Parallelized Proximity-Based Query Processing Methods for Road Networks

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ABSTRACT

In this paper, we propose a paradigm for processing in parallel graph joins in road networks. The methodology we present can be used for distance join processing among the elements of two disjoint sets $R, S$ of nodes from the road network, with $R \sim S$, and we are in search for the pairs of vertices $(u, v)$, where $u \in R$ and $v \in S$, such that $\text{dist}(u, v) \leq \theta$. Another variation of the problem would involve retrieving the $k$ closest pairs $(u, v)$ in the road network with $u \in R$ and $v \in S$, such that $\text{dist}(u, v) \leq \text{dist}(w, y)$, where $w, y$ do not belong in the result.

We reckon that this is an extremely useful paradigm with many practical applications. A typical example of usage of our methods would be to find the pairs of restaurants and bars (in that order) from which to select for a night out, that either fall within walking distance for example, or just the $k$ closest pairs, depending on the parameters. Another entirely different scenario would involve finding the points of two distinct trajectories that are within a certain distance predicate, or the $k$ closest such points. For example, we would like to transfer from one train to another a few tones of freight, and hence, we want to minimize the distance we have to cover for moving the cargo from the carrying train to the other. We reckon that this endeavor of ours covers exactly those needs for processing such queries efficiently.

Moreover, for the specific purposes of this paper, we also propose a novel heuristic graph partitioning scheme. It resembles a recursive bisection method, and is tailored to the requirements of the problem, targeting at establishing well separated partitions, so as to allow computations to be performed simultaneously and independently within each partition, unlike hitherto work that aims at minimizing either the number of edges among different partitions, or the number of nodes thereof.

1. INTRODUCTION

The majority of the research that has been conducted in the area of graph partitioning addresses the $k$-way partitioning problem, according to which the vertices of the graph are partitioned into $k$ disjoint sets in such a way that the sum of weights of the edges whose incident vertices belong to different sets is minimized. The problem can be extended so that we have an equal number of vertices in each set. Despite the fact these works address a very similar problem, they have an entirely different motivation than ours. For instance, the efficient execution of many parallel algorithms tacitly requires the solution to a graph partitioning problem, where vertices represent tasks and edges represent data exchanges. Depending on the amount of the computation performed by each task, the vertices are assigned to a proportional weight. Likewise, the edges are assigned weights that reflect the amount of data that need to be exchanged. Hence, by assigning to each processor tasks whose computational cost is almost the same and by minimizing the communication overhead that corresponds to the edge-cut the overall response time is optimized. The same problem definition is used for the fast sparse matrix-vector multiplication, when representing graphs as sparse matrices. Also, to compute a fill-reducing ordering that leads to a high degree of concurrency in the factorization phase of solving sparse system.

Our work has a similar optimization incentive though for processing spatial graphs and a different formulation of the problem from a different prospective needed to be provided in order to obtain a similar effect, capturing the essential differences in the nature of the problem and an entirely different approach had to be followed. Before that we should define the types of queries we are interested in. Then, it will be easier to describe the specifications of a graph partitioning scheme that would boost the performance for those types of queries. More formally, among the elements of two disjoint sets $R, S$ of nodes from a road network, with $R \sim S$, we are in search for the pairs of vertices $(u, v)$, where $u \in R$ and $v \in S$, such that $\text{dist}(u, v) \leq \theta$. According to a variation of the problem, we are in search for the $k$ closest pairs $(u, v)$ in the road network with $u \in R$ and $v \in S$, such that $\text{dist}(u, v) \leq \text{dist}(w, y)$, where $w, y$ do not belong in the result. Most importantly, all distances are computed over the road network and do not relate to the respective distances in the Euclidean space. Albeit a seemingly small and intricate detail, it completely changes the techniques that can be employed and the nature of the methods to be developed. Moreover, for processing those types of queries, we propose a novel heuristic graph partitioning scheme which resembles a recursive bisection method and targets at establishing well separated partitions, so as to allow computations to be performed simultaneously and independently within each partition, unlike hitherto work that aims at minimizing either the number of edges among different partitions, or the number of nodes thereof. To the best of our knowledge, this paper constitutes the very first effort to address the problem of graph partitioning in the context of distance join and closest pairs computations. More importantly, we are in position of speeding up the processing of such queries by parallelizing the process as much as possible by processing each partition of the graph independently and also min-
imizing the cost involved in merging the partial results. Last but not least, we can easily extend our methods to operate over mobile objects as well, by specifying appropriately the distances of each from the two ends of the edge it moves on. This information can either be incorporated within the graph (but carefully maintained), or kept updated in a different spatial data structure for faster retrieval. Those objects can naturally belong in either set or S without any loss, and search can be initiated from them just as efficiently with a minor twist at the beginning of processing each such query.

The remainder of the paper is organized as following: In Section 2 we discuss the relevant literature, in Section 3 we propose a heuristic partitioning scheme, in Section 4 we present our paradigm for processing such queries, in Section 5 we evaluate our methods, and finally, in Section 6 we conclude and summarize our contributions.

2. RELATED WORK

In this section we present the relevant literature regarding graph partitioning and schemes for query processing in road networks.

2.1 Graph Partitioning

Arguably the most successful class of partitioning algorithms are the multilevel graph partitioning schemes. Those algorithms try to reduce the graph by collapsing vertices and edges, partitions the smaller graph, and then uncoarsens it to the most preferable outcome. In this context, the authors in [5] present a multi-level algorithm in which the graph is approximated by a sequence of increasingly smaller graphs that are partitioned using a spectral method. A variant of the Kernighan-Lin algorithm [6] is applied periodically to refine the partition. More specifically, the KL algorithm examines all vertices with respect to the improvement that they bring to the partitioning. This corresponds to the net reduction in the weight of cut edges that would result from switching a vertex to a different set. Vertices with the opposite effect are also considered since several moves that reduce the partition quality may lead to later moves that compensate for the initial regression. To this feature can be attributed the ability of the algorithm to climb out of local minima. Of course, with each assignment, the ranks of all adjacent vertices are updated accordingly. Eventually, the best partition that is encountered in this sequence is selected with each iteration. An improved linear time implementation of this is proposed in [2].

A meticulous study on the characteristics of these methods can be found in [4] together with improvements in terms of response time that rely on a finer refinement heuristic, and in quality due to the policy they adopt during contracting nodes that preserves the properties of the original graph. Many strategies are investigated for coarsening, including selecting random nodes, tracing cliques, and others. In addition a greedy graph growing partitioning algorithm is proposed that resembles breadth-first search. A parallel implementation of this is proposed in [5] that relies on graph coloring.

It is shown that these works provide better partitions than spectral methods at lower cost for a variety of finite element problems.

In retrospect, spectral methods are expensive since they require the computation of the eigenvector corresponding to the second smallest eigenvalue. Geometric partitioning algorithms tend to be fast but often yield partitions that are worse than those obtained by spectral methods. However, they are applicable only if coordinates are available for the vertices of the graph, a feature that is not always available.

More recently, in [12] a streaming model is adopted for graph partitioning, which can be used in combination with a number of different heuristics that can be employed under different circumstances. Different criteria are used, like trying to balance the size of each partition, the cardinality of the cut edge set, hashing, etc. Furthermore, distributed technologies like map-reduce and peer-to-peer technologies have lavished attention for the last years. Towards this trend, the authors in [10] propose a distributed scheme for solving the balanced k-way graph partitioning problem. The intuition of their method is quite simple. They assign each vertex to a separate partition with a probability analogous to the desired size of the partition. Then, each node iteratively selects another node from either its neighbors or a random sample, and examines the pair-wise benefit of a color exchange. In a simulated annealing fashion, if the color exchange results in a more preferable partitioning, then the two nodes swap their colors. Hence, non-preferable outcomes are also acceptable since they can lead to a better partitioning than a greedy heuristic approach would.

Notably, all of the above partitioning schemes have an entirely different motivation and used under different circumstances. Only a dearth of work can be found regarding partitioning schemes for processing road networks. The most similar work can be found in [13], where the authors propose using certain paths of the graph in order to partition it. Under this setting, the boundary of a (sub)graph corresponds to the sequence of edges that form a cycle bounding a planar embedding of it. In particular, those paths are chosen in such a way that with each cut the graph is divided recursively into partitions of approximately equal size. As long as the end nodes of each cut are selected from the boundary of the original graph (not from nodes on a cut), no cuts generated in this manner intersect with each other. In other words, we end up with a set of “parallel” non-intersecting cuts. This approach works well for city maps where most of the streets are parallel forming a grid-like pattern. On the downside, processing the studied query types involves a computational overhead owing to the fact that the different partitions are too close to each other as there is no mechanism to guarantee that the partitions are enough far apart from each other in order to prevent that. Last but not least, our scheme was designed under the spectrum of performing parallel operations.

2.2 Graph Processing

One of the earliest efforts in this field can be traced in the seminal paper [9] that addresses processing spatial queries in road networks efficiently using lower bounds that rely on the Euclidean distance between the nodes. In particular, they present algorithms for (i) range queries, (ii) nearest neighbor queries, (iii) closest pairs retrieval, and (iv) θ-joins according to network distance. For each query type they present two algorithms, for relying on Euclidean space before operating over the road network, and vice versa. However, the Euclidean distance is a rather coarse metric that not always associates with the weights of the edges. If, for instance, the edge cost is defined as the expected travel time, the Euclidean distance cannot confine the search space (unless we make additional assumptions, such as maximum speed). In addition, the lack of an upper bound to guide the network expansion leaves a margin for improvements.

The authors in [7] present a scheme for processing range queries and kNN queries in road networks fast by relying on graph embedding, a structure that is built during a preprocessing stage to compute the distances of all nodes from specific landmarks. In particular, their methods rely on the notion of a set of reference nodes, from which a subset of distances is kept from each node. Notably, they showed in their evaluation that keeping just the five such closest reference nodes (and thus the set of global reference nodes is allowed to grow larger) is enough to accomplish stellar performance. In addition, suitable functions are proposed so that a lower and an upper bound can be established that can be used in
a filter/refinement query processing architecture. Also, those can be exploited in an A* implementation to outperform any approach relying on Euclidean distances. An extension of that work can be found in [3] where the authors propose a hierarchical embedding that scales well to large traffic networks. A number of layers of reference nodes forming a complete graph by necessity is kept, and by processing each time a different partition rather than just the flat embedding at the bottom layer, performance ameliorates. Albeit a successful approach for processing range and kNN queries, the query types studied in this paper require different tools for performing searches simultaneously in different parts of the graph, while thoroughly coordinating the radius of each local search according to the other partial results, so that it does not exceed any unnecessary levels to render our approach inefficient. Even though, a partition hierarchy is fundamental for our processing techniques too, the one proposed in the context of this work is built differently taking completely different parameters into consideration, and we process it in a bottom-up fashion instead, starting from the relevant leaf nodes, after a short top-down preparation phase to find those and plan the execution of the query throughout the levels of the hierarchy. We reckon that no other form of indexing is required for the query types we address in this paper. Even for geographically constrained queries of the kind, we can easily restrict processing so as to involve only the partitions that satisfy the constraints by a simple comparison with the MBR of the partition and prevent from processing the rest. Other than that, the exact same processing steps are undertaken.

In [11], the authors approximate distances with close values relying on the observation that the distance distortion (i.e., the ratio of the network distance to the spatial distance between two vertices) decreases as the separation between the vertices increases. In other words, large distortions occur at small spatial distances, while the distortion quickly reduces to smaller values as the sources and destinations get farther away. They use bounds from above and below for the distance between two vertices which are used to select distance approximations within an $e$ factor. In another line of work, query processing in [13] relies on proximity relations differs from the range query and nearest neighbor query, as it operates over, constrain, and monitor the constellation among sets of moving objects. The authors in [13] consider scenarios in road networks for monitoring spatial relations and the efficient evaluation of queries for large numbers of concurrently moving objects over the road network.

3. HEURISTIC GRAPH PARTITIONING

The method we present in this section takes as input a graph partition and splits it into two parts, in such a way that the two derived graph partitions are well separated, in a sense that we want to distance them as far from each other as possible. The two derived partitions may be connected with each other with edges that have their two ends in different clusters, which from now on we will refer to as cross-edges. We will call the vertices that are adjacent to those edges border nodes. Since this is a NP-hard problem of combinatorial nature, we rely on greedy heuristics, and propose an approximation scheme on how to solve this problem. Most importantly, we can perform this way the required computations simultaneously and independently within each partition, so as to come up with as many partial and local results, which of course need to be combined accordingly at a higher level. Apart from that, separate computations need to be performed starting from the edges that run through the different partitions. Thereby, the further apart the partitions are, and the stricter the thresholds arising from the local results, the less computations need to be performed and the performance of our paradigm ameliorates. As a matter of fact, the less computations are required to derive results among different partitions, the greater the throughput and the performance gain because of the parallelism we enforce with our methods.

Algorithm [1] takes as input two vertices of the road network in order to perform the partitioning process. From those two vertices we initiate two graph traversals in a best-first search fashion, as in a bidirectional expansion, and each time we insert the vertices we encounter from either of the two horizons into the appropriate cluster. The nodes in those two clusters will constitute the nodes of the respective derived partitions. With each iteration we choose to expand the cluster with the shortest edge on its horizon. Thereby, we can prove that if there is just one edge left at the end of the process to serve as a cross-edge, it will be necessarily the longest one. Arguably, when the set of cross-edges comprises of more edges, it consists of very long edges, as well, among which is the longest edge of course. Most importantly, we are interested in maximizing the minimum distance between any two partitions of the whole constellation of partitions.

Furthermore, we provide a smoothing parameter $\alpha$ that takes values in $[0, 1]$, according to which we can allow taking into consideration the relative populations of the graph partitions, upon the decision of which partition to chose for a given vertex. Thereby, we can use for clustering the updated weights for the two clusters, each time normalizing the weight of the edge at the top of respective heap as following:

$$w'_1 = \frac{|V_1|}{|V_1| + \alpha|V_2|} w_1$$

$$w'_2 = \frac{|V_2|}{\alpha|V_1| + |V_2|} w_2$$

where $|V_1|$ the current population of the first partition, and $|V_2|$ the population of the second. Of course, $|V_1| + |V_2|$ the population of the parent graph partition. Subsequently, for $\alpha = 0$, we have that $w'_1 = w_1$ and $w'_2 = w_2$, whereas for $\alpha = 1$, we take $w'_1 = \frac{|V_1|}{|V_1| + |V_2|} w_1$ and $w'_2 = \frac{|V_2|}{|V_1| + |V_2|} w_2$.

This smoothing parameter when configured appropriately can prevent the formation of partitions with immense population discrepancies. The selection of the optimal value for $\alpha$ is not straightforward and is affected by a large number of parameters. To elaborate, we reckon that it is important creating partitions that are located as distant as possible from each other, as this is the best way to minimize the required computations that takes place in the above layers when merging the partial results. Nevertheless, this sophistication is far from unnecessary as extravagant population imbalances, would not allow reciprocate the load at the bottom levels of the hierarchy. For instance, a thread processing the left child partition of a node could terminate unexpectedly earlier than the thread processing the right. Unless the thread manager/scheduler detects those occurrences and reacts by joining the terminated thread so as to allow its resources to be allocated by a thread processing another partition, those processing resources would soon be idle. And still, even though the load at the higher levels would be diminished, we would have to wait until the computations in both partitions end before we start processing their results further at the higher levels. Therewith, we soon recognized the need to mitigate and blunt those imbalances with a configurable parameter so as to allow for compromising the trade-off between the two extreme cases.
4. PARALLEL JOIN PROCESSING

In this section, we present a scheme for retrieving the $k$ closest pairs $(u,v)$ of a road network, with $u \in R$ and $v \in S$. Nevertheless, we have formalized the interface of our paradigm in such a way that we can limit processing withing a predefined distance $\theta$ from any point of $R$, as we do not allow search for matches to extend beyond that distance threshold. Thereby, by setting the threshold parameter $\theta$ appropriately, and by not defining a restrictive number of results $k$, we can perform a distance join operation according to the specific distance predicate $\theta$. And withal, the versatility and usefulness of our paradigm becomes clear. More formally, this operation given two sets of points to be matched $R$ and $S$, a distance predicate $\theta$, and a distance predicate $\theta$, would return a result comprising the pairs of points $(u,v)$, where $u \in R$ and $v \in S$, such that $\text{dist}(u,v) \leq \theta$.

The main intuition behind our paradigm is to process each partition independently using Algorithm 2, so as to retrieve the $k$ local closest pairs, and then, process their associated cross-edges in Algorithm 3 in such a way that they are expanded in Algorithm 4 only as much as it is required for the results to be updated accordingly. We also incorporate a distance predicate $\theta$, so as not to allow matching of nodes beyond that threshold and by not defining an expected result size, a different query type is also supported. Then, the derived results are merged together to form a single set by removing each time the worst ranked elements until just $k$ items can be found.

More importantly, we can parallelize the process, and build a structure for processing the graph partitions of the hierarchy in such a way that each time we can process up to a number of partitions simultaneously according to the desired degree of parallelism. For parallel processing, we create recursively a pool of threads with Algorithm 2 according to the partition hierarchy, and we execute those threads in reverse with the help of the stack we create in Alg. 2 line 4. First, we insert in lines 6, 7 the thread that is associated with processing the top partition, in other words, for merging the results from the lower partitioning layers, which of course is
run last. In lines 9–13, we examine the next thread from the stack and check if it is ready to run, and by this, we mean that the threads associated with the partitions of the lower layer have been executed and their results are made available to the upper layer. Otherwise, we create for the thread pool the threads that correspond to the next layer for further processing. Additionally, an auxiliary priority queue is used to keep track of the running threads, and manage them appropriately in lines 5, 12. The executed threads are prioritized according to their distance from the closest leaf they subsume. The motivation behind this is that since we have initiated the execution of threads that are either running or are waiting for the results of other threads, we should first gather the results of the threads associated with the lower levels of the hierarchy, and also make available the resources they had allocated as part of their local processing tasks. Otherwise, by waiting to free the resources of the waiting threads, we waste significant time and the level of parallelism of the applications drops dramatically. Therefore, we choose to join first the threads that are associated with the partitions at the bottom levels, since they are most likely to be involved with processing over the part of the graph they represent, rather than combining the results of subsumed layers.

Algorithm 3: combinePairs (GraphPartition gp, MaxHeap left-pairs, MaxHeap right-pairs, Set R, Set S, int k)

1. while elements from both local results more than k do
   2. if worst item from the left better than worst from the right then
      3. remove worst item from the right;
   4. else
      5. remove worst item from the left;
   6. insert the k remaining items into a single result-set;
   7. foreach cross-edge from the left child partition to right do
      8. if weight of cross-edge greater than all k result items then
         9. break;
      10. foreach match in expandCrossEdge (gp, crossedge, leftbordernodes.get(crossedge.from), R, S, k, Θ) do
         11. update the result inserting new match;
         12. read global threshold Θ atomically;
         13. if required, update global threshold Θ;
      14. foreach cross-edge from the right child partition to left do
      15. if weight of cross-edge greater than all k result items then
         16. break;
      17. read global threshold Θ atomically;
      18. foreach match in expandCrossEdge (gp, crossedge, leftbordernodes.get(crossedge.from), R, S, k, Θ) do
      19. update the result inserting new match;
      20. read global threshold Θ atomically;
      21. if required, update global threshold Θ;
      22. return result;

Since we already know in advance the desired level of parallelism P, we can tweak scheduling in such a way that the overall throughput is maximized. In practice, we do not want to process locally just the leaf nodes of the hierarchy, but instead, we want to stop traversing through the partitions at the levels of the hierarchy that would ensure us that the degree of parallelism is maximized. This is accomplished by carefully selecting the appropriate degree of granularity the we process the graph partitions, neither finer, nor rougher.

Algorithm 2 retrieves the k local closest pairs (u, v), where u ∈ R, v ∈ S and \(\text{dist}(u, v) \leq \text{dist}(w, y), \forall w \in R, y \in S\). Starting from each element \(w \in R\), we perform best-first search, and each time, we encounter the next adjacent node \(y\), we test whether it belongs in \(S\) or not. If so, we compare it against the up to \(k\) best matched pairs that we have retrieved so far, and if it is better than the worst of them, then, we remove that and insert the better element, so as to have \(k\) items at all times. This is used in Algorithm 2 that takes as input a partition \(p\), two sets of points \(R, S\) to be matched, and the expected result-size \(k\). In lines 1–5, we remove all redundant heap elements so as to keep only the \(k\) closest pairs from both heaps. The remaining elements are merged together appropriately into a single heap in line 6. Next, we examine in lines 7–22 whether there are any additional pairs that run through the cross-edges of both partitions, left child first in lines 7–14 and right child in lines 15–22, following the same procedure for both. We are allowed to stop early in lines 8–9 and 16–17, since we examine the respective cross-edges in ascending order, we are hence in position of ascertaining whether it is futile to continue for no better pair can be found to update the result. Moreover, in lines 10, 12–14, 18 and 20–22, we access for read or write a global distance threshold that is used to limit local search within specific bounds that are dictated by the best \(k\)-th element among all partial results. If each parallel thread operated independently then that threshold would be much looser for every operation until the final merging at the root of the hierarchy. In practice, this is translated into more expensive search operation that overlap with additional partitions, something we could easily avoid with a global threshold variable and the appropriate read and write locks that suit that kind of concurrent operations.

Algorithm 4: expandCrossEdge (GraphPartition gp, Edge crossedge, Map insideroutes, Set R, Set S, int k, double Θ)

1. initialize an empty result;
2. create an empty heap to store examined paths;
3. insert the input cross-edge to the heap;
4. while there are more paths to be expanded do
   5. examine the next shortest path from the heap;
   6. if path cost is greater than threshold \(Θ\) then
      7. return matches;
   8. if adjacent node is contained in \(S\) then
      9. foreach partial path in insideroutes do
         10. if result can be improved or has less than \(k\) items then
            11. update result with examined path;
   12. foreach edge from front end of the examined path do
   13. if it is undiscovered and not a cross-edge then
   14. extend the examined path with the edge;
   15. insert the new path into the heap;
   16. return result;

Furthermore, we invoke Algorithm 2 in lines 11 and 19 for expanding in tandem the cross-edges that separate the processed partition from its sibling. Algorithm 4 also takes as input a threshold parameter \(Θ\) according to the distance of the worst pair of the derived result. This method enacts a search for all pairs that contain the examined cross-edge and their distance does not surpass the given local threshold. In lines 6–7 we terminate the execution of the method for the next retrieved pair exceeds the given threshold. In particular, each retrieved pair consists of a vertex from \(R\) in the
partition at the back end of the cross-edge, and another vertex from $\mathcal{S}$ (line 8) in the partition at the front end of it. Moreover, we are in position of exploiting the work we have done in the previous stage during processing locally each partition. More specifically, whenever we encountered a cross-edge as part of local processing, we keep track of the distance from any point $u$ within the previously processed lower level partition such that $u \in R$ to the back end of the cross-edge when integrating the elements of the various local results into one at a higher level. This way, the paths are expanded only from one side here, since the back side of the cross-edge has already been previously expanded from an element of set $R$. This happens in lines 4 and 5 that operate on the inside routes map structure given as input. Of course, the returned result would contain no more than $k$ elements.

5. EXPERIMENTAL EVALUATION

In this section, we evaluate the performance of our methods for various scenarios and configurations of the partition hierarchy.

5.1 Setting

A variety of different parameters has been investigated to illustrate the efficiency of our method: (1) The value of the smoothing parameter $\alpha$ used when constructing the graph partitions, so as to smooth between the effect of the size of the partition, and their pairwise distances. (2) The degree of parallelism expressed in the number of running threads. (3) The cardinality of the set at the left of the join operation. This is expressed as a percentage over the total number of vertices in the road network. (4) The cardinality of the set at the right of the join operation. (5) The expected result-size for $k$ closest pairs. Table 1 presents all parameters along with the range of values that they take and their default values.

| Parameter        | Range     | Default |
|------------------|-----------|---------|
| smoothing $\alpha$ | 0.0, 0.25, 0.50, 0.75, 1.0 | 0.0     |
| parallelism      | 2, 4, 6, 8, 10, 12, 14 | 8       |
| result-size $k$  | 20, 40, 60, 80, 100, 120, 140 | 80      |
| $R$ size         | 2%, 4%, 6%, 8%, 10%, 12%, 14% | 8%      |
| $S$ size         | 2%, 4%, 6%, 8%, 10%, 12%, 14% | 8%      |

Table 1: System parameters.

Furthermore, we use two real datasets from [11], we shall henceforth refer to as NA and SF, which correspond to the interstate network of whole North America containing 175,813 nodes and 179,179 edges, and San Francisco containing 174,956 nodes and 223,001 edges. Upon each of these datasets we created the sets $R,S$ of vertices to be joined together in such a way that correspond to certain proportions of the dataset according to the parameters we defined earlier. All queries were executed in a 16-core AMD Opteron processor tweaked at 2.3 GHz running a server Linux distribution.

5.2 Results

To begin with, in Figure 1(a) we illustrate how performance scales with regard to the smoothing factor $\alpha$ as it varies in $[0,1]$. Interestingly, we observe that execution times do not follow the same pattern. The reasons for this phenomenon lie with the different nature of each dataset. In particular, NA corresponds to the network of interstates in North America, whereas SF for the road network of San Francisco. Hence, the former is much sparser and the distances between the vertices are significantly greater while the fan-out degree is also significantly larger. The latter corresponds to a much denser network. Apparently, smoothing the edges over the population clusters has a more beneficial effect. Evidently the edge weights for partitioning the graph is more important as specific long edges server better so as to separate the different partitions and need to be used as cross-edges that isolate the vertices that are located closer to each other, so as to minimize the processing cost at the higher levels for merging the different partial results.

In Figure 1(b) we present how execution time scales with the degree of parallelism. Apparently, there is an immense gain as the number of threads increases, a benefit that gradually fades for larger values. For the maximum gain that we observe for the NA dataset, just 22.5% of the initial time is required for 8 threads, while for the SF dataset 34% for the same number of threads. We reckon that this is a drastic improvement in the execution times. Another important observation is that our policy of having one global threshold which we can access only through acquiring the appropriate locks, does not pay off for a small number of partitions. In particular for a very small number of partitions, it would be more preferable if each thread had just one local distance threshold that does not share with any other thread as each partition is being processed, as if each partition was processed in isolation and in a later stage those results were combined accordingly. The overhead of having a subsequent is not dramatic since we propose this kind of processing for just 2 or 3 partitions, whereas for more partitions the hierarchical scheduling policy that we propose for processing the different partitions is ideal. The reason is that for just a few large partitions a separate distance threshold can be close enough to the distance value of the $k$-th element of any partial answer-set without the overhead that accompanies a global variable (e.g. waiting to acquire a lock, etc.). However, since we are interested in having small search areas, we see the balance leaning towards a global distance threshold for a greater number of partitions.

In Figure 2(a) we have a chance to study how the size of the result affects performance. Remarkably we observe two contradicting patterns. For SF we see that as the expected size of the result grows the required time increases. Interestingly though, the exactly opposite phenomenon is observed for NA, as we notice the execution time diminishing with $k$. Evidently, we can attribute this to the difficulty in building a result with the best pairs for low $k$ values, as with numerous local results we constantly have to read and update in a synchronized fashion the global distance threshold appropriately, given the default setting of partitions and threads. Clearly, there is an extremely high level of concurrency for that critical section of code where the answer-set is augmented with new tuples for low $k$-values that causes a noticeable overhead as the threads have to wait so as to acquire the respective read and write locks. On the other hand, for the bigger by approximately 50,000 edges road network of San Francisco (SF), we have larger partitions (their number remains the same, but their size increases) and even though more effort is required within each separate partition, concurrency works best given the very different nature of the dataset: a densely populated area where the fan-out degree is significantly higher and the vertices have short distances from their neighbors. This is naturally reflected accordingly on the performance of the method.

In Figure 2(b) we illustrate the effect of the cardinality of the left operand of the join operation, while in Figure 2(c) the effect of the right operand. Evidently, there is a trade-off as these parameters increase. More specifically, it becomes easier to create a result-set of $k$ elements, and hence, performance seems to ameliorate with this parameter. However, for even greater values the processing cost dominates on performance and this is illustrated accordingly with an increase in the required time as $|R|$ and $|S|$ grow even further.
6. CONCLUSIONS

To recapitulate, in this paper we presented a paradigm for processing in parallel graph joins in road networks. In particular, we address an otherwise computationally expensive operation in the context of road networks. The methodology we propose matches the elements of two disjoint sets of nodes from the road network, with one preceding the other, say we want to visit a restaurant before a bar. We hence retrieve in parallel using concurrent mechanisms all eligible pairs of vertices \((u, v)\), where \(u\) is a restaurant and \(v\) is a bar, such that \(\text{dist}(u, v) \leq \theta\), with \(\theta\) the distance predicate, e.g., a walking distance. A variation of the problem would involve retrieving the \(k\) closest pairs \((u, v)\), such that \(\text{dist}(u, v) \leq \text{dist}(w, y)\), where \(w, y\) do not belong in the result. Moreover, we make use of a variety of parameters in order to tweak the partitioning scheme and we study their effect in our experimental evaluation. Finally, we relied on real-world data and showed how vulnerable and affected execution time is by the data distribution, and the way skewness can be mitigated using an appropriate system configuration.

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