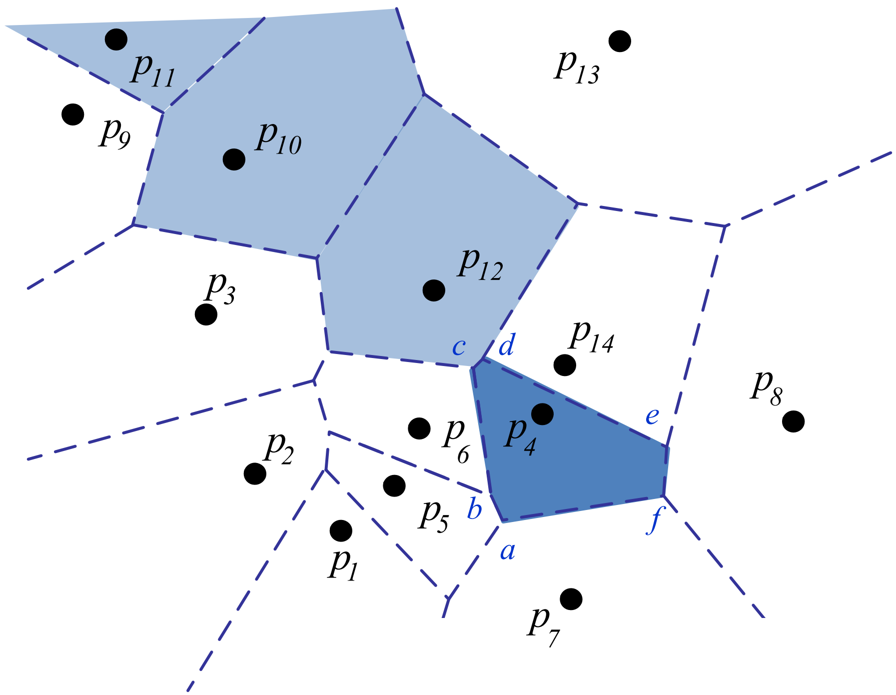
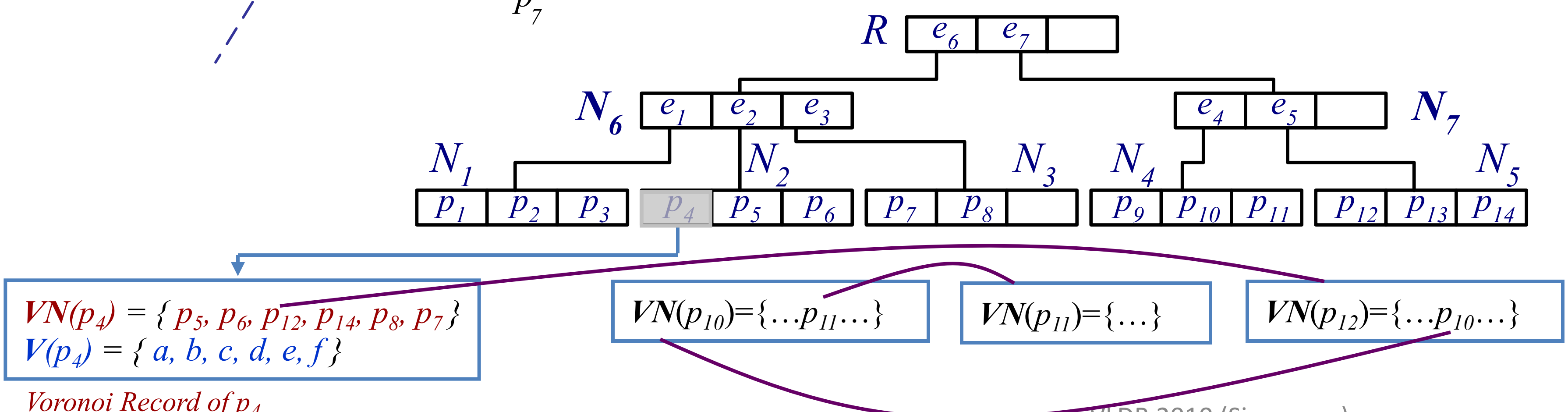
VoR-tree = R-tree + Voronoi Diagram



- We incorporate Voronoi diagram into R-tree -→ VoR-tree
  - Voronoi records are stored with the data of each point
  - All R-tree-based algorithms are still applicable using VoR-tree
  - VoR-tree facilitates exploring the space (e.g., p_4-p_{11})



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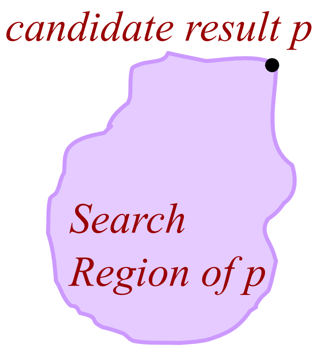
Query Processing using VoR-tree

- I/O-efficient query processing
  - Use the information provided in VoR-tree to find the result with the least number of I/O operations
  - When a candidate result *p* is found, examine only the points inside the search region of *p*



- Disk space overhead -> ok for enterprise applications

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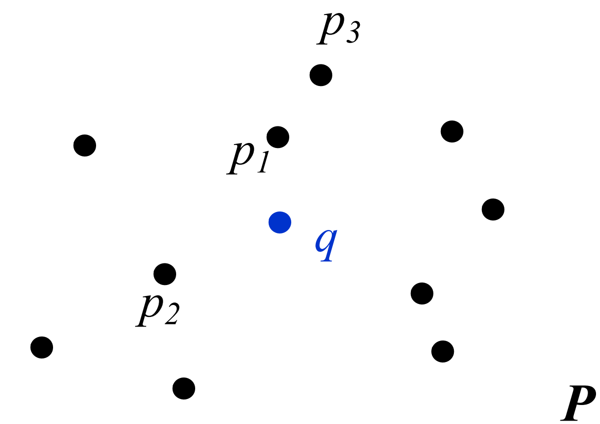
Related Work

- k Nearest Neighbor (kNN)
  - Roussopoulos et al., SIGMOD'95
  - Korn et al., VLDB'96
  - Cheung et al., SIGMOD Record, 1998
  - Seidl et al., SIGMOD'98
  - Hjaltson et al., TODS 42(2), 1999
  - Jung et al., IEEE TKDE 2002
- Reverse k Nearest Neighbor (RkNN)
  - Korn et al., SIGMOD'00
  - Yang et al., ICDE'01
  - Stanoi et al., VLDB'01
  - Benetis et al., VLDB Journal, vol. 15, 2006
  - Tao et al., VLDB'04
  - *Wu et al., VLDB'08*
- k Aggregate Nearest Neighbor (kANN)
  - Papadias et al., ICDE'04
  - Papadias et al., TODS 30(2), 2005
- Spatial Skyline
  - Borzsonyi et al., ICDE'01
  - Tan et al., VLDB'01
  - Kossmann et al., VLDB'02
  - Chomicki et al., ICDE'03
  - Papadias et al., SIGMOD'03
  - Sharifzadeh et al., VLDB'06, TODS'09

kNN: k Nearest Neighbor Query

- Given: point *q* and int *k*
- Goal: find the *k* closest data points to *q*; *k* points p_i in *P* where $D(q,p_i) <= D(q,p)$ for all points *p* in $P \setminus \{p_1,..,p_k\}$
- R-tree-based Algorithm:
  BFS [Hjaltson et al., TODS 1999]
- Our VoR-tree-based Algorithm:
  VR-kNN



$k = 3$

$3NN(q) = \{p_1, p_2, p_3\}$

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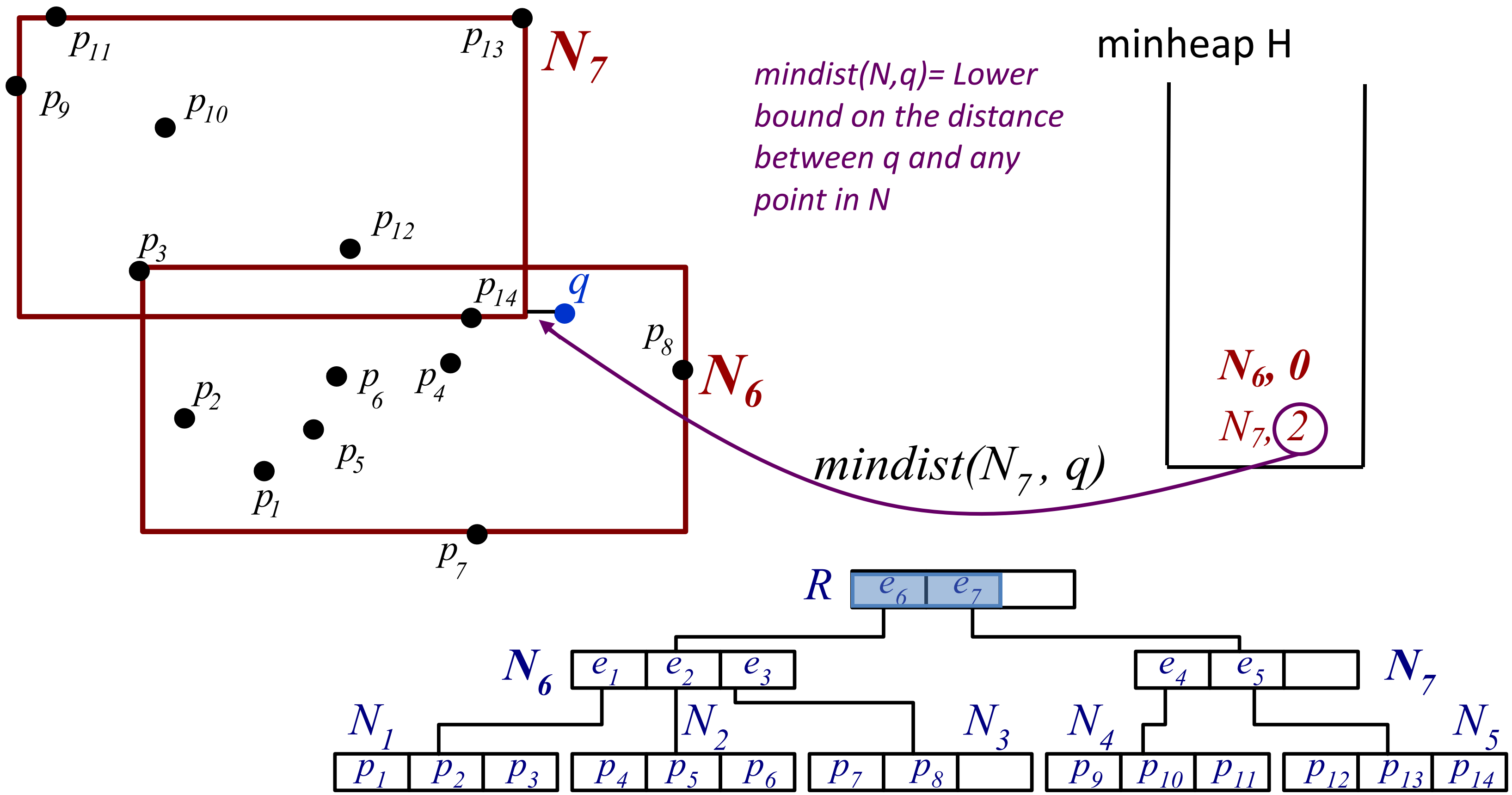
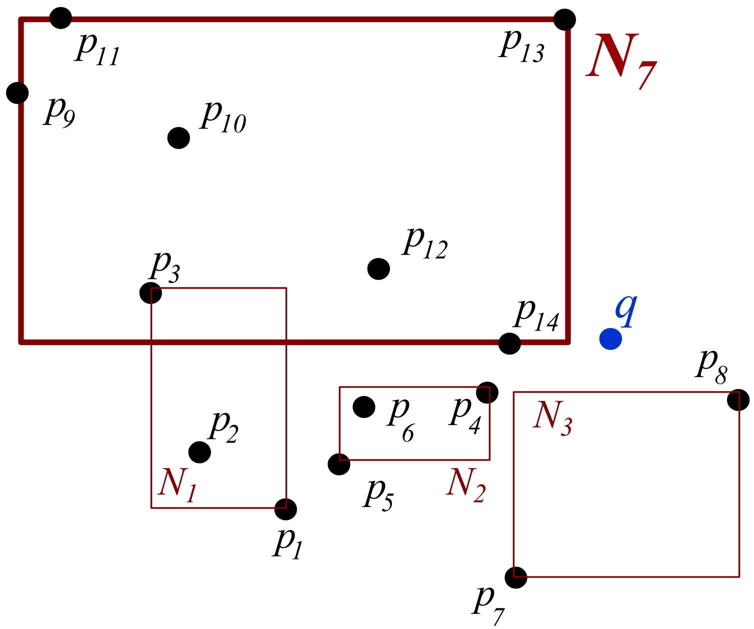
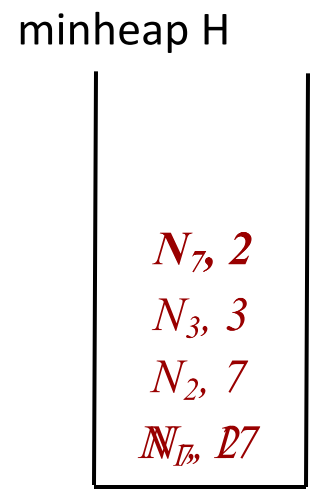
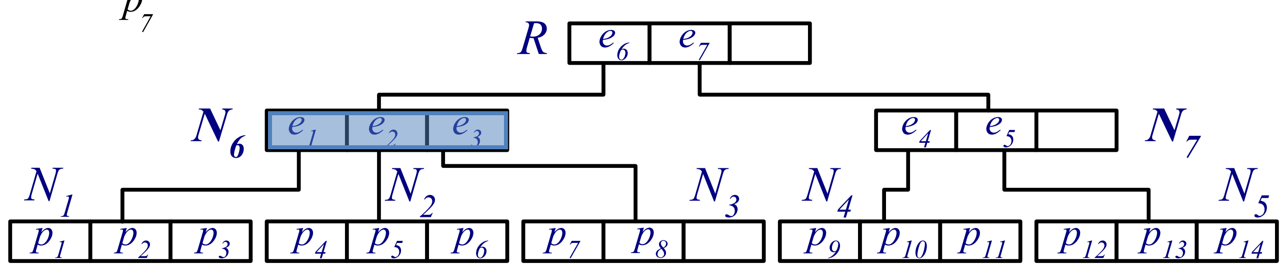
VR-1NN: step 1



VR-1NN: step 1


p_{11}
p_{13}
N_7
p_9
p_{10}
p_{12}
p_3
p_{14}
q
p_8
p_2
p_6
p_4
N_3
N_1
p_5
N_2
p_1
p_7


minheap H
N_7, 2
N_3, 3
N_2, 7


R
e_6 e_7
N_6
e_1 e_2 e_3
e_4 e_5
N_7
N_1
N_2
N_3
N_4
N_5
p_1 p_2 p_3
p_4 p_5 p_6
p_7 p_8
p_9 p_{10} p_{11}
p_{12} p_{13} p_{14}

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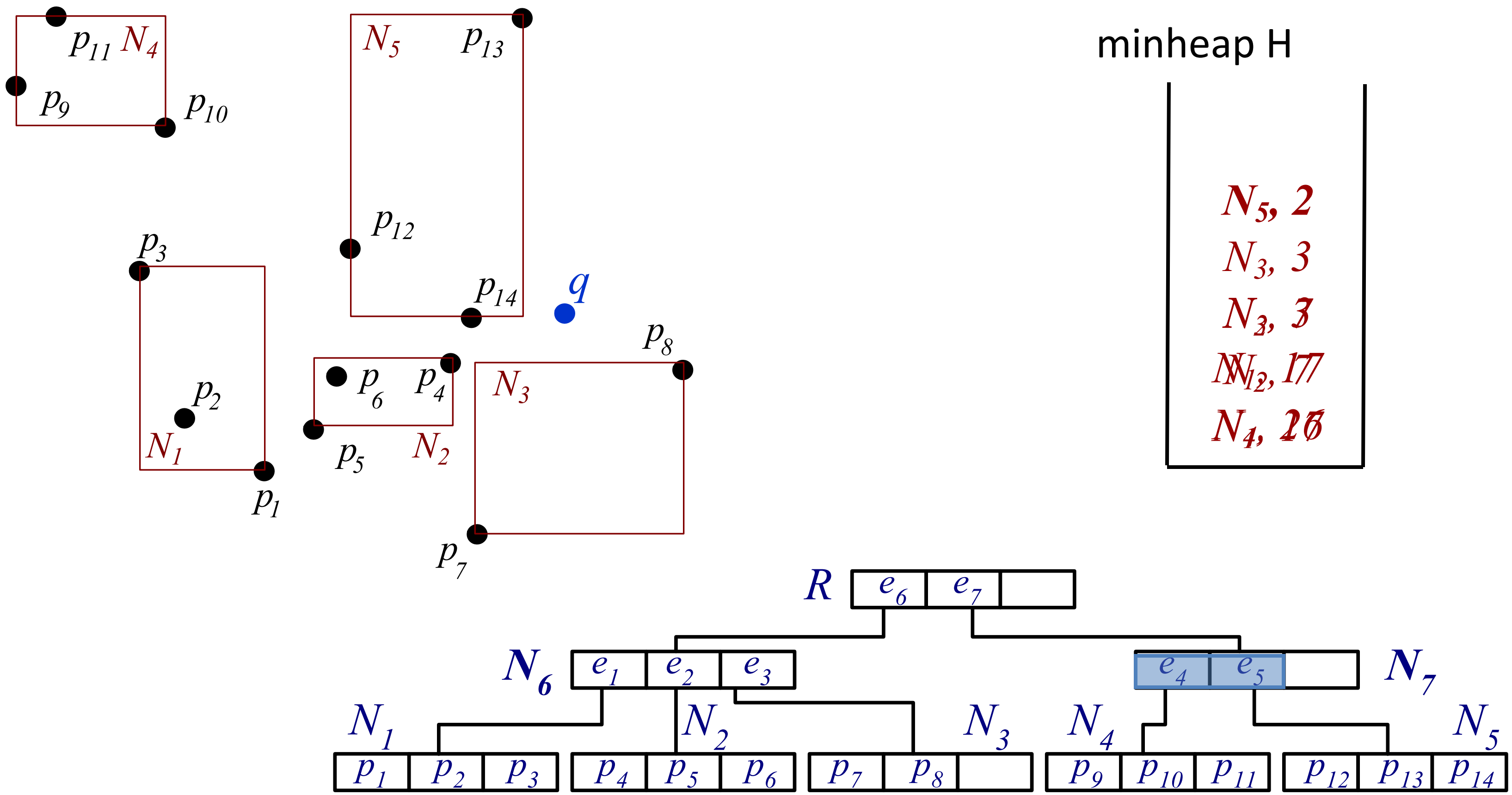
VR-1NN: step 1



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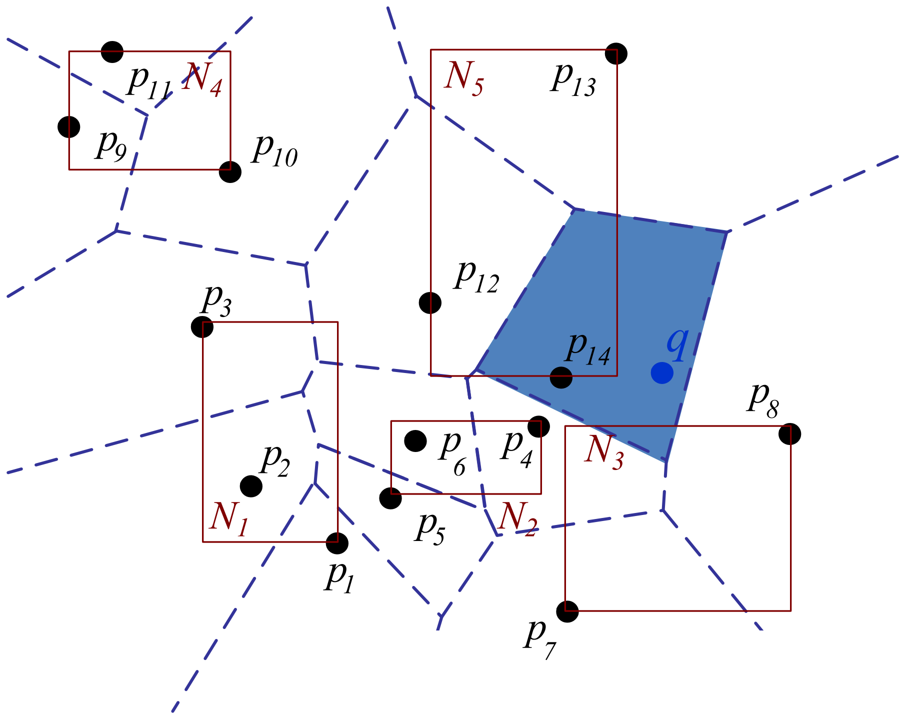
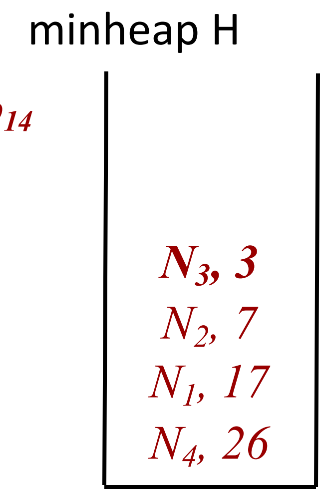
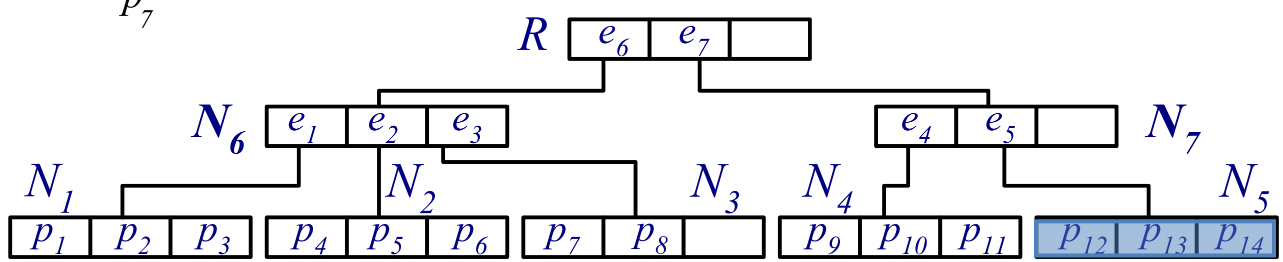
VR-1NN: step 1



==> 1^{st} NN = p_{14}





candidate 1^{st} *NN* = p_{14}

VR-1NN terminates but BFS must examine N_3 => $D(q, p_{14}) = 5 > mindist(q, N_3)$

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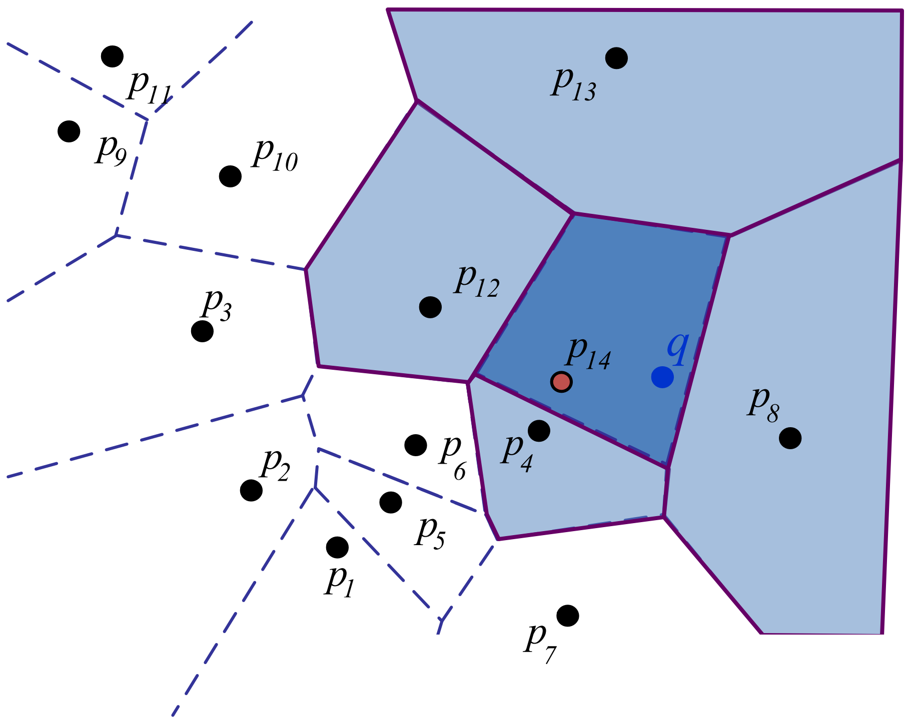
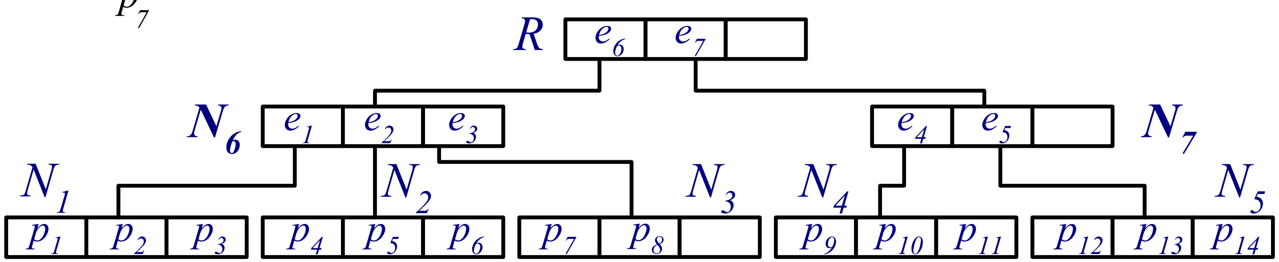
VR-kNN: step 2



Finding more NNs by navigating Voronoi diagram

==> 1st NN = p_{14}

==> 2nd NN = p_4



Lemma: 2nd NN of q is one of Voronoi neighbors of the 1st NN of q.

candidate 2nd NNs = $\{p_4, p_8, p_{13}, p_{12}\}$

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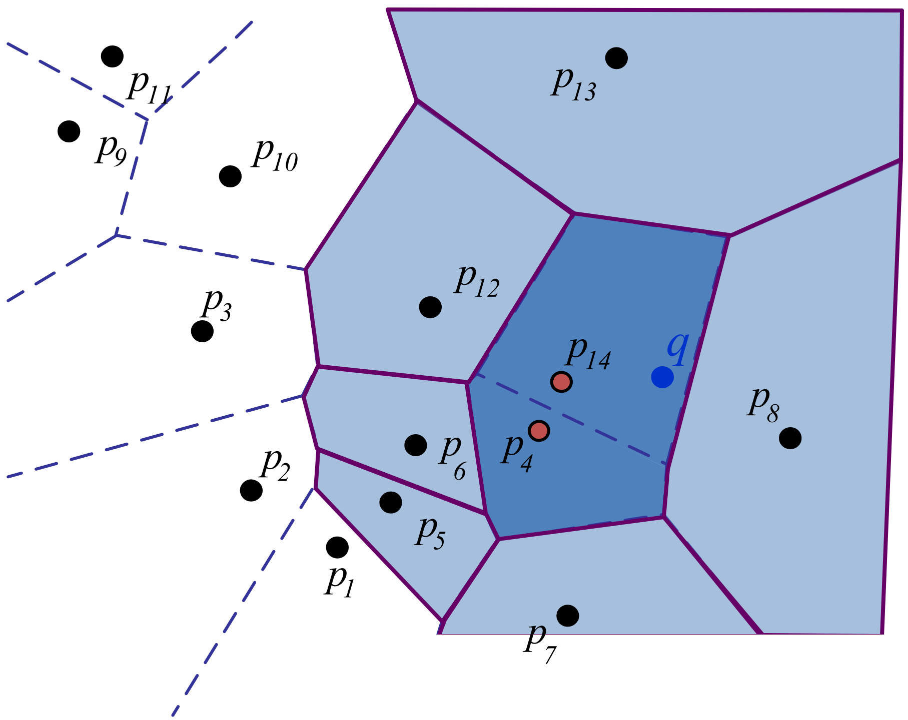
VR-kNN: step 2

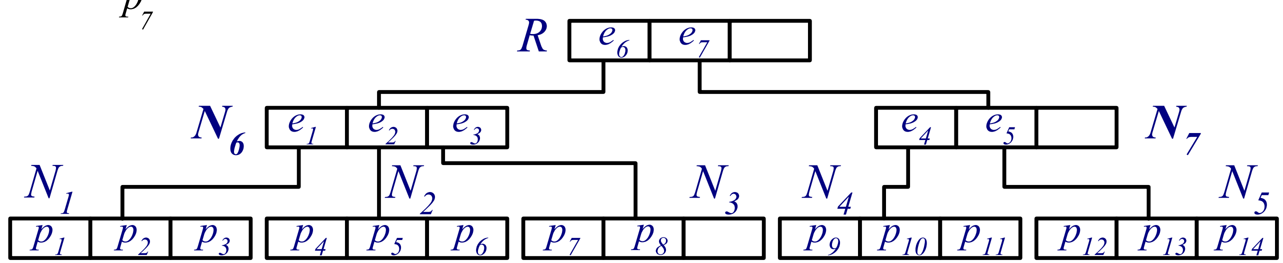


Finding more NNs by navigating Voronoi diagram

==> 1^{st} NN = p_{14}

==> 2^{nd} NN = p_4

==> 3^{rd} NN = p_8



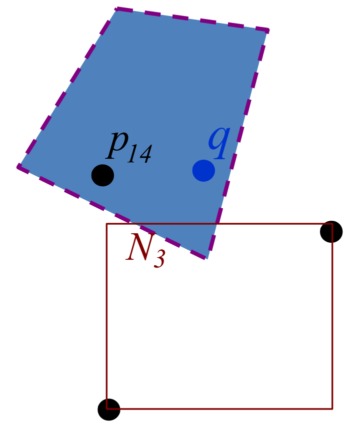
Lemma: kth NN of q is Voronoi neighbor of one of 1^{st}, 2^{nd},…, k-1th NN of q.

candidate 3^{rd} NNs = $\{p_8, p_{13}, p_{12}, p_5, p_6, p_7\}$

VR-kNN

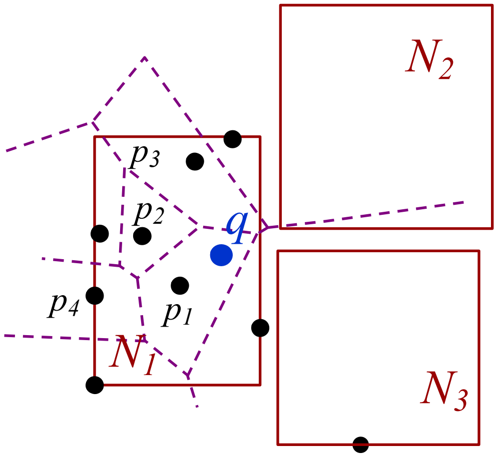
Performance Improvements:

- Using Voronoi cells for 1NN
  - e.g., no access to N_3
- Using Voronoi neighbors for kNN
  - e.g., no access to N_2 and N_3 for $k < 5$



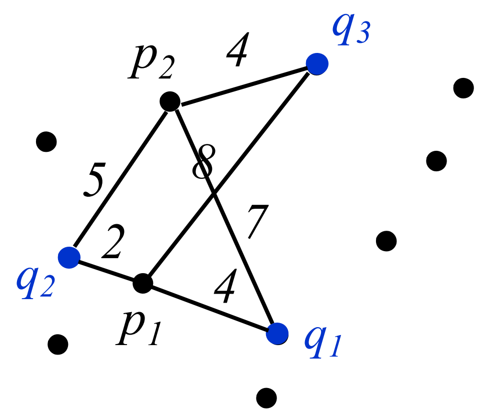
I/O Complexity:

O(Φ(|P|) + k) where *Φ(|P|)* is the complexity of finding the 1st NN of *q*



kANN: k Aggregate Nearest Neighbor

- Given: $Q=\{q_1, \ldots, q_n\}$, integer k, and aggregate distance f
- $adist(p,Q) = f(D(p,q_1), \ldots, D(p,q_n))$
- Goal: find k data points p with smallest $adist(p,Q)$
- *f=sum -> the points that minimize the total distance to Q*
- *f=max -> the points that minimize max distance to Q*
- *Variations: weighted sum, …*

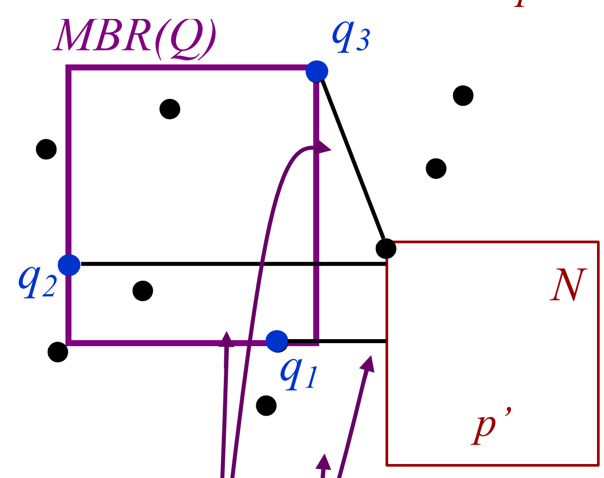


kANN

- R-tree-based Algorithm: MBM [Papadias et al, TODS'05]
- Similar to BFS for kNN
- Heuristics to prune nodes
  - Lower bounds on *adist(p', Q)* :
  - *adist(p', Q) = f(D(p', q_1), …) >=* *amindist(N, MBR(Q)) =* *f(mindist(N, MBR(Q)), …)* > adist(p, Q) → do not access N
  - *adist(p', Q) = f(D(p', q_1), …) >=* *amindist(N, Q) =* *f(mindist(N, q_1), …)* > adist(p, Q) → do not access N
- Problem: too conservative

→ No optimal coverage of SR

Assume: candidate result = p



VR-kANN

- Search Region of *p* for *f=sum*

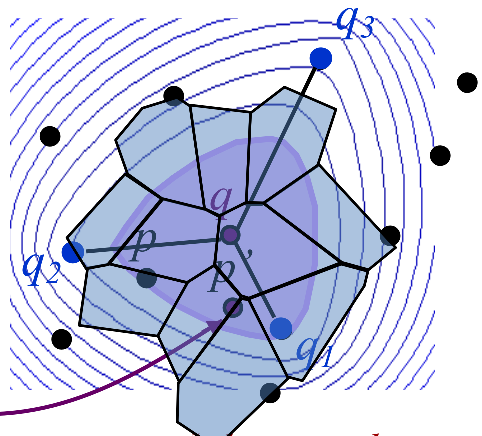
  p' where adist(p', Q) <= adist(p, Q)
- Co-circular areas for many functions
- VR-kANN's two steps:
  1. Find a point close to the 1st ANN of Q

     q in R^2 = centroid of Q that minimizes adist() = center of all SRs
  2. Traverse the space using Voronoi diagram to finalize the result
- To ensure the coverage

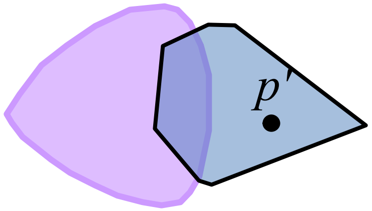
  amindist(V(p'), Q) <= adist(p,Q)

  Use to check that V(p') is intersecting SR

  (p' may be outside the search region but its voronoi still overlaps so exploration should continue)



Assume: candidate result = p



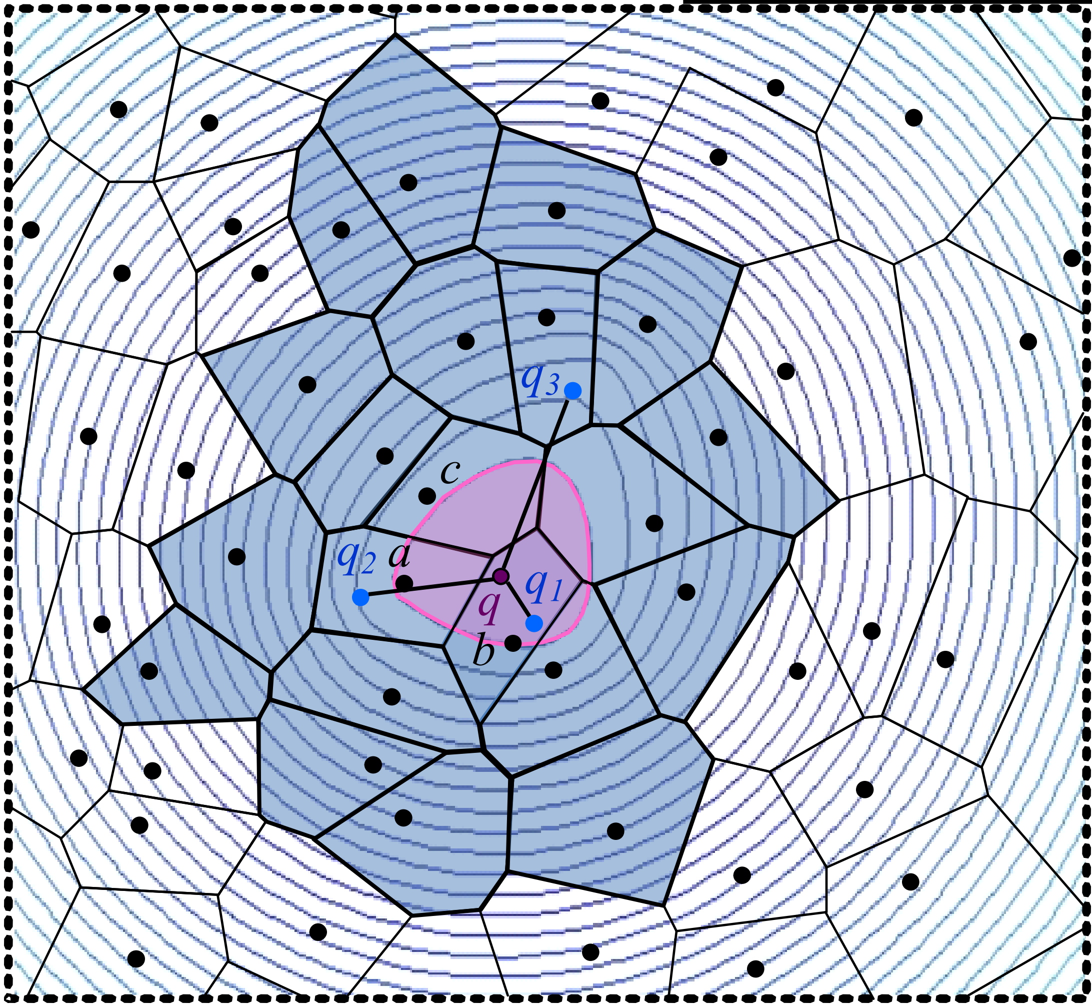
VR-kANN

F(p): lower bound of sum(p',Q) for p' in V(p)

Extracted Points

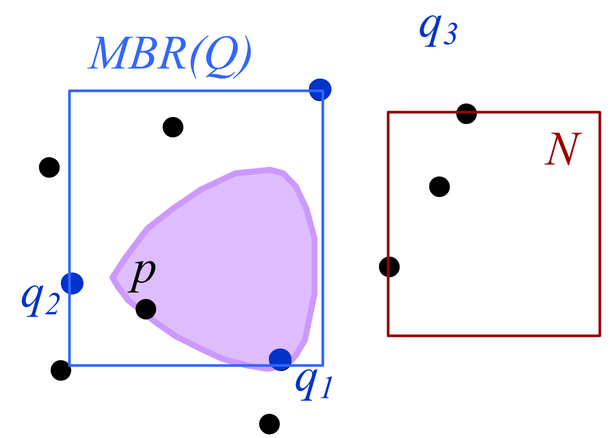
Contents of the heap

- find *b*, the closest point to centriod *q* (use VR-1NN)
- add *b*'s neighbors into a minheap *H* ordered by *F()*
- *add each visited point to candidate result*
- *iterate: remove the top, add its neighbors to H*
- *STOP condition: return a candidate a when adist(a,Q) <= key of top of H (we've covered b's SR)*
- *NOTE: key of top of H is lower bound on sum() for all extracted points. min(amindist(V(p'),Q)) → we have covered p's SR*



Continue to cover more SRs and find more results…

VR-kANN



Performance Improvements:

- Using Voronoi cells to cover SR
  - e.g., heuristics used by MBM [Papadias et al., TODS 30(2), 2005] suggests to examine N but no access to N in VR-kANN

I/O Complexity:

O(Φ(|P|) + k) where *Φ(|P|)* is the complexity of finding the cell including centroid *q*

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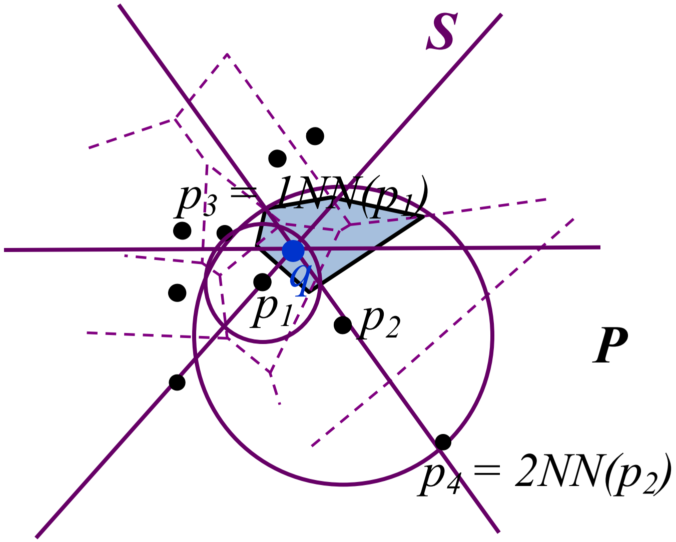
RkNN: Reverse k Nearest Neighbor Query

- Given: point *q* and int *k*
- Goal: find the data points that have *q* as one of their *k* NN; points *p* in *P* where $D(q,p) <= D(q,p_k)$ where p_k is *k*-th NN of *p*
- R-tree-based Algorithm:

  TPL [Tao et al., VLDB'04]
- VR-RkNN: Uses two filters based on*:*
  - *L1: k*-th RNN of *q* is in less than *k* distance from *q*
  - *L2 [Stanoi et al., VLDB'01]:* R*k*NN of *q* is one of *q*'s *k*NNs in each partition *S*
- *Briefly, VR-RkNN locates q in VD, navigate to the points less than k points away from q, stop when q's kNN in each sector is found*



$R1NN(q) = \{p_1\}$
$R2NN(q) = \{p_1, p_2\}$

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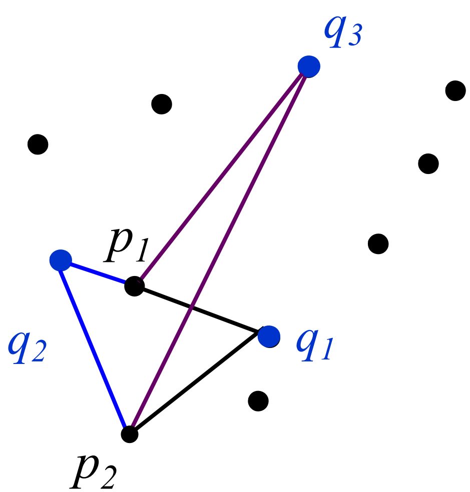
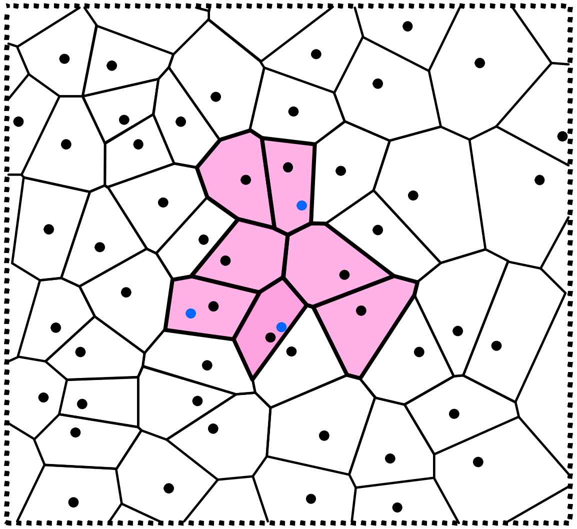
Spatial Skyline Query [VLDB'06, TODS'09]

- Given: $Q=\{q_1, \ldots, q_n\}$
- Goal: find data points *p* for which *there is no point closer than p to all q_i's*
- R-tree-based Algorithm: B^2S^2 [Sharifzadeh et al., VLDB'06]
- Voronoi-based Algorithm: VS^2 [Sharifzadeh et al., VLDB'06]
- VR-S^2: similar to VS^2 and VR-kANN
- Improvement over B^2S^2 and VS^2
  - Fixing the stop condition:
    - If amindist(V(p), Q) <= adsit (top, Q) then we need to examine P
  - I/O-optimality
  - Ability to report in the order of given function





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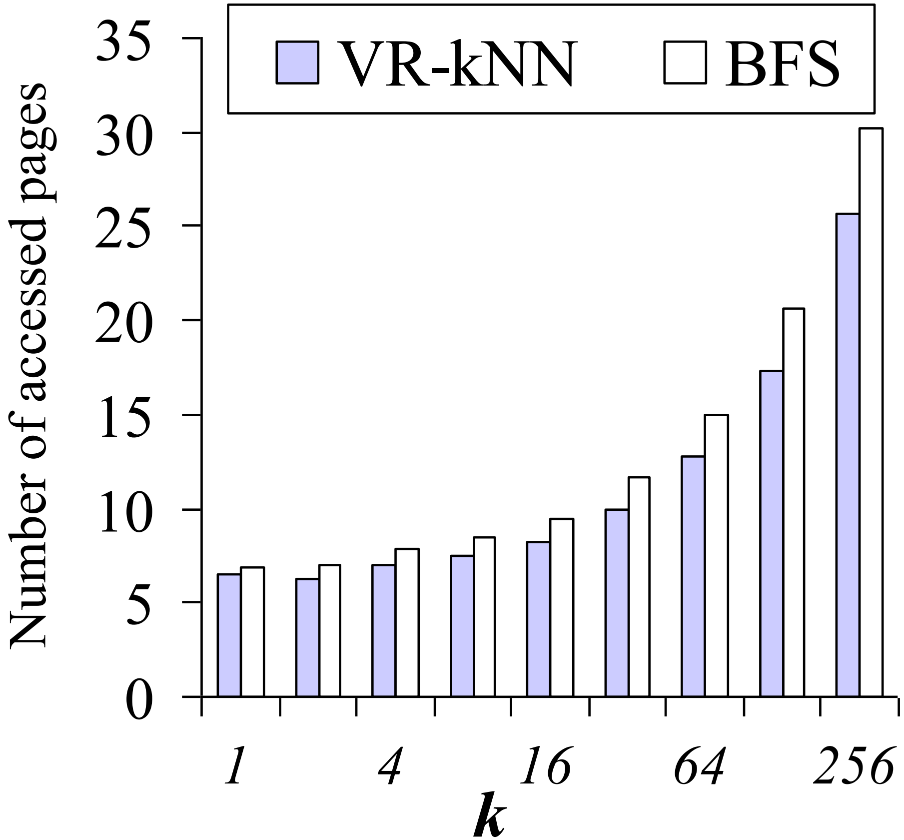
Performance Evaluation

- **Real-world datasets (data points):**
  - ***USGS*** including one million locations in U.S.
  - ***NE*** including 124K locations in New York, Philadelphia and Boston
- **Methodology:** issuing 1000 NN queries of each type with random query points
- **Evaluating VoR-tree-based algorithms**
  - **Number of accessed disk pages (I/O cost)**
- **Parameters**
  - **Size of result set (k) for kNN, RkNN, and kANN**
  - **Number of query points (|Q|) for kANN and SSQ**
  - **Extent of query points (size of MBR(Q)) for kANN and SSQ**
- **Competitor approaches:**
  - BFS [Hjaltson et al., TODS 1999] for kNN
  - MBM [Papadias et al., TODS 30(2), 2005] for kANN
  - TPL [Tao et al., VLDB'04] for RkNN

Performance Evaluation

- Dataset: USGS
- I/O cost of VR-kNN
- Competitor approach:
  - BFS that utilizes an R-tree on data points



- VR-kNN examines less number of disk pages when k grows
- Up to 18% improvement for large k

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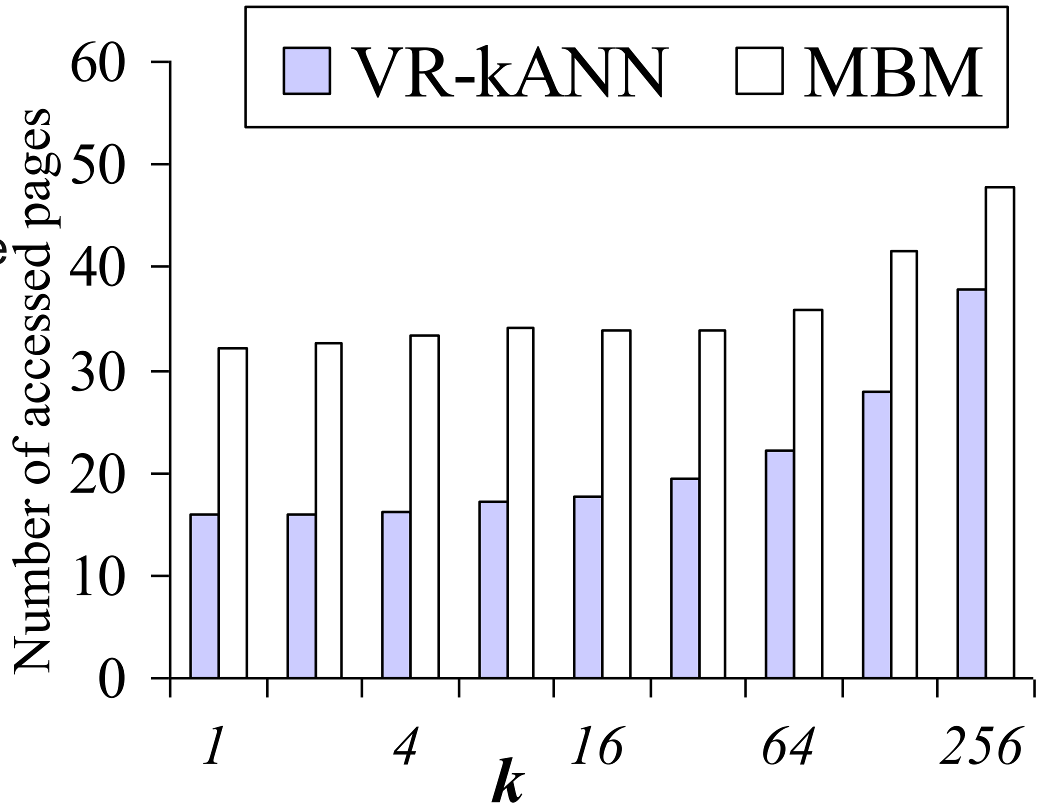
Performance Evaluation

- Dataset: USGS
- I/O cost of VR-kANN
- Competitor approach:
  - MBM that utilizes an R-tree on data points



- Up to 64% improvement for VR-kANN
- VR-kANN's I/O is almost half of MBM's for small k
- for large k, they converge

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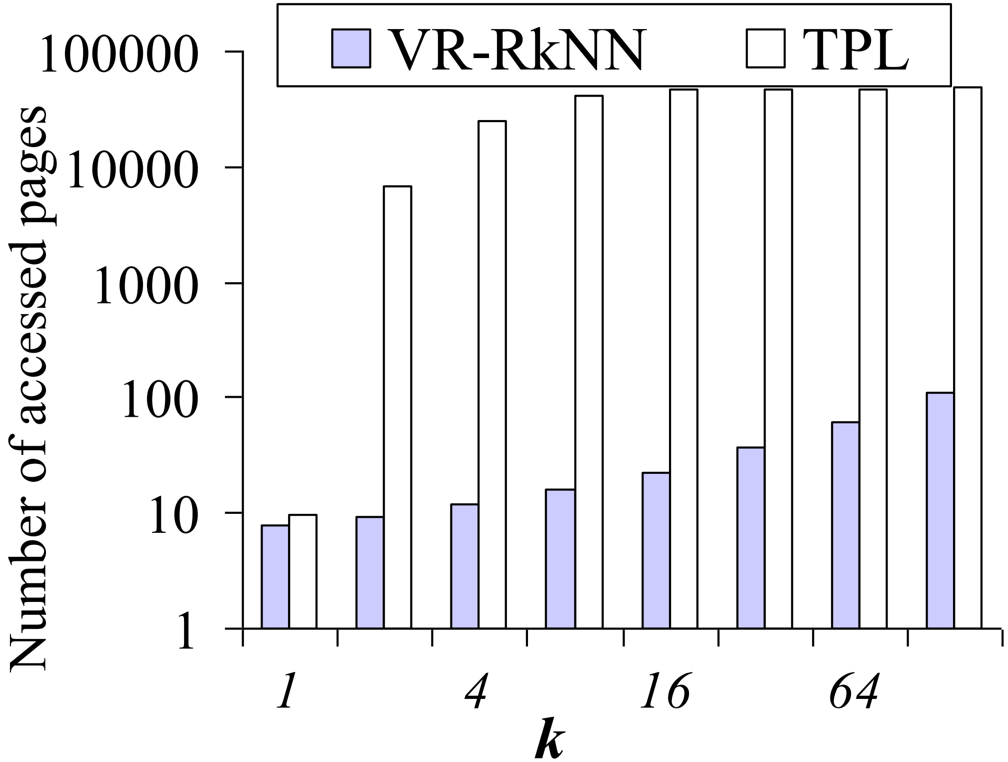
Performance Evaluation

- Dataset: USGS
- I/O cost of VR-RkNN
- Competitor approach:
  - TPL that utilizes an R-tree on data points



- Logarithmic scale
- VR-RkNN's I/O is much less than TPL (0.1% even for small k)
- TPL uses a very conservative filter because the best theoretical filter is very complex to compute so it collects large candidate sets. VR-RkNN instead used Voronoi neighborhood information.
- TPL examines almost all pages for large k

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Summary and Future Directions

- We designed VoR-tree = R-tree + Voronoi diagram
- We developed I/O-efficient algorithms for NN queries
- We showed that our algorithms outperform their R-tree-based competitors
- Future Work:
  - Utilizing VoR-tree for other spatial spaces
  - Extending algorithms for non-point datasets

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References

- M. Sharifzadeh and C. Shahabi, " VoR-Tree: R-trees with Voronoi Diagrams for Efficient Processing of Spatial Nearest Neighbor Queries", VLDB 2010, Singapore, Sep 2010.