System G Distributed Graph Database

ABSTRACT
Motivated by the need to extract knowledge and value from interconnected data, graph analytics on big data is a very active area of research in both industry and academia. To support graph analytics efficiently a large number of in memory graph libraries, graph processing systems and graph databases have emerged. Projects in each of these categories focus on particular aspects such as static versus dynamic graphs, off line versus on line processing, small versus large graphs, etc.

While there has been much advance in graph processing in the past decades, there is still a need for a fast graph processing, using a cluster of machines with distributed storage. In this paper, we discuss a novel distributed graph database called System G designed for efficient graph data storage and processing on modern computing architectures. In particular we describe a single node graph database and a runtime and communication layer that allows us to compose a distributed graph database from multiple single node instances. From various industry requirements, we find that fast insertions and large volume concurrent queries are critical parts of the graph databases and we optimize our database for such features. We experimentally show the efficiency of System G for storing data and processing graph queries on state-of-the-art platforms.

1. INTRODUCTION
Data is generated at an increasing rate and researchers in industry and academia are faced with novel challenges on how to extract knowledge from it that subsequently can bring value to a community or company. A first set of problems that need to be addressed when working with big data is how to efficiently store and query them. In this paper we focus on these challenges in the context of large connected data sets that are modeled as graphs. Graphs are often used to represent linked concepts like communities of people and things they like, bank accounts and transactions, or cities and connecting roads. For all these examples vertices are in order of hundred of millions and edges or relations are in the order of tens of billions. For a property graph model which is the focus of our work, there can be an additional arbitrary number of properties for each vertex and edge thus largely increasing the size of data to be maintained and queried.

The interest in graph databases has rapidly grown in the past decade with many discussions on multiple aspects including internal data structures and storage, query languages, programming models and analytic algorithms. As a result, a few open-source based graph database solutions have arisen and there are attempts to standardize public APIs and frameworks to query the graph data. Also, a number of programming models for fast processing of OLAP (On-Line Analytical Processing) and OLTP (On-Line Transaction Processing) have been proposed. However, there is not enough discussion on optimizing for performance in the distributed OLTP targeted graph databases and ways to design such databases are still under debate. Compared to OLAP-oriented approaches, OLTP systems need to support massive changes to the data usually with continuous, large volume insertions and numerous small-scale neighborhood searches. These performance requirements forces certain design choices and performance versus functionality trade-offs that need to be considered.

In this work, we introduce the main components of the IBM System G graph database ecosystem: a fast, ACID-compliant, single node graph database and a distributed graph database that relaxes some of the ACID properties in order to achieve high performance. The scenarios we are currently targeting with our database are from financial world where the graph is constantly updated with hundreds of thousand of edges per second corresponding to transactions between various accounts while at the same time performing thousands of queries per second to look for spe-
cial patterns in small-scale neighborhoods. Additionally, we found out that many users do not keep the graph database as their primary database engine. Instead, they often choose to migrate data from another type of database, often SQL, and run analytics on the graphs. In those cases, building the graph may take several days to even weeks, dominating the time for the actual analytics phase. Therefore, the requirements for our graph database are: 1. Fast insertions of vertices and edges on the order of 100,000 per second. 2. Support hundred of thousands parallel queries, which are often small scale searches around a given vertex or edge. We built SystemG because as far as we know, existing solutions could not provide enough performance for the requirements above, for some of our industry collaborators.

The contributions of our paper are a very fast single node graph database implemented on top of a key value store and a distributed graph database designed as a composition of a set of single node databases referred to as shards. To support high throughput insertions and low latency queries we introduce a novel runtime supporting thousands of concurrent requests per second and a Remote Procedure Call (RPC) based communication model to allow the database to move data efficiently between various machines hosting different shards. On top of our distributed design we introduce two novel techniques for adding edges, techniques that reduces the number of exchanged messages compared to a trivial implementation. We evaluate quantitatively our design and compare the performance of our database with existing solutions such as Neo4J [37] and JanusGraph [6].

The remainder of the paper is organized as follows. In Section 2 we present related work. Section 3 briefly introduces our single node graph database. Section 4 delves into our distributed graph database design and organization. Section 5 describes a general approach for writing graph queries on the distributed graph. Section 6 introduces two novel techniques for adding edges. Section 7 describes the consistency model supported by our current API. Section 8 includes our evaluation and comparison with other graph databases and Section 9 concludes our paper.

2. RELATED WORK

In this section we discuss related projects and we classify them into four broad categories: graph datastructure libraries, graph processing frameworks, where the emphasis is on the programming models, graph databases, where the focus is on storage, and hardware based approaches.

Graph libraries: Graph libraries for in-memory-only processing have been available for a long time. For example Boost Graph Library (BGL) [10] provides a generic graph library where users can customize multiple aspects of the datastructure including directness, in memory storage, and vertex and edge properties. This flexibility gives users great power in customizing the datastructure for their particular needs. Parallel Boost Graph Library [13], STAPL [22] and Galois [29], provide in memory parallel graph datastructures. Pegasus [26] implements graph algorithms as matrix multiplications, on top of MapReduce framework, and GraphBLAS [25] is another open-forum effort in a similar approach. All these projects provide generic algorithms to access all vertices and edges, possibly in parallel, without knowledge of the underlying in-memory storage implementation. System G Native Store employs a similar design philosophy with these libraries but it extends these works with support for persistent storage and a flexible runtime for better work scheduling.

OLAP Graph processing frameworks: TinkerPop [18] is an open-source graph ecosystem consisting of key interfaces/tools needed in the graph processing space including the property graph model (Blueprints), data flow (Pipes), graph traversal and manipulation (Gremlin), graph-object mapping (Frames), graph algorithms (Furnace) and graph server (Rexster and Gremlin Server). Interfaces defined by TinkerPop are becoming popular in the graph community. As an example, Titan [11] and JanusGraph [6] adheres to a lot of APIs defined by TinkerPop and uses data stores such as HBase and Cassandra as its scale-out persistent layer. TinkerPop focuses on defining data exchange formats, protocols and APIs, rather than offering a software with good performance.

OLTP Graph processing frameworks: Pregel and Giraph [33, 9, 12] employs a parallel programming model called Bulk Synchronous Parallel (BSP) where the computation consists of a sequence of iterations. In each iteration, the framework invokes a user-defined function for each vertex in parallel. This function usually reads messages sent to this vertex from last iteration, sends messages to other vertices that will be processed at the next iteration, and modifies the state of this vertex and its outgoing edges. GraphLab [31] is a parallel programming and computation framework targeted for sparse data and iterative graph algorithms. PowerGraph [17] extends the GraphLab with gather-apply-scatter model to optimize the distributed graph processing. Pregel/Giraph and GraphLab are good at processing sparse data with local dependencies using iterative algorithms. PGX.D [23] boosts performance of parallel graph processing by communication optimization and workload balancing. GraphX [19] is another Pregel based distributed framework that runs on Spark [3].

Another type of approach to reduce their network communication overhead is out-of-memory graph processing [28, 39, 15, 32, 20]. They try to utilize the large storages (e.g., HDD, SSD). These frameworks are often focused on minimizing the number of storage accesses [28, 45], utilizing sequential accesses [39], or maintain multiple outstanding I/O transactions to draw maximum bandwidth out of flash devices [14, 20]. There are also attempts to use mmap for efficient storage management [52, 50]. However, none of these are designed to answer ad hoc, small scale queries or process graph with rich properties.

Hardware Based Approaches: There also have been attempts to take hardware into account for graph processing. Tilera [14] introduces a computer architecture suitable for graph processing, tuning for irregular memory accesses. To exploit the parallelism, using GPUs is also a popular way. [21] presents CUDA implementations for graph processing algorithms, and [21] optimizes BFS by combining top-down and bottom-up approaches. There are custom hardware accelerators designed to draw maximum memory bandwidth
and utilize the parallelism of graph processing [35, 19]. ExtraV [29] is a near-data accelerator that uses coherent interface [41] to increase the performance of out-of-memory processing. Tesseract [12] places small computing units on the logic die of 3D stacked memories, and multiple blocks work together as an accelerator for graph processing. However, none of those approaches handle processing dynamic property graphs.

3. SINGLE NODE GRAPH DATABASE

The single node graph database implements a property graph model. Each graph is identified by a user-specified name and consists of vertices, edges, and the properties (i.e., attributes) associated with vertices and edges. Each vertex is identified by a unique external vertex identifier specified by the user and an automatically generated unique internal vertex identifier. Each edge is identified by the vertex IDs of its source and target vertices and an automatically generated unique edge ID. Multiple edges between the same pair of vertices are allowed. Each vertex or edge is associated with a label string which can be used to categorize vertices/edges and facilitate efficient traversal (e.g., only traverse edges of a specific label).

A rich set of graph APIs is provided to support all fundamental graph operations, including graph creation/deletion, data ingestion (add vertex/edge one at a time or via batch loading of files in CSV format), graph update (delete vertex/edge, set/update/delete vertex/edge properties), graph traversal (iterate through vertices and edges of each vertex), data retrieval (get vertex/edge properties), graph search (find vertex/edge by ID, build/search property index).

Internally, vertex-centric representations are used to store vertices and edges, along with the maps for vertex and edge properties. For the current version evaluated in this paper, LMDB (Lightning Memory-Mapped Database) [17], a high-performance key-value store is used to store the above representations both in memory and on disk. In the rest of the section, the implementations of graph components using key-value stores will be explained in detail.

3.1 Vertices

Information about the existence of individual vertices is maintained by two key-value store databases: \( ex2i \) (external id-to-internal id) and \( i2ex \) (internal id-to-external id). The \( ex2i \) uses the external identifier as the key and internal id as the value, and vice versa for \( i2ex \). As mentioned above, we assume the user always accesses a vertex using its external identifier. A unique internal id exists for each external id, and those internal ids are used in reference to other components (i.e., edges and properties). The reverse-mapping database, \( i2ex \), is also maintained to convert the internal ids back to the external id and make this information available to the user.

3.2 Edges

Edges are managed by the \( v2e \) key-value database. In \( v2e \), the source vertex internal identifier is used as the key to locate edges outbound from the vertex. The value stored for each edge includes the internal id of the target vertex, label id, and the edge id. The edge id is unique, and is used to distinguish between the edges with the same source and target vertices. Also, it is used to index the properties of edges. In the case where the graph is directed, SystemG maintains another key-value store database for tracking inbound edges from a vertex. The structure is exactly the same as \( v2e \), except that the destination vertex id is used as the key. The same edge identifier is used between the two edge databases (i.e., inbound and outbound) to mark that they belong to the same edge instance.

3.3 Properties

The property set of a vertex/edge is essentially a list of key-value pairs where each key is a property name and the value associated with the key is the value of the corresponding property for this vertex/edge. Property values can be strings, numbers (integer, float, double), vector of numbers, or composite values consisting of strings and numbers. Multiple values for a single property, and properties (e.g., meta data) of properties are supported for compliance with Apache TinkerPop 3.

There are two property key-value store databases, \( vid2pkv \) and \( eid2pkv \), each for vertex properties and edge properties, respectively. As in the vertex ids, the property names are mapped into a property ids and the property ids are used for those two databases. In those databases, the vertex id or the edge id is used as the key, and the property id and the property value are stored as the value. Since LMDB allows entries with duplicate keys, and stores values in a sorted order, the correct property can be found by looking for the matching property id. Alternatively, one could concatenate vertex id/edge id with the property id and use the concatenated data as the key. In that way, the key will always be unique and no matching for property ids is required. However, we found out that using an integer (the vertex id) as the key gives a hint for internal optimizations in the key-value store, and makes it often faster than the alternative method avoiding the property id matches, unless the number of properties is large. We provide the trade-off as a configuration option for the database, and use the former method in the remaining of the paper.

3.4 ACID Transactions

The single node graph database is fully ACID compliant by exploiting the feature of the underlying key value store used which in our case is LMDB. The graph database exposes a transactional API where users can start a read/write or read only transaction. The LMDB uses copy-on-write technique for transactions and under this model a read/write transaction will create new memory pages with the data being modified and these pages will be made visible to the other threads when the transaction commits. While multiple threads or processes can start read/write transactions, they will be serialized by the database with only one being active at any time. Read only transactions are not restricted from accessing the database at any time and they can all proceed in parallel.

4. DISTRIBUTED GRAPH DATABASE

The distributed graph database is a composition of a fixed set of single node graph databases called shards. The distributed graph maintains a list of computation nodes, the mapping of shards to nodes and implements an API such that callers see only one database instance and not a collection of distributed services. Thus upon instantiating a distributed graph, a naive user will have access to the same interface as with the single node graph database and the
4.1 Messaging Layer

The graph database will run in a Single Program Multiple Data (SPMD) fashion similar to MPI. The binary corresponding to an application (e.g., graph database) will be executed on multiple machines and each process will have its own identity and know how many other processes are part of the overall computation. After an application starts it can access local memory and local storage. When remote data needs to be processed, communication will be employed. Our distributed graph system uses Remote Procedure Call (RPC) as its core communication abstraction.

The RPC is abstracted on top of a native communication library like sockets, MPI, PAMI or GASNet, inheriting advantages and disadvantages of the underlying layers. The RPC provides to the distributed system developers a high level abstraction that improves productivity and portability of the system.

4.2 Runtime

In general each individual process will receive RPC requests from multiple sources. In order to provide a high throughput (executed RPCs per second) we employ a multi-threaded task based runtime. Within our system, each RPC invocation received from the network is encapsulated within a task and placed into the runtime scheduler for execution. The runtime scheduler maintains a pool of worker threads and dispatches individual tasks to individual threads. The scheduler also allows for work stealing to keep the load balanced. The same runtime is also used within our framework to execute parallel computations within one SPMD node.

When an RPC request is received on one of the incoming communication channels, the messaging layer will receive the message and quickly queue a task for execution by the worker threads. The number of RPC’s that can be executed concurrently will be proportional to the number of worker threads used by the scheduler. Individual RPC can invoke additional RPCs as part of their body thus allowing us to implement certain functionality in a distributed asynchronous fashion.

4.3 Query Manager

The System G architecture includes two categories of clients: query managers and regular clients. The query manager is a database client that is usually deployed on a powerful node. The query manager will open a communication channel with each individual shard of the distributed database and afterwards is capable of posting RPCs to any of the nodes of the database to perform various graph operations. Regular clients will not connect to the distributed database directly but rather they will connect to the query manager and the query manager will execute the query on behalf of the client.

The extra level of indirection has the following advantages. Firstly it allows the query manager to control the load on the database. The query manager may decide to briefly delay the processing of some requests rather than overload the database. Secondly it is often the case that a query on a graph database is a complex computation like a breadth first search (BFS) or finding a path between a source and a target. For these queries the query manager may end up accessing all shards of the database multiple times. Thus the query manager can maintain all this partial state while performing the query and it returns to the client when the final answer is available.

There can be more than one query manager per system but usually not more than tens. On the other hand, there can be hundreds of clients communicating with the query managers over a network protocol. Currently a query manager provides multiple interfaces, such as REST, nanomsg or native C++. For REST interface, a query manager can start an HTTP server and accept REST queries from clients that are subsequently mapped into graph operations. The REST requests can be issued from a browser, JavaScript, Java or Python program.
4.4 Firehose

In many large scale practical graph applications, the graph database needs to process a large number of vertex or edge creation requests in addition to read-only query requests. In this case, directing all ingest to the query manager often overloads the query manager and creates a bottleneck. To address these limitations, we introduce the Firehose module, an extension for optimizing the ingestion of data. The single node graph database that we use to implement the distributed graph database is optimized for a single writer, multiple readers scenario. For this reason in our design each process running a shard of the database creates an additional thread that is in charge of read-write transactions. For these applications the Firehose module will be in charge of requests requiring write access, possibly in a batched mode. By bypassing the query manager and directly talking to the dedicated thread in the shards, much higher bandwidth for data retrieval.

We also implement the Pregel runtime so that developers can write their graph analytic algorithms in a vertex-centric manner. By having the Pregel runtime, the computation is performed in a parallel and distributed manner. Thus such a tightly coupled integration of distributed databases and the distributed computing framework is also one of the novel features. More detailed information on the Pregel runtime will be described in a separate paper.

Algorithm cost analysis: At a very high level the BFS algorithm introduced in the previous section consists of a set of rounds as shown in Figure 3. Each round spawns a set of asynchronous requests (1) followed by remote execution of the requests (2) followed by the results being sent back (3) and the postprocessing step where the new frontier is assembled (4).

For a given architecture (compute nodes, storage network) one can measure individual performance metrics that can be used to estimate the overall cost of the computation. Thus the total time for one iteration of the BFS algorithm can be estimated as $T_{step} = T_1 + T_2 + T_3 + T_4$. The total time will be $T = \sum_{depth} T_{step}$. To approximate $T_1$ we need to have an estimate of the latency ($Lat$) and bandwidth ($Bw$) of the network used. The values for this parameter is usually in order of a few hundreds microseonds for a gigabit type network. The time to read the neighborhood of a set of vertices ($T_2$) depends on the performance of the key value store utilized which in turn depends on the computation node and more specifically the storage used. This time is often in the order of one millisecond range. Returning the neighbors back from the network ($T_3$) is similar to collect and retrieve all neighbors of this set of source vertices (lines 7-10). This is performed using the graph method get_all_edges_async() which internally will use the RPC mechanism previously described. This method runs asynchronously, allowing the calling function to submit multiple requests before polling for results (line 17). It is possible that by the time the last method invocation is finished, some of the results are available, thus this flexible RPC mechanisms allows us to overlap communication with data retrieval.

5. GRAPH QUERIES AND ANALYTICS

The query manager will handle all basic queries like add/delete/get vertex, edge, property. Additionally the query manager will implement graph specific queries like various traversals. In this section we describe how queries for the distributed graph can be internally implemented. As a simple example let’s consider a simplified breadth first search where we traverse only a given number of levels deep. The relevant source code is included in Figure 2.

As parameters, the analytic takes a reference to the distributed graph instance, the starting vertex and the number of levels to traverse (line 1). First it instantiates a partitioned frontier which will maintain a list of vertex identifiers grouped by the shard to which they belong. We start by adding the initial starting vertex to it (Lines 2-3). Next we start an iterative process where we compute the next BFS frontier based on the current frontier. For this we extract from the frontier vertices that all live in a certain shard and we post an asynchronous request to that shard to
6. VERTEX AND EDGE MANAGEMENT

In the distributed graph database presented here each vertex and edge is uniquely identified by an internal vertex and edge identifier respectively. In this section we discuss how identifiers are generated and managed while adding items to the database. Edges (outgoing and incoming) are stored as tuples of such identifiers to save storage and improve the data lookup performance. Additionally vertex and edge properties are stored as key, value pairs using the vertex or edge identifiers as keys as explained in section 3.3.

**Internal Vertex identifiers** Each vertex has a unique numeric internal identifier. This is allocated when the vertex is created and it won’t be reused for any other vertex in the database. In a single node graph database producing an unique id is done by incrementing a variable each time a vertex is added. We will refer to this variable as \(\text{MAX\_VID}\). For a distributed graph database we ensure a unique vertex identifier by using the following protocol. First a vertex is uniquely associated with a shard by using either a default hash function or an arbitrary placement function provided by the user. When adding a vertex to a shard a vertex identifier is generated by incrementing a variable each time a vertex is added. The vertex identifier can be generated by shard1 and communicated to shard2 together with the rest of the arguments when adding the incoming edge. It is also valid to generate the id in shard2 and communicate to shard1. In either case the shard identifier also must be embedded in the most significant bits of the edge identifier to make it globally unique.

6.1 Efficient edge addition for a distributed database

A very common operation for graph databases is adding an edge between a source and a target vertex without adding vertices in a prior step. For example add_edge(\(A, \text{Knows}, B\)). This turns out to be a complex operation as shown in Figure 4. First the operation will add two vertices \(A, B\) if they don’t exist already (Figure 4 Lines 2 and 3), create a label “Knows” if it doesn’t exist already (Figure 4 Line 4), add the outgoing edge for \(A\) (Figure 4 Line 5) and add the incoming edge to \(B\) (Figure 4 Line 6). Note that each of these invocations produces vertex and edge ids that are subsequently used creating data dependencies between the five steps of the method.

```
1 add_edge(A, Knows, B)
2 VIDS=check_or_create(A)
3 VIDT=check_or_create(B)
4 LID=check_or_create_lid(Knows)
5 EID=add_outgoing_edge(VIDS, VIDT, LID)
6 add_incoming_edge(VIDT, VIDS, EID, LID)
```

**Figure 4: Add edge steps.**

6.2 Basic algorithm

A straightforward approach to implement the steps depicted in Figure 3 is to execute the code on a client or query manager node and execute all 5 steps synchronously one after another. Thus for each of the steps 2 to 6 except step 4 we will have two messages exchanged over the network: one to invoke remotely the operation and one to return results used in the subsequent steps. Step 4 does not incur network traffic since checking for label ids is often performed locally by the query manager using caching. Thus there will be a total of at least seven messages exchanged (the last step...
doesn’t have to return anything). If confirmation of the final step is required then this approach will take a total of eight steps. To reduce the number of steps, SystemG optionally stores an in-memory cache of vertex list, which keeps the recently used external id to internal id mapping. If the cache hits, there is no need for message round-trip to the corresponding shard. For the rest of the paper, we assume that this cache is deployed.

6.3 Asynchronous algorithm
A first improvement we propose in this paper is to use asynchronous RPC mechanism that our runtime natively supports. For this approach we first forward the add edge method to the node where the destination is allocated (DEST_SHARD). On this shard the destination vertex is found or created and its id (VIDT) is forwarded with the rest of the arguments to the machine where the source is located (SOURCE_SHARD). Here the source vertex will be located or created (VIDS), the outgoing edge will be created \{VIDS, VIDT, LID, EID\} and finally forward the invocation back to DEST_SHARD to add the incoming edge using the edge id previously generated. Thus we reduce the number of communication steps from seven down to three. A fourth step can be optionally employed if a confirmation of the method termination is required on the client initiating the operation.

6.4 Batched edge and vertex addition
It is often the case that edges and vertices are added to the database at very high rates and it is acceptable by the user’s application that the vertices or edges are added in a delayed, batched fashion. In this section we describe a novel mechanism for adding items using batches. We introduced in Section 4.4 the notion of Firehose for optimizing fast insert rate operations and the batching mechanism presented in this section is implemented as part of the Firehose. Let’s assume a set of edges are to be added to the database using the semantic described in Figure 4. The Firehose will collect a batch of them of size N and perform the following processing:

1. Create 2×P queues where P is the number of shards. For each shard there will be one outgoing and one incoming edges queue.
2. For each add edge request place one entry in the outgoing edges queue corresponding to the shard where the source vertex of the edge is allocated. Similarly we place an entry in the incoming edges queue corresponding to the shard where the target vertex is allocated.
3. Instead of protecting the queues with locks, we create another set of queues to do double-buffering and avoid the problem of simultaneous reader-writer problem.
4. For each pair of queues for each shard we collect the set of vertices to be added to the shard and we send one bulk request to the shard to add the vertices. This step can be done in parallel for all pairs of queues and their corresponding shard. The request will return the vertex identifiers for all newly added vertices. It will also reserve an edge id range on the shard and the edge id range is also returned to the Firehose.
5. The mappings from external vertex id to internal vertex ids are inserted into a map datastructure (cached) as subsequent steps will look for this mapping.
6. Based on all vertex identifiers returned and edge ranges reserved the Firehose will prepare the final tuples corresponding to the edges to be added. The edge tuples containing only internal ids will be sent to the database shards to be inserted. This insertion also happens in parallel for all shards.
7. Optionally, the mapping from external vertex id to internal vertex id can be cached on the Firehose such that to minimize the number of vertices information sent to the shards in step 3.

This novel approach for performing batched edge addition provides the highest amount of parallelism and the lowest number of messages exchanged compared to the other two methods previously introduced. For a given batch of N method invocations, the basic algorithm will perform \(7 \times N\) communication messages, synchronizing for each step. The asynchronous algorithm performs \(3 \times N\) messages if the invoking thread doesn’t require confirmation termination or \(4 \times N\) messages if confirmation is required. The batched approach will exchange four larger granularity messages per shard for the whole set of N invocations for a total of \(P \times 4\) messages. Usually \(P\) will me much smaller than \(N\). While the batched method sends much fewer messages, there is more data per message sent. However most networks perform better when data is aggregated in bigger chunks.

7. FAULT TOLERANCE, TRANSACTIONS AND CONSISTENCY MODEL
When designing a distributed graph database one faces additional challenges that one does not face designing a single node graph database. In this section we discuss the ACID properties, consistency model and fault tolerance guarantees.

As discussed in Section 5 the single node database is fully ACID compliant. While the single node graph database is fully ACID, our distributed graph database implementation is not. Currently we don’t support transactions for arbitrary sets of operations acting on multiple shards. We are only ACID within one shard. In our model adding one vertex and its associated properties is atomic and durable. However adding two or more vertices is considered to be multiple transactions with one for each vertex added. When adding edges, that is also a composed operation consisting of one transaction to add the outgoing edge and another transaction to add the incoming edge. These transactions may happen on two different shards.

Deleting an edge can also involve two transactions. Deleting a vertex is the most complex operation on the distributed graph database as it causes one transaction where the vertex lives to remove the vertex, its properties and its outgoing edges and their properties, followed by NI transaction on shards hosting edges pointing to this vertex, where NI is the number of incoming edges.

7.1 Memory Consistency
For distributed algorithm writers the fact that we are not fully ACID requires certain caution when accessing the data.
For example when looking for an edge one should not assume that both outgoing and incoming ends are present. For a transient interval of time the fact that the outgoing end exists, doesn’t imply that the incoming end will be found. Additionally, one must retrieve a vertex and its adjacency as one operation to ensure atomicity. For example if two operations are used, the second one may fail to find the vertex if an intervening delete operation occurred.

Unlike a single node graph database, a BFS traversal on the distributed graph is not one transaction. For BFS accessing the neighborhood of each vertex is a transaction, but it is possible that edges and vertices will be added/deleted between collecting adjacencies for multiple vertices. For the practical situation for which we are using the current solution, data is mainly added to the database, so this modality of querying will return all the adjacency when the query started plus some eventual new vertices and edges added since the query started. The fact that vertices/edges can be deleted while the traversal is in progress requires the algorithm writer to not assume that a vertex was found during one call, it will be found on the next call.

While this programming model sounds complex it does allow the user to write fast queries. While providing full transaction support for distributed graph is on our agenda, currently we suspect this will come at a great performance cost, requiring the database to potentially lock most of the shards for read and write transactions.

7.2 Fault Tolerance

In the current version of the database there is no fault tolerance implemented. In our experience the graph database is often not the main data repository but it is often used as an accelerator for graph queries and it runs along side the main data repository. We support the use of Apache Kafka [2] for fault-tolerance communications in firehose ingestions. However, we found Kafka to be not a good fit for normal queries. Kafka is highly optimized for bandwidth and tradeoffs the latency. Also, Kafka does not naturally support request-reply style communication, making it hard to use for queries that have return values. We do have work in progress to implement a fault tolerance protocol by providing replicas for the shards.

| Resource         | Value                        |
|------------------|------------------------------|
| Server Product   | IBM S824L                    |
| NUMA nodes       | 4                            |
| Number of cores  | 24                           |
| Core:            |                               |
| Frequency        | 3.3GHz                       |
| SMT              | 8                            |
| TLB              | 2048 entries                 |
| Cache:           |                               |
| L1               | Private 64KB                 |
| L2               | Private 512KB per core       |
| L3               | Shared 8MB per core          |
| L4               | Shared 16MB per DIMM         |
| Main Memory:     |                               |
| Technology       | DDR3                         |
| Capacity         | 2TB                          |
| Bandwidth        | 460GB/s                      |
| Page size        | 4KB                          |
| Cache line size  | 128B                         |
| Storage          | IBM Flashsystem 840          |

Table 1: System parameters of the server machines

8. EXPERIMENTAL RESULTS

In this section we evaluate the performance of core graph database operations by adding vertices, adding edges and performing simple Breadth First Search (BFS) queries. We look at the scalability of the distributed graph database, analyze sources of overhead when comparing the distributed database versus the single node. We also compare SystemG against other existing graph databases: Neo4J Enterprise [27], version 3.2.1, and JanusGraph [10], 0.1.1, a successor of Titan [11] using Apache Cassandra 3.7 [1] as its backend. We faithfully did our best to optimize the performance of Neo4J and JanusGraph by carefully writing the application scripts, choosing the right batching and size of clusters.

The experiments were performed using a cluster with five IBM S824L [5] machines. The configuration is displayed in Table 1. Each had 4 numa nodes, 24 POWER8E cores with smt8 at 3.3GHz, 2TB memory. One machine was used to run query manager and others were used for shards, which we call the servers. The machine for query manager connects to an external IBM FlashSystem 840 Enterprise SSD storage [4] for loading input data files. We will refer to this machine as the frontend. It is used to run clients in the distributed experiments for our SystemG, Neo4J, and JanusGraph. The machines are connected to each other through a 100 Gbit switch [7].

8.1 Vertex Addition

In this section we analyze the performance of adding vertices to the database. We analyze several different configurations measuring throughput for adding vertices and the results are included in Figure 5. The input data file used is derived from Twitter datasets [27] and it contains 58,269,482 vertices, each vertex with its external identifier and two properties. We assume the user will perform look-ups based on this identifiers so they need to be indexed. While both SystemG and JanusGraph provide by default an index for external identifiers, for Neo4J we had to explicitly create an index on a property “ID” and treat the external id as an indexed property.

The first configuration analyzed is the single node version of the SystemG using the C++ API (SG-Single), we committed every 1 million operations making sure data was completely persisted to disk. In our model this is achieved using graph::tx_commit (RDWR). The next configuration considered was distributed graph database using one shard, a query manager node and a Firehose node (SG-1shard). The database shard and query manager were run on a server and the Firehose was run on the frontend. The protocol used for adding vertices in the distributed mode was to read from the input file entries, aggregate up to 100,000 entries and then send them as one command to the shard to insert. A third scenario is the distributed database with 12 shards (SG-12shard), 3 in each of the 4 servers. We choose this number because we observed through experimentation that ingesting data scales up to three-six shards per node. After this point adding more shards will not benefit much as the available resource becomes saturated (see Section 8.3). When using 12 shards the Firehose will batch 1.2 million vertices (12*100K) in 12 queues and then 12 threads will contact shards to insert queued vertices in parallel. Thus we expect very good scaling when adding vertices using multiple shards. The transactions are generated and maintained on
In this section we analyze the performance of adding edges to the database. The semantic of adding an edge is as described in Figure 1. The data input considered is a set of edges derived from bitcoin transactions and it contains three columns: source, target, and weight which is a double value. A first experiment shown in Figure 6(a), was to evaluate the performance of the three methods of adding edges as described in section 6. First method called synchronous (SYNC) will follow through the eight communication steps sequence described in Section 6.2. The second method we evaluate is the asynchronous version (ASYNC) described in Section 6.3. We performed the four communication steps required to confirm to the user that the method finished all its steps on the various shards. Finally we evaluate the batched Firehose method as shown in Section 6.4. For SYNC and ASYNC we execute with 1 shard and 12 shards with four machines. Then we vary the number of threads requesting the add edge methods at the query manager side from one to 16. In the legend, for SYNC and ASYNC methods, nTbms is used to represent the configuration with n requesting threads with m shards. While concurrent write transactions against a single node database or shards does not add much benefit due to serialization of transactions, in a multishard environment we do expect improved throughput from run-
ning multiple client threads to ingest data. When inserting concurrently with P threads the input file was split in P chunks and each thread inserted one chunk, thereby avoiding duplicate edge insertions.

In Figure 6(a), we see the SYNC methods achieving 2,223 edges/sec in Sync-1Th-1Sh to 7,571 edges/sec in Sync-16Th-12Sh. For the experiment in this section we only ingest 10 million bitcoin edges. When going from one shard to multiple shards there is a small overhead for maintaining additional state. However this overhead is compensated for by running inserts concurrently. In this particular case we obtain a 3.4× speedup by ingesting data with 16 threads on 12 shards versus one thread and one shard.

For ASYNC methods, the performance ranges from 4,393 edges/sec in Async-1Th-1Sh to 26,025 edges/sec in Async-16Th-12Sh. The reduced number of messages exchanged and the use of asynchronous methods leads to a good performance improvement compared to the synchronous version. For eight threads and six shards the speedup of the asynchronous version is 5.9× relative to one thread and one shard.

The Firehose batched version implements the more complicated protocol described in Section 4.4 but it has the advantage of committing methods in bulk thus increasing the granularity of transactions and improve the overall throughput. In Figure 6(a) the Firehose will commit in batches of 100K edges when using one shard and batches of 12×100K when using 12 shards. Overall, for the two cases we obtain 67,249 and 140,208 edges per second for the single shard, and 12 shards, respectively.

On the single shard configurations, speedup of ASYNC was 2.0× over SYNC, and that of Firehose was 30.3×. With 12 shards, ASYNC was 3.4× over SYNC, and Firehose was 18.5× faster than SYNC method. While the Firehose is definitely the solution for ingesting large amount of edges it may not be appropriate in every situation. If an add edge method can not be batched and it needs to be visible right away the SYNC or ASYNC version will have to be used.

In Figure 6(b) we show the overall ingestion rates when ingesting 10 million edges from the bitcoin dataset. We commit every 100k edges for SystemG and JanusGraph tests except distributed with 12 shards where we commit every 12x100k edges. For Neo4J, we committed every 20k edges for each test due to the same issue of performance degradation for large Cypher HTTP API transactions. We tested SystemG with distributed one shard and distributed 12 shard, Neo4J in a highly available configuration with one-, two-, and three-instance clusters, and JanusGraph with one, four Cassandra instance. The JanusGraph benchmark was written in Java using TinkerPop Core API version 2.5 and run in embedded mode (e.g., we did not run JanusGraph as a server). We used separate servers for running Cassandra.

The single node SystemG achieves 74,247 edges/second, and distributed one shard gets 67,249 edges/second with a small expected drop from the single node SystemG. Distributed 12 shards shows 140,208 edges/second, which scaled well despite the multiple round-trip communications per transaction. Performances of Neo4J are one instance 4,530 edges/second, two instance 5,280, and three instance 7,634. While Neo4J replica instances theoretically does not improve the addition of edges itself, checking for vertices can be done locally because all instances are exact same clones. That results in a slight speedup when multiple nodes are used, but was not very significant. JanusGraph achieved 3,614 edges/second for 1 Cassandra instance, and 3240 edges/second for 4 Cassandra instances on average during the run, and logs indicate a marked drop in performance as more vertices were inserted into the database.

Performance for SystemG was significantly higher, The speedup of SystemG on single node is 16.4× over Neo4J and 20.5× over JanusGraph. With multiple shards, SystemG was 18.3× faster than Neo4J, and 38.8× over JanusGraph on their best configurations.

8.3 Query analysis

In this section we analyze the performance of a simple BFS query against the data in various databases. While the distributed database is often very good at ingesting data and improving the query throughput, the tradeoff is that it often increases the execution time or latency for a single graph query. The reason for this is the fact that for most graph queries which takes the form of a graph traversal the data will be collected from multiple shards in an iterative process. The algorithm that we evaluate in this section was introduced in Section 5 Figure 2 We basically perform
BFS from a starting point and we stop the traversal after a given graph depth. This pattern is the backbone for various graph searches. We bound the depth of the traversal as the number of edges traversed may grow exponentially to the point where it can very quickly reach the whole graph. While this may be required in certain situations in practice, various application domain may impose a bound on the search space to guarantee certain performance bounds for a particular query. For example in the financial domain when deciding if a bank transaction is fraudulent or not for a particular query. For example in the financial domain when deciding if a bank transaction is fraudulent or not for a particular query.

For all BFS queries discussed in this section, we used the Higgs Twitter dataset which depicts a sparse graph of 14,855,842 directed edges in edgelist format, without property values.

For all BFS queries analyzed in this section we stop after four levels deep and we return as part of the query all unique vertices accessed by the traversal. For Neo4J we implemented the algorithm using the native Java API and we run the experiment in embedded mode similar to the SystemG single node. For the distributed case we evaluated one and twelve shards case, similar to previous experiments. While running distributed there is a query manager on one of the servers together with the shards of the database. Each shard will employ one master thread and the scheduler will use another four threads for executing incoming RPC with requests for data. In Figure 7 we show the result for performing 100K queries using 100K different start vertices. We used the same starting vertices, identified by external IDs, for all solutions considered and we verified that all solutions return the same number of edges traversed for each starting vertex. We considered a variable number of threads and when running with P threads the set of 100K start vertices was split in P blocks each thread performing the queries in one block. This is not a perfect way to split the work across threads because each query will be different, causing different amounts of work and possible leading to some unbalance between threads. However we don’t refine this in this work.

As we can see the SystemG single node graph database has the best performance overall finishing all 100K queries in 37.6 seconds using one thread. The results returned for individual traversals vary in size from one edge to a couple of thousand edges for the Higgs Twitter edge set considered. When using 16 concurrent threads the execution time for all queries reduces to 3.5 seconds for a 10.7× speedup. The speedup is not linear even though we mainly do read only operations. This is because all threads are running in the same memory address space and each query will allocate memory for internal queues and result vectors causing contention on the memory allocator. Neo4J scales from 67.3 seconds when using one thread to 41.1 seconds when using 4 threads and goes up after that. For Neo4J running more user threads impacts the database threads when running in embedded mode as they will all need to be scheduled on the same resources. For distributed one shard we pay the communication and one extra indirection overhead. In this case the client which runs on the frontend sends the request to the query manager which will execute the traversal for the client. The traversal involves a number of communications with the shards and when finished, the query manager will send the results back to the client. For the case when using one shard we essentially measure the overhead of the distributed implementation. We see the total execution time to be 125.7 seconds when using one client thread and 30.9 seconds when using 16 client threads for a speedup of 4.1×. For distributed with 12 shards we scale from 67.4 seconds for one thread to 20.9 seconds with 16 threads. With 12 shards, it still pays the communication delay, but the running time decreases due to parallel query processing for retrieving neighbor edges. Thus, we conclude that while there is a significant overhead of distributed querying compared to a single shard this is compensated for as we run more client threads, and more shards. The speedup of SystemG over Neo4J was 19.7× with the single node. Even with the overhead of distributed settings, SystemG obtained 1.3× speedup with 1 shard and 2.0× speedup with 12 shards.

We performed the query benchmark for JanusGraph as well using essentially the same code as for Neo4J with only few lines changed corresponding to the differences in API. The execution times however were much longer compared to Neo4J and SystemG. We estimated it will take hours to finish the initial set of 100K queries and decided not to complete the full test. This correlates with other results discussed in the literature.

### 8.4 Scalability

In this section, we show how the performance of SystemG scales with the number of Servers and shards. In Figure 8 (a), (b), and (c), the performance change of adding edges is shown, with the three methods of adding edges (SYNC, ASYNC, and Firehose). For the configuration, we used the combinations of 1, 2, 4 Servers and 1, 3, 6, 12 shards per server. We used 16 threads that make queries for SYNC and ASYNC edge additions. For SYNC and ASYNC algorithms, the performance scales well as the number of shards go up. The trend is more clear on ASYNC algorithms, since the number of communications between the query manager and the servers is much less. However, it can be seen that the performance starts to drop at around 3-6 shards per server. Each SystemG shard uses 6 threads internally, and if there are more threads in total than the number of cores (24 cores, which fits around 4 shards per server), context switching and scheduling overhead causes adversarial effects to the database even though the number of hardware threads are much more since the cores are running with smt8.

With Firehose however, the performance saturates quicker. The addition rate goes up steeply with one server.
Figure 8: Performance scalability of SystemG.

Figure 9: Timing breakdown on vertex addition.

9. CONCLUSION

In this paper, we presented SystemG, a single node graph database and its extension as a distributed graph database designed for ingesting and querying big relational data to meet the industry needs. We have shown the high level design and the main supporting modules like an efficient task based runtime system and RPC driven communication to allow for high throughput insertions as well as many parallel low latency queries. We introduced two novel concepts for a graph database: Firehose used for fast batched insertions and the Query Manager that will perform complex queries for client before returning results. We also presented two novel methods for adding edges in the context of undirected or directed with predecessors graphs. We evaluated the performance of both the single node and distributed graph database and provided for comparison performance numbers for two well established graph databases. Our graph solutions provide significantly better performances overall at the cost of a more relaxed consistency model that need to be compensated for by the programmer. As a future work, we are working on adding some very important features such as fault tolerance, distributed asynchronous queries and eventually distributed transaction support.

10. ADDITIONAL AUTHORS

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