Architectural Implications on the Performance and Cost of Graph Analytics Systems

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ABSTRACT

Graph analytics systems have gained significant popularity due to the prevalence of graph data. Many of these systems are designed to run in a shared-nothing architecture whereby a cluster of machines can process a large graph in parallel. In more recent proposals, others have argued that a single-machine system can achieve better performance and/or is more cost-effective. There is however no clear consensus which approach is better. In this paper, we classify existing graph analytics systems into four categories based on the architectural differences, i.e., processing infrastructure (centralized vs distributed), and memory consumption (in-memory vs out-of-core). We select eight open-source systems to cover all categories, and perform a comparative measurement study to compare their performance and cost characteristics across a spectrum of input data, applications, and hardware settings. Our results show that the best performing configuration can depend on the type of applications and input graphs, and there is no dominant winner across all categories. Based on our findings, we summarize the trends in performance and cost, and provide several insights that help to illuminate the performance and resource cost tradeoffs across different graph analytics systems and categories.

CCS CONCEPTS

• **Information systems → Data management systems**; • **Computer systems organization → Distributed architectures**;

KEYWORDS

Graph analytics systems, experiments, performance, resource cost

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1 INTRODUCTION

In recent years, there have been a proliferation of graph analytics systems that aim to perform complex graph analytics, such as shortest-paths and clustering algorithms efficiently on large graphs. One of the first systems, Pregel [21], uses a distributed vertex-centric computation framework to partition a large graph into groups of vertices for parallel processing. Recent graph analytics system proposals that aim to enhance Pregel's model can be taxonomized along two dimensions. First, these systems can either be *distributed* (in a cluster) or *centralized* (in a single machine). For example, systems such as Galois [24] show that if one can fit an entire graph dataset into the memory of a single machine, its performance may even outperform a cluster for some workloads. Second, in memory usage, these systems can either be *in-memory* or *out-of-core*. To work around memory limitations, systems such as GraphChi [18] and Pregelix [6] resort to out-of-core execution.

In this paper, we aim to carry out a comprehensive evaluation of various open-source graph analytics systems that are publicly available. As input data, we consider five well-known datasets from Twitter, Youtube, Orkut, Friendster and road network, with the largest dataset up to billions of edges. We use four representative graph analytics applications that have different execution characteristics in the number of iterations and cost of each iteration. Using the input data and applications, we benchmarked eight different graph analytics systems (Galois [24], GraphChi [18], PowerGraph [12], Giraph [3], X-Stream [28], Pregelix [6], GraphD [40], Chaos [27]) with different settings on centralization vs distribution, and in-memory vs out-of-core operations.

In our study, performance is not the only dimension to consider when evaluating graph analytics systems. In many organizations, cost is also a consideration, and one often has to find tradeoffs between cost and performance. Unfortunately, there is no one-size-fits-all solution, as the cost/performance ratio of each system is also dependent on the applications and data. As an example, a distributed graph analytics system may have higher throughput, but if the entire graph can fit into the memory of one machine, in-memory centralized systems may be a better option for some workloads given the low cost of memory today. In other cases, users may be less concerned about timeliness, and are willing to allow batch jobs to complete over a longer period, negating the need to run on high-end hardware. In a pay-as-you-go cloud model, execution times become more important than initial sunk-cost of equipment.

Unlike prior studies [7, 10, 11, 14, 16, 20, 30], our study is significantly broader in the scope of data and applications being evaluated, the breadth of systems selected and hardware configurations used. We observe that there is no one-size-fits-all solution, as the

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cost/performance ratio of each system is also dependent on the input applications and data, suggesting the need for an automated tool to help data scientists determine the best deployment option for their workloads. Specifically, the paper makes the following contributions:

Graph analytics system taxonomy. We surveyed existing graph analytics systems and taxonomized them along the dimensions of centralized vs distributed, and in-memory vs out-of-core. In some cases, a system may belong to more than one category. We further summarize the characteristics of each category as well as each of these systems surveyed.

Performance measurements. Using a wide range of datasets and applications, we carried out a comprehensive evaluation study of the above systems with different hardware configurations. We observed that graph analytics system performance can vary significantly based on the input graphs and queries of interest. Our performance results are illuminating, and in some cases surprising. For example, for workloads that require many iterations where each iteration is fairly simple, in-memory execution on a single machine is preferable to running in a distributed environment. On the other hand, for workloads that require a small number of iterations where each iteration is an expensive operation, an in-memory distributed approach often provides the best performance. Within workloads that require a small number of iterations, there are further distinctions in performance based on whether each iteration is bandwidth or computation intensive. We further observe that out-of-core centralized approaches are desirable for small datasets, while in-memory distributed approaches work best for large datasets.

Cost/performance analysis. We next conducted our performance evaluation by taking cost of hardware into consideration. We defined a new performance-aware cost (PAC) metric, that allows us to normalize performance based on cost. The PAC metric takes into account resource cost and execution time, and serves as a framework that can be customized as cost varies in future. Our results here are also illuminating. While in-memory approaches will result in better performance than out-of-core approaches, once cost is factored in, this may no longer be true. We observed that there is no clear winner in the cost/performance analysis, and the choice of graph analytics systems is often highly dependent on the nature of the workload. For example, for applications with large number of iterations, centralized in-memory approaches continue to have the best performance given the PAC metric. However, for applications with small number of iterations, centralized out-of-core approaches are actually the most preferred option, outperforming distributed approaches, when the input graph is under billion scale. Surprisingly, even taking cost into account, out-of-core distributed systems are less desirable compared to in-memory distributed systems due to long execution times.

This paper is presented as follows. Section 2 gives a taxonomized analysis on existing graph analytics systems. Section 3 surveys the most representative systems in each category. Section 4 details the benchmark for our evaluation. Sections 5 and 6 present the evaluation results and our analysis. Section 7 describes the novelty of our work to related studies and explains our system selection. Section 8 concludes the work.

2 TAXONOMIZED ANALYSIS

Our work studies general-purpose graph systems that are used for developing scalable solutions for a wide range of graph analytics tasks, rather than specialized systems that are designed for a particular graph task. These systems share the common features of (1) *programming simplicity* and (2) *transparent scalability*. With (1) and (2), a user only needs to specify how a vertex should interact with other vertices and update its own state, and the computation can automatically scale, either out (for distributed systems) or up (for centralized systems), to handle graphs of arbitrary size without the need to change the user's code/algorithm.

The APIs of existing general-purpose graph systems mainly fall into the following two types. (1) *Message passing*, where vertices communicate with each other by sending messages. The computation is often iterative and synchronized at each iteration to eliminate race conditions. (2) *Shared-memory abstraction*, where a vertex can directly access the data of its adjacent neighbors/edges. This incurs race conditions and data values need to be synchronized among all replicas. However, asynchronous execution can be supported to bring faster convergence, and this programming model is more suitable for a centralized system.

We studied the design and implementation of existing graph systems, and categorized them based on their hardware requirements and data access patterns. We classify an existing system according to (i) whether it is designed to run on a single machine, or on a cluster of machines, and (ii) whether the entire graph data reside in memory during the computation, or are streamed on disk(s). Accordingly, we obtain four categories of graph systems:

- **In-memory centralized (IC) systems** [24, 25, 33, 34], typically running on a high-end server with large memory space (e.g., 1TB) in order to hold a big graph;
- **In-memory distributed (ID) systems** [3, 8, 12, 13, 15, 17, 21, 29, 32, 35–37, 39, 44], which are run on a cluster of machines whose aggregate memory space can accommodate a big graph;
- **Out-of-core centralized (OC) systems** [9, 18, 28, 38, 45], which are typically run on a desktop PC (or a laptop) that has sufficient disk space to hold a big graph;
- **Out-of-core distributed (OD) systems** [6, 27, 40], which are run on a cluster of machines whose aggregate disk space can accommodate a big graph.

Next, we analyze the strengths and limitations of the systems in each category, with a summary of the results given in Table 1.

- **Hardware resource cost.** Out-of-core centralized systems have the lowest hardware resource cost (often a commodity

Category	Machine Cost	Scalability	Fault Tolerance	Startup Overhead	Expressiveness
IC	High	Low	✘	Medium	High
ID	High	High	✔	Low	High
OC	Low	Medium	✘	High	Medium
OD	Medium	High	✔	Low	Medium

Table 1: Strengths and limitations of in each category

PC or a laptop is sufficient). In contrast, in-memory centralized systems require a high-end server with large memory, and such a machine is still considerably more expensive and less commonly available to most companies/institutes. Distributed systems usually require a relatively high initial investment on the hardware, e.g., to purchase a cluster of servers/PCs along with network components, although for many companies/institutes a commodity cluster commonly exists for their own operational tasks.

- **Scalability.** Distributed graph systems become popular thanks to their horizontal scalability: one may increase the aggregate memory (and disk) space in a cluster by simply adding more machines, in order to process a bigger graph. Since the memory (resp. disk) of all machines are accessed (resp. streamed) concurrently, distributed graph systems can utilize the memory (resp. disk) bandwidth from all machines. However, network communication among the machines often becomes the performance bottleneck of such systems, especially for data-intensive tasks, because commodity clusters are more common today and they are equipped with Gigabit Ethernet only. Furthermore, additional resources are required to buffer and manage messages, leading to larger total memory (and/or disk) consumption than a centralized system.
  Centralized systems, on the other hand, are constrained by the limitation of the graph size that they can handle with the available memory (resp. disk) space. Moreover, while network communication is avoided, the performance of these systems is often limited by the memory (resp. disk) bandwidth of a single machine, leading to long execution time for computation-intensive tasks on big graphs.
- **Fault tolerance.** A centralized system is a single point of failure. In contrast, distributed systems are designed to be fault tolerant: if any machine fails, its data/results can be recovered from checkpoints/logs.
- **Data loading/dumping overhead.** Large-scale data loading is much faster in distributed systems than in centralized systems as the cost is shared by all machines in the cluster. An out-of-core centralized system does not need to load the entire graph into memory but stream the disk-resident graph in each iteration; however, often expensive pre-processing is required to reorganize the graph representation on disk so that the data access pattern can be as sequential as possible. Similarly, large-scale data dumping is also much faster in distributed systems than in centralized systems.
- **Expressiveness.** Some out-of-core systems are less expressive than in-memory systems, because efficient data streaming in out-of-core systems requires vertex state and edge value to have fixed size. For example, in triangle counting, a vertex needs to obtain the adjacency lists of its neighbors, and since the length of adjacency lists is not fixed, it is not clear how one can implement efficient triangle counting in such a system. Some out-of-core systems such Pregelix [6] relax this restriction by organizing vertices using B-tree structures, but additional overhead is incurred by the access and maintenance of the B-tree structure.

	Centralized	Distributed
In-memory	Galois, GraphChi-IM	PowerGraph, Giraph
Out-of-core	GraphChi, X-Stream	Pregelix, GraphD, Chaos

Table 2: Representative systems

In Sections 5 and 6, we will analyze all categories in details regarding their system performance and resource cost for processing various applications and datasets.

3 GRAPH ANALYTICS SYSTEM SURVEY

Given the long list of existing graph analytics systems, it is impractical to enumerate every one of them. In this section, we briefly describe some of the most representative systems in each category (details can be found in the full version[1]), as summarized in Table 2. The emphases of our selection are availability, efficiency and deployability. Some of them are state-of-the-art [27], and some are widely used [3] in industry. We also use this list in our comparative study in Sections 5 and 6. More systems and related work are mentioned in Section 7.

3.1 In-Memory Distributed Systems

Pregel [21]. Pregel [21] pioneered the idea of vertex-centric computation for graph analytics. With the vertex-centric model, a user thinks like a vertex and only needs to specify the computation logic of a vertex in a user-defined function (UDF), *compute*(*msgs*), and the system automatically executes the *compute* function on all vertices. A Pregel program proceeds in iterations, and a vertex can be either *active* or *inactive* during processing. When the current iteration has no active vertex and no message to be processed, then the program terminates.

Giraph [3]. Apache Giraph is the open-source implementation of Pregel, which we used in our experimental study. Giraph was initially developed by Yahoo! and then optimized by Facebook researchers, who improved CPU utilization of Giraph by multithreading and reduced memory consumption by serializing vertex/edge and message objects into byte arrays.

PowerGraph [12]. PowerGraph partitions a graph by the edges and adopts a new computation model called *Gather-Apply-Scatter* (*GAS*). In the *Gather* phase, a vertex collects data from its adjacent vertices and edges. The gathered data are then aggregated and used to update the value of the vertex in the *Apply* phase. In the *Scatter* phase, the vertex may activate its neighbors (to perform computation) along the adjacent edges.

3.2 Out-of-Core Centralized Systems

GraphChi [18]. In GraphChi, vertices communicate with each other by putting and getting values on adjacent edges. To process a large graph using limited memory, GraphChi pre-partitions the vertices in multiple *shards*, where each shard also stores the value of each incoming edge of its vertices. Shards are loaded into memory for processing one after another. GraphChi also supports a selective

[1] http://cis.upenn.edu/~qizhen/graph_work.pdf

mode to avoid loading a shard if there is no active vertex in the shard.

X-Stream [28]. X-Stream adopts an edge-centric scatter-gather model. Like in GraphChi, vertices are partitioned so that each partition fits in memory. An X-stream program has two phases in each iteration: scatter and gather. In both phases, each memory-resident partition itself is further partitioned into cache-resident chunks for parallel processing to improve cache locality. The weakness of X-Stream is that there is no mechanism like the selective mode of GraphChi.

3.3 Out-of-Core Distributed Systems

Pregelix [6]. Pregelix is an out-of-core distributed system. It models the Pregel API as a logical query plan, which is executed on a parallel dataflow engine called Hyracks [4]. In each iteration, the generated messages are joined with the set of vertices on the destination vertex ID, and then each vertex calls *compute*(.) to process its received messages, update its value and generate new outgoing messages. To efficiently support sparse computation where vertices are managed by B-tree structures.

Chaos [27]. Chaos [27] is the distributed version of X-Stream that attempts to use the aggregated disk bandwidth in a cluster. Edge scattering and gathering workloads are distributed among multiple machines, and work stealing is adopted for load balancing. To achieve desirable performance, Chaos requires that machines should be connected by high-speed network (e.g., 40GigE).

GraphD [40]. GraphD is an out-of-core Pregel-like system designed to run in a cluster of commodity machines connected by Gigabit Ethernet. It only requires each machine to keep the state information in memory, while the corresponding adjacency lists and incoming/outgoing messages are streamed on local disk. It skips inactive vertices to save disk IO, and message streams are organized into chunks to allow concurrent sending and appending. It claims to achieve similar performance to those of in-memory systems.

3.4 In-Memory Centralized Systems

Galois [24]. Galois keeps the graph in memory and adopts a domain-specific language (DSL) to fully exploit the parallelism of all cores. The DSL follows *amorphous data-parallelism* (ADP) model [26] that supports speculative execution. Galois also schedules the computation of vertices in a machine-topology-aware manner.

GraphChi-IM. The GraphChi system described in Section 3.2 also supports an in-memory mode that keeps the array of vertex values in main memory. In this case, there is no need to write values to edges, since a vertex can directly obtain its in-neighbors' values from memory to update its own value. We denote the in-memory mode of GraphChi by *GraphChi-IM*, and include it in our experiments by running it on a high-end server.

Algorithm	Vertex Access Pattern	Edge Direction	# of Iterations
SSSP	Always low access rate	No requirement	Linear to diameter
HashMin	High access rate at first, drastically decreasing	Undirected	Linear to diameter
PageRank	Always high access rate	No requirement	Fixed
Triangle Counting	Always high access rate, with random accesses	Undirected	Fixed

Table 3: Applications used for system evaluation

4 EVALUATION SETUP

In this section, we describe the setup for our comparative study, including the applications and datasets, the hardware environments and the metrics of evaluation.

4.1 Applications

To comprehensively evaluate the performance of the various systems we described in Section 3, we select four applications that exhibit very different but representative vertex access patterns during their execution, which are summarized in Table 3. Those applications are either classic graph algorithms or frequently used in production. Among them, in every iteration, *SSSP* only accesses a fraction of vertices, while both *PageRank* and *Triangle Counting* access all vertices. The difference between *Triangle Counting* and *PageRank* is that, the former requires every vertex to fetch the adjacency lists of its neighbors for computation, and thus a large amount of random accesses to adjacency list data are inevitable. Finally, *HashMin* accesses every vertex in the first iteration, but the fraction of vertices that are accessed decreases rapidly in each subsequent iteration. We now describe these four applications in more details.

4.1.1 SSSP.

The SSSP algorithm finds the shortest-path distance from a user-specified source vertex s to every vertex v in the input graph, which is recorded as an attribute of v, i.e., $d(v)$. Initially, $d(s)$ is set to 0 and $d(v)$ is set to $+\infty$ for every vertex $v \neq s$, and only s is activated. In each iteration, every active vertex v sends $(d(v)+w(v,u))$ to each out-neighbor u, where $w(v,u)$ is the weight of edge (v,u). Then, when a vertex u receives the distance values from its in-neighbors, it checks whether the smallest value min is less than $d(u)$; if so, $d(u)$ is updated as min, and u is activated for the next iteration. This process converges when every vertex v has its shortest-path distance from s in $d(v)$. In each iteration of SSSP, only vertices at the distance-propagation frontier perform computation.

4.1.2 HashMin.

HashMin computes the connected components of an undirected graph by letting every vertex v propagate the smallest vertex ID that v has received, which is recorded as an attribute of v, i.e., $min(v)$. Initially, every vertex v initializes $min(v)$ as its own ID, and all vertices are activated for ID propagation. In each iteration, each active vertex v passes $min(v)$ to its neighbors.

Then, when a vertex u receives the ID values from its neighbors, it checks whether the smallest value min is less than $min(u)$; if so, $min(u)$ is updated as min and u is activated for the next iteration. This process converges when every vertex v has $min(v)$ equal to the minimum vertex ID in v's connected component. In each iteration of HashMin, only those vertices whose attributes are not converged perform computation.

4.1.3 PageRank. This algorithm [5] computes PageRank value for every vertex v (denoted by $pr(v)$), based on the graph topology. All vertices are active during the entire computation, and initially $pr(v)$ is set to 1 for every vertex v. In each iteration, each vertex v distributes $pr(v)$ to its out-neighbors evenly by sending $pr(v)/deg(v)$ to each neighbor, where $deg(v)$ is the out-degree of v; each vertex v then sums all received values, denoted by sum, and updates $pr(v)$ as $((1-d)+d \cdot sum)$, where d is the damping factor typically set to 0.85. This process stops either when the sum of PageRanks of all vertices converges, or when a pre-specified maximum iteration number is reached.

4.1.4 Triangle Counting. Let us denote the adjacency list of a vertex v by $\Gamma(v)$. The algorithm counts the number of triangles in an undirected graph. Specifically, each vertex v obtains $\Gamma(u)$ from each neighbor u, to compute their common neighbors $\Gamma(u) \cap \Gamma(v)$. The number of triangles that involve v is computed by summing $|\Gamma(u) \cap \Gamma(v)|$ of all neighbors $u \in \Gamma(v)$. Note that each triangle $\triangle v_i v_j v_k$ is counted three times, by v_i, v_j and v_k, respectively. To avoid duplicate counting, we may use $\Gamma_>(v) = \{u \in \Gamma(v) \mid u > v\}$ in place of $\Gamma(v)$, so that each triangle $\triangle v_i v_j v_k$ (w.l.o.g., assume $v_i < v_j < v_k$) will only be counted by v_i. Note that some out-of-core systems (e.g., GraphChi [18] and X-Stream [28]) fix the size of the data passed from one vertex to another, and thus this particular triangle counting algorithm cannot be implemented in those systems.

4.2 Environment Setup and Datasets

Our experiments were run under three hardware settings available in our institution to evaluate the systems described in Section 3. The settings are listed as follows.

- **Setting #1**: A desktop PC with 4GB DDR3 RAM, a 3.2GHz CPU and 1TB 7.2K rpm hard drive. OS is 64 bit Ubuntu 14.04 LTS with Linux kernel 3.10.
- **Setting #2**: A server with 1TB DDR3 RAM, eight 2.2GHz CPUs and 600GB 15K rpm hard drive. OS is CentOS 7.3 with Linux kernel 3.10.
- **Setting #3**: A cluster of 21 servers (1 master and 20 slaves), each with 42GB DDR3 RAM, two 2.0GHz Intel Xeon E5-2620 CPUs and a 2TB 10K rpm hard drive, and OS is CentOS 6.5 with Linux kernel 2.6. The machines are connected by Gigabit Ethernet.

These settings are selected to cover the hardware required by the systems described in Section 3. We ran in-memory centralized systems in Setting #2 with 1TB RAM, so that a big graph can be kept in memory for processing. We ran out-of-core centralized systems in Setting #1 since those systems are designed to run on a cheap commodity PC [18]. Finally, distributed systems were run on the cluster of Setting #3. Although we ran both out-of-core and in-memory distributed systems in Setting #3, we monitored the actual resources consumed during execution, to calibrate the resource costs (e.g., memory space) of various systems. Table 4 summarizes the settings used for each category of systems.

Category	IC	ID	OC	OD
Setting	#2	#3	#1	#3

Table 4: Hardware used for each system category

Dataset	**Youtube**	**USA Road**	**Orkut**	**Twitter**	**Friendster**
Type	undirected	undirected	undirected	directed	undirected
|V|	1.1M	24M	3.1M	52.6M	65.6M
|E|	3M	58.3M	117.2M	2B	3.6B
Max Degree	28.8K	9	33.3K	780K	5214
Avg Degree	5.27	2.4	76.28	37.3	55.1
Diameter	20	6142	10	18	32
File Size	46.8MB	715.4MB	1.7GB	13.7GB	30.6GB

Table 5: Datasets (B = 1,000M, M = 1,000K, K = 1,000)

We used five real-world graph datasets in our experiments: *Youtube*[2], *USA Road*[3], *Orkut*[4], *Twitter*[5], and *Friendster*[6]. These graphs have different scales and characteristics (e.g., average degree, diameter), which are summarized in Table 5.

4.3 Performance Metrics

We next introduce the performance metrics that we adopt to report our experimental results.

- **Running Time (seconds)**: This metric measures the end-to-end execution time a system takes to complete a job, including the time of loading a graph from disk(s) to memory, and that of dumping the result to disk(s). Note that all the systems we evaluated are open-source projects, and there are online tutorials about how to compile, execute and tune their performance. While we used the default configuration of each system to test their performance, we also carefully set other parameters to maximally utilize our hardware resources, for example, full cores were used and sufficient memory was allocated.
- **Performance-Aware Cost (PAC)**: This metric combines resource cost and running time together, so that a job that takes longer to run on the same hardware will have a higher PAC. The details on the PAC definition are described below.

The PAC metric is defined in terms of the resource cost of a job, which is as follows:

$$ResourceCost = |CPU| \times Price_{cpu} + |Mem| \times Price_{mem},$$

where $|CPU|$ is the number of CPUs used, $|Mem|$ is the unit of memory consumed, $Price_{cpu}$ is the price of each CPU of that setting and $Price_{mem}$ is the price of per unit memory. $ResourceCost$

[2] https://snap.stanford.edu/data/com-Youtube.html
[3] http://www.dis.uniroma1.it/challenge9/download.shtml
[4] http://konect.uni-koblenz.de/networks/orkut-links
[5] http://konect.uni-koblenz.de/networks/twittermpi
[6] http://snap.stanford.edu/data/com-Friendster.html

Instance	A1	A2	A3	A4	A5	A6	A7
# of Cores	1	2	4	8	2	4	8
RAM (GB)	1.75	3.5	7	14	14	28	56
Price ($/h)	0.09	0.18	0.36	0.72	0.33	0.66	1.32

Table 6: Pricing of Microsoft Azure Standard Tier VMs [1]

indicates the hardware capacity in order to handle the workload, which is related to instance prices (per time unit) in commercial cloud platforms. We do not include cost of local disk storage as they tend to be significantly cheaper than memory and CPU. In our calculations of $ResourceCost$, we use the maximum number of CPU cores as the degree of job parallelism permits. Likewise, we use the maximum memory consumption by a job for $|Mem|$, since this is what one needs to do in a cloud platform to run the job. Also, we assume that the memory expense is proportional to $|Mem|$, which is in accordance with the existing cloud services.

Since the hardware used in our experiments is not exactly identical to an existing public cloud, we plug in values that are consistent with the pricing models of public clouds, yet reflect the relative price differences across different hardware that we use. For each hardware setup in our experiments, we use the publicly available pricing information to set the value of $Price_{cpu}$ and $Price_{mem}$. This is a tunable parameter in our framework and can be updated in future as prices change. Note that our $ResourceCost$ formulation is in line with pricing models in public clouds. For example, in Microsoft Azure, the instance pricing of Standard Tier VMs is shown in Table 6, where the price is proportional to the RAM size when the number of cores is fixed.

The PAC metric is proportional to both the running time and the resource cost.

$$PAC = RunningTime \times ResourceCost.$$

Intuitively, the PAC metric is based on a typical pricing model in a public cloud infrastructure, which charges based on running time on a particular instance. We report the normalized PAC results for comparison in Section 6. Comparing the PAC values between different jobs approximates the comparison of their monetary costs in a commercial cloud computing platform.

5 RUNNING TIME EVALUATION

In our experimental section, we compare the running time of different systems across different applications and datasets. We defer PAC to the next section.

5.1 Summary

We aggregate the running time of each system by application and dataset respectively, and select the top four systems. The overall system performance ranking for each application is shown in Table 7. Note that in Triangle Counting, only three systems are able to finish within twenty-four hours. Our table lists the four applications based on the overall computation load (SSSP being the lightest, while Triangle Counting the heaviest). Note that even though Triangle Counting has the least number of iterations, each iteration is computationally expensive, and hence it incurs the highest load overall.

	System Ranking			
Algorithm	#1	#2	#3	#4
SSSP	Galois	PowerGraph	Giraph	GraphD
HashMin	Galois	Giraph	PowerGraph	GraphD
PageRank	PowerGraph	Giraph	GraphD	Galois
Triangle Counting	PowerGraph	Galois	GraphD	N/A

Table 7: System running time ranking by application

	System Ranking			
Dataset	#1	#2	#3	#4
Youtube	Galois	GraphChi-IM	GraphChi	X-Stream
USA Road	Galois	GraphChi-IM	Giraph	PowerGraph
Orkut	Galois	PowerGraph	GraphChi-IM	Giraph
Twitter	PowerGraph	Giraph	Galois	GraphChi-IM
Friendster	PowerGraph	Giraph	Galois	GraphD

Table 8: System running time ranking by dataset

We rank the systems based on their performance, breakdown by application (Table 7) and dataset (Table 8). In Table 7, to provide an aggregate performance value, we sum up the processing time for each application across all the datasets and take the average. We make the following observations. Likewise, when aggregating by datasets, we take the average processing time that each system takes for all successful applications.

Many iterations, low compute-intensive applications. First, we observe that when an application runs for a large number of iterations and the computation in each iteration is not heavy (typified by SSSP and HashMin), an in-memory centralized system such as Galois always gives the best performance. This is because there is no synchronization overhead on disk or network I/O between iterations for in-memory centralized systems[7] Two in-memory distributed systems (PowerGraph and Giraph) also perform well, taking in the second and the third positions. Between PowerGraph and Giraph, the differences in running time is negligible.

Few iterations, compute-intensive or bandwidth-intensive applications. For computationally intensive jobs such as PageRank and Triangle Counting, however, distributed systems (PowerGraph and Giraph) tend to outperform centralized systems (Galois). PowerGraph has the best performance, demonstrating the benefits of parallel processing of compute intensive jobs. Here, we observe that even the out-of-core distributed system, GraphD, outperforms the in-memory Galois for PageRank computation. On the other hand, for Triangle Counting, Galois performs better than GraphD because it is more bandwidth-intensive compared to PageRank, since an entire adjacent list (and not just a vertex value) needs to be transmitted for each iteration. This significantly increases network and disk I/O overhead, which penalizes out-of-core systems such as GraphD.

[7] The other in-memory centralized system GraphChi-IM, however, is not in the list as the system has difficulty completing the processing of the *Friendster* graph, which is our largest dataset.

Scalability analysis. We observe interesting trends across datasets as they scale (Table 8). For the smallest dataset (*Youtube*), all centralized systems, no matter in-memory or out-of-core, out-perform distributed systems. The reason is that the overhead of communication among machines outweighs the computation reduction gained by a distributed system. When the input dataset becomes larger, as on *USA Road*, although in-memory centralized systems still have the best performance, centralized out-of-core systems are not as efficient as in-memory distributed systems. However, when the dataset size continues to increase, as in the case of *Orkut*, PowerGraph overtakes GraphChi-IM in second place, while Giraph is in fourth place. When the dataset reaches billion-edge scale, as in the cases of *Twitter* and *Friendster*, the two in-memory distributed systems PowerGraph and Giraph provide the best performance. All in all, our scalability analysis suggests that in-memory centralized systems are best suited for small datasets, while large datasets benefit from in-memory distributed systems.

5.2 Detailed Analysis

We now analyze the running time of different systems in each application and on each dataset. Due to space limit, we simplify the analysis here. More details can be found in the full version [1].

Running time of SSSP. In this set of experiments, for each dataset, we randomly selected ten source vertices for running SSSP. Each reported result was averaged over the 10 runs. Figure 1 reports the running time of various systems over the datasets. We do not report the performance of Pregelix, since even though we tried our best to tune the configuration of Pregelix, the experiment of SSSP kept crashing and could not finish successfully.

Figure 1a) shows that on *Youtube*, Galois has the best performance, and all the centralized systems exhibit much better performance than distributed systems. It is because running distributed systems on small graphs is inefficient as the communication cost between machines outweighs the per-machine computation workload.

Although *USA Road* is also not big, Figure 1b) shows that GraphChi is slower than the distributed systems, while X-Stream and Chaos could not even finish in 24 hours. The drastic performance difference is caused by the larger diameter of *USA Road*, and thus the computation takes many iterations. Out-of-core systems need to stream the entire graph from disk(s), and thus each iteration is much more costly than in-memory systems.

In Figure 1c), although Galois continues to outperform the other systems, GraphChi-IM is slower than PowerGraph and comparable to Giraph. This shows that the size of *Orkut* is large enough so that the reduced per-machine computation workload offsets the communication overhead. As a distributed version of X-Stream, Chaos has slightly better performance than X-Stream.

Figure 1d) reports the results on *Twitter* which is tens of times larger than *Orkut*. Figure 1d) shows that all the distributed systems, except Chaos, outperform GraphChi-IM, demonstrating their strength for processing big graphs. Figure 1e) reports the results of the largest dataset, *Friendster*, and only five systems could complete the processing within 24 hours. In particular, GraphChi-IM could not even finish preprocessing within 24 hours (and thus no results for all applications).

Figure 5 compares the systems in terms of categories (rather than individually). For each category, we use the fastest system as its representative (for each dataset). Except *USA Road*, the result shows that the running time increases with the graph size for all categories. IC is always the fastest while OC is good at processing small datasets, but it becomes much slower than the other categories as the dataset size becomes larger, as the disk bandwidth is the bottleneck and cannot be increased by scaling out. Overall, the running time is ranked as IC < ID < OD < OC. For large-diameter graphs like *USA Road*, distributed (resp. out-of-core) systems are much slower than IC since expensive network synchronization (resp. disk streaming) is performed for many iterations.

Running Time of HashMin. We ran HashMin on undirected graphs. Figure 2 reports the results. HashMin has a heavier computation workload than SSSP, since all vertices are active at the beginning of the application. Thus, we could not obtain more results for HashMin within reasonable time than for SSSP.

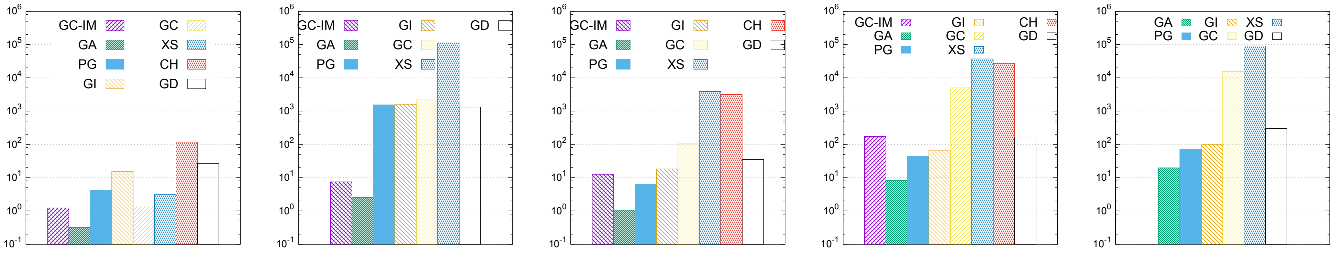
Figure 2a) shows that centralized systems still beat distributed systems on *Youtube*. Figure 2b) shows the results when a large number of iterations are required, for which in-memory systems are much faster than out-of-core ones. Figures 2c) and d) show that for larger graphs, the performance gap between OC systems and other categories of systems becomes larger (almost two orders of magnitude for *Friendster*). Also, the performance of IC systems and distributed systems (except Chaos) is relatively close for the two larger graphs.

Figure 6 compares the running time of HashMin at the system-category level. We observe similar patterns as in Figure 5, but the performance gap between IC and ID is now much smaller on the large graphs, because HashMin has a heavier computation workload and hence distributed computing helps more than in the case of SSSP.

Running Time of PageRank. PageRank is not a traversal style application (like SSSP and HashMin), and hence the number of iterations needed for computing PageRank does not depend on the graph diameter. We ran 10 iterations in each experiment. But note that each iteration has a heavier computation workload than HashMin, since all vertices are active in every iteration. Except for GraphChi-IM, which did not finish on *Friendster*, all the experiments successfully finished in 24 hours.

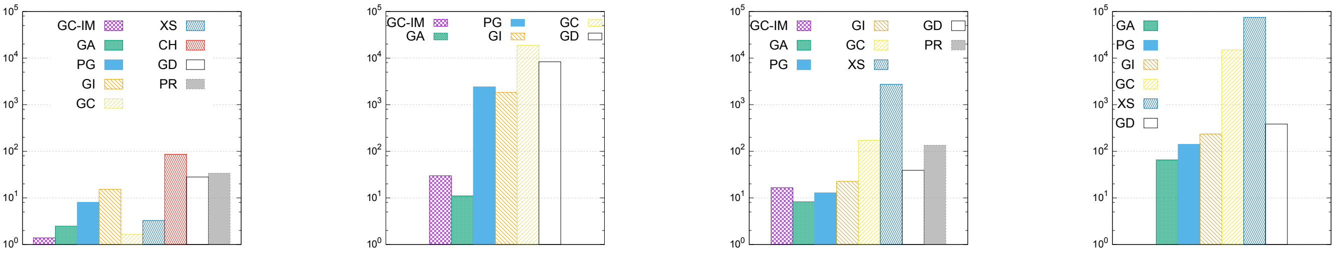
Figure 3a) shows that for this smallest dataset, centralized systems still have better performance than distributed ones due to the overhead of distributed computing. Among distributed systems, PowerGraph has the best performance. In Figure 3b), GraphChi competes all OD systems, and the performance of GraphD is close to Giraph, which is an in-memory distributed system.

Chaos is now many times faster than X-Stream in Figures 3c)–e), since for the larger datasets the reduced per-machine computation workload offsets the communication overhead. PowerGraph achieves comparable performance as Galois and GraphChi-IM in Figure 3c), and is the fastest system in Figures 3d) and e), which shows that *in-memory distributed architecture is the fastest for processing heavy-workload computation on large graphs (when the number of iterations is not large)*. This is very different from what we observed in Figure 1, where Galois always has the best performance.



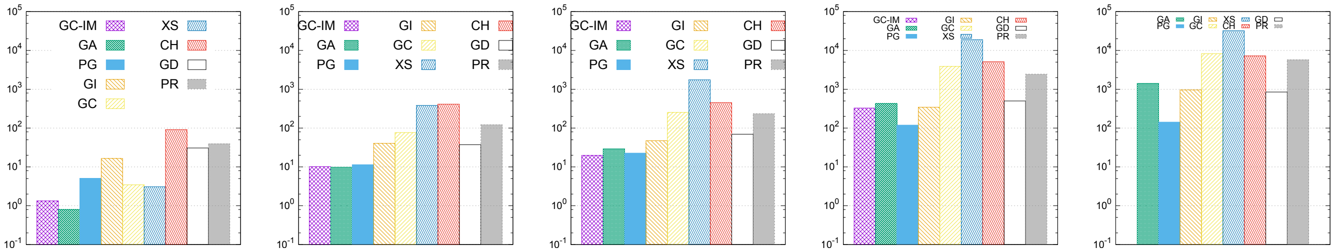
(a) Youtube (b) USA Road (c) Orkut (d) Twitter (e) Friendster

Figure 1: Running time of SSSP (seconds). GC-IM, GA, PG, GI, GC, XS, CH, and GD represent GraphChi-IM, Galois, PowerGraph, Giraph, GraphChi, X-Stream, Chaos, and GraphD respectively. The categorization of the systems are as follows: (IC: GC-IM, GA), (ID: PG, GI), (OC: GC, XS), (OD: CH, GD). Note that the legends apply to Figures 1-4.



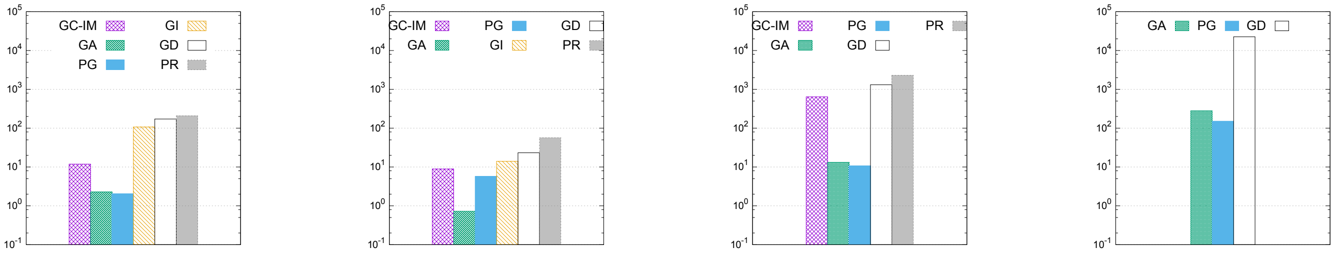
(a) Youtube (b) USA Road (c) Orkut (d) Friendster

Figure 2: Running time of HashMin (seconds). PR represents Pregelix (which is in OD).



(a) Youtube (b) USA Road (c) Orkut (d) Twitter (e) Friendster

Figure 3: Running time of PageRank (seconds)



(a) Youtube (b) USA Road (c) Orkut (d) Friendster

Figure 4: Running time of Triangle Counting (seconds)

Figure 7 shows the PageRank running time comparison at the system-category level, which is quite different from Figure 5 and Figure 6. Firstly, the "IC" curve is no longer always at the bottom, and is actually surpassed by distributed systems (i.e., ID and OD) on *Friendster*, which means the scalability of "IC" is worse than distributed systems for this application with heavier workload.

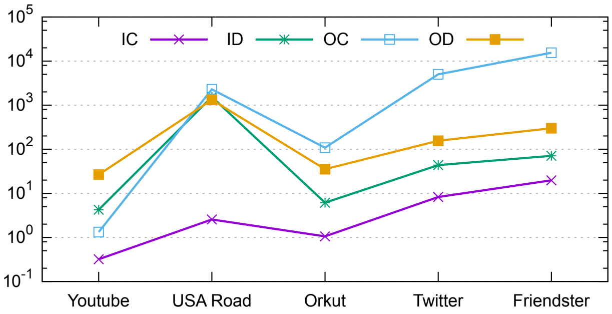


Figure 5: Categorical comparison of SSSP running time (seconds)

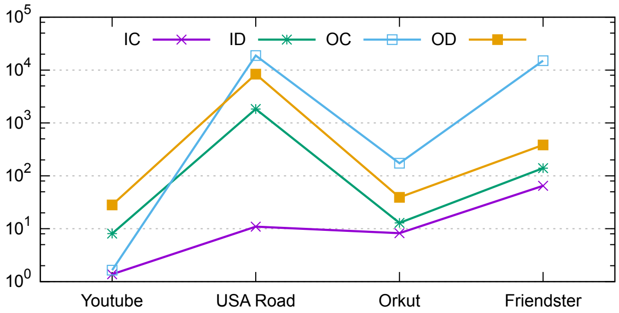


Figure 6: Categorical comparison of HashMin running time (seconds)

Figure 7 also shows that in-memory systems are always faster than out-of-core systems.

Running Time of Triangle Counting. Triangle counting requires each vertex to obtain its neighbors' adjacency lists. It has the heaviest workload among all the applications, and the number of iterations is the smallest.

This application needs the input graph to be undirected, thus, we exclude *Twitter* from the experiments. Moreover, GraphChi, X-Stream and Chaos fix the size of a message, and thus cannot implement triangle counting which requires transmitting variable-length adjacency lists. Giraph ran out of memory on *Orkut* and *Friendster*. Finally, Pregelix could not finish processing *Friendster* within 24 hours.

The results are shown in Figure 4. PowerGraph is always the fastest system because of the heavy computation workload (except for USA Road which only has few triangles, as shown in Figure 4b). All other distributed systems, Giraph, Pregelix and GraphD, adopt the message-passing model rather than a shared-memory abstraction as does in PowerGraph. Thus, the adjacency list data of a vertex need to be pushed to its neighbors, icurring data transmission and storage. As a result, they are much slower than PowerGraph and the IC systems.

We show the categorical comparison results in Figure 8. ID is faster than IC on the large graphs, and thus has better scalability. In contrast, OD has the worst performance, and much worse than both ID and IC.

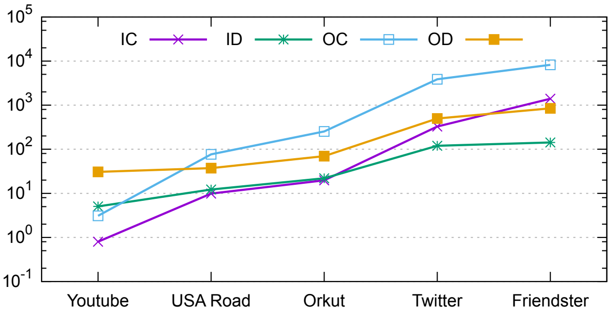


Figure 7: Categorical comparison of PageRank running time (seconds)

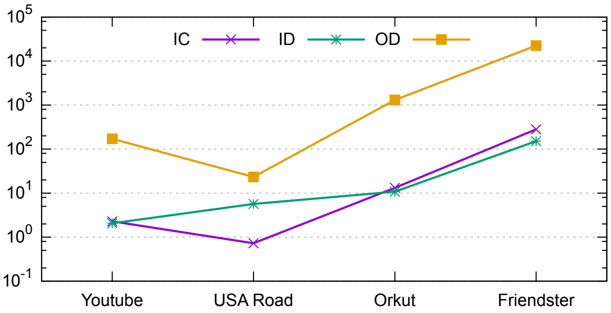


Figure 8: Categorical comparison of Triangle Counting running time (seconds)

	System Ranking			
Algorithm	**#1**	**#2**	**#3**	**#4**
SSSP	Galois	GraphChi	PowerGraph	Giraph
HashMin	Galois	GraphChi	Giraph	PowerGraph
PageRank	GraphChi	PowerGraph	X-Stream	GraphD
Triangle Counting	PowerGraph	Galois	GraphD	N/A

Table 9: System PAC ranking by application

	System Ranking			
Dataset	**#1**	**#2**	**#3**	**#4**
Youtube	GraphChi	X-Stream	Galois	GraphChi-IM
USA Road	Galois	GraphChi-IM	GraphChi	Giraph
Orkut	GraphChi	PowerGraph	Galois	GraphChi-IM
Twitter	PowerGraph	GraphChi	Galois	GraphD
Friendster	PowerGraph	GraphChi	Giraph	GraphD

Table 10: System PAC ranking by dataset

6 PAC EVALUATION

The comparison based on running time only concerns about which system (or category of systems) can finish a job faster. However, efficiency may often come at the expense of higher hardware cost. If time is not the most critical criterion (e.g., in an offline graph analytics such as PageRank computation), a more economical solution could be more attractive. We now describe the comparison based on the performance-aware cost (PAC) of different systems, the findings of which are quite different from those in Section 5.2.

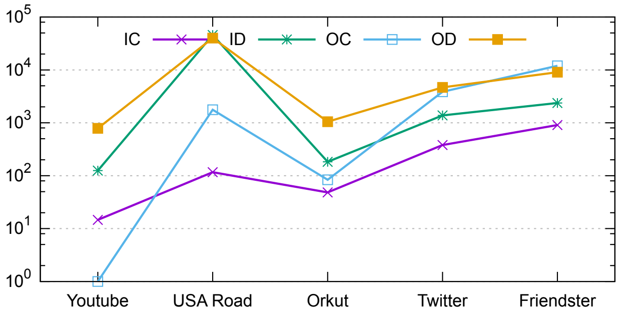


Figure 9: Categorical comparison of PAC for SSSP

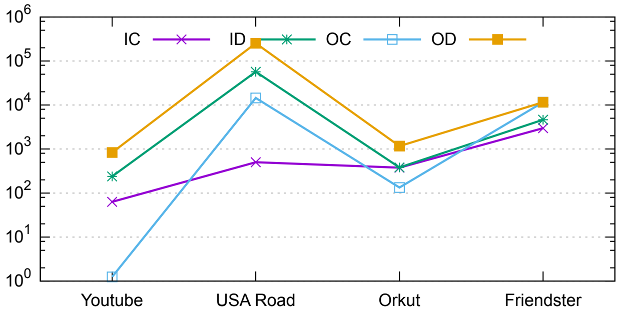


Figure 10: Categorical comparison of PAC for HashMin

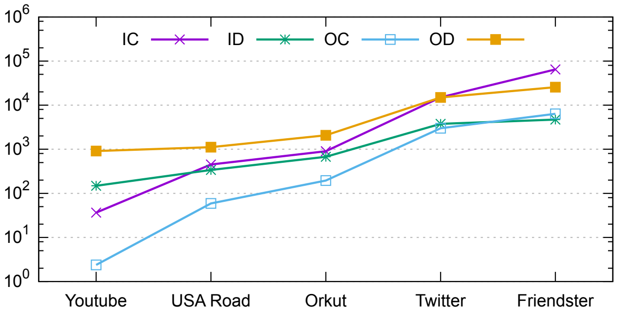


Figure 11: Categorical comparison of PAC for PageRank

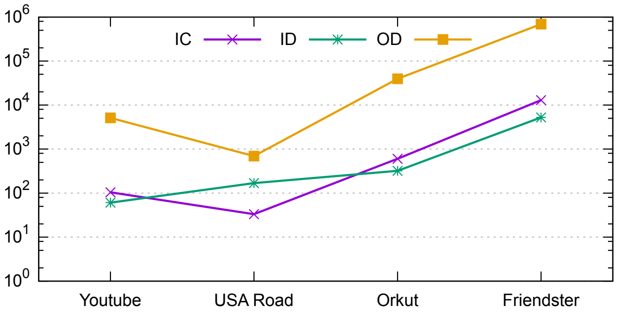


Figure 12: Categorical comparison of PAC for Triangle Counting

6.1 Summary

Table 9 and Table 10 show the relative rankings of the top 4 systems using the PAC metric, aggregated by the application and dataset, in a similar fashion as described in Section 5.1. We make the following observations.

Many iterations, low-compute intensive applications. Revisiting the earlier SSSP and HashMin applications, we note that the best performing system (Galois) also has the lowest PAC. GraphChi is in second place because of its low resource cost (given that it does out-of-core operations) and reasonable speed. Although X-Stream consumes similar resources as GraphChi, it is not among the top four due to its longer running time. Instead, GraphChi is followed by two in-memory distributed systems (PowerGraph and Giraph). The strong performance of these systems cannot compensate for their higher costs compared with GraphChi.

Few iterations, high compute/bandwidth intensive applications. For the PageRank applications, GraphChi has the lowest PAC, and the other two out-of-core systems, X-Stream and GraphD, also make into the top four. This shows that out-of-core systems (especially centralized) are cost effective in applications with heavier computation but few iterations. The second-ranked PowerGraph requires more costly resources, but this is compensated by its high throughput (and hence fast completion time). The ranking for Triangle Counting is the same as Table 7. This is because for this heaviest-workload task, both PowerGraph and Galois have short running time, which offsets their higher costs, resulting in lower overall PAC. (see Section 6.2 for details.)

Scalability analysis. When the dataset is small, as in the case of *Youtube*, out-of-core centralized systems are the best choice because of low resource cost and reasonably high speed. However, the comparison of PAC for *USA Road* and *Orkut* shows that they are not good choices for large-diameter graphs that requires multiple iterations (even when the dataset itself is small). Instead, in-memory centralized systems are the best choices for handling large-diameter graphs. When datasets become larger, as in the case of *Twitter* and *Friendster*, PowerGraph replaces GraphChi to become the best system that balances resource cost and job processing speed. But GraphChi still has a lower PAC than the other systems. Overall, we observe that when the input graph reaches billion-edge scale, it is always better to choose in-memory distributed systems for high speed or out-of-core centralized systems for saving costs.

6.2 Cross-Category Analysis of PAC

We omit the detailed analysis of different systems' PAC in each application and for each dataset due to space limit. These details can be found in the full version report [1]. We analyze the cross-category comparison results in PAC metric, where we normalize all PACs to the smallest one to get relative PACs as mentioned in Section 4.3.

PAC of SSSP. Figure 9 shows the PAC comparison at the system-category level, where we selected the system with the lowest PAC in each category to represent the PAC of that category. IC is always the best except on the smallest dataset and OD is always the worst except on the largest dataset, where the two exceptions are both OC. Thus, OC cannot scale to handle large graphs as what we observed in Figure 5. However, compared to Figure 5 where OC is always the worst category except on the smallest graph, OC's PAC is significantly lower than distributed systems on most graphs. This shows the advantages of OC on saving cost. ID always performs better than OD, which shows that running out-of-core distributed systems is costly.

PAC of HashMin. Figure 10 reports the PAC comparison at the system-category level for HashMin, which is similar to that in Figure 9. The difference is that IC is not as dominant as in Figure 9 and OC becomes better. Except on the large-diameter graph, i.e., *USA Road*, the gap between IC and OC on the large graphs is much smaller than in Figure 9 and so is the gap between IC and ID/OD. In fact, for *Orkut* and *Friendster*, the PAC of ID is nearly the same as that of IC, which shows that ID works better when the workload is more computationally intensive. OC is now better than all distributed systems, except worse than ID on the largest graph. In contrast, although OD is also designed to be cost effictive, it has has the greatest PAC in this application.

PAC of PageRank. Figure 11 reports the results for PageRank, which shows that the PAC is consistently ranked as OC < IC and ID < OD on all datasets. As the graph size becomes larger, the curves of distributed systems grow slower than centralized systems, which shows that distributed systems have better PAC scalability on dataset size than centralized systems. This result is interesting as it shows that *out-of-core systems may not be always more cost-effective, and there is a point distributed systems can be the most cost-effective choice.* Compared with Figure 7, OC turns from the worst to the best system category overall, which means that OC performs well in heavy workloads considering the available resources.

PAC of Triangle Counting. The results for triangle counting are shown in Figure 12. OD still has the largest PAC, which shows that out-of-core execution is not suitable for this application due to the huge amount of intermediate data (i.e., adjacency lists). Although ID has higher PAC on *USA Road* than IC because of few triangles and thus light computation, it is better than IC in all the other cases (even on small graphs). Combined with the results shown in Figure 8, we can see that ID not only achieves high processing speed but also is cost efficient, and hence the best choice for this type of workloads.

7 RELATED WORK

System selection. Many distributed [3, 6, 8, 12, 13, 15, 17, 21, 29, 32, 35–37, 39, 44] and centralized [9, 25, 33, 34, 38, 45] graph analytics systems have been developed. Even though we selected various representative systems covering all categories, there are still a number of systems we did not include in our study, and here we explain why they were not considered besides the limited space. GraphX [13] is a graph engine built on top of Spark [43] providing both vertex-centric and GAS abstractions. It is optimized for graphs, and thus much more efficient than Spark. However it is outperformed by PowerGraph and Giraph in some applications as reported in [13]. Recently, some systems have been developed to efficiently evaluate declarative graph queries, such as SociaLite [31] and Emptyheaded [2]. However, such systems focus on abstractions and their performance cannot compete with low level graph engines, for example, Galois, as reported in [2].

Graph analytics system measurement. There have also been a number of experimental studies on some graph analytics systems, but they are all limited to the comparison of systems within the same category/setting. Elser et al. [10] compared Pregel-like systems with MapReduce, but the datasets used are small, and most of the systems are not the state-of-the-art or representative systems. Guo et al. [14] designed a benchmark to evaluate graph processing platforms, but only in-memory distributed systems were considered. Satish et al. [30] designed various metrics to evaluate several systems in both centralized and distributed environments, but systems were compared only within the same environment. Han et al. [16] and Lu et al. [20] conducted comprehensive comparison of in-memory distributed vertex-centric systems, while [20] also compared the running time of these systems with GraphChi. Li et al. [19] analyzed the performance differences of a number of general-purpose distributed systems such as Spark, Flink, Naiad [23], and Husky [41, 42]. They also examined the performance of these systems on some graph algorithms, but the scope is rather limited. [22] showed that some distributed systems have worse performance than a raw single-threaded implementation, but it may not be fair to compare the performance of general-purpose graph systems with that of a specialized implementation of a graph algorithm. *We are the first to cover all the quadrants of the two dimensions, and the findings from our systematic study are insightful for graph analytics system selection and development.*

8 CONCLUSIONS

We classified existing graph analytics systems into four categories according to their hardware requirements and architectural differences, analyzed the strengths and limitations of the systems in each category, and compared them in terms of their running time and resource cost. Many interesting findings are observed. For example, in-memory centralized systems are always the best for graph traversal applications on large-diameter graphs and fastest for processing small graphs with lighter workloads, but they perform worse (even when memory is sufficient) than in-memory distributed systems when computation workload is heavy and the input graph is large. For in-memory execution, distributed systems are generally slower than centralized ones for jobs that require many iterations, as synchronization between machines is costly. Out-of-core systems are not suitable for processing large-diameter graphs due to the high cost of streaming data from/to disk, but out-of-core centralized systems are a good choice to balance resource cost and running time for computationally intensive workloads (even on large graphs). More detailed conclusions about our analysis are given in Sections 2, 5 and 6. A follow-up to this work is to perform an in-depth analysis on the performance difference between selected pairs of systems, and study whether the performance gap and what fraction of the gap comes specific system design and implementation choices such as barrier synchronization, shuffling, message combiner, memory access patterns, etc. We will also investigate the performance of various systems on extremely large graphs with different graph characteristics.

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