Top-k Dominating Queries, in Parallel, in Memory

Sean Chester, Orestis Gkorgkas, Kjetil Nørvåg
Norwegian University of Science and Technology (NTNU), Trondheim, Norway
{sean.chester,orestis,noervaag}@idi.ntnu.no

ABSTRACT
Top-k dominating queries return the k points that are better than the largest number of other points. Current methods for answering them focus on indexed data and sequential algorithms. To exploit modern-day parallelism and obtain order-of-magnitude improvements in execution time, we introduce three algorithms, the respective strengths and potential of which are revealed experimentally.

1. INTRODUCTION
Top-k dominating queries [6] elegantly fuse top-k queries [4] with skyline queries [2] to produce ranked data without user intervention. Intuitively, a point is ranked highly if it is unequivocally better than many other points. Unsurprisingly, however, it is expensive to evaluate which k points are better than the most others.

Given the recent emergence of manycore architectures, terabyte-sized RAM, and low-latency, non-volatile memory, it is natural to ask whether top-k dominating queries can be answered more efficiently in a shared, main-memory parallel context. Until now, research has focused on sequential computation in high-latency, disk-based settings [5, 8] and on parallel computation in large, distributed systems [1], or on applications such as web-service ranking [7] and network analysis [5]. This paper investigates how significant efficiency improvements can be had on just a single machine.

More formally, a data point dominates another, distinct data point if it has equal or better values on every attribute. The dominance score of a point p is simply the number of other points that it dominates. The responses to a top-k dominating query are the k points with the highest dominance scores. Given an unindexed, memory-resident dataset, we wish to find those k points as fast as possible.

This paper presents preliminary work towards that goal. In the absence of previous ones, we define three quite distinct algorithms for answering top-k dominating queries on multicore architectures and explore their relative strengths experimentally. We find that each shows promise for maturation, while already executing quickly.

2. THREE PROPOSED ALGORITHMS
For multicore top-k dominating queries, we introduce an adaptation of the sequential state-of-the-art and two novel algorithms.

FILTER As a baseline, we adapt the sequential, filter-and-refine algorithm for non-indexed data [8]. The algorithm consists of three passes: 1) build a static grid over the data and calculate score bounds for every grid cell; 2) for every cell that cannot be immediately pruned, iterate the points in the cell and filter out those that clearly cannot be in the solution; and 3) refine the solution by computing the exact score for the remaining candidates. The counting and refining steps parallelise readily, since processing is local to each point, but the filtering step would incur a lot of write contention between threads: processing for each point p will update scores for other points in addition to p. Therefore, we select the faster but ≈ 2× less effective filter option (Algorithm 5) of [8] to adapt: within reason, it is better to process excess points in the high-throughput refinement phase than filter them sequentially.

SORTED Our next algorithm maximises throughput, but with heuristics to improve efficiency. We first sort the data by Manhattan Norm. Then, for each point in parallel, we iterate the sorted list. For a point p at index i, we conduct one-sided dominance tests with points at index < i to count how often p is dominated. Clearly, if p is dominated by at least k other points, it cannot be a top-k solution; so, we break if the count reaches k. Points that reach their own index are candidates for the solution. Over the remaining indexes > i, we flip the dominance test and instead count how many points are dominated by p as a score. Finally, we re-sort the data based on the scores; the solution consists of the first k sorted points.

PIVOTED Multicore skyline algorithms benefit from pivot-based partitioning to identify incomparability in addition to dominance [3]; this algorithm attempts it for top-k dominating queries. We will select a series of pivot points (those with the largest dominance area) one-by-one, and use them to globally, dynamically split the data space into a non-uniform grid. We maintain the set of points independently of the grid. Each pivot point newly partitions the entire set of points and the number that end up in the resultant north-east quadrant is exactly the dominance score of that pivot. Meanwhile, the grid is further sub-divided and upper bounds of scores for points in each sub-partition can be updated. Once no cell has an upper bound score better than that of the k’th best pivot that we have seen, we terminate. The intuition of the algorithm is that partitioning is easy to parallelise and that the continual fracturing of the data space quickly introduces more knowledge of incomparability and thus very quickly drives down all the upper bound estimates.

3. EXPERIMENTS
This section empirically compares our three parallel proposals.

Setup We implement the three algorithms in C++ using OpenMP.

©2016, Copyright is with the authors. Published in Proc. 19th International Conference on Extending Database Technology (EDBT), March 15-18, 2016 - Bordeaux, France: ISBN 978-3-8393-070-7, on OpenProceedings.org. Distribution of this paper is permitted under the terms of the Creative Commons license CC-by-nc-nd 4.0
some unpromising partitions can improve performance here. Similarly, somehow parallelising the second phase of Filter could yield sizeable improvements for that algorithm.

On filters and pivots Figure 1 internally inspects the performance of the algorithms by counting “important” points. For Pivot, these are the pivots. For the other methods, these are the candidate points that cannot be pruned. The pivots and candidates are exactly those points for which the dominance score is expensively, explicitly computed. We study how variations in $k$, $n$ (measured in millions), and $d$ (all on independent data) affect this value.

While it is clear from Figure 1 that Pivot computes by far the fewest exact scores, each pivot additionally further partitions the grid, creating much more overhead than evaluating candidates in the other algorithms; so, it is dangerous to compare these values directly across algorithms. Nonetheless, the low number of explicit counts required does suggest that Pivot could emerge as the clear best algorithm if the partitioning overhead can be reduced.

The filtering of the other methods is very sensitive to $d$: filtering less than 65% of the input at $d = 10$, but for $d \leq 5$, both prune $\geq 99%$. This indicates a reasonable trade-off for Filter, because sophisticated pruning replaces parallel work with sequential work.

Summary and future work Sorted outperforms the other methods on account of good throughput, but we plan to further develop Filter (perhaps by trading off more filtering granularity for parallelism) and Pivot (trying to bridle the exponential growth of explicitly managed partitions) to see if this result can be overturned. The strong single-threaded performance of Pivot in particular, especially on less extreme workloads, suggests that improving its parallel scalability could lead to an extremely fast algorithm.

4. REFERENCES

Table 1: Execution time of each algorithm when run on a single core ($t = 1$), single socket ($t = 14$), all physical cores ($t = 28$), and all virtual cores ($t = 56$). Data distribution varies, but $n = 10^6$, $d = 3$, and $k = 16$ are fixed to match [8]. Times are reported in milliseconds.