GoFFish: A Sub-Graph Centric Framework for Large-Scale Graph Analytics

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November 26, 2013

†Under Review for a Conference, 2014
Abstract

Large scale graph processing is a major research area for Big Data exploration. Vertex centric programming models like Pregel are gaining traction due to their simple abstraction that allows for scalable execution on distributed systems naturally. However, there are limitations to this approach which cause vertex centric algorithms to under-perform due to poor compute to communication overhead ratio and slow convergence of iterative superstep. In this paper we introduce GoFFish a scalable sub-graph centric framework co-designed with a distributed persistent graph storage for large scale graph analytics on commodity clusters. We introduce a sub-graph centric programming abstraction that combines the scalability of a vertex centric approach with the flexibility of shared memory sub-graph computation. We map Connected Components, SSSP and PageRank algorithms to this model to illustrate its flexibility. Further, we empirically analyze GoFFish using several real world graphs and demonstrate its significant performance improvement, orders of magnitude in some cases, compared to Apache Giraph, the leading open source vertex centric implementation.
1 Introduction

The well-recognized challenge of “Big Data” manifests itself in many forms, ranging from data collection and storage, to their analysis and visualization. Massive datasets from large scientific instruments (e.g., Large Hadron Collider, Large-Synoptic Sky Survey) and enterprise data warehouses (e.g., web logs, financial transactions) offered the initial grand challenges for data-intensive computing that led to transformative advances such as distributed and NoSQL databases, the MapReduce programming model and datacenters based on commodity hardware. The unprecedented volume of data was the dimension of “bigness” that was addressed here.

With the proliferation of ubiquitous physical devices (e.g., urban monitoring, smart power meters [?]) and virtual agents (e.g., Twitter feeds, Foursquare check-ins) that sense, monitor and track human and environmental activity, the volume of intrinsically interconnected datasets is increasing. Indeed, a defining characteristic of such datasets endemic to both the Internet of Things [?] and Social Networks is the relationships that exist within them. Such graph datasets offer unique challenges to scalable Big Data management and analysis even as they are becoming pervasive.

There has been significant work on parallel algorithms and frameworks for large graph applications on HPC clusters [?], massively multithreaded shared memory architecture [?], and GPGPUs [?]. Our focus in this paper, however, is on leveraging commodity hardware for scaling graph analytics, as such distributed infrastructure, including cloud infrastructure, have democratized access to computing resources. This is evident from the proliferation of Big Data programming models and frameworks, such as Hadoop/MapReduce [?], for composing and executing applications. Besides resource access, another reason for MapReduce’s success [?] is the simple programming model, which is constantly evolving [?] and lowering the barrier to build scalable applications. However, its tuple-based approach is ill-suited for many graph applications [?]

Recent platforms for graph analytics range from graph databases to vertex-centric programming abstractions [?]. In particular, Google’s Pregel [?] marries the ease of specifying a uniform application logic for each vertex with a Bulk Synchronous Parallel (BSP) execution model [?]. Vertex executions that take place independently in a distributed environment are interleaved with synchronized message exchanges across them to form supersteps that execute iteratively Apache Giraph [?] is a popular open-source implementation of Pregel [?] that has been scaled to trillions of edges\footnote{https://www.facebook.com/notes/facebook-engineering/scaling-apache-giraph-to-a-trillion-edges/173551957882092}

\footnote{http://www.graph500.org}
However, there are a few short-comings to this approach. (1) Operating on each vertex independently, without a notion of shared memory, requires costly message exchanges at superstep boundaries. (2) Porting shared memory graph algorithms to a vertex centric one is also not simple, as it limits algorithmic flexibility. A trivial mapping can have punitive performance. (3) The programming abstraction is decoupled from the data layout on disk. Using naïve vertex distribution across machines can cause I/O penalties at initialization and at runtime. Recent research suggest some benefits from intelligent partitioning [?].

In this paper, we propose a sub-graph centric programming abstraction, **Gopher**, for performing distributed graph analytics. This abstraction balances the flexibility of reusing well-known shared-memory graph algorithms with the simplicity of a vertex centric iterative programming model that elegantly scales on distributed environments. We couple this abstraction with an efficient distributed storage, **Graph oriented File System (GoFS)**. GoFS partitions graphs across hosts while coalescing connected components within partitions to optimize sub-graph centric access patterns. Gopher and GoFS are co-designed as part of the **GoFFish** framework to ensure that the data layout is intelligently leveraged during execution time.

We make the following specific contributions in this paper:

1. We propose a sub-graph centric programming model for composing graph analytics (§3), and map common graph applications to this model (§5).

2. We present the GoFFish architecture which includes **GoFS** for distributed graph storage and **Gopher** for executing sub-graph centric applications (§4).

3. We experimentally evaluate the proposed model for scaling common graph algorithms on real world graphs, and compare it against Giraph (§6).

## 2 Related Work

The popularity of MapReduce [?] for large scale data analysis has extended to graph data as well [?], with research techniques to scale it to peta-bytes of graph data for some algorithms [?, ?]. However, the tuple-based approach of MapReduce makes it unnatural to develop graph algorithms, often requiring multiple MapReduce stages [?], additional programming constructs [?] or specialized platform tuning [?]. While the platform may scale, it is not the most efficient or intuitive for many graph algorithms, often reading and writing the entire graph to disk several times.

edges/10151617006153920
Message passing has been an effective model for developing scalable graph algorithms [?]. In particular, the Bulk Synchronous Parallel (BSP) model proposed by Valiant [?] has been adopted by Google’s Pregel [?] for composing vertex centric graph algorithms. GraphLab takes a similar vertex centric approach [?]. Here, the computation logic is developed from the perspective of a single vertex. The vertices operate independently (in parallel) and are initially aware only of their neighboring vertices. After the computation step, the vertices perform bulk message passing with their neighboring vertices (or other vertices they discover). Computation is done iteratively through a series of barriered supersteps that interleave computation with bulk message passing [?]. This approach naturally fits a distributed execution model, eliminates deadlock and race concerns of asynchronous models, and simplifies the programming.

Despite its growing popularity, the vertex centric model has its deficiencies. Shared memory algorithms cannot be trivially mapped to such a vertex centric model and novel algorithms for standard graph operations need to be developed. For many graph algorithms the work performed on each vertex is negligible, and the overhead of massive parallelization per vertex and the synchronization overhead per superstep can out-weigh the benefits. Our sub-graph centric model of computing offers the additional flexibility of using shared memory algorithms to deliver significant performance benefits.

Apache Giraph [?] is an open source implementation of Google’s Pregel that is being adopted by Facebook, among others. Alternatives such as Hama [?], Pregel.NET [?] and GPS [?] also exist. Giraph executes the vertex centric program using Hadoop Map-only tasks. It also offers additional programmatic extensions and engineering optimizations such as master-compute model, message aggregation, and memory compression. Many of these focus on reducing the number of messages passed since the messaging overhead is dictated by the number of edges in the graph. For graphs with power-law edge distribution, highly connected vertices can overwhelm the network and memory with messages.

GPS [?] studies the effect of static partitioning on the Pregel model and introduces runtime optimizations by performing dynamic partition balancing and replicating highly connected vertices to neighbors. Our own work on Pregel.NET [?] used a swathe-based incremental scheduling to amortize the messaging overhead across staggered supersteps for all-pairs algorithms like Betweenness Centrality and All Pairs Shortest Path. While these optimizations by Giraph, GPS and Pregel.NET attempt to reduce inefficiencies through engineering approaches, we posit in this paper that the vertex centric model in itself needs to be enhanced to a sub-graph centric model to address critical performance deficiencies.

Besides Pregel, there are other distributed graph processing systems such as Trinity [?] that offer a shared memory abstraction within a distributed memory in-
Algorithms can use both message passing and a global distributed address space called memory cloud. However, it assumes large memory machines with high speed interconnects. We focus on commodity cluster and do not make any assumptions about the underlying infrastructure. Others such as Kineograph focus on realtime analysis of streaming graphs. Our focus here is on static graphs that are analyzed offline on distributed commodity systems. Separately, there is ongoing work to support analytics over timeseries of graphs using GoFFish.

There is a large body of work on parallel graph processing for high performance systems such as HPC clusters, massively multithreaded architectures like the Cray XMT and GPGPUs. Our focus in this paper is on commodity clusters and infrastructure Clouds that are interconnected by high-latency Ethernet, spinning disks and no shared memory. We evaluate the scalability of our framework on such accessible commodity hardware, and do not compete with high end infrastructure or runtimes optimized for them. However, parallel graph algorithms developed for these other platforms may still be relevant. Indeed, the BSP model we leverage was developed by Valint for parallel computing in 1980.

3 Sub-graph Centric Programming Abstraction

3.1 Vertex Centric Programming Model & Gaps

Vertex centric programming models like Pregel offer a simple abstraction for composing graph algorithms for distributed systems. Vertices in the graph are partitioned across machines. Users implement a Compute method that gives them access to a single vertex and its value(s), the outgoing edge list for the vertex, and the ability to send custom messages to vertices that these edges are incident upon. The execution model is iterative, based on a Bulk Synchronous Parallel (BSP) paradigm. The Compute method is executed independently for each vertex and messages it generates to neighboring vertices are available to them only after Compute completes for all vertices. This forms one superstep. A barrier synchronization at the end of a superstep ensures that all generated messages are delivered to destination vertices before the next superstep’s Compute method is invoked for each vertex with the input messages. The vertices can VoteToHalt in their Compute method; any vertex that has voted to halt is not invoked in the next superstep unless it has input messages. The application terminates when all vertices have voted to halt and there are no new input messages available in a superstep.

Pseudocode to find the maximum value among all vertices is shown in Algorithm. Each vertex sends its value to neighboring vertices in the first superstep. In later supersteps, it updates its value to the highest value among all incoming messages. If changed, it sends its value to its neigh-
bors; otherwise, it votes to halt. The application terminates when all vertices have reached a steady state value, which equals the largest vertex’s value.

**Algorithm 1** Max Vertex using Vertex Centric Model

1: procedure **COMPUTE**(Vertex myVertex, Iterator(Message) M)
2:     hasChanged = (superstep == 1) ? true : false
3:     while M.hasNext do  
4:         Message m ← M.next
5:         if m.value > myVertex.value then
6:             myVertex.value ← m.value
7:             hasChanged = true
8:     if hasChanged then  
9:         **SEND**TO**AL**L**NEIGH**B**ORS**(myVertex.value)
10:     else
11:         **VOTE**TO**HALT**()

Despite the simplicity of programming, there are two key scalability bottlenecks in this vertex centric approach: (1) the number of messages exchanged between the vertices, and (2) the number of synchronized supersteps required for completion. Typically, vertices are hashed and distributed across multiple machines (assuming one worker per machine). Message passing is done either in-memory (for vertices on the same machine) or over the network, while barrier synchronization across vertices on distributed machines is centrally coordinated. Vertices can often perform only light computations, making them communication bound. Network messaging is costly given the commodity hardware of data centers, and not every algorithm can benefit from Combiners to reduce messages generated within a worker. The default mapping of vertices to machines using (random) hashing exacerbates this though better a priori partitioning shows only limited improvements. Even when passing messages in-memory to co-located vertices, the number of intermediate messages between superstep can overwhelm the physical memory, requiring disk buffering for algorithms such as Betweenness Centrality. At the same time, the number of supersteps taken by a vertex centric algorithm can be large. Some like PageRank may use a fixed number of supersteps (e.g. 30) while others such as Max Vertex are bound by the diameter of the graph. For e.g., the LiveJournal social network with ~4.8M vertices has edge degrees with powerlaw distribution and a diameter of 16 while the California road network with ~1.9M vertices has a diameter of 849 (Table I). The synchronization time is cumulative over supersteps and can thus be significant.
3.2 Sub-graph Centric Programming

We propose a sub-graph centric programming abstraction that targets these deficiencies. As with Pregel, we operate in a distributed environment where the graph is $k$-way partitioned over its vertices across $k$ machines. Further, we define a sub-graph as a connected component within a partition of an undirected graph; they are weakly connected if the graph is directed (Fig. 1).

Let $P_i = \{V_i, E_i\}$ be a graph partition $i$ where $V_i$ and $E_i$ are the set of vertices and edges in the partition. We define a sub-graph $S$ in $P_i$ as $S = \{V, E, R\}$ where $V$ is a set of local vertices, $E$ is a set of edges and $R$ is a set of remote vertices. Two sub-graphs do not share the same vertex but can have remote edges that connect their vertices, as long as the sub-graphs are on different partitions. If two sub-graphs on the same partition share an edge, by definition they are merged into a single sub-graph. A single partition can have one or more sub-graphs and the set of all sub-graphs forms the complete graph. Specific partitioning approaches are discussed later, and each machine holds one partition. In other words, sub-graphs behave like “meta vertices” with remote edges connecting them across partitions.

As with a vertex centric model, each sub-graph is treated as an independent unit of computation within a superstep. Users implement the following method signature:

$$ \text{Compute}(\text{Subgraph}, \text{Iterator<Message>}) $$

The Compute method can access the sub-graph topology and values of the vertices and edges. The values are mutable though the topology is constant. This
allows us to fully traverse the sub-graph up to the boundary remote edges in-memory, within a single superstep and accumulate values of the sub-graph or update values for the local vertices and edges. There is no shared memory across sub-graphs. Instead, they communicate by message passing, with messages being exchanged at synchronized superstep boundaries, as with the BSP model. Several methods enable this messaging.

Algorithms often start by sending messages to neighboring sub-graphs. These are by definition on remote partitions.

SendToAllSubGraphNeighbors(Message)

As other sub-graphs are discovered, as part of the traversal and as messages propagate, two other methods are useful:

SendToSubGraph(SubGraphID, Message)
SendToSubGraphVertex(SubGraphID, VertexID, Message)

We also allow a global broadcast to all sub-graphs, though this is costly and should be used sparingly.

SendToAllSubGraphs(Message)

As with a vertex centric approach, the Compute method can invoke VoteToHalt() on the sub-graph and the application terminates when all sub-graphs have halted and there are no new input messages.

Algorithm 2 presents the sub-graph centric version for finding the maximum value among all vertices in a graph and Fig. 2 shows its execution. Instead of a vertex, the Compute method operates on a sub-graph mySG. Lines 2–6 are executed only for the first superstep, where all sub-graph’s value are initialized to largest value among its vertices. Subsequently, the algorithm is similar to the vertex centric version: we send the sub-graph’s value it its neighboring sub-graphs and update the sub-graph’s value to the highest value received, halting when there is no further change. At the end, each sub-graph has the value of largest vertex.

Compared to the vertex centric algorithm, the sub-graph centric version reduces the number of supersteps taken since the largest value discovered at any superstep propagates through the entire sub-graph in the same superstep. For e.g., for the graph in Fig. 2, the vertex centric approach takes 7 supersteps while we use 4. In addition to reducing the superstep synchronization overhead, this also reduces the cumulative number of messages exchanged over the network. In the worst case, when a sub-graph is trivial (has just one vertex), we degenerate to a vertex centric model.
Figure 2: Sub-graph centric maximum value computation for graph from Fig. 1.

Top row shows the graph at start with vertices having the initial value. Each row of rectangles is one superstep; each rectangle is an independent sub-graph computation. Dashed arrows show messages passed at superstep boundaries. Vertices in a sub-graph have shared memory; those across sub-graphs do not. Vertex values are shown for the end of each superstep. Shaded sub-graphs have voted to halt.

Algorithm 2 Max Vertex using Sub-Graph Centric Model

1: procedure COMPUTE(SubGraph mySG, Iterator(Message) M)
2:   if superstep = 1 then ▶ Find local max in subgraph
3:     mySG.value ← −∞
4:     for all Vertex myVertex in mySG.vertices do
5:       if mySG.value < myVertex.value then
6:         mySG.value ← myVertex.value
7:     hasChanged = (superstep == 1) ? true : false
8:   while M.hasNext do
9:     Message m ← M.next
10:    if m.value > mySG.value then
11:      mySG.value ← m.value
12:      hasChanged = true
13:   if hasChanged then
14:     SENDTOALLSUBGRAPHNighbors(mySG.value)
15:   else
16:     VOTEToHALT( )
3.3 Benefits

More generally, this simple and elegant extension from the vertex centric model offers several important benefits.

1) Messages Exchanged. Access to the entire sub-graph enables the application to make a significant progress within each superstep while reducing costly message exchanges that cause network transfer overhead, disk buffering costs or memory pressure, between supersteps. Even if messages are generated for every remote edge from a sub-graph, messages destined to the same sub-graph can be intelligently grouped to mitigate network latency. While Pregel allows Combiners to be defined per worker, their ability to operate only on the generated messages limits their utility. Access to the entire sub-graph topology and values allows for more flexible and efficient algorithms that inherently reduce the number of generated messages.

2) Number of Supersteps. Depending on the type of graph application, a sub-graph centric model can also reduce the number of supersteps required to complete the application. This can reduce the time spent on superstep synchronization. Further, the time taken by a superstep is based on its slowest worker and there can be a wide distribution between the fastest and slowest workers [?]. Reducing the number of supersteps mitigates the cumulative impact of this skew. For traversal based algorithms, the number of supersteps is a function of the longest shortest-path distance between any two vertices in the graph i.e. the diameter of the graph. Intuitively, the diameter corresponds to the maximal height of the BFS tree rooted at any vertex in the graph. In a sub-graph centric model, this becomes the diameter of the meta-graph where the sub-graphs form meta-vertices. In the best case (a linear chain), the number of supersteps can reduce by a factor proportional to the number vertices in the sub-graph, while at the other extreme (trivial sub-graph), it is no worse than the number of supersteps taken for a vertex-centric model. We should note that this improvement may be nominal for small-world networks with small diameters, and also for non-traversal based algorithms, like PageRank, as we discuss later.

3) Reuse of Single-machine Algorithms. Lastly, the programming overhead introduced by a sub-graph centric approach relative to a vertex-centric approach is incremental. Often, it involves using a shared-memory graph algorithm on the sub-graph (e.g. Algorithm 2, lines 2–6 with shaded line numbers) and then switching to an approach similar to a vertex-centric one but treating sub-graphs as vertices (lines 7–16). Given that efficient graph algorithms for single machines are known, even leveraging many cores or accelerators, the potential impact on programming ease is offset by the increase in programming flexibility and performance.
Figure 3: Bulk Synchronous Execution of Sub-graph centric computation across supersteps.

4 Architecture

GoFFish is a scalable software framework for storing graphs, and composing and executing graph analytics in a Cloud and commodity cluster environment. A Graph oriented File System (GoFS) and Gopher execution engine are co-designed ab initio to ensure efficient distributed storage for sub-graph centric data access patterns during loosely coupled execution. The design choices target commodity or virtualized hardware with Ethernet and spinning disks rather than HPC environments with low latency networking and disks. GoFFish is implemented in Java.

https://github.com/usc-cloud/goffish
4.1 GoFS Distributed Graph Store

GoFS is a distributed store for partitioning, storing and accessing graph datasets across hosts in a cluster. Graphs can have both a topology and attributes associated with each vertex and edge. The former is an adjacency list of uniquely labeled vertices and (directed or undirected) edges connecting them. Attributes are a list of name-value pairs with a schema provided for typing. Input graphs are partitioned across hosts, one partition per machine, using the METIS tool \[?\] to balance vertices per partition and minimize edge cuts (Fig. [3]).

GoFS uses a sub-graph oriented model for mapping the partition’s content to slice files, which form units of storage on the local file system. We identify all sub-graphs in the partition – components that are (weakly) connected through local edges, and a partition with \( n \) vertices can have between 1 to \( n \) sub-graphs. Each sub-graph maps to one topology slice that contains local vertices, local edges and remote edges, with references to partitions holding the destination remote vertex, and several attribute slices that hold their names and values. We use Kryo to efficiently convert slices objects into a compact binary form on file with smaller disk access costs.

GoFS is a write once-read many scalable graph data store rather than a database with rich update and query support. The GoFS Java API allows clients to access a graph’s metadata, attribute schema and sub-graphs present in the local partition. Specific sub-graphs and select attributes can be loaded as a Java object for in-memory traversals of local vertices and edges. Remote edges in a sub-graph resolve to a remote partition, sub-graph and vertex ID that are then accessed locally on that machine.

4.2 Gopher Sub-graph Centric Framework

Gopher is a programming framework that offers our proposed sub-graph centric abstractions (Sec. [3.2]), and executes them using the Floe \[?\] dataflow engine on a Cloud or cluster in conjunction with GoFS. It inherits the natural scalability of the vertex centric model but extends it further. Users implement their algorithm in Java within a Compute method where they get access to a sub-graph and data messages from the previous superstep. They can use the Send* methods to send messages to sub-graphs in the next superstep and call the VoteToHalt method. The same Compute method logic is executed on every sub-graph in the graph, on all partitions, for each superstep.

The Gopher framework has a compute worker service running on each machines in the cluster and a additional manager service on one machine. Gopher deploys the user’s compute logic to the workers to operate on a particular graph.
The workers initially load all local sub-graphs for that graph into memory using GoFS. For every superstep, it uses a thread pool optimized for multi-core CPUs to invoke the Compute on each sub-graph. Send* data messages emitted by the Compute are resolved by GoFS to the remote partition and host. The worker aggregates messages destined for the same host and sends them over TCP sockets to the remote worker asynchronously as the compute continues to run.

When the Compute for all sub-graphs in a partition complete in a superstep, the worker flushes all pending messages to the remote workers and then sends a synchronization control message to the manager. Once the manager receives sync messages from all workers, it broadcasts a resume control message to the workers to start their next superstep. The workers then call the Compute method again on their sub-graphs and also pass them a list of data messages received from the previous superstep. The method is stateful for each sub-graph; so local variables are retained across superstep. Compute is called for a sub-graph only if (1) it has not voted to halt in the previous superstep and (2) it has received no input messages. When a worker does not have to call Compute for any of its sub-graphs in a superstep, it sends a ready to halt control message to the manager. When all workers are ready to halt at a superstep, the manager sends a terminate control message for the workers to stop.

4.3 Storage-Compute Co-design

Designing data layout and execution models together helps data-intensive applications, as seen with Hadoop and HDFS. Unlike their tuple-based model, GoFFish emphasizes sub-graphs as a logical unit of storage and compute. Hence our data distribution is based on graph partitioning followed by sub-graph discovery. While there is a higher overhead in loading data into GoFS, this layout minimizes runtime network data movement in Gopher. The distributed layout also maximizes cumulative disk read bandwidth across machines when loading sub-graphs into Gopher. We also balance the disk latency (# of unique files read) against sequential bytes read: having separate slice files for a sub-graph’s topology and attributes allows only those slices to be read from disk, but they can be read in their entirety. For e.g. a graph with 10 attributes on its vertices and edges but using only the edge weight for a Gopher algorithm needs to only load that slice.

Partitioning can impact the performance of several sub-graph centric algorithms we have analyzed and will show empirically. Since we use out-of-the-box tools like METIS for partitioning, these help balance vertices and minimize edge cuts. However, ideally, we should be balancing the number of sub-graphs across partitions and have uniform sizes, in addition to reducing edge cuts. This can help workers complete a superstep in the same time. Also, if the number of sub-graphs
in a partition is a multiple of the number of cores in a machine, we can optimally leverage the parallelism. While some of these partitioning schemes are for future work, the design sets clear goals for this optimization.

5 Sub-Graph Centric Graph Algorithms

We present several sub-graph centric algorithms for common graph analytics, both to illustrate the utility and discuss the benefits of our proposed abstraction. We also highlight the algorithmic optimizations that are possible using a sub-graph centric model, relative to a vertex centric one.

5.1 Connected Components

Connected components identify maximally connected sub-graphs within an undirected graph such that there is path from every vertex to every other vertex in the sub-graph. The sub-graph centric algorithm (and the vertex centric one) for connected components is similar to the Maximum Value algorithm (Algorithm 2). It in itself is based on the HCC algorithm [2]. Briefly, assuming each vertex has a unique identifier, we propagate the ID of the vertex with the largest ID value within a sub-graph to its connected neighbors. In effect, we perform a breadth first traversal rooted at the sub-graph with the largest vertex ID, with each superstep traversing one more level till the farthest connected sub-graph is reached. We will eventually have vertices labeled with the component ID (i.e. largest vertex ID) they belong to. The number of unique vertex values gives us the number of components.

The computational complexity of this algorithm is $O((d + 1) \times v/p)$, where $d$ is the diameter of the graph (specifically, of the largest connected component) constructed by treating each sub-graph as a meta vertex, $v$ is the number of vertices in the graph and $p$ is the degree of parallelism. $p$ equals the number of machines (or partitions) in the cluster, assuming the number of vertices per machine is balanced. In fact, if there are at least as many uniformly sized sub-graphs per partition as the number of cores, the value of $p$ approaches the total number of cores in the cluster. The key algorithmic optimization in this case comes from reducing the number of supersteps $(d + 1)$ relative to the vertex centric model.

5.2 Single Source Shortest Path (SSSP)

Single Source Shortest Path (SSSP) determines the shortest distance from a source vertex to every other vertex in the graph. Intuitively, the sub-graph centric algorithm finds the shortest distances from the source vertex to all internal vertices (i.e. not having a remote edge) in the sub-graph holding the source in one superstep.
using Dijkstra’s (Algorithm 3). It then sends the updated distances from the vertices having a remote edge to their neighboring sub-graphs. These sub-graphs propagate the changes internally, in one superstep, and to their neighbors, across supersteps, till the distance values quiesce.

The time complexity of this algorithm is a function of the time taken to perform Dijkstra on the sub-graphs in a superstep and the number of supersteps. Using a priority queue in Dijkstra, we take $O(\log(v))$ for vertex lookups, and this is performed for each of $e$ edges in a sub-graph with $v$ vertices. This gives a compute time of $O((e \cdot \log(v)))$ per superstep, where $e$ and $v$ are typically dominated by the largest active sub-graph in a superstep. The number of supersteps is a function of the graph diameter $d$ measured through sub-graphs, and this takes $O(d)$ supersteps. For a partitions having a large number of small sub-graphs, we need to multiple this by a factor $s/c$ where $s$ is the number of sub-graphs in a machine and $c$ the level of concurrency (i.e. number of cores) on that machine. As compared to a vertex centric approach, the time complexity per superstep is larger since we run Dijkstra (rather than just update distances for a single vertex), but we may significantly reduce the number of supersteps taken for the algorithm to arrive at the shortest vertex distances.

5.3 PageRank and BlockRank

PageRank calculates the rank of a web page based on the probability with which an idealized random web surfer will end on that page [?]. For each superstep in a vertex centric model [?], a vertex adds all input message values into $sum$, computes $0.15/v + 0.85 \times sum$ as its new value, and sends value/g to its $g$ neighbors. The value is $1/v$ initially, for $v$ vertices in the graph. An equivalent sub-graph centric approach does not confer algorithmic benefits; it takes the same $\sim 30$ supersteps to converge and each vertex operates independently in lock step, with an $O(30 \cdot v^p \cdot c \cdot g)$, for $g$ average edge degree.

The BlockRank algorithm, however, uses the property that some websites are highly inter-connected (i.e. like sub-graphs) to set better initial vertex values that hasten convergence. It calculates the PageRank for vertices by treating blocks (sub-graphs) independently (1 superstep); ranks each block based on its relative importance (about 1 superstep); and normalizes the vertex’s PageRank with the BlockRank to use as an initial seed before running classic PageRank ($n$ supersteps). The first superstep is costlier as the sub-graphs estimate PageRanks for their vertices, but converges in fewer (local) iterations [?]. Similarly, the last $n$ supersteps too converge more quickly than $\sim 30$, thus using fewer supersteps than classic PageRank.
Algorithm 3 Sub-Graph Centric Single Source Shortest Path

1: procedure COMPUTE(SubGraph mySG, Iterator<Message> M)
2:     openset ← ∅ ▶ Vertices with improved distances
3:     if superstep = 1 then ▶ Initialize distances
4:         for all Vertex v in mySG.vertices do
5:             if v = SOURCE then
6:                 v.value ← 0 ▶ Set distance to source as 0
7:                 openset.add(v) ▶ Distance has improved
8:             else
9:                 v.value ← −∞ ▶ Not source vertex
10:         for all Message m in M do ▶ Process input messages
11:             if mySG.vertices[m.vertex].value > m.value then
12:                 mySG.vertices[m.vertex].value ← m.value
13:                 openset.add(m.vertex) ▶ Distance improved
14:     remoteSet ← DIJKSTRAS(mySG, openset)
15:     for all (remoteSG, vertex, value) in remoteSet do
16:         SENDTOSUBGRAPHVERTEX(remoteSG, vertex, value)
17:     VOTEToHALT()  
18: 
19: procedure DIJKSTRAS(Set<Vertex> openset)
20:     remoteOpenset ← ∅
21:     while openset ≠ ∅ do
22:         Vertex v ← GETSHORTESTVERTEX(openset)
23:             for all Vertex v2 in v.neighbors do ▶ Update neighbors, notify if remote.
24:                 if v2.isRemote() then
25:                     remoteOpenset.add(v2.subgraph, v2, v.value + 1)
26:                 else if v2.value > v.value + 1 then
27:                     v2.value ← v.value + 1
28:                     openset.add(v2) ▶ Distance has improved
29:             openset.remove(v) ▶ Done with this local vertex
30:     return remoteOpenset
5.4 Discussion

In summary, the relative algorithmic benefits of using a sub-graph centric abstraction can be characterized based on the class of graph algorithm and graph. For algorithms that perform full graph traversals, like SSSP, BFS and Betweenness Centrality, we reduce the number of supersteps to a function of the diameter of the graph based on sub-graphs rather than vertices. This can offer significant reduction. However, for powerlaw graphs that start with a small vertex based diameter, these benefits are muted. For algorithms that use fixed numbers of iterations, like classic PageRank, there may not be any reduction unless we use alternatives like BlockRank.

The time complexity per superstep can be larger since we often run the single-machine graph algorithm on each sub-graph. The number of vertices and edges in large sub-graph will impact this. If there are many small sub-graphs in a partition, the number of sub-graphs becomes the limiting factor as we approach a vertex centric behavior. For graphs with high edge density, algorithms that are a linear (or worse) function of the number of edges can take longer supersteps. Also, for algorithms like SSSP, such graphs offer more paths through remote vertices thus taking more supersteps to converge.

6 Performance Analysis

We evaluate the GoFFish framework against Apache Giraph, a popular open source implementation of Google’s Pregel vertex centric programming model that uses HDFS storage. We use the latest development version of Giraph, at the time of writing, which includes performance enhancements like lazy de-serialization, staggered aggregators, and multi-threaded data reads contributed by Facebook. We analyze the relative performance of sub-graph centric Gopher and vertex centric Giraph for representative graph algorithms: Connected Components, Single Source Shortest Path (SSSP) and (classic) PageRank, as discussed in Sec. [5]

6.1 Experimental Setup and Datasets

We run these experiments on a cluster of 12 nodes, each with an 8-core Intel Xeon CPU, 16 GB RAM and 1 TB SATA HDD, and connected by Gigabit Ethernet. Both Giraph and GoFFish are deployed on all nodes. Giraph is configured with the default two workers per node and 8 GB RAM per worker. GoFFish runs a single worker per node with 16 GB RAM, with one node also hosting the manager. Both run on Oracle Java 7 JRE for 64 bit Ubuntu Linux.
Table 1: Characteristics of graph datasets used in evaluation

| Dataset          | Vertices   | Edges        | Diameter | WCC   |
|------------------|------------|--------------|----------|-------|
| RN: California Road Network | 1,965,206  | 2,766,607    | 849      | 2,638 |
| TR: Internet from Traces   | 19,442,778 | 22,782,842   | 25       | 1     |
| LJ: LiveJournal Social Network | 4,847,571  | 68,475,391   | 10       | 1,877 |

We choose a range of real world graphs (Table 1): California road network (RN), Internet route path network constructed from a CDN traceroute dataset (TR), and a snapshot of the LiveJournal social network (LJ). These graphs are diverse. RN is a relatively small, sparse network with an even distribution of small edge degrees and a large diameter. LJ, on the other hand, is dense graph with powerlaw edge degrees and a small diameter. TR has a powerlaw edge degree too, with a small number of highly connected vertices (ISPs and a vertex used to indicate trace timeouts).

Unless otherwise stated, we report average values over three runs each for each experiment. The entire cluster is dedicated to either GoFFish or Giraph during a run.

6.2 Summary Results

We compare the end-to-end time (makespan) for executing an algorithm on GoFFish and on Giraph which includes two key components: the time to load the data from storage and the time to run the sub-graph/vertex centric computation. Fig. 4(a) summarizes the total execution time for various algorithms and datasets for both platforms. Also shown in Fig. 4(c) is the number of supersteps taken to complete the algorithm for each combination. Lastly, Fig. 4(b) highlights the data loading time per graph on both platforms – the time to initially fetch the graphs from disk to memory objects, which does not change across algorithms if the same attributes are loaded.

One key observation is that GoFFish’s makespan is smaller than Giraph for all combination but two, PageRank and SSSP on LJ. The performance advantage ranges from being $81 \times$ faster for Connected Components on RN to $11\%$ faster for PageRank on TR. These favorable numbers span across graphs and algorithms, but result from abstraction, design and layout choices; likewise for the two slower runs. In some, Giraph’s data loading time from HDFS dominates (TR), in others, Gopher’s sub-graph centric algorithmic advantage significantly reduces the number.
of supersteps (RN for Connected Components and SSSP), while for a few, the Gopher’s compute time over sub-graphs dominates (PageRank on LJ). These are discussed further.

6.3 Connected Components

Connected Components for GoFFish performs significantly better than Giraph for all three data sets – from $1.4 \times$ to $81 \times$. This is largely due to the algorithmic advantage that is offered by a sub-graph centric model. Fig. 4(c) shows the number of supersteps is much smaller for Gopher compared to Giraph, taking between 5 (TR, LJ) and 7 (RN) supersteps for Connected Components while Giraph takes between 11 (LJ) and 554 (RN). This reduction in the number of supersteps is the key reason that we see the makespan reduce sharply for GoFFish, and the superstep time in itself is dominated by the synchronization overhead since the actual sub-graph/vertex computation done for Connected Components is negligible.

As posited before, the number of supersteps for a traversal algorithm like Connected Components is bounded by the graph diameter. For sub-graph centric algorithms, this is the graph diameter when considering each sub-graph as a meta vertex. If we remove the data loading time (Fig. 4(b)) from the makespan to look at just at the ratio of compute times between Giraph and Gopher for Connected Components, we observe that this compute improvement ratio is highly correlated ($R^2 = 0.9999$) with the vertex-based diameter of the graph (Table 1), i.e., larger the vertex-based graph diameter, greater the opportunity to reduce sub-graph-based diameter, lesser the number of supersteps for traversal algorithms, and better that Gopher performs.

The TR graph has a smaller vertex-based diameter and yet its makespan performance for Connected Components on Gopher is $21 \times$ better than Giraph. This improvement is primarily due to much faster data loading in GoFS ($38$ secs) compared to HDFS ($798$ secs) for TR (Fig. 4(b)). The data layout of GoFS was designed for Gopher and ensures that network transfer is not needed when loading the sub-graphs initially. However, Giraph uses HDFS, which by default balances the vertices across partitions. In this case, there is one vertex with a large edge degree (O(millions)) that takes punitively long to load into memory objects. The compute time itself is just $1$ sec and $23$ secs for Gopher and Giraph respectively.

For LJ, we do not see a significant improvement for GoFFish over Giraph, with a $3$ sec improvement in load time and $18$ sec advantage in compute time. LJ is a dense, highly connected graph with a small vertex-based diameter. It does not offer a large reduction in the number of supersteps from Giraph to Gopher ($11 \rightarrow 5$), nor does HDFS under-perform for this graph. In fact, as other results show, LJ is the kind of graph that offers limited benefits for a sub-graph centric
6.4 SSSP

SSSP for GoFFish out-performs Giraph by $78\times$ and $10\times$ for RN and TR, respectively, while it is marginally slower for LJ by 5secs, compared to Giraph’s 60secs. Gopher takes similar number of supersteps for both Connected Components and SSSP, but its computational complexity per superstep is different for the two algorithms: $O(v)$ vs. $O(e \cdot \log(v))$. As a result, the time spent on running Dijkstra on the sub-graphs for SSSP is comparable to the time spent on I/O (for Connected Components, compute time was negligible). This fraction is higher for graphs with higher edge density, such as LJ. E.g., we spend 4secs for SSSP compute on RN ($\sim 2M$ vertices, 2.7M edges) while we spend 42secs on LJ ($\sim 4.8M$ vertices, 68M edges).

This heightened computational complexity of SSSP for Gopher impacts its relative performance with Giraph too. Giraph’s vertex centric Compute performs a simple check and forward operation, with constant time complexity. As a result, we see that for LJ with high edge density, the sub-graph centric model cumulatively takes as long as Giraph for the compute time, at 43secs against Giraph’s 42secs, and both spend about the same time on initial data loading. As noted before, LJ is a small world network with small diameter, and the reduction in the number of supersteps between Giraph and Gopher is modest (Fig. 4(c)). Hence, for LJ, the advantage of fewer supersteps is offset by the higher cost per superstep.

Gopher does outperform Giraph on compute time, data loading time and number of supersteps for RN and TR, taking 4secs and 53secs for computation against Giraph’s 1,182secs and 102secs. Both these graphs have sparse edges densities (smaller impact on compute time) and RN has a wider vertex based diameter too (fewer supersteps).

6.5 PageRank

PageRank is a canonical web graph algorithm and well suited for a vertex centric model. All vertices can operate independently, and converge iteratively to their rank value. The computation per superstep is uniform as is the messages exchanged in each. The vertex parallel algorithmic simplicity of PageRank gives it good performance on Giraph. Gopher implements the classic PageRank, simulating one iteration of vertex rank updates within a sub-graph per superstep, and running for the same 30 supersteps as Giraph. As a result, it does not benefit from reducing the number of supersteps.
As shown in Fig. 4(a), Gopher shows the least improvement against Giraph for PageRank. It is $4 \times$ and $1.5 \times$ faster for RN and TR. However, it is $2.6 \times$ slower than Giraph for LJ. In fact, if we ignore the initial graph loading time (Fig. 4(b)), both TR and LJ are slower in Gopher by $2.6 \times$. The cause for this can be traced to under-utilization of cores within a machine and machines across the cluster due to the variable times taken by different sub-graphs to complete.

In TR, there is one partition 5 that is a straggler in Gopher, taking $\sim 2.4 \times$ longer to complete than the next slowest, partition 3 (Fig. 5(a)). This means that workers in the 11 other machines are idle for over 58% of the superstep duration as the worker in partition 5 completes. This under-utilization of machines accumulates over the 30 supersteps.

For LJ, the problem is subtly different. While many of the partitions complete their superstep within a narrow range of 23 – 26 secs (Fig. 5(b)), these are due to single large sub-graphs in each partition, i.e., these sub-graphs are stragglers within a machine causing under-utilization of the three other cores. In fact, across partitions, the second slowest sub-graph finishes within 0.1 secs, causing 75% of the cores to be idle for most of the superstep. This again is cumulative across the 30 supersteps. The RN does not suffer from such imbalances; its plot is omitted for brevity.

Giraph, on the other hand, has uniform vertex distribution across machines and each worker takes almost the same time to complete a superstep while fully using the multi-core support through fine grained vertex level parallelism. This highlights the deficiencies of the default partitioning model used by GoFS that reduces edge cuts and balances the number of vertices per machine, without considering the number of sub-graphs that are present per partition, and their sizes.

7 Conclusions

We introduce a sub-graph centric programming abstraction for large scale graph analytics on distributed systems. This model combines the scalability of vertex centric programming with the flexibility of using shared-memory algorithms at the sub-graph level. The GoFFish framework offers Gopher, a distributed execution runtime for this abstraction, co-designed with GoFS, a distributed sub-graph aware file system that pre-partitions and stores graphs for data-local execution. Our abstraction offers algorithmic benefits while our architecture offers design optimizations.

We empirically showed that GoFFish performs significantly better than Apache Giraph, the popular implementation of the vertex centric programming model for several common graph algorithms. These performance gains are achieved due to
both the partitioned graph storage and sub-graph based retrieval from GoFS, and a significant reduction in the number of supersteps that helps us complete faster, with lower framework overhead, that is attributable to the programming model. This offers a high compute to communication ratio. While data parallelism is not at the vertex level, we offer parallelism across sub-graphs and the option to use fast, shared-memory kernels within a sub-graph.

We do recognize some shortcomings, that offer further research opportunities into this promising model. Sub-graph centric algorithms are vulnerable to imbalances in number of sub-graphs per partition as well as non-uniformity in their sizes. This causes stragglers. Better partitioning algorithms to balance the sub-graphs can help. The framework is also susceptible to small-world network graphs with high edge degrees that have high sub-graph level computational complexity, such as Live Journal. Trivial mapping of convergence algorithms like PageRank need to be replaced by algorithms such as BlockRank that effectively leverage the abstraction. Our early software prototype offers further opportunities for design and engineering optimizations.

**Acknowledgment**

This work was supported by the DARPA XDATA program. The views and opinions of authors expressed herein do not necessarily state or reflect those of the United States Government or any agency thereof. We thank H. Chu, N. Ma, D. Tong, M. Frincu and C. Chelmis from USC, and other XDATA performers for their help in preparing this manuscript.
Figure 4: Comparison of GoFFish and Giraph for all Graph Algorithms and Datasets. Plots are in log scale.
Figure 5: Distribution of sub-graph compute times within each partition for first superstep of PageRank