Abstract—High-performance analysis of unstructured data like graphs now is critical for applications ranging from business intelligence to genome analysis. Towards this, data centers hold large graphs in memory to serve multiple concurrent queries from different users. Even a single analysis often explores multiple options. Current computing architectures often are not the most time- or energy-efficient solutions. The novel Lucata Pathfinder architecture tackles this problem, combining migratory threads for low-latency reading with memory-side processing for high-performance accumulation. One hundred to 750 concurrent breadth-first searches (BFS) all achieve end-to-end speed-ups of 81% to 97% over one-at-a-time queries on a graph with 522M edges. Comparing to RedisGraph running on a large Intel-based server, the Pathfinder achieves a 19× speed-up running 128 BFS queries concurrently. The Pathfinder also efficiently supports a mix of concurrent analyses, demonstrated with connected components and BFS.

Index Terms—graph analysis, hardware architecture, migratory threads

I. INTRODUCTION

Graph databases and analysis provide the basis for applications dealing with unstructured data coming from business intelligence, medicine, security, and more [1], [2]. These require rapid non-obvious relationship analysis [3] across large-scale data sets. Often graph databases are kept resident in memory; their irregular access patterns defeat most optimizations for slower storage.

Providing enough memory, possibly across multiple systems, incurs a substantial monetary cost. Ideally these graph databases would support multiple different analysis queries running concurrently. These can come from one source, an analyst or program trying multiple options, or from a large number of sources as in a web-accessible graph database.

The irregular accesses in many graph analysis algorithms also cause problems for current computer architectures. These are designed primarily for dense operations either in relational databases or linear algebra and machine learning. Modern processors, including general-purpose graphics processing units (GPGPUs), optimize memory access through aggregation in cache lines or “warps” and vectors. The optimizations are detrimental when the algorithm only needs one or two pieces of data from the collection of eight to hundreds [4], [5].

The mis-alignment between application needs and current architectures has lead to many new ideas and architectural innovations. One considered in this paper is the Lucata (née Emu Technology) architecture based on migratory threads, narrow-channel memory, and in-memory processing [6]. The 32-node Lucata Pathfinder used in for evaluation in Section IV is ranked at 219 in the June 2022 Graph500 BFS results\(^1\) and at 52 in the June 2022 Green Graph500 Big Data results\(^2\). These results are from an FPGA-based implementation with processor cores running at only 225 MHz, demonstrating that the other platforms are bottlenecked by their memory systems.

This paper provides the first study of running multiple graph analyses concurrently on the Lucata Pathfinder, the latest version of the Lucata architecture. We compare performance of multiple concurrent breadth-first searches (BFS) from unique source vertices with the same searches run in sequence. These find performance improvements of 81% to 97% without any explicit scheduling or allocation of resources (Section IV-B).

Running a mix of BFS and an architecture-specific connected components algorithm provides improvements of 70% on an eight-node configuration and 38%–47% on the full Pathfinder (Section IV-C). The connected components algorithm leverages a unique feature of the Lucata architecture to achieve high performance: in-memory computation of integer minimum operations.

We additionally provide an initial comparison against RedisGraph, a commercial graph database that supports concurrent queries. Including an approximation for the client-server overhead, the Pathfinder achieves a 19× speed-up compared to RedisGraph running on high-end Intel Xeon servers (Section IV-D).

The next section provides a brief overview of the Lucata architecture. Section III references the BFS algorithm used and explains the adaptation of the Shiloach-Vishkin connected components algorithm [7] to the architecture. Section IV provides implementation details and experimental results. A brief overview of related work follows in Section V. Finally, Section VI summarizes our observations and provides future directions for further study.

II. LUCATA ARCHITECTURE

The Lucata architecture improves random-access memory bandwidth scalability by migrating threads to data and emphasizing fine-grained memory access. A single Lucata Pathfinder node consists of the following processing elements, as illustrated in Figure 1:

- a stationary processor runs the OS (Linux) and manages storage and network devices,
- eight sets of banked memory coupled with an in-memory processor,

\(^1\)https://graph500.org/?page_id=1073
\(^2\)https://graph500.org/?page_id=1077
A Pathfinder chassis includes eight nodes. Each node contains 64 GiB of narrow-channel memory: a chassis contains 512 GiB of memory. These elements are combined with a RapidIO fabric spanning the entire system. The nodes also include SSDs for external storage, but they are not used for these experiments beyond storing the executable and graph data set. Both are loaded before any timings.

For programmers, the programs are compiled for and run on the Lucata cores. The memory is globally addressable, forming a partitioned global address space (PGAS). Parallelization is expressed through Cilk [8], [9] fork-join tasks with Lucata extensions. The extensions provide a mechanism to launch a thread and create its initial stack on the same node as a specific address.

A launched thread only performs local reads. Any remote read triggers a migration which transfers the thread’s context to a processor local to the memory channel containing the data. This eliminates high-latency remote reads when many reads are clustered in one memory. The Pathfinder minimizes thread migration overhead by limiting the size of a thread context, implementing the transfer efficiently in hardware, and integrating migration throughout the architecture. Memory writes, however, do not trigger migrations and are handled by the memory-side processors described below.

Hardware supports multiple views of memory via fields in the addresses beyond the 48 bits used for global physical addresses. View zero provides a fixed address to the same physical address on each node. These provide access to “constants” like the count of a graph’s vertices without migration. View one is the global address. View two, however, stripes 64-bit elements across nodes. For an address \( p \) on node \( n \), \( p + 8 \) is on node \( n + 1 \). Arrays based on view-one addresses are balanced across the system.

The highly multi-threaded Lucata cores read only local memory and do not have caches, avoiding cache coherency traffic. Each core supports 64 hardware thread contexts with round-robin issue of one thread per cycle. The configuration in Figure 1 supports 1536 active thread contexts per node. Additionally, memory-side processors (MSPs) provide a set of remote write operations like addition that can be used to modify small amounts of integer or floating-point data without triggering unnecessary thread migrations.

A node’s memory size is relatively large but with multiple, Narrow-Channel DRAM (NCDRAM) memory channels. Each DIMM has a page size of 512B and a row size of 1024. The smaller bus means that each channel of NCDRAM has only 2GB/s of bandwidth, but the system makes up for this by having many more independent channels. Because of this, it can sustain more simultaneous fine-grained accesses than a traditional system with fewer channels and the same peak memory bandwidth.

### III. Graph Algorithms

The experiments in Section IV consider two algorithms: breadth-first search (BFS) and connected components. The tuned algorithm for breadth-first search leverages thread migrations but balances migrations with memory writes that can be remote without migrating. Details do not fit in this paper but are detailed fully in [10], [11]. The connected components algorithm uses a feature unique to the Lucata architecture: computing the minimum of two integers in-memory through the memory-side processors (MSP).

In Algorithm 2, \( G = (V, E) \) is the undirected graph, where \( V \) and \( E \) denote the graph’s set of vertices and edges, respectively. We assume all graphs are undirected but are represented in a directed format. Hence the representation contains both \((i, j)\) and \((j, i)\).
and \((j, i)\) whenever either is in \(E\). The integer array \(C\) holds the current component label of each vertex. The array \(pC\) stores the labels before performing another round of “hooking” or connecting tentative components. The operator \(\text{Neig}(v)\) denotes the set of neighbor vertices of \(v\), so the end point \(j\) of all edges \((v, j) \in E\). We have experimented with many of the more recent sampling-based algorithms [12], [13] but have yet to match the simpler algorithm’s performance. Investigating remote operations in label-propagation algorithms [14] is future work.

The algorithm in Figure 2 essentially describes the Shiloach-Vishkin algorithm [7] but with one Lucata-specific twist. We use the remote min operation provided by the MSP to “push” the minimum labels on line 1. These remote operations are performed while the MSP accesses the physical memory, encapsulating the operation in a read-modify-write cycle. Moreover the MSPs act independently from the processing cores. The remote operations do not interfere with local thread scheduling or execution, although all compete for memory access. Having eight MSPs per node eliminates most contention; we continue evaluating the appropriate trade-offs.

While remote min eliminates thread migrations in the first phase, the compress phase that flattens the min-based trees does migrate. The number of migrations, however, is bound by the depth of each tree, and that is reduced to one by each compress phase.

Additionally, the changed variable is kept in view-zero storage. Each node then may have a different value of the changed flag. We reduce these to a single value on the primary node (line 2) through a simple loop that migrates a across the nodes by casting the pointer back to a global, view-one address.

IV. Evaluation

The Pathfinder installed at Georgia Tech’s Center for Research into Novel Computing Hierarchies (CRNCH) [15], includes four chassis and a total of 2 TiB of narrow-channel memory. The instruction set and other engineering parameters in the Lucata cores is changing, so they are implemented in FPGAs. The Pathfinder for these experiments use 24 cores per node running at 225 MHz. The CRNCH Pathfinder was the first system delivered, and the first system outside Lucata running at the four-chassis scale. A few hardware issues that affect performance were identified and are described in Section IV-B.

A. Implementation and Dataset Details

We represent graphs in a loose sparse row format. The vertex records are stored in a dense array, and each record points to an edge block. We use a directed representation for the undirected graph \(G\); we store both \((i, j)\) and \((j, i)\) for every edge. The edge block is an array of neighbor vertices, storing each \(j \in \text{Neig}(i)\) for vertex \(i\). The vertex array is striped across the system, and the edge block is stored on the same node as the vertex’s entry. So vertex 0 and its neighbor array is on node 0, vertex 1 and its neighbors on node 1, and so on. All integers are 64 bits wide.

The graph used for all experiments is generated by the Graph500\(^3\) / R-MAT [16] generator using scale 25 and edge factor 16. After ensuring the represented graph is undirected and removing duplicate edges, the resulting graph has 33,554,432 vertices and 522,475,613 edges. This roughly 4 GiB graph is relatively small for a 2 TiB system but permitted running experiments more rapidly.

The source vertices for BFS tests are reproducibly pseudo-randomly generated. Running experiments multiple times produced little enough time variation that we do not report those results here but pick the minimum time. The variations will depend heavily on how hardware schedules threads, and that is an area under heavy development.

B. Performance of Concurrent v. Sequential BFS

Figure 3 shows the total time taken for running unique BFS queries both sequentially and concurrently using both eight and all 32 nodes of the CRNCH Pathfinder system. On 32 nodes, running 750 concurrent breadth-first searches from unique starting nodes requires 467 s (7.78 min) while running the same searches one after the other requires 884 s (14.7 min). On eight nodes, running 128 queries concurrently requires 226 s (3.77 min) while running sequentially requires 493 s (8.21 min). Running 256 concurrent queries on eight nodes exhausted the memory used for thread contexts. Further experiments will find the boundary between the two and provide advice to users on determining an appropriate split for their needs.

Note that the scaling from 8 to 32 nodes is not linear. Running the same 128 queries on both sees only a 2.69x speed-up concurrently and 3.24x speed-up sequentially.

\(^{3}\)https://graph500.org
are multiple reasons being investigated. One is that the 128 queries may not provide sufficient parallelism for the 32-node configuration.

Another is that hardware issues with RAM and network connections on two chassis of the four requires reducing memory and network speed for stability. This does not affect the chassis used for the eight-node runs. The particular configuration also causes a two-chassis configuration to run more slowly. Those results are not included, but sample runs appear to require approximately twice the time as with all four chassis.

The times increase linearly with the number of BFS queries in all cases, but running concurrently provides a significant improvement as shown in Figure 4. The single chassis, eight-node case consistently provides a greater than 2× speed-up of running queries concurrently rather than sequentially. Because of the hardware issues mentioned previously, the four-chassis configuration does not quite achieve the same speed-up but still runs concurrent queries 81% to 97% faster than sequential queries.

The improvement for concurrent queries over sequential ones remains relatively stable across the number of queries. Table I provides the quantiles for the average time per BFS when run concurrently. For eight nodes the min-max spread is 2.2 s, while for 32 nodes the spread is 0.61 s. The eight-node results contain only 12 samples of the number of concurrent queries. The 32-node results have 28 samples, so that 50% of the times lie outside the interval [0.63 s, 1.19 s] is perhaps more interesting than the total spread, nearly the same interval. This is worth further investigation.

### C. Combining BFS and Connected Components

We expect that many to most uses will run a mix of queries concurrently. Table II provides the concurrent and sequential times for running 80%-20% and 90%-10% mixes of BFS and connected components. These particular mixes were chosen somewhat to balance the execution times of single evaluations of each. The combination of the read-heavy BFS and the remote_min heavy connected component algorithms also led to some system instability at higher details. This currently is under heavy investigation but likely is because of the relative priorities of read and write (like remote_min) operations at the memory-side processors.

As with pure-BFS, concurrent execution of the mixed queries provides a significant improvement. Concurrently running queries on the eight-node, single chassis reliably performs 70% better than sequentially running all the breadth-first searches followed by all the connected components evaluations. There are no caches, so the equivalent connected component queries do not benefit from any data pre-loading.

The four chassis results do not achieve as much improvement, performing concurrent queries from 38% to 47% faster than running them sequentially. Our current hypothesis is that the hardware issues mentioned in Section IV-B are exacerbated by the increased global memory traffic from the connected components algorithm’s remote writes. The recently implemented hardware performance counters should provide more insight.

### D. Comparison with RedisGraph

Another available platform, RedisGraph [17] running on Intel Xeon systems, also provides concurrent queries. RedisGraph is based on modified implementations of GraphBLAS [18], [19] and LAGraph [20]. We compare the same BFS queries using RedisGraph with the Pathfinder, although we modify the Pathfinder times to approximate overhead in the RedisGraph parsing and client-server interface as specified below.

The hardware platform used for Redis Enterprise is an instance of a x1e.32xlarge Amazon Web Service (AWS) server running Red Hat Enterprise Linux 8.6. The server uses Intel Xeon E7-8880v3 2.3 GHz processors to provide 128 vCPUs, or 64 cores with 2 threads per core, and 4 TiB of memory. RedisGraph’s work pool is set to 128 threads, the maximum number of hardware contexts available to these vCPUs. The experiments all use less than 2 TiB of memory, the same as available on the Pathfinder. Redis Enterprise is version 2.6.6, and the RedisGraph module is version 2.8.

To run concurrent queries with RedisGraph, we run multiple instances of `redis-cli`. This was found to be much faster than using a C interface library not provided by Redis. Figure 5 shows a specific query; the query uses RedisGraph’s built-in BFS routine.

Using `redis-cli` imposes quite some overhead in parsing and communication with the server, although much of that overhead itself overlaps across the concurrent `redis-cli` invocations. We attempt to adjust the Pathfinder results that do not include equivalent overhead to provide a more reasonable comparison. Our assumption is that the single `redis-cli` instance provides a reasonable approximation to the overhead, and we add that to all the Pathfinder results when computing time ratios.

Table III provides both the times for concurrent BFS queries and adjusted speed-ups of 8- and 32-node Pathfinder configurations. The RedisGraph times increase approximately linearly until running more than 32 concurrent queries. This AWS server does not support enough hardware thread contexts
to provide meaningful data beyond 128 queries, so we cannot check further scalability. Additionally, some of the threads will be preempted for other tasks like keeping the client-server connections alive.

In the 16- to 32-query range, the 32-node Pathfinder provides around a 10× adjusted speed-up over RedisGraph running on a higher-end Intel Xeon. The single-chassis, 8-node configuration provides an adjusted speed-up of around 5×. When running 128 concurrent queries, which almost certainly goes beyond the Xeon’s 128 hardware thread contexts, the Pathfinder’s speed-up jumps to 19×. Section IV-B shows that the Pathfinder’s total time increases linearly up to 750 concurrent queries on the full system, far beyond the AWS server. A single chassis with FPGA-implemented processors running at 225 MHz still outperforms the AWS server, providing some evidence for the the Pathfinder memory system’s benefits and its ability to keep the memory busy.

V. Related Work

Beyond RedisGraph, there is a decided uptick in work on concurrent graph database queries and analysis. The Congra [21] and CongraPlus [22] systems schedule to optimize usage of typical shared-memory systems assigning CPU subsets to each. They find limited thread scalability on the individual graph analyses because of the limited memory access, so restricting parallelism within each concurrent query provides higher total throughput.

For distributed systems, Wukong [23] and Wukong+G [24] implement concurrent queries on an RDF database using remote direct memory access (RDMA), the latter across GPUs and GPUDirect4. RDMA provides efficient remote reads but at large granularities. These platforms partition the graph across memory spaces through an algorithm designed for skewed degrees [25]. Then they fetch chunks of the graph for local exploration.

GraphX [26] runs on the Spark data-parallel framework and provides fault-tolerant implementations of multiple “vertex-centric” abstractions. Apache Giraph [27] provides similar capabilities atop Hadoop. Both can support concurrent queries through their underlying frameworks, but the cost of fault-tolerance and the implementation technologies is substantial.

Multiple data structures have been designed to support concurrent access with streaming graph modifications. STINGER [28] is an early example that alternates between concurrent queries and graph updates. Later work extended STINGER to support some graph analysis kernels concurrently to the graph updates [29], [30]. Recent work on functional data structures in Aspen [31] support efficient snapshot views of a changing graph for multiple analysis kernels.

VI. Conclusions and Future Work

Running 750 multiple, concurrent breadth-first searches on the CRNCH Pathfinder provides a speed-up of 1.9× over running the same queries one after the other. The Pathfinder does not include caches, and its cores run at a relatively slow 225 MHz. The speed-up almost certainly comes from the large number of memory controllers / memory-side processors as well as the ability of its highly multi-threaded cores to keep the memory channels busy. This is a substantial improvement over an earlier generation, the Emu Chick, which often was limited by its inability to generate enough memory operations [10]. The average time per concurrent search shows moderate variation. The time for 128 searches does not scale perfectly from eight to 32-nodes, likely because of hardware issues in the first external Pathfinder.

When running a mix of breadth-first searches and connected components queries, the full Pathfinder provides 38% to 47% better end-to-end times for concurrent queries than the same queries run in sequence. A single-chassis configuration provides

![Fig. 4. Improvement (%) of concurrent queries over sequential queries](image_url)

![Fig. 5. RedisGraph query used where id(n) indicates the source vertex](image_url)
a 70% improvement for fewer total queries. The two algorithms have markedly different memory characteristics. Each search level of the BFS implementation performs memory work proportional to the size of that level, and the size varies widely in this Graph500 dataset [32]. The connected components algorithm performs a remote_min write-style operation in the controller nearest every edge endpoint on each of its fewer iterations. Mixing the two stresses the interconnect and the MSPs’ read/write priority balance.

A rough comparison with RedisGraph Enterprise on a large AWS server shows the Pathfinder performing significantly better up to 64 concurrent breadth-first searches. At 128 searches, the Xeon-based server performs far worse than with fewer searches, while the Pathfinder keeps scaling predictably. This comparison does not fully account for the differences in overhead, however.

This study’s experiments and methods can lead to Pathfinder improvements, including

- appropriate sizing of the in-memory thread context reservations relative to the application data,
- evidence for advise or heuristics for balancing read/write priorities in the MSPs,
- tools for evaluating different numbers of cores and clock speeds, and
- additional system diagnostics for identifying underperforming memory or network links.

Recently, the Pathfinder has gained hardware performance counters. Future work will use these to drill down into the timings and provide evidence for some of our hypotheses. Additionally, the counters should help diagnose the variance in average time per BFS seen in Table I.

Because the implementation primarily uses Cilk with only a few Lucata extensions, we also intend to compare with a direct translation to OpenCilk [9] on traditional architectures. This will provide a more equivalent comparison between architectures than our RedisGraph experiments. This requires some thought on mapping remote memory operations like remote_min to traditional architectures. A straight-forward method would use standard atomic operations that well could give the current Pathfinder architecture an “unfair” advantage over traditional NUMA machines, not to mention the upcoming new architecture version.

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5https://jfly.uni-koeln.de/color/
