

# CSI 695: Scientific Databases

Fall Term 2017

## Lecture 6: Similarity Search Algorithms

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Exercises: TBA

## Similarity Search Algorithms: Outline

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- Range Query Algorithms
- (k)-Nearest Neighbor Query Algorithms
- Reverse (k)-Nearest Neighbor Query Algorithms
- Skyline Query Algorithms
- Evaluation of Similarity Search Methods

# Similarity Search Algorithms: Range Query

## ■ Range Query (RQ)

### □ Definition

#### ■ Properties:

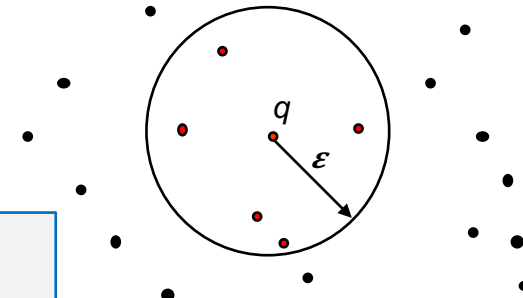
- User defines **query object  $q$**  and a **distance range  $\varepsilon \in \mathbb{R}_0^+$**
- The result of a range query  $RQ(DB)$  contains all objects in database  $DB$ , having a distance to  $q$  of at most  $\varepsilon$ .

#### ■ Formal:

$$RQ(DB, q, \varepsilon) = \{o \in DB \mid \text{dist}(q, o) \leq \varepsilon\}$$

### □ Basic Algorithm (sequential scan)

```
RQ-SeqScan ( $DB, q, \varepsilon$ )  
  result =  $\emptyset$ ;  
  FOR  $i=1$  TO  $n$  DO  
    IF  $\text{dist}(q, DB.\text{getObject}(i)) \leq \varepsilon$  THEN  
      result := result  $\cup$  getObject( $i$ );  
  RETURN result;
```



## Similarity Search Algorithms: Range Query

- Range Query (RQ) (cont.)

- Index-based Algorithm

- How can we support the search in an efficient way using a **spatial index** (e.g. R-tree)?

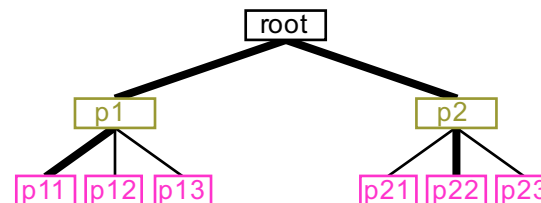
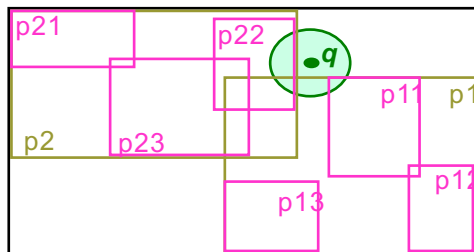
- Observation and basic idea:

- Using spatial keys (page regions) to guide the search.

- Every region that intersect the query range could contain candidates

- Start at the root, and access all children where the corresponding regions intersect the query range

- Repeat the last step for all accessed nodes recursively

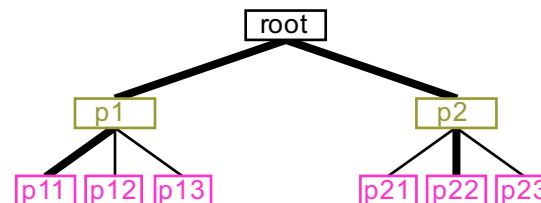
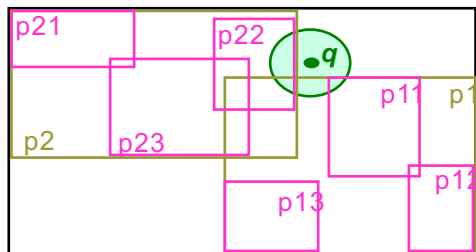


# Similarity Search Algorithms: Range Query

## ■ Range Query (RQ) (cont.)

### □ Index-based Algorithm: Depth-first-search

```
RQ-Index(pa, q,  $\epsilon$ )  // pa := Disk address e.g. root of index (R-tree)
  result =  $\emptyset$ ;
  p := pa.loadPage();
  IF p.isDataPage() THEN
    FOR i=0 TO p.size() DO
      IF dist(q, p.getObject(i))  $\leq \epsilon$  THEN
        result := result  $\cup$  getObject(i);
  ELSE  // p is index directory page
    FOR i=0 TO p.size() DO
      IF MINDIST(q, p.getRegion(i))  $\leq \epsilon$  THEN
        result := result  $\cup$  RQ-Index(p.childPage(i), q,  $\epsilon$ );
  RETURN result;
```



## Similarity Search Algorithms: Range Query

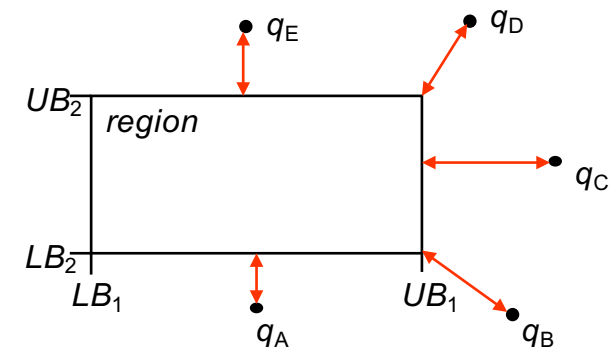
### ■ Range Query (RQ) (cont.)

#### □ What is the MINDIST(..) function?

- Used to test if an index page region intersects with the query range.
- MINDIST() is the minimal distance between the query object and all objects covered by the rectangular page region (lower bound distance).

$$\text{MINDIST}(\text{region}, q) = \sqrt{\sum_{0 \leq i \leq d} \begin{cases} (\text{region.LB}_i - q_i)^2 & \text{if } q_i \leq \text{region.LB}_i \\ 0 & \text{if } \text{region.LB}_i \leq q_i \leq \text{region.UB}_i \\ (q_i - \text{region.UB}_i)^2 & \text{if } \text{region.UB}_i \leq q_i \end{cases}}$$

- In other words: For all  $o \in \text{region}$ :  $\text{MINDIST}(\text{region}, q) \leq \text{dist}(o, q)$
- Consequence: For a  $\text{RQ}(\text{DB}, q, \epsilon)$ : if  $\text{MINDIST}(\text{region}, q) > \epsilon$   
=> For all  $o \in \text{region}$ :  $\text{dist}(o, q) > \epsilon$   
=> there is **no candidate in region** !



## Similarity Search Algorithms: Range Query

- Range Query (RQ) (cont.)
  - Multi-Step Query Processing Algorithm
    - How can we support the search in an efficient way using a filter-refinement strategy?
    - Observation and basic idea:
      - Assume we can compute lower-bounding (LB) and upper-bounding (UB) filter distances between objects in an efficient way, s.t.: For all  $q, o \in DB$ :  $LB\text{-}dist(q, o) \leq dist(q, o) \leq UB\text{-}dist(q, o)$  holds.
      - Basic idea is to scan the database by applying the two filter distances (LB-dist and UB-dist) to filter out results (hits) and non-results (drops).
      - Identify a drop (non result) by LB-dist: If  $LB\text{-}dist(q, o) > \varepsilon$ , then  $o$  can't be a result  $\Rightarrow$  drop  $o$ .
      - Identify a hit (result) by UB-dist: If  $UB\text{-}dist(q, o) \leq \varepsilon$ , then  $o$  is definitely a result  $\Rightarrow$  report  $o$  as part of the result.
      - All remaining candidates have to be refined, i.e. compute the exact distance  $dist(q, o)$  and check against  $\varepsilon$  to finalize the result.

## Similarity Search Algorithms: Range Query

- Range Query (RQ) (cont.)
  - Multi-Step Query Processing Algorithm (cont.)
    - Lower bounding filter distance LB-dist (LB), Upper bounding filter distance UB-dist (UB)

```
RQ-MultiStep(DB, q,  $\varepsilon$ )
    result =  $\emptyset$ ;
    candidates =  $\emptyset$ ;

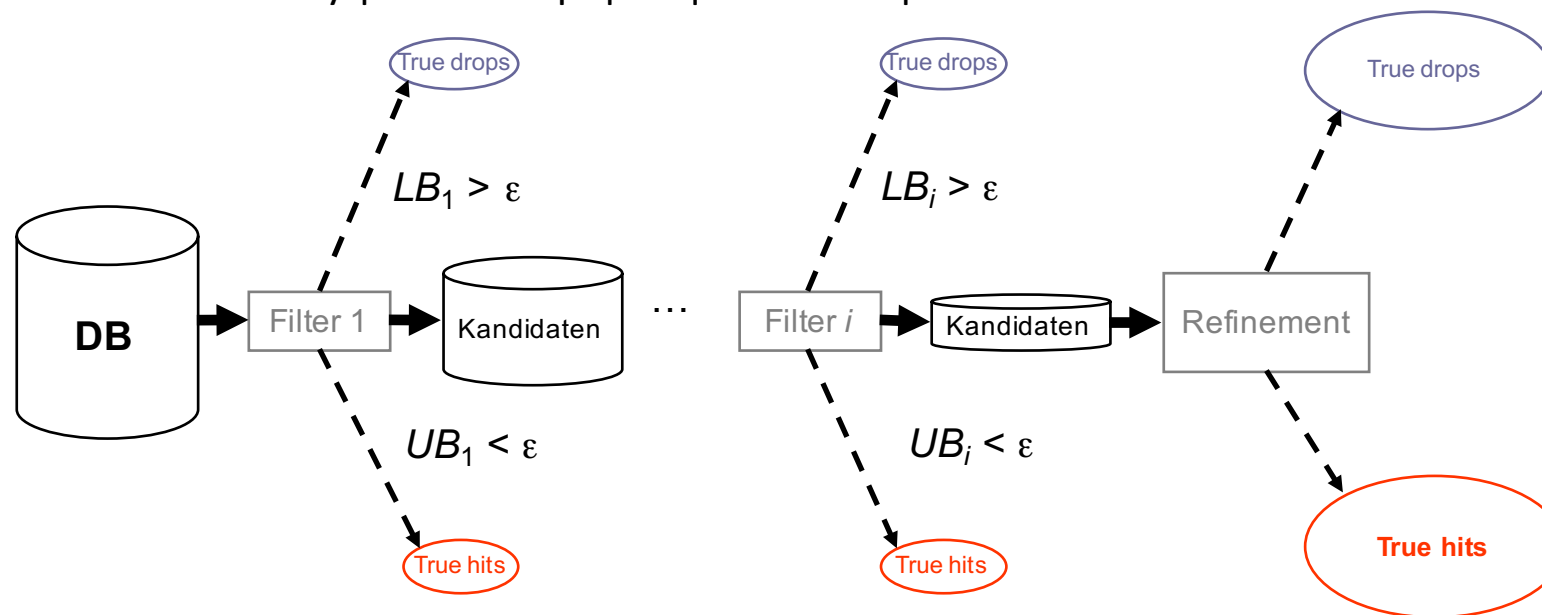
    // Filter
    FOR i=1 TO n DO
        IF UB(q, DB.getObject(i))  $\leq \varepsilon$  THEN
            result := result  $\cup$  getObject(i);
        ELSE IF LB(q, DB.getObject(i))  $\leq \varepsilon$  THEN
            candidates := candidates  $\cup$  getObject(i);

    // Refinement
    FOR i=1 TO candidates.size() DO
        IF dist(q, candidates.getObject(i))  $\leq \varepsilon$  THEN
            result := result  $\cup$  candidates.getObject(i);
    RETURN result;
```



## Similarity Search Algorithms: Range Query

- Range Query (RQ) (cont.)
  - Multi-Step Query Processing Algorithm (cont.)
    - Often only **lower bounding** filter distance (LB-dist) is used, because usually  $|\# \text{ true drops}| \gg |\# \text{ true hits}|$



## Similarity Search Algorithms: Outline

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- Range Query Algorithms
- (k)-Nearest Neighbor Query Algorithms
- Reverse (k)-Nearest Neighbor Query Algorithms
- Skyline Query Algorithms
- Evaluation of Similarity Search Methods

# Similarity Search Algorithms: Nearest Neighbor Query

## ■ Nearest Neighbor Queries (NNQ)

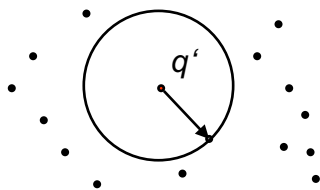
### □ Definition

#### ■ Properties:

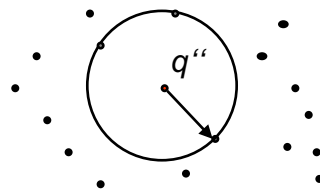
- User defines query **object q**
- The result is the object (or objects) in database DB, having the **smallest distance** to q.
- Ambiguities have been resolved appropriately.

### □ Formal:

$$NN(q) = \{o \in DB \mid \forall x \in DB : dist(q, o) \leq dist(q, x)\}$$



*unique result*



*ambiguous result*

## Similarity Search Algorithms: Nearest Neighbor Query

- Nearest Neighbor Queries (NNQ) (cont.)
  - Basic Algorithm (sequential scan): non-deterministic

```
NN-SeqScan (DB, q)
  result = ∅;
  stopdist = +∞;
  FOR i=1 TO n DO
    IF dist(q, DB.getObject(i)) ≤ stopdist THEN
      result := getObject(i);
      stopdist = dist(q, DB.getObject(i));
  RETURN result;
```

- Deterministic- vs. non-deterministic NNQ
  - **Deterministic:** Query produces always the same result regardless of the order the objects are accessed.
  - **Non-deterministic:** Query produces a correct result, but the result depends on the order the objects are accessed.

## Similarity Search Algorithms: Nearest Neighbor Query

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- Nearest Neighbor Queries (NNQ) (cont.)
  - Algorithm with spatial index: simple depth-first search
    - Difference to Range Query (RQ):
      - Nearest neighbor can be arbitrarily far away from the query object.
      - Shape of the query region unknown.
      - A (single) page region does not suffice to make decisions about potential coverage of a candidate.
      - The need to access a page depends on the content of other pages or objects.
      - As soon as the distance to the nearest neighbor (NN-dist) of query object  $q$  is known, the query can be processed as range query.
      - The distance from query object  $q$  to any object  $o \in DB$  can be used to upper bound the NN-dist.
      - If more distances between  $q$  to other objects are known, the smallest can be used as better NN-dist approximation.

## Similarity Search Algorithms: Nearest Neighbor Query

- Nearest Neighbor Queries (NNQ) (cont.)
  - Algorithm with spatial index: simple depth-first search
    - NNQ-Algorithm: Reformulation of the RQ-Algorithm
      - Idea: Use smallest found distance to any object  $o \in DB$  as distance range  $\varepsilon$ .

```
global variable: stopdist = +∞;
NN-Index-Simple-DS(pa,q) // pa := Disk address e.g. root of index (R-tree)
    result = ∅;
    p := pa.loadPage();
    IF p.isDataPage() THEN
        FOR i=0 TO p.size() DO
            IF dist(q,p.getObject(i)) ≤ stopdist THEN
                result := getObject(i);
                stopdist = dist(q,p.getObject(i));
    ELSE // p is directory page
        FOR i=0 TO p.size() DO
            IF MINDIST(q,p.getRegion(i)) ≤ stopdist THEN
                result := NN-Index-Simple-TS(p.childPage(i),q);
    RETURN result;
```

## Similarity Search Algorithms: Nearest Neighbor Query

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- Nearest Neighbor Queries (NNQ) (cont.)
    - Algorithm with spatial index: simple depth-first search
    - Weakness of simple depth-first search algorithm:
      - Initialization: stopdist =  $+\infty$
      - Search starts with arbitrary path in the index tree
      - First accessed object(s) can be very far away from the query object  
=> filter by stopdist is not selective
      - Better approach:
        - Use initial search path that is close to the query point
        - Access pages having a high probability that they contain the nearest neighbor to q
        - Instead of depth-first tree traversal, allow to switch to more promising search pathes during the tree traversal
- => Traversing index by best-first search

## Similarity Search Algorithms: Nearest Neighbor Query

- Nearest Neighbor Queries (NNQ) (cont.)
  - Algorithm with spatial index: Priority-Based Search [Hjaltason, Samet, SSD 1995]
    - Instead of a recursive traversal an active page list (APL) is managed
    - A page (node) P is active if
      - P is not yet visited
      - A parent page of P has been visited
      - $\text{MINDIST}(q, P) \leq \text{stopdist}$
    - APL is initialized with the root of the index tree
    - Pages in APL are sorted by increasing MINDIST to the query
    - At each step, the first entry in APL (page with smallest MINDIST) is processed



## Similarity Search Algorithms: Nearest Neighbor Query

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- Nearest Neighbor Queries (NNQ) (cont.)
  - Algorithm with spatial index: Priority-Based Search [Hjaltason, Samet, SSD 1995]
    - Leaf nodes: update the value of stopdist and keep potential hits.
    - Directory nodes: child nodes with  $MINDIST \leq stopdist$  are inserted into APL.
    - If the value of stopdist is updated (decreased), pages with  $MINDIST > stopdist$  in APL can be ignored.

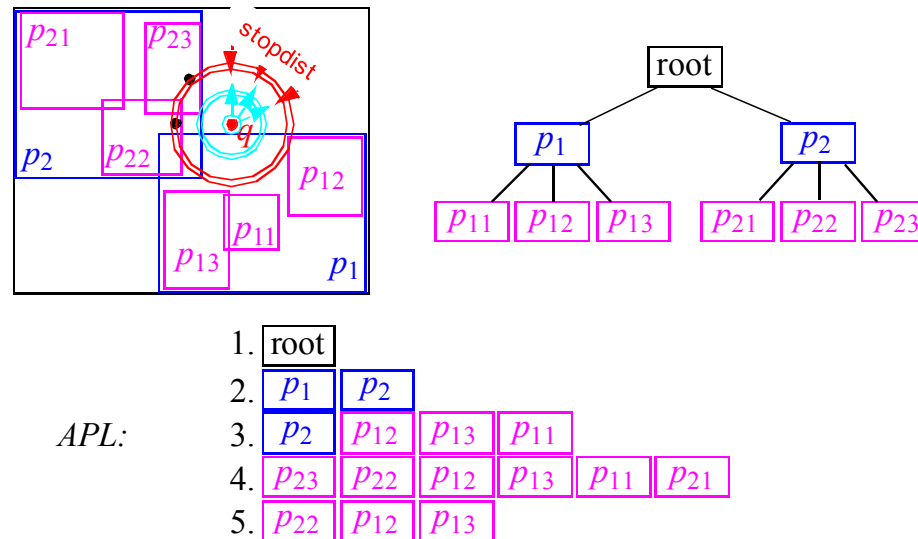
## Similarity Search Algorithms: Nearest Neighbor Query

- Nearest Neighbor Queries (NNQ) (cont.)
  - Algorithm with spatial index: Priority-Based Search [Hjaltason, Samet, SSD 1995]

```
Global variable: stopdist = +∞;
NN-Index-HS(pa,q)          // pa = Disk adress e.g. the root of the index
  result = ∅;
  apl = LIST OF (dist:Real, da:DiskAdress) ORDERED BY dist ASCENDING
  apl = [(0.0, pa)]
  WHILE NOT apl.isEmpty() AND apl.first().dist ≤ stopdist DO
    p := apl.getFirst().da.loadPage();
    apl.deleteFirst();
    IF p.isDataPage() THEN
      (* processed as in NN-Index-Simple-DS(pa,q) *)
    ELSE          // p is directory page
      FOR i=0 TO p.size() DO
        IF MINDIST(q,p.getRegion(i)) ≤ stopdist THEN
          apl.insert(MINDIST(q, p.getRegion(i)), p.childPage(i));
  RETURN result;
```

## Similarity Search Algorithms: Nearest Neighbor Query

- Nearest Neighbor Queries (NNQ) (cont.)
  - Algorithm with spatial index: Priority-Based Search [Hjaltason, Samet, SSD 1995]
  - Example



- The priority-based NN-Index-HS algorithm is optimal in the number of page accesses.

# Similarity Search Algorithms: Nearest Neighbor Query

## ■ Nearest Neighbor Queries (NNQ) (cont.)

### □ Multi-step NNQ Algorithm

#### ■ Principles:

□ Algorithms often only use lower-bounding (LB) filter

□ Using multiple filter steps:  $\text{distLB1} \leq \text{distLB2} \leq \dots$

□ Difference to Range Queries (RQ):

- RQs can be processed step by step in a simple cascade of filter-refinement steps.

Range Query



- Not possible with NNQs. For the first filter-step, NNQs need feedback from the last step (refinement) to prune (reject) candidates while conserving the exact results.
- With an appropriate filter distance, it is likely that the first candidates contain the exact nearest neighbor (NN).

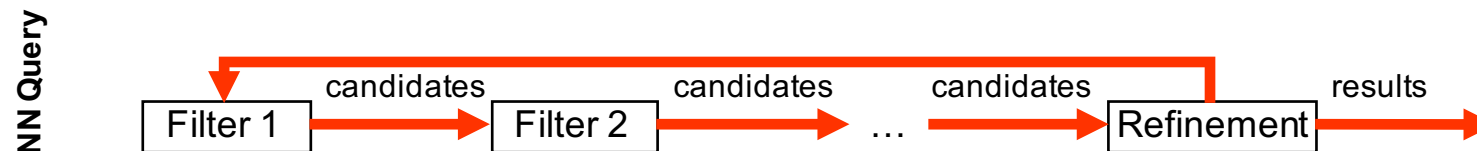
## Similarity Search Algorithms: Nearest Neighbor Query

### ■ Nearest Neighbor Queries (NNQ) (cont.)

#### □ Multi-step NNQ Algorithm

##### ■ Principles (cont.):

- Filter-Refinement Feedback: Feedback with the refined distances from the refinement step to the first filter steps.
- The filter-refinement cascade will be processed in a loop.



##### ■ In the following:

- Different query processing strategies
- Here, we will consider just one filter step (easy transfer to multiple filter steps possible)

## Similarity Search Algorithms: Nearest Neighbor Query

### ■ Nearest Neighbor Queries (NNQ) (cont.)

#### □ Multi-step NNQ Algorithm

##### ■ NNQ with Range Query

[Korn, Sidiropoulos, Faloutsos, Siegel, Protopapas. Proc. Int. Conf. Very Large Databases (VLDB), 1996]

[Korn, Sidiropoulos, Faloutsos, Siegel, Protopapas. TKDE 10(6), 1998]

##### ■ Idea:

- Refinement distance  $\varepsilon$  of an arbitrary object serves as upper bounding NN distance.
- Consequence: Is object  $p \in \text{NNQ}(q) \Rightarrow \text{dist}(p,q) \leq \varepsilon$  and  $\text{distLB}(p,q) \leq \varepsilon$ , i.e.  $p \in \text{RQ}(q, \varepsilon)$ .
- The smaller the initial distance  $\varepsilon$ , the better the query performance in the second filter-refinement round.
- The nearest neighbor of  $q$  based on  $\text{distLB}$  usually provides a good distance  $\varepsilon$ .

## Similarity Search Algorithms: Nearest Neighbor Query

### ■ Nearest Neighbor Queries (NNQ) (cont.)

#### □ Multi-step NNQ Algorithm

##### ■ NNQ with Range Query

[Korn, Sidiropoulos, Faloutsos, Siegel, Protopapas. Proc. Int. Conf. Very Large Databases (VLDB), 1996]

[Korn, Sidiropoulos, Faloutsos, Siegel, Protopapas. TKDE 10(6), 1998]

##### ■ Principle:

1. Perform an NN query based on the (lower bounding) filter distance
2. The resulting object  $o$  will be refined and  $\varepsilon := \text{dist}(q, o)$
3. Perform a range query  $\text{RQLB}(q, \varepsilon)$  based on the filter distance  $\text{distLB}(q, .)$
4. Refine the distances of all objects reported by  $\text{RQLB}(q, \varepsilon)$
5. Report the object with the smallest refined distance to  $q$  as result

## Similarity Search Algorithms: Nearest Neighbor Query

- Nearest Neighbor Queries (NNQ) (cont.)

- Multi-step NNQ Algorithm

- Algorithm:

```
NN-MultiStep-RQ(DB, q)
  // (first) filter step
  r = NN-Query based on filter distanz;    // with or without index
   $\epsilon$  = dist(q, r);                    // refinement of object r
  candidates = RQ-MultiStep(DB, q,  $\epsilon$ );

  // Refinement
  result = r ;
  stopdist =  $\epsilon$ ;
  FOR EACH p  $\in$  candidates DO
    IF dist(p, q)  $\leq$  stopdist THEN
      stopdist = dist(q, p);
      result = p;
  RETURN result;
```



# Similarity Search Algorithms: Nearest Neighbor Query

## ■ Nearest Neighbor Queries (NNQ) (cont.)

### □ Multi-step NNQ Algorithm

#### ■ NNQ with Range Query (cont.)

##### □ Pros:

- Very simple algorithm (simple implementation and integration)

##### □ Cons:

- Performance highly depends on the filter selectivity:  
weak filter  $\Rightarrow$  large  $\varepsilon \Rightarrow$  large result set of RQLB  $\Rightarrow$  high refinement cost

##### □ Can we do better ?

- Main problem is that the filter is based on the refinement result of just one object sample (first object retrieved by the first filter)
- Basic idea: Use the result of each refined object to improve the filter step-by-step

**$\Rightarrow$  multiple filter-refinement iterations**

**$\Rightarrow$  Apply filter after each refinement**

# Similarity Search Algorithms: Nearest Neighbor Query

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## ■ Nearest Neighbor Queries (NNQ) (cont.)

### □ Multi-step NNQ Algorithm

#### ■ Priority-based NNQ

[Seidl, Kriegel. Proc. ACM Int. Conf. Management of Data (SIGMOD), 1998]

#### □ Perform “Ranking Query” based on the filter distance $\text{distLB}(q, \cdot)$

- Function `getNext()` reports the first nearest neighbor to  $q$  with the first call, the second one with the second call, etc.
- Start with the first call of `getNext()`
- Refine each reported object immediately and setup stopdist (analog to  $\varepsilon$  value) with the smallest exact distance found so far.
- Repeat `getNext()` calls + immediate refinement (see two steps above) as long as the filter distance  $\text{distLB}(q, o)$  of the reported object  $o$  is below or equal stopdist.

#### □ Priority-based NNQ is optimal w.r.t. the number of refinements.

# Similarity Search Algorithms: Nearest Neighbor Query

## ■ Nearest Neighbor Queries (NNQ) (cont.)

### □ Multi-step NNQ Algorithm

#### ■ Algorithm

```
NN-MultiStep-Optimal (DB, q)
  Ranking = initialize ranking query w.r.t. q based on  $\text{dist}_{\text{LB}}$ 
  result =  $\emptyset$ ;
  stopdist =  $+\infty$ ;
  REPEAT
    p = Ranking.getNext();
    filterdist =  $\text{dist}_{\text{LB}}(p, q)$ ;           // filter step
    IF filterdist  $\leq$  stopdist THEN
      IF  $\text{dist}(q, p) \leq$  stopdist THEN      // refinement step
        result = p;
        stopdist =  $\text{dist}(q, p)$ ;
  UNTIL filterdist > stopdist;
  RETURN result;
```

## Similarity Search Algorithms: Nearest Neighbor Query

- Refinement Optimal Multi-Step (k)-Nearest Neighbor Queries
  - Cost criteria:
    - Cost for accessing index pages (secondary storage accesses): I/O cost
    - Cost for computing exact distances (refinement): CPU cost
  - For multi-step query processing strategies, we are more interested in reducing the CPU cost.
  - Generally: The cost in a multi-step query processing approach mainly depends on the selectivity of the filter (filter steps)

Higher filter selectivity → less candidates to be refined → less objects have to be refined (maybe also less I/O cost)

- The more information of objects we use in the filter, the higher the selectivity of the filter, but also the higher the cost of the filter itself.

## Similarity Search Algorithms: Nearest Neighbor Query

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- Refinement Optimal Multi-Step (k)-Nearest Neighbor Queries
  - Basic idea:
    - Use a little bit more (already available and cost wise easy to get) information for the filter step to reduce the candidates.
    - In addition to the lower bounding filter distance, use the **upper bounding** filter distance.
    - Constraints: Upper bounding filter distance can only be applied for k-NN queries with  $k > 1$ . **WHY?**