Determining Top-K Candidates by Reverse Constrained Skyline Queries

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Abstract: Given a set of criteria, an object *o* is defined to dominate another object *o*' if *o* is no worse than *o*' in each criterion and has better outcomes in at least a specific criterion. A skyline query returns each object that is not dominated by any other objects. Consider a scenario as follows. Given three types of datasets, including residents in a city, existing restaurants in the city, and candidate places for opening new restaurants in the city, where each restaurant and candidate place has its respective rank on a set of criteria, e.g., convenience of parking, we want to find the top-*k* candidate places that have the most potential customers. The potential customers of a candidate place is defined as the number of residents whose distance to this candidate is no larger than a given distance *r* and also regard this candidate as their skyline restaurants. In this paper, we propose an efficient method based on the quad-tree index and use four pruning strategies to solve this problem. A series of experiments are performed to compare the proposed method with a straightforward method using the R-tree index. The experiment results demonstrate that the proposed method is very efficient, and the pruning strategies very powerful.

1 INTRODUCTION

In the past decade, various spatial queries on spatial databases have attracted much attention, such as the *k*-nearest-neighbor (*kNN*) queries, the reverse *k*-nearest-neighbor queries (*RkNN*), the range queries, and the skyline queries. There are also many studies focusing on the skyline computation since it plays an important role in the applications of multi-criteria decision making. Given a *d*-dimensional dataset, a data point *p* is said to dominate another data point *q* if it is better than or equal to *q* in all dimensions and with at least one dimension better than that of *q*. A data point is defined to be a skyline point if no data points can dominate it. Many different approaches have been proposed for efficient skyline computation, such as BNL (Borzsonyi, 2001), D&C (Borzsonyi, 2001), Bitmap (Tan, 2001), SFS (Chomicki, 2003), LESS (Godfrey, 2005), BBS (Papadias, 2005), SaLSA (Bartolini, 2006), ZSearch (Lee, 2007), and OSP (Zhang, 2009).

Sharifzadeh and Shahabi (Sharifzadeh, 2006) addresses the s*patial skyline queries* which consider the Euclidean distances between a set of query points and a set of data points. Deng et al. (Deng, 2007) addresses the *multi-source skyline* query and proposes efficient algorithms on its query processing in road networks. Chen and Lian (Chen, 2009) and Fuhry et al. (Fuhry, 2009) propose the *metric skyline query*, whose dynamic attributes are defined in the metric space. Papadias et al. (Papadias, 2005) is the first paper that mentions the *dynamic skyline* in which the preference on an attribute is defined to be better close to the requirement of the user. Dellis and Seeger (Dellis, 2007) introduces the *reverse skyline query*, which is a special skyline query and has the similar concept to reverse *k*-nearest-neighbor queries. Given a query point *q*, the reverse skyline query returns the data points whose dynamic skyline results contain *q*. For example, two features including manufacture year and engine displacement are considered while buying a second-hand car. The operator of a second-hand car shop may want to retrieve the number of customers who consider a specific car as their dynamic skyline results for deciding whether to import this car. We can make more profitable decisions through the reverse skyline query. On the other hand, the reverse *k*-

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nearest-neighbor (*RkNN*) query (Kang, 2007), (Korn, 2000), (Lin, 2003), (Stanoi, 2000), (Stanoi, 2001), (Tao, 2004), (Wu, 2008), (Yang, 2001) has also received significant research attentions since it was introduced in (Korn, 2000). An *RkNN* query regarding a query point *q* finds all data points which regard *q* as one of their corresponding *k* nearest neighbors. Since *q* is close to such data points, *q* is said to have high influence on these data points. The *RkNN* answer set with respect to *q* is called the influence set of *q* (Korn, 2000).

In some applications, skyline queries may be issued with a range constraint. Consider a scenario as follows. There are some office buildings and restaurants located in a city. Each restaurant has its own scores in different criteria such as service or average price. A lot of workers from the office buildings have to find a restaurant for lunch. They may issue a range query with a distance *r* to indicate that only the restaurants within this distance will be considered. Moreover, they most likely will choose the skyline restaurants within this distance to have lunch. That is, a worker may issue a *constrained skyline query* to find their target restaurants. For a restaurant, we define its *popularity* by the number of times it appears as an answer in the constrained skyline queries issued from the workers. The popularity of a restaurant can be computed by reverse constrained skyline queries.

Now assume we want to open new restaurants in the city at several candidate locations. We want to determine top-k candidates based on their popularity such that a good business can be expected. For solving this novel top-k query, in this paper, we propose a basic method and an advanced method. Three pruning strategies are provided for reducing the number of competitors while computing the number of potential customers for each candidate. Moreover, a pruning strategy focuses on reducing the number of customers which cannot be the potential customers of a target candidate. Rooted at these four strategies, the advanced method outperforms the basic method, substantially reducing the computation time. The experiment results demonstrate that the pruning strategies have a strong pruning power.

The remainder of the paper is organized as follows. The formal problem definition and a basic solution to this problem are given in Section 2. An advanced solution and its index structures are described in Section 3. The performance evaluation on the proposed algorithm is reported in Section 4. Finally, Section 5 concludes this work.

2 PRELIMINARIES

In this section, we formally define the problem to be solved and also propose a basic solution for it.

2.1 Problem Formulation

Referring to the scenario mentioned in Section 1, we have two datasets including a set of office buildings (customers) and a set of existing restaurants. In addition, we have another dataset of candidates for opening new restaurants. All of the datasets are on a two dimensional space used to represent their locations and moreover, the datasets of candidates and the existing restaurants have the other *n* attributes representing the features of the restaurants such as service or average price.

Assume each customer finds a restaurant within a distance *r* from his/her location. This search area forms a circle with the center being the location of the customer and a radius of *r* as shown in Figure 1, where the triangle point represents the customer. If a restaurant is located within this search area and is the skyline point among all restaurants in this area considering the other *n* attributes, this restaurant gets one point from the corresponding customer. For example, there are five restaurants located in the search area as shown in Figure 1. The values of the other 2 attributes of these restaurants representing service ranking and food ranking are (6, 3), (5, 4), (4, 5), (7, 5), and (6, 6), respectively. As a result, the three restaurants with attributes (6, 3), (5, 4), and (4, 5) are skyline restaurants in this search area (assuming smaller values of the attributes are better). Each of them gets one point from the corresponding customer.

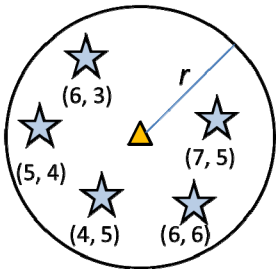


Figure 1: An illustration of the search area of a customer.

The problem of *determining the top-k candidates by reverse constrained skyline queries* is formally defined as follows. There are three sets of data points on a two dimensional space, representing customers, competitors, and candidates. Moreover, the competitors and candidates have the other *n*

attributes. Given the above three datasets and a distance r, we return k data points which have the highest scores from the set of candidates. The scoring function is mentioned as above and in addition, when we compute the score of a candidate, we only consider the dominating relationship between the candidate and competitors but not the candidate and other candidates.

2.2 The Basic Solution

The basic approach to this novel top-k query is based on the R-tree index (Guttman, 1984). We assume that the R-tree indices of the set of customers R and the set of competitors C are constructed in advance. Each data point in the set of candidates is kept in a sequence. We sequentially process each of them to compute their corresponding scores and then return the top-k results.

For a candidate, we trace the index of customers to find the customers whose distance to the candidate is less than r. On the other words, a range query with a center equal to the location of the candidate and a distance r is issued. The returned customers are kept in another sequence. Then, for each returned customer, another range query is issued to find the competitors whose distance to the customer is less than r. The index of competitors can help to efficiently answer this query. After that, we compare the candidate with the corresponding competitors on the other n attributes to check whether the candidate is a skyline point. If yes, it gets one score from the corresponding customer. Following the above steps, the score of each candidate can be computed.

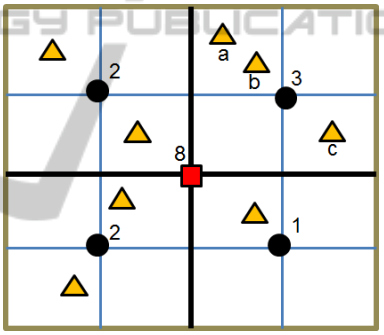
3 TOP-K QUERY PROCESSING

In this section, an advance approach to solving the top-k query considering dominating relationship is proposed. The index structure used in this approach is discussed in Subsection 3.1 and then we detail this approach in Subsection 3.2.

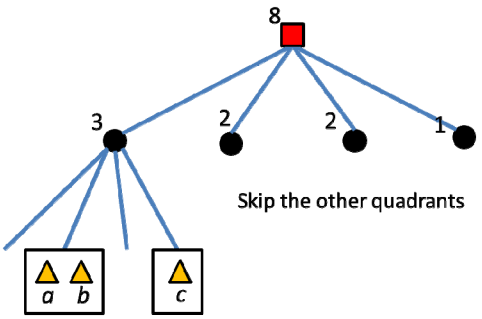
3.1 The Index Structures

The advance approach is based on two types of index structures. One is built for customers, while the other is built for competitors. Each of them is an instance of *quadtree*. A quadtree index is a tree data structure in which each internal node has four children. Quadtree is often used to partition a two-dimensional space by recursively subdividing it into four quadrants (regions). Initially, we subdivide the whole space into four regions with equal sizes. If a new region still contains objects, it will be further subdivided into four smaller regions as well. A region will be recursively subdivided into smaller regions until no objects contained in a region or the amount of objects in a region is less than a suitable number.

We use the quadtree structure to index customers, called *amount-quadtree*. In each internal node, we additionally record the amount of the customers in its child nodes. An example is shown in Figs. 2(a) and 2(b). The triangle points are regarded as customers. As mentioned, while computing the quadtree index, the whole space is recursively subdivided into smaller regions. The circles are viewed as the internal nodes of amount-quadtree and moreover, the square point is the root node of amount-quadtree. As shown in Fig. 2(b), for the root node and each internal node, we record the amount of the customers in it corresponding child node.



(a) An example of the index structure of customers.



(b) An illustration of amount-quadtree.

Figure 2: Examples of the index structure of customers and amount-quadtree.

We also use the quadtree structure to index competitors, called *superiority-quadtree*. Again, initially, we subdivide the whole space into four regions with equal sizes. If a new region still contains objects, it will be further subdivided into four smaller regions as well. In each internal node,

we additionally record the best value of each n dimension with respect to its child nodes. An example is shown in Figs. 3 and 4. The star points are regarded as competitors. The circles are used to represent the internal nodes of superiority-quadtree. The square is the root of superiority-quadtree. As shown in Fig. 4, we use the second quadrant to explain the concept of superiority-quadtree. We find the best values in x-dimension and y-dimension from all of the child nodes of a corresponding internal node. Suppose that we prefer the smaller value in both x-dimension and y-dimension. The data point (1, 4) is the competitor that has the best value in x-dimension. The data point (2, 2) is the competitor that has the best value in y-dimension. Then, we record (1, 2) in the corresponding internal node.

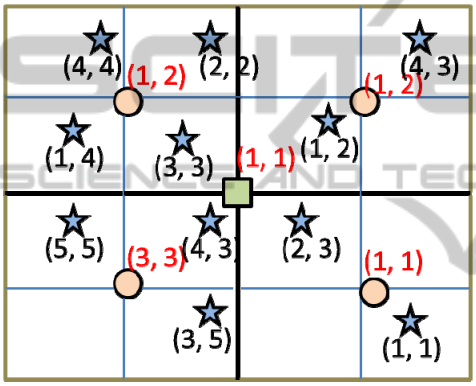


Figure 3: An example of the index structure of competitor.

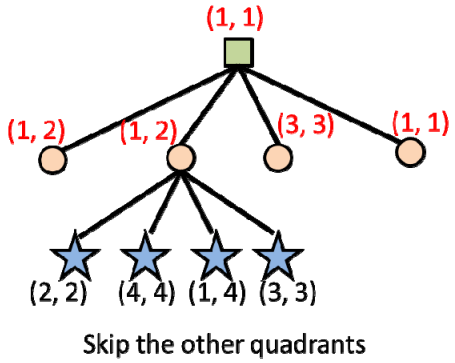


Figure 4: An illustration of superiority-quadtree.

3.2 The Advanced Solution

In the following, we first introduce four strategies used in our advanced algorithm for efficiency enhancement, three of which are used to reduce the amount of competitors and the other one is used to reduce the amount of customers when computing the score values for candidates. Then, we detail the advanced algorithm.

Property 1. Given a candidate, if the distance between the candidate and a specific competitor is larger than $2r$, this competitor cannot affect the score of the given candidate.■

This property is quite straightforward. The *influence region* of the competitor, i.e., the circle with a center equal to the location of the competitor and a radius of r cannot overlap the influence region of the candidate since the distance between the candidate and competitor is larger than $2r$. Accordingly, this competitor cannot affect the score of the candidate.

Property 2. Given a candidate, the competitors which cannot dominate the given candidate cannot affect the score of the candidate.■

For a candidate, the competitors who cannot dominate the candidate cannot decide whether the candidate is a skyline result or not, no matter where the locations of the competitors are. Since only the skyline results can get the score from a customer, these competitors cannot affect the score of the candidate. On the other hand, if a candidate is dominated by a specific competitor, we can ensure that the candidate cannot get any score from the customers located at the overlap of the two corresponding influence regions. This is because due to the competitor, the candidate cannot be the skyline result with respect to the customers in the overlap.

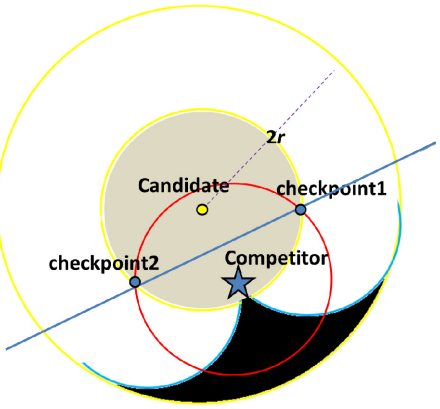


Figure 5: An example of Property 3.

Property 3. Given a competitor within a distance r to a specific candidate, which dominates the specific candidate, the competitor forms a *do-not-care area* in which the other competitors need not be considered while computing the score of the specific candidate.■

We use an example shown in Fig. 5 to introduce the do-not-care area with respect to a competitor and detail the concept of Property 3. As mentioned in Property 3, there are two intersection points (denoted checkpoint1 and checkpoint2 in Fig.5) generated by the influence region of the start-shape competitor and that of the specific candidate. A line, passing through checkpoint1 and checkpoint2, partitions the circle with the center equal to the location of the candidate and a radius of $2r$ into two semicircles, one of which contains the candidate while the other one contains the start-shape competitor. The area formed by the semicircle containing the start-shape competitor subtracting the influence region of checkpoint1 and that of checkpoint2 is the do-not-care area with respect to the start-shape competitor. The dark black area shown in Fig.5 is the do-not-care area with respect to the start-shape competitor.

Any other competitors located at the do-not-care area need not be considered to compare with the specific candidate. This is because the overlap of the influence region of the candidate and that of another competitor located at the do-not-care area is always fully contained in the overlap of the influence region of the candidate and that of the start-shape competitor. To the customers in the overlap of the influence region of the candidate and that of another competitor located at the do-not-care area, the candidate need not be compared with the competitor since the candidate is already dominated by the start-shape candidate, not able to get scores from the customers.

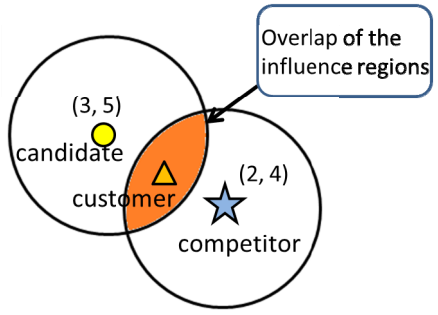


Figure 6: An example of Property 4.

Property 4. Given a competitor which dominates a specific candidate, any customers located in the overlap of the two corresponding influence regions formed by the candidate and competitor cannot contribute scores to the candidate.■

As shown in Fig. 6, suppose that we prefer small values in both attributes, the candidate with (3, 5) is dominated by the competitor with (2, 4). Any customers located in the overlap of the two corresponding influence regions formed by the candidate and competitor will not contribute scores to the candidate since to these customers, the candidate always cannot be the skyline results due to the competitor who dominates it.

Algorithm 1: (The ECE algorithm).

Input: amount-quadtree of customers R, superiority-quadtree of competitor S, candidates, r, and k
Output: Top-k results from candidates

```
Main function ( ):
1   For each candidate c
2      Trace amount-quadtree to compute the number of
       customers located within a distance r to c
3      Sort the candidates into a decreasing order
       according to the number of counted
       customers.
4   Compute the scores for the first k candidates in
    the sorted list. The smallest score is used to be
    the threshold T and these k candidates are
    regarded as potential results
7   For the unchecked candidate c in the sorted list
8      If the number of customers located within a
       distance of r to c < T
9         Prune c
10     else
11        Compute the score of c
12        If the score of c is larger than T
13           T = the score of c
14           Replace the candidate with the smallest score
             in the potential result by c
15  Return the top-k results
```

The advanced algorithm named *ECE* (Efficient Candidate Elimination) detailed in the following is based on the amount-quadtree index of customers and the superiority-quadtree index of competitors. We assume that the amount-quadtree index and the superiority-quadtree index are constructed in advance. The pseudo codes of the ECE method are shown in Algorithm 1.

First, we sequentially process each candidate by tracing amount-quadtree from the root to get the number of customers located in the influence region of a candidate. By using the amount-quadtree index structure, we can efficiently get the number of customers located in the influence region of a corresponding candidate because in some cases, we can obtain the number of customers from the records of the internal nodes, without reaching for leaves. After that, we sort the candidates into a decreasing order according to the number of customers located in their corresponding influence regions. For each

candidate in the sorted list, we calculate its exact score. Once we get k exact scores, the smallest score is used to be the lower bound. The candidates in the sorted list with the number of customers located in the corresponding influence regions can be pruned as they have no chances of being the top-k results. In the following, we focus on how to compute the exact score of a candidate.

By Properties 1-3, we can prune most of the competitors that need not be considered while computing the exact score for a specific candidate. For a specific candidate, we first prune the competitors with a distance to it more than $2r$ by Property 1. Then, by using the superiority-quadtree index structure, we can efficiently get the competitors that dominate the candidate because of the record kept in the internal node. When traversing superiority-quadtree, if the records kept in the internal node are dominated by the target candidate, we can prune the competitors in that branch by Property 2 since the competitors who cannot dominate the target candidate cannot affect the score of the candidate. Then, by sequentially checking the competitors that dominate the target and are with a distance to the candidate smaller than r, we can prune the competitors located in the corresponding do-not-care area. After the above checking, the remainder competitors are really taken into accounts for computing the exact score of the target candidate. At the very beginning, issuing a range query from the target candidate, we find the customers that we need to check. Before processing each corresponding customer, we can reduce the number of customers to be checked by Property 4. After all of the above pruning check, we use the concept of Basic to compute the exact score for the target candidate.

4 EXPERIMENTS

In this section, a series of experiments are performed to evaluate our approaches and the experiment results are also presented and analyzed.

4.1 Experiment Setup

We use the data generator RandD to generate three synthetic datasets with the independent, correlated, and anti-correlated distributions as shown in Table 1. All objects in the datasets have coordinates within the range of ([0, 2000], [0, 2000]). The competitors and candidates have two attributes within a range of ([0, 2000], [0, 2000]). We also conduct the experiments on a real dataset, obtained from the website (http://www.census.gov/geo/www/tiger). Its distribution is shown in Fig. 7. The real dataset represents the resident locations in Los Angles. The data size of this real dataset is approximate 360K. We regard this data points as the customers. We also generate 100K of the competitors and 1K of the candidates with two attributes by the independent generator [RandD]. The coordinates of each object are within the range of ([0, 3100], [0, 1800]) and the two attributes are within the range of ([0, 3100], [0, 3100]).

Four variables including r, *number of customers*, *number of competitors*, and *number of candidates* are used to be the factors in the experiments as shown in Table 2. Moreover, k is set to 5 in the experiments. All of the algorithms are implemented in C++ and performed on a PC with the Intel Core i5-2500 3.30GHz CPU, 8GB main memory, and under the windows7 64bits operating system.

Table 1: The distributions of the test datasets.

Distribution	Description
Independent	The attributes of each data point are generated uniformly and randomly.
Correlated	If a data point has an attribute with low value, the other attributes of this data point may likely have low values as well.
Anti-Correlated	If a data point has an attribute with a low value, the other attributes of this data point may likely have high values.

Table 2: Experimental factors.

Factors	Default	Range
# of customers	200K	150K - 300K
# of competitors	5K	3K - 6K
# of candidates	500	250 - 1000
R	200	160 - 240

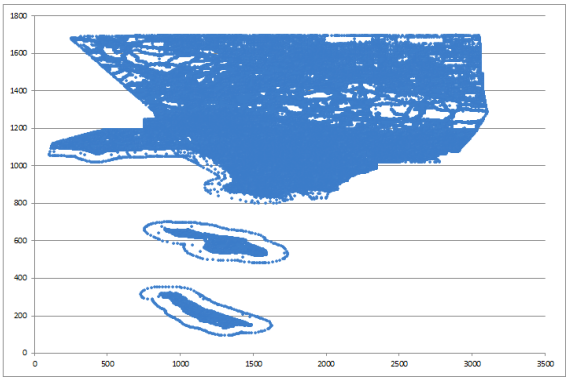
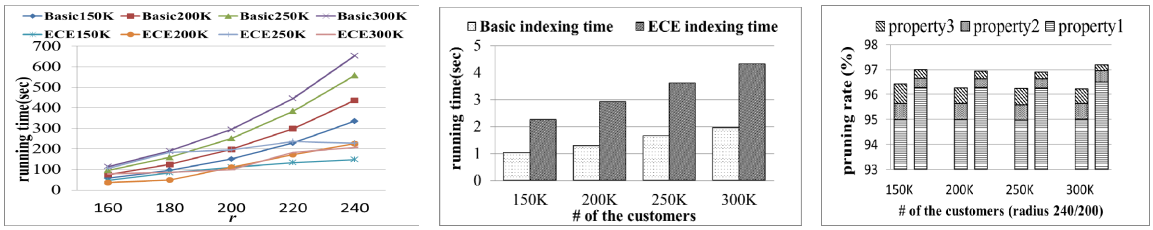
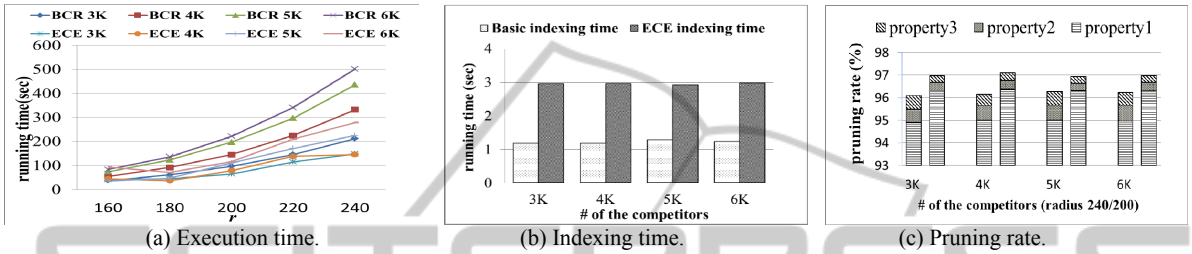


Figure 7: The data distribution of the real dataset.



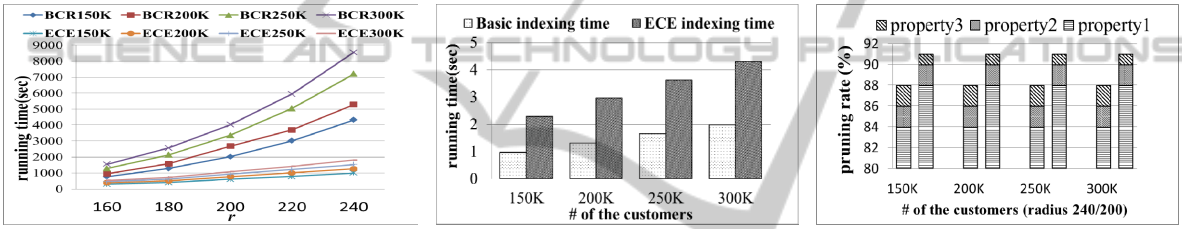
(*a*) Execution time. (*b*) Indexing time. (*c*) Pruning rate.

Figure 8: The varying number of customers on the independent dataset.



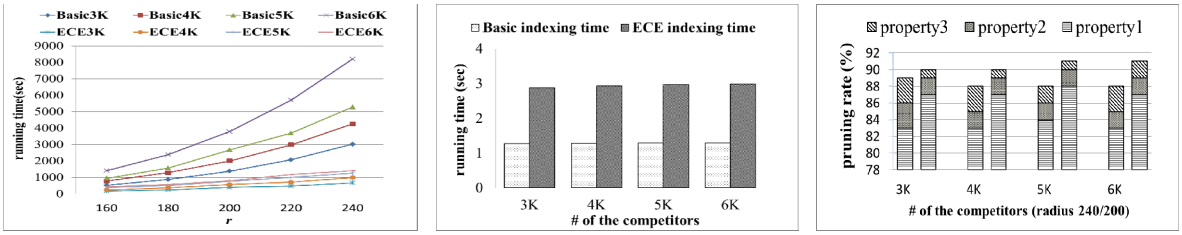
(a) Execution time. (b) Indexing time. (c) Pruning rate.

Figure 9: The varying number of competitors on the independent dataset.



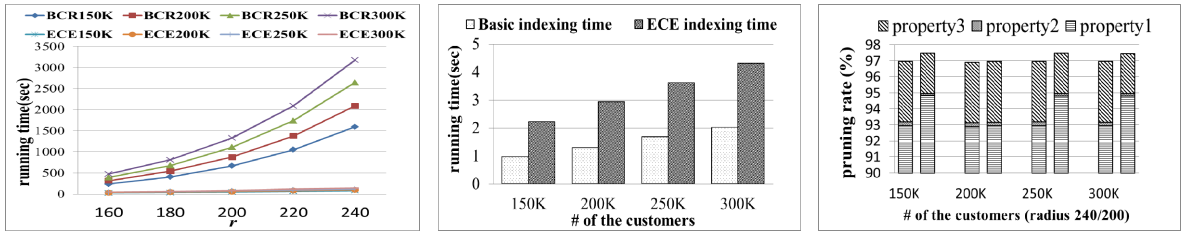
(*a*) Execution time. (*b*) Indexing time. (*c*) Pruning rate.

Figure 10: The varying number of customers on the correlated dataset.



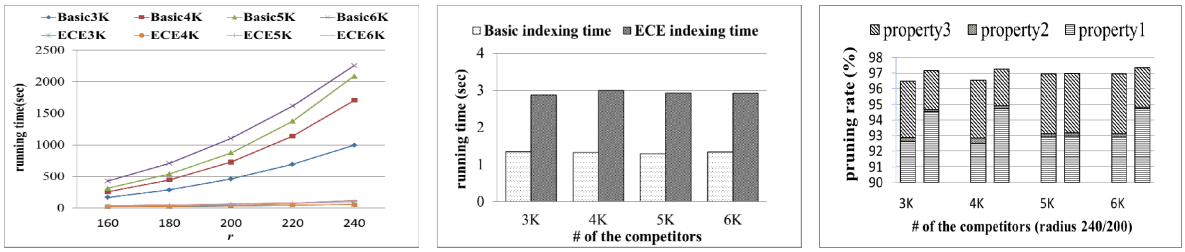
(*a*) Execution time. (*b*) Indexing time. (*c*) Pruning rate.

Figure 11: The varying number of competitors on the correlated dataset.



(*a*) Execution time. (*b*) Indexing time. (*c*) Pruning rate.

Figure 12: The varying number of customers on the anti-correlated dataset.

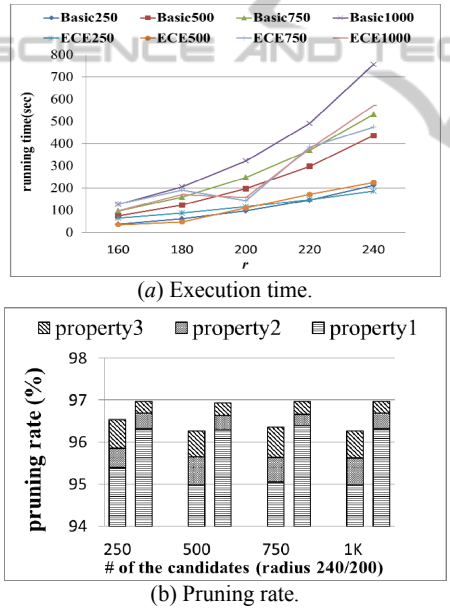


(*a*) Execution time. (*b*) Indexing time. (*c*) Pruning rate.

Figure 13: The varying number of competitors on the anti-correlated dataset.

4.2 Experiment Results

As mentioned, we use three synthetic datasets in the experiments, including the independent dataset, the correlated dataset, and the anti-correlated dataset. The results on varying number of competitors and the results on varying number of customers are shown in Figs. 8-13. The running time of these two methods is shown in the type (*a*) of Figs. 8-13.

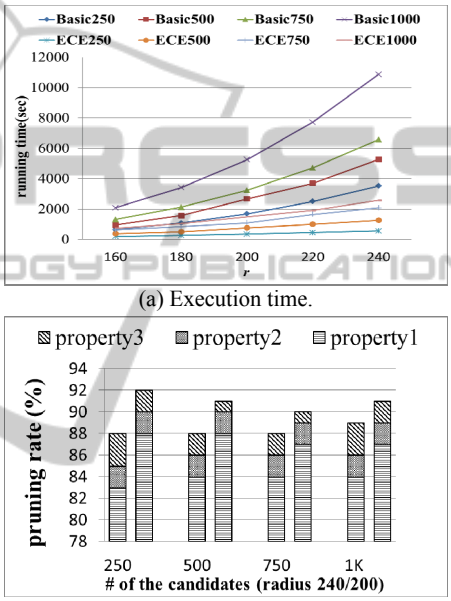


(*a*) Execution time.

(b) Pruning rate.

Figure 14: The varying number of candidates on the independent dataset.

When *r* becomes large, the curve of running time becomes sharp. This is because a large distance *r* may have more chances of making the number of competitors and customers large. Obviously, in both of the two methods, the more the *r* value is, the longer the running time will be. Moreover, the more the competitors and customers are, the longer the running time will be. In each case, the running time of ECE is much shorter than that of Basic, since ECE computes the upper bound of the score for each candidate and also uses four strategies to substantially reduce the computation of calculating the exact scores.



(a) Execution time.

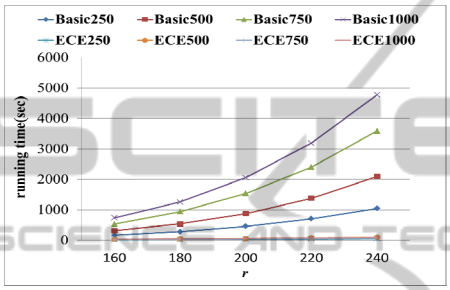
(b) Pruning rate.

Figure 15: The varying number of candidates on the correlated dataset.

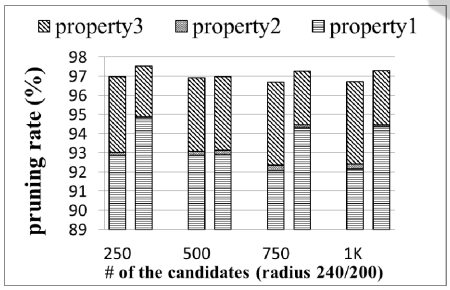
The indexing time of the two methods is shown in the type (*b*) of Figs. 8-13. The indexing time of ECE is a bit longer than that of Basic, yet both of them use just several seconds for dealing with customers at the scale of approximate 200K even 300K. These two methods both are practicable in the index construction phase.

The pruning capabilities of the strategies on reducing the number of competitors are shown in the type (*c*) of Fig. 8-13. As can be seen, the pruning capability of each strategy is different in each synthetic dataset, yet overall, the pruning rate of adopting these three properties is quite high in each dataset, e.g., over 90%, and even achieving approximate 97% in the independent dataset. The pruning rate is defined as the radio of pruned data points. We show the pruning rate with the executing order of adopting Properties 1, 2, and 3.

The results on varying number of candidates are shown in Figs. 14-16. The running time and the pruning rate are shown in the types (*a*) and (*b*) of Figs. 14-16, respectively. The indexing time is fixed due to the fixed number of customers and that of competitors. Similarly, ECE outperforms Basic in terms of running time. The pruning rates are also quite high in this experiment. Moreover, the experiment results on the real dataset are shown in Fig. 17. From the experiment results shown above, we conclude that under the environment of setting a reasonable *r* and a reasonable *k*, even varying the number of customers, competitors, or candidates, ECE outperforms Basic.



(*a*) Execution time.



(*b*) Pruning rate.

Figure 16: The varying number of candidates on the anti-correlated dataset.

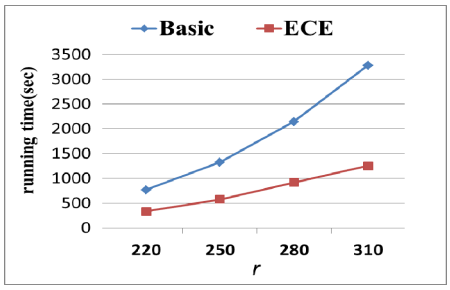


Figure 17: Execution time on the real dataset.

5 CONCLUSION

In this paper, we make the first attempt to issue a new top-k query which takes into account reverse constrained skyline queries on spatial data. Given three types of datasets, including customers, candidates, and competitors, and a restricted distance of *r*, the novel top-*k* query returns *k* candidates with the most potential customers. We propose a basic method denoted *Basic*, and an advanced method named *ECE* to solve this problem. The basic method uses the *R*-tree index while ECE is rooted at the extended quad-tree index. Three pruning strategies are provided for reducing the number of competitors while a pruning strategy is provided to focus on reducing the number of customers unable to contribute the score for a target candidate, when computing the score for each candidate. Based on these four strategies, ECE outperforms the basic method, substantially reducing the computation time.

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