LinkBench: a Database Benchmark Based on the Facebook Social Graph

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ABSTRACT

Database benchmarks are an important tool for database researchers and practitioners that ease the process of making informed comparisons between different database hardware, software and configurations. Large scale web services such as social networks are a major and growing database application area, but currently there are few benchmarks that accurately model web service workloads.

In this paper we present a new synthetic benchmark called LinkBench. LinkBench is based on traces from production databases that store "social graph" data at Facebook, a major social network. We characterize the data and query workload in many dimensions, and use the insights gained to construct a realistic synthetic benchmark. LinkBench provides a realistic and challenging test for persistent storage of social and web service data, filling a gap in the available tools for researchers, developers and administrators.

Categories and Subject Descriptors

H.2 [**Information Systems**]: Database Management

General Terms

Experimentation, Measurement, Performance

Keywords

Social networks; database workload analysis; database benchmarks; MySQL; HBase

1. INTRODUCTION

Much of the data powering Facebook is represented as a *social graph*, comprised of people, pages, groups, user-generated content and other entities interconnected by edges representing relationships. Such graph data models have become popular as sophisticated social web services proliferate.

At Facebook, persistent storage for the social graph is provided by sharded MySQL[1] databases. Facebook's memcached and TAO cache clusters [2, 3] provide a caching layer that can serve most reads, so the MySQL layer's production workload is comprised of cache-miss reads and all writes.

The Database Enginering team at Facebook has a growing need for benchmarks that reflect this database workload to assist with development, testing, and evaluation of alternative database technologies. Facebook's software architecture abstracts storage backends for social graph data, allowing alternative database systems to be used.

Given the scale of Facebook's infrastructure, any changes in technology require careful evaluation and testing. For example, in the past we performed a thorough evaluation of HBase [4] as an alternative social graph storage backend. Facebook already uses HBase for major applications including its messaging backend [5]. To accurately compare performance of MySQL and HBase, we mirrored part of the production workload on "shadow" clusters running our tuned and enhanced versions of MySQL and HBase. Contrary to expectation, MySQL slightly outperformed HBase in latency and throughput while using a fraction of the CPU and I/O capacity. Further experiment details are in Appendix A

This benchmark effort was time-consuming, which motivated a more streamlined approach to database benchmarking for the Facebook MySQL workload. Assessing new database systems will be crucial in the near future due to hardware trends such as solid state storage and increasing core counts. These new technologies could allow impressive performance gains, but systems well-suited to the previous bottleneck of rotating disks cannot always exploit the I/O capacity of solid state drives or the processing power of many-core. Significant efforts are underway in industry and academia to better exploit this new generation of hardware, including key-value stores such as FlashStore [6], SILT [7], embedded databases such as WiredTiger [8] and new storage engines for relational databases such as TokuDB [9].

Many of these developments are promising, as are ongoing efforts to improve and adapt current technologies such as MySQL/InnoDB. We intend to conduct ongoing benchmarking on new and existing systems to guide decisions about the future of social graph storage at Facebook.

In aid of ongoing benchmarking, we have constructed a synthetic benchmark that aims to predict the performance of a database when used for persistent storage of Facebook's production data. We believe the benchmark will be of interest to the broader database community since, in recent years, large-scale social applications have become a major application area. Our workload can serve as an exemplar of such applications, many of which have similar graph-structured data and data access patterns. A synthetic benchmark has

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advantages in comparison to alternative approaches, such as capturing and replaying traces. We can share the benchmark with the broader research community without any risk of compromising users' privacy. It also allows the benchmark to be parameterized, allowing the simulated data and workload to be varied to test systems of different scales and to explore different scenarios and workloads.

The contributions of this paper are:

- A detailed characterization of a large-scale social graph workload using traces collected from production databases.
- LinkBench, a configurable open-source database benchmark[1] that is closely based on this characterization.

Together we hope that these two contributions can provide the knowledge and tools necessary to enable realistic benchmarks of persistent storage for large-scale web services.

2. RELATED WORK

Previous authors [10, 11] have made the case for application-specific benchmarking where a benchmark is derived from application data and traces. Tay [11] highlights the challenges in scaling up or down complex data sets such as social graphs while retaining important correlations in the data.

Standard database benchmarks have different characteristics from the Facebook MySQL workload. Transactional benchmarks such as TPC-C [12] are typically based on business transaction-processing workloads and extensively exercise the transaction handling properties required to maintain ACID. Analytic benchmarks such as TPC-H [13] focus on complex queries that involve large table scans, joins and aggregation. The Facebook MySQL workload places different demands on database systems from either type of benchmark and could be served by database systems without full ACID or SQL support. Queries are fairly simple and short-lived with no full table scans or joins. Similararly, some ACID properties are needed, but transactions are simple and short-lived.

Existing graph [14, 15] and object database benchmarks [16] operate on graph-structured data, but emphasize multi-hop traversals and complex graph analysis, in contrast to the simpler single-hop queries in our workload.

The Yahoo Cloud Services Benchmark [17] is a benchmark designed to measure performance of different database systems, particularly distributed "cloud" database systems. The Facebook workload has similarities to the YSCB benchmark, but the data, supported operations, and workload mix are different. YCSB's data model is not graph-structured, rather using a simpler tabular key-value data model. The variety of queries in YCSB comprises point reads and writes and range scans, while our workload uses distinct node and edge operations and also edge count operations. The richer variety of operations can require additional database features such as secondary indices and multi-row atomic updates to implement efficiently. LinkBench's workload and data model is also grounded directly in measurements from production systems to increase our confidence in the relevance of the benchmark. Additionally, LinkBench aims to benchmark the persistent storage layer, because row-level caching is external to the database. This focus simplifies measuring the implication of design choices such as disk storage layout, without confounding factors that arise from varying implementations of caching and replication in distributed databases.

BG [18] is a recently developed benchmark that simulates users of a social network. BG's approach differs from LinkBench: it is based on simulation of individual, stateful, users who carry out various social networking actions, while LinkBench uses a (mostly) stateless parameterized workload generator. BG is based on an artificial (but plausible) data model and workload, while LinkBench's parameters are derived from the production database workload at Facebook. BG emulates the entire storage stack, including in-memory caches, while LinkBench aims to benchmark the persistant storage layer only. The different benchmark designs reflect these different goals: simulating stateful users adds temporal and spatial locality, which is a dominant factor in the pre-cache workload, but less significant post-cache.

3. WORKLOAD CHARACTERIZATION

This section presents a characterization of Facebook's social graph workload, identifying key characteristics that we will replicate in a synthetic benchmark.

3.1 Social Graph Data Model

id	int64	unique identifier
type	int32	type of object
version	int64	tracks version of object
update_time	int32	last modification (UNIX timestamp)
data	text	data payload

(a) Object (graph node). id is unique key.

id1, id2	int64	IDs of edge's endpoints
atype	int64	type of the association
visibility	int8	visibility mode of the edge
timestamp	int32	a client-provided sort key
data	varchar	small additional data payload

(b) Association (graph edge). (id1, atype, id2) is unique key.

Table 1: Database schema for social graph storage.

The social graph at Facebook comprises many *objects*, the nodes in the graph, and *associations*, directed edges in the graph. There are many different types of objects and associations. Examples of entities represented as objects include users, status updates, photo albums, or photos/video metadata: typically entities which have some associated data. Associations are a lightweight way to represent relationships between objects, for example if a user posted a photo, a user liked a photo or if a user is friends with another user.

Table 1 shows the schema used to represent objects and associations. The *data* fields are stored as a binary string. A system at a higher level in the software stack supports richer data types with per-object-type schemas which can then be serialized into the data field. The *version* and *update_time* fields of the objects are updated with each change to the object's data, with the version incremented and update_time set to the current time. The *timestamp* field of an association is a general-purpose user-defined sort key (often a true timestamp), where high values are retrieved first. The *visibility* field allows data to be hidden for use cases that require data to be retained, for example a user temporarily disabling their account. Other use cases, such as a user deleting their

[1]http://github.com/facebook/linkbench

post, will result in database-level deletes. Only visible associations are included in any query results (including counts). This graph schema is the foundation upon which many services are built: for example, rules about privacy of graph nodes and edges or services for managing the life-cycle of data can be implemented in higher-level services.

3.2 Sharding and Replication

The entire Facebook graph is far too large to fit on a single server, so must be split into many *shards*. The nodes (objects) in the graph are allocated to shards based on *ID*, with a function mapping the ID to a shard. Associations (edges) are assigned to shards by applying the same mapping to *ID1*, meaning that all out-edges for a node are in the same shard. Client applications have some control over the location of newly created objects. For example, a new object could be colocated with a related object (yielding some performance benefit from locality) or assigned to a random shard. The number of shards is chosen so that there are many shards per database instance, allowing rebalancing if necessary.

Each database instance has multiple replicas, with one master and multiple slaves. Replicas are geographically distributed, with reads handled from local replicas, which reduces latency and inter-datacenter traffic. Maintaining multiple replicas also allows for manual failover in the event of node or datacenter outages. All writes are applied synchronously at the master database, and replicated to slaves asynchronously (but under normal circumstances, quickly). In the current MySQL/InnoDB system, the data storage layer supports ACID, so the master MySQL instance has a fully consistent snapshot at all times. The overall system therefore provides timeline consistency [19], which is stronger than the eventual consistency supported by some other systems.

3.3 Structure of the Social Graph

One component of a benchmark is a data generator that can produce synthetic data with similar characteristics to real data. To understand the salient characteristics of our real data, such as graph structure and typical record size, we looked in detail at the data in a single MySQL instance.

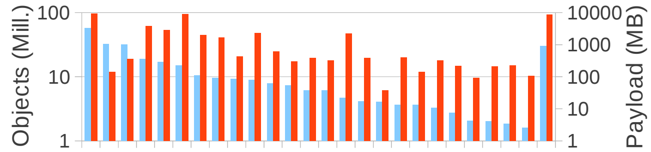
Due to some non-uniformity in the data between different shards, the numbers and charts presented in this section do not cover the entire data set, but we expect that they are representative.

3.3.1 Object and Association Types

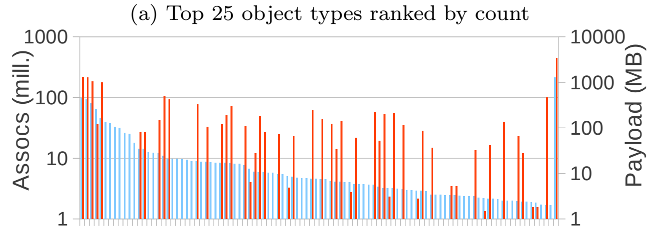
Figure 1 shows the breakdown of graph data by object and association type. The results indicate that the social graph have evolved to comprise a diverse array of data types, representing not only connections between users, but a web of many objects including pages, posts, comments connected by various edge types, each having some particular meaning. The variety of data size and counts, indicates that, for the purposes of benchmarking, there may be significant non-uniformity between types.

3.3.2 Payload Data

The mean payload per object is 87.6 bytes, while the average payload per association is much smaller at 11.3 bytes. 49% of associations have no payload: their purpose is purely to indicate a connection, rather than to carry additional



(a) Top 25 object types ranked by count



(b) Top 100 association types ranked by count

Figure 1: Distribution of social graph nodes (objects) and edges (associations) among data types, showing total counts (light blue) and total payload data size (dark red) in a single MySQL instance. Some types are extremely common, with many instances per user, yet the "tail" of uncommon types comprises a large portion of the entire social graph. The rightmost category is *Other*.

	Compression ratio
Objects in database	61.3%
Object insert queries	46.0%
Object update queries	67.2%
Associations in database	30.6%
Association insert queries	30.3%
Association update queries	57.5%

Table 2: Compressibility of object payload data from different sources. Payload data from a random sample of rows was concatenated into a single file separated by newlines and compressed using bzip2.

data. Figure 2 shows the overall distributions of data size for objects and associations. The distributions are similar to log-normal distributions, aside from the significant number of objects and associations with no payload. Further analysis also found this distribution to exist at the level of individual data types.

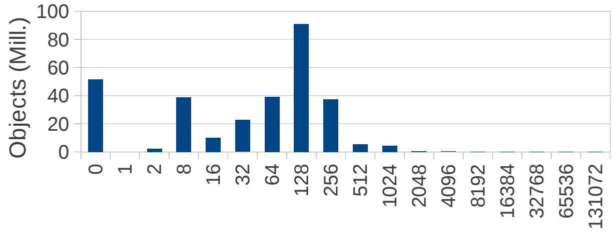
Payload data uses a mix of formats, including text-based and binary formats. Large payloads are compressed above the database tier. Compressibility of this data can have significant implications for disk, I/O, memory and CPU usage if the database system compresses data. This applies to our use case, where we rely on page-level compression of MySQL InnoDB tables to improve storage efficiency.

Compressibility was estimated by sampling data from several sources and compressing with bzip2, an effective but slow compression algorithm. Results are shown in Table 2. Compressibility varies between sources, but 60% and 30% for object and association payload data respectively are representative compression ratios.

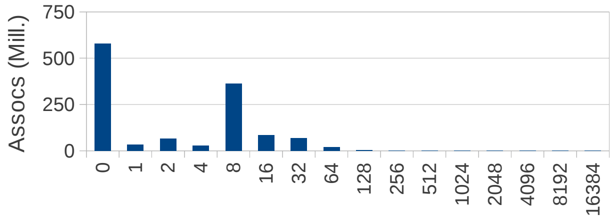
3.3.3 Graph Structure

Understanding certain properties of structure of the social graph for generation of realistic benchmark data.

The outdegree distribution for each object is one important property. Every object has at least one out-edge, however there are also out-edges for node IDs that do not corre-



(a) Object payload bytes distribution



(b) Association payload bytes distribution

Figure 2: Payload size distributions. Both follow roughly log-normal distributions, aside from an additional peak at 0 bytes. In both cases payload sizes cluster within an order of magnitude around different modes. Histogram buckets are labeled with the lower bound.

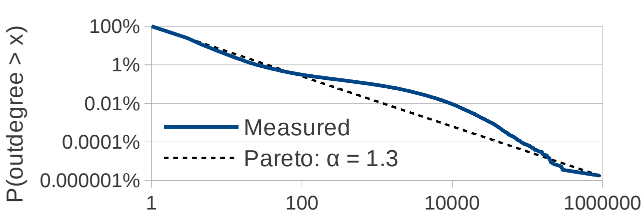


Figure 3: Distribution of node outdegree (logarithmic scale)

spond to objects: some data types are allocated identifiers but are not represented as objects. Figure 3 shows the outdegree distribution. We see that the trend is consistent with a pareto distribution, but with a bulge showing more nodes with outdegree between 100 and $100,000$ than a pareto distribution.

Previous analysis of online social networks [20, 21] has reported similar heavy-tailed power-law distributions for social networks comprised solely of people and relationships between people. Our results show that a power-law distribution still occurs with the additional variety of nodes and edges of the full Facebook social graph.

Further higher-order properties of the social graph structure could be examined, such as clustering coefficient [22] or community structure [23]. However, for the purpose of modeling our database workload, we believe that higher-order graph structure in communities or correlations between properties of neighboring nodes will have only a small effect on database performance. For the operations in our workload, locality of access for a given ID and the average result size for range scans are the main factors influencing performance of each operation. There are certainly patterns of temporal and spatial locality in our social network workload as users navigate the social graph. The amount of locality at the database layer, however, is likely to be small and unpredictable because aggressive row-level caching before the database absorbs a great deal of locality. Since we will not model this particular source of locality, a generative model that neglects higher order graph structure is sufficient to evaluate database performance.

Graph Operation	Result	# Queries	% Queries
obj_get(ot, id)	object	45.3M	12.9
obj_insert(ot, version, time, data)	id	9.0M	2.6
obj_delete(ot, id)	-	3.5M	1.0
obj_update(ot, id, version, time, data)	-	25.8M	7.4
assoc_count(at, id)	count	17.1M	4.9
assoc_range(at, id1, max_time, limit)	assocs	177.7M	50.7
assoc_multiget(at, id1, id2_list)	assocs	1.8M	0.5
assoc_insert(at, id1, id2, vis, time, version, data)	-	31.5M	9.0
assoc_delete(atype, id1, id2)	-	10.5M	3.0
assoc_update(atype, id1, id2, vis, time, version, data)	-	28.1M	8.0

Table 3: The set of social graph operations received by database instance over a six day period. Operation parameters and return values are shown, *ot* stands for object type and *at* stands for association type. Other parameters correspond to fields described in Section 3.1.

3.4 Operation Mix

The set of operations used by the web front end and other services to access the social graph include standard insert, update, and delete operations to modify data, along with variations on key lookup, range, and count queries. The set of operations covers most of the common access patterns required to serve data to users and is deliberately kept simple, to allow easier caching and system implementation. There are features, such as complex search queries, that cannot be efficiently implemented using this interface and are implemented as separate specialized services.

The queries issued to databases are classified into a few basic operations, shown in Table 3. These include:

- Point reads for associations and objects identified by primary key, with the option of batching multiple association reads batched into a single query.
- Simple create, delete, and update operations for associations and objects identified by primary key.
- Association range queries for a given ID, type, and timestamp range, ordered from latest to oldest. For example, a range query might obtain be used to obtain edges leading to the most recent comments on a post. A row limit, N, must be specified. The most recent N associations before the provided timestamp are returned.
- Association count queries, for the number of visible out-edges of a given type from a given node. For example, a count query might count a user's friends.

To understand the database workload, we collected a trace of queries issued by TAO, the distributed in-memory caching

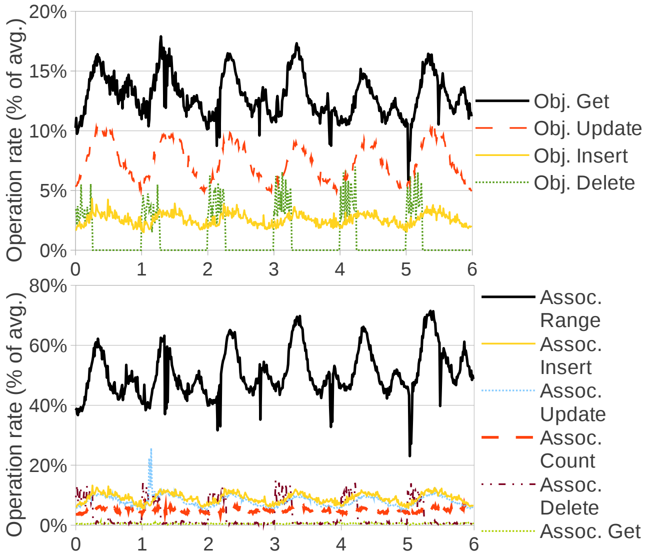


Figure 4: Temporal variation in operations per second in workload over six days, normalized to the average total operations per second over the period. Top: object operations. Bottom: association operations.

Row limit	% of range queries
1	0.86%
1000	0.39%
6000	7.44%
10000	91.54%
Other	0.07%

(a) Row limit for range queries observed in read workload

# rows	% of range queries
0	26.6%
1	45.4%
2	5.4%
3-5	6.4%
6-10	4.2%
11-20	4.2%
21-50	3.5%
51-100	1.6%
101-500	2.0%
501-1000	0.4%
1001-10000	0.3%
>10000	0.01%

(b) Range scan row count distribution

# keys	% of assoc. get queries
1	64.6%
2	8.8%
3	3.1%
4	1.9%
5	1.6%
6	1.4%
7	10.6%
8	0.8%
9	7.1%
10	0.2%

(c) Lookup key count for multi-get queries

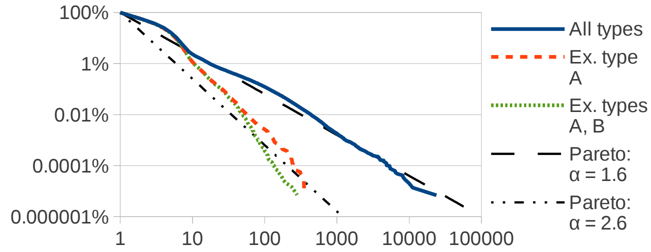
Table 4: Rows read for social graph edge read queries

system through which Facebook's production web infrastructure accesses the social graph. We logged all social graph database queries for the same MySQL instance for a six day period. This section presents an analysis of the trace.

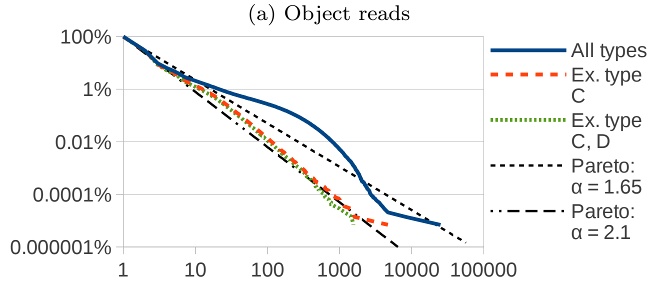
Table 3 shows a 2.19 : 1 ratio of read to write queries and a 3.19 : 1 ratio of association of object queries, with association range queries alone making up half of the workload. System load varies over time (see Figure 4) with a high base level and major and minor peaks every day.

Although the workload was fairly balanced between read and write operations, we saw 40.8 rows read per row written, since write operations only affect a single row but many read operations return multiple rows. The workload is surprisingly read heavy given that all writes hit the databases, but cache clusters serve most reads. Most range scans had a large upper limit on the result size (Table 4a). The large limits are due to aggressive caching that prefetches and caches ranges of associations. Analysis of read logs showed that the mean range scan result, ignoring limits, was 21.9 rows. Table 4b shows the full distribution. Range limits only slightly reduce this: uniform limits of of 10000 or 6000 would result in 20.9 or 20.1 rows respectively. The average number of keys per association multiget query was 2.62. Table 4b shows the full distribution.

Most range queries were for the n most recent items: 0.96% of range scan queries specified a maximum timestamp, typically because they were trying to fetch older history that was not retrieved in the first query.



(a) Object reads



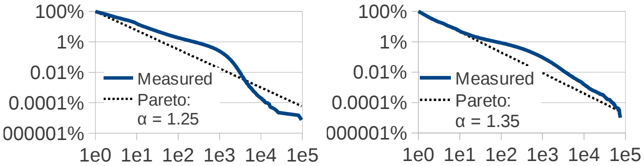
(b) Object writes

Figure 5: Distribution of accesses for different kinds of operations based on ID of object. Pareto distributions are shown for comparison. Distributions are also shown excluding the two top types for reads and writes, which exhibited unusual behavior.

3.5 Access Patterns and Distributions

In database deployments, some "hot" data is far more frequently accessed than other data, while there is often also "cold" data that is infrequently accessed, if at all. Stated differently, some rows of data are orders of magnitude more likely to be read or written than others. When constructing a synthetic benchmark, it is important to have realistic data access patterns because the interaction between patterns of hot and cold rows and a database system's caches is an important factor in overall performance.

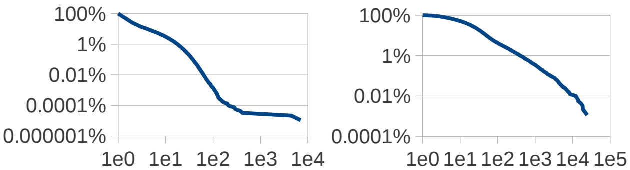
In order to do an initial characterization of the distribution of "hotness" for data, we examined the distribution of operations between different node IDs. We aggregated all different varieties of reads and writes. Different categories of operation show similar skewed access distributions, where the majority of items are rarely accessed, but a small minority are read and written frequently. These patterns occur



(a) association reads (get, count, and range queries)

(b) association writes (update, insert, and delete queries)

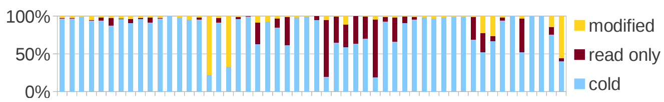
Figure 6: Distribution of accesses for different kinds of operations based on ID1/type of association



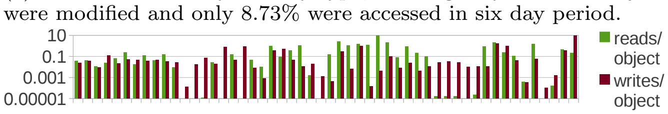
(a) Edges from user to object liked

(b) Edges from objects to user they were liked by

Figure 7: Distribution of reads for the "like" association showing that power law behavior is still present for individual association types.

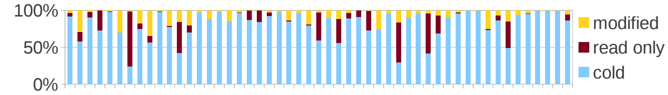


(a) Cold and read-only data by type, showing only 4.78% of objects were modified and only 8.73% were accessed in six day period.

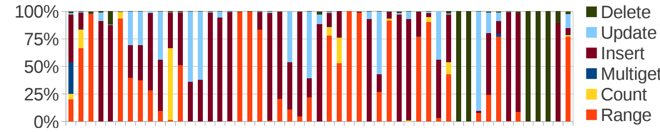


(b) Intensity of reads and writes per row of data

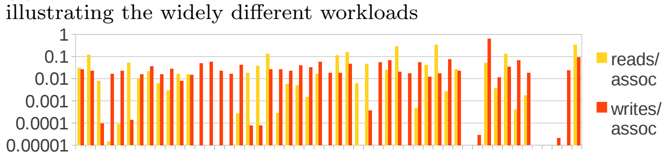
Figure 8: Workload metrics for top object types, illustrating the disparity in data access patterns for different types



(a) Proportion of association lists (identified by unique ID1, assoc_type pair), which are accessed or modified. Overall 3.2% of lists were modified and 7.8% were accessed.



(b) Relative proportions of different operations per association type, illustrating the widely different workloads



(c) The number of operations relative to the total number of associations of that type

Figure 9: Workload metrics for top association types, illustrating the disparity in data access patterns

even in spite of the extensive caching of data outside of the database. Figure 5 and Figure 6 show the access distributions for objects and associations respectively. A power-law distribution, such as the pareto distribution, looks to be a reasonable approximation. We examined several of the most popular association and object types and determined that the power law distribution remains when looking at individual data types. E.g. Figure 7 shows the access distribution for the *like* association, one of the top association types.

In order to produce a realistic benchmark, we want to understand what affects frequency of access of graph nodes and edges so that we can emulate important correlations in a benchmark. We looked into a number of possibilities to better inform the design of LinkBench, which we explore in the next two sections.

3.6 Access Patterns by Data Type

Some of the variation may be explained by different access patterns for different types. For example, a person's profile is probably more frequently accessed than a given post.

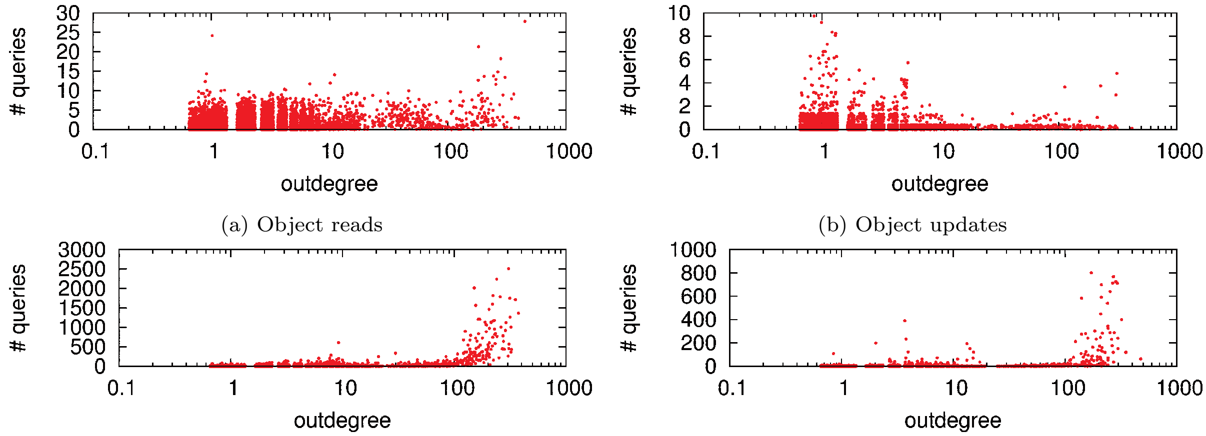
Figure 8 illustrates varying access patterns for different object types, with different types having widely varying ratios of reads to writes. We looked at what fraction of objects were never accessed, or *cold*. Overall a large proportion of objects, 91.3%, are cold data that was never accessed during the 6 day trace. 95.2% were read-only during that period. This is unsurprising since nodes in the social graph, such as posts and status updates, become less relevant and less discoverable as they age. Much data is also in practice read-only: it is rarely, if ever, modified once present. Some types are far more intensely read and written than other types, with average read and write intensity varying by two to three orders of magnitude between types.

Access patterns for associations are more complex, because of the variety of supported operations, and because range queries return variable numbers of rows. Figure 9 compares metrics between association types. As with objects, the workload varies greatly between association types in composition of queries and frequency of reads and writes.

We looked at what proportion of associations were cold. Breaking down the associations into lists, identified by a (id1, assoc_type) pair, we saw that 92.2% of these lists were cold and not the subject of any read or write operations in 6 day period and 96.6% were not modified. 23.3% of queried lists were only counted, without any association data returned. Interestingly, 92.2% of association lists were cold, but only 74% of association rows were cold. This indicates a correlation between the length of an association list and the likelihood of it being accessed.

3.7 Graph Structure and Access Patterns

Another possible explanation for varying access patterns is graph structure. For example, the "popularity" of a node in the graph is likely to be related to he number of edges to or from the node: its indegree or outdegree. For example, a post that has been shared by many people or a page for a popular figure with many followers will be frequently accessed. Objects with high degrees are more "discoverable" with more paths through the social graph leading to them. They may also accumulate more new edges, due to processes such as preferential attachment that can occur in social networks[24], where nodes with high degree accumulate even more edges as a graph evolves over time.



(a) Object reads

(b) Object updates

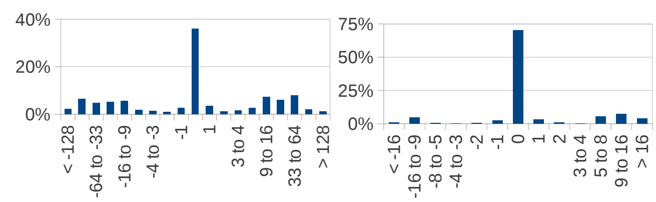
(c) Association read queries

(d) Association insert/delete/update queries

Figure 10: Correlation between social graph node's outdegree and read/write frequency The outdegree is correlated with operations on edges (associations), but not operations on nodes (objects). Jitter added to show density.

Field	% Assoc. Updates
Visibility	12.0%
Timestamp	84.4%
Version	98.4%
Data	46.3%

Table 5: Fields modified by association update operations



(a) Object updates

(b) Association updates

Figure 11: Distribution of payload size change in bytes upon update operation. Most data updates only change the size a small amount.

To investigate, we took a random sample of 1% of nodes with outdegree ≥ 1 and compared the outdegree with the number of queries for that ID in the trace. Figure 10 shows the results for various classes of queries. There is a correlation between outdegree and association read queries (mostly range scans), while there is little correlation for node read queries, possible because simple object retrievals are cached more effectively than complex association queries. Similar patterns can be seen for write queries. This indicates that a realistic benchmark needs to have a query mix that is biased towards graph nodes with high outdegree.

3.8 Update characterization

The nature of in-place updates may have some impact on performance of the system, for example causing fragmentation if data shrinks or forcing additional page allocations.

Updates to objects always update the version, timestamp, and data fields. Updates to associations often only update one or two fields, such as the timestamp or the visibility, as shown in Table 5. Typically the payload data size only changes by a small amount, illustrated by Figure 11. For objects, over a third of updates do not change the data size, while the majority of other updates alter it less than 128 bytes. Associations exhibit a similar pattern. In both cases, when the data size stays constant it is typically because a data field, such as a number or other identifier, is modified such that representation length does not change.

4. BENCHMARK DESIGN

In this section we present the LinkBench database benchmark, describing the architecture of the system, the configurable building blocks that allow the benchmark to be customized, and the process of generating a synthetic social graph and database workload of graph operations.

The benchmark is designed to test performance of a single database instance in isolation. We have a client-server architecture, shown in Figure 12 with the LinkBench client implemented in Java driving a *graph store*. We currently have implemented a MySQL graph store, but any database system that meets the requirements in Section 4.1 can be benchmarked. We describe key decisions made in the design of the client in Section 4.2.

The LinkBench driver operates in two phases. The first phase populates the graph store by generating and bulk-loading a synthetic social graph. The generative model used is described in Section 4.3 and Section 4.4. In the second phase the driver benchmarks the graph store with a generated workload of database queries and collects performance statistics. Generation of the simulated workload is discussed in Section 4.5 and the metrics collected are discussed in Section 4.6. Both phases have many configurable parameters that can be used to scale up or down the workload, or to explore workloads with different characteristics.

4.1 LinkBench Graph Store Implementation

LinkBench is designed so that the same benchmark implementation can be used for many different database systems. A database can be used as a LinkBench *graph store* with an adapter implementing the operations in Table 3.

To ensure comparability of benchmark results, we impose

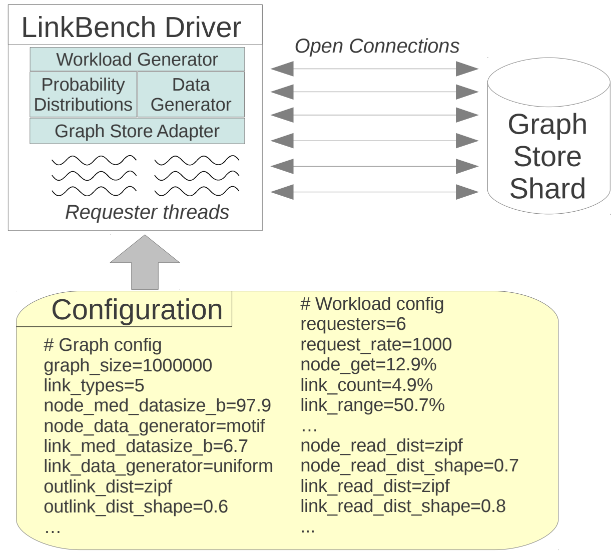


Figure 12: LinkBench architecture, showing the datastore under benchmark (which could logically be considered a single shard of a larger system), a subset of configuration settings, and the internal components of the LinkBench driver.

some constraints on the implementation. The entire social graph should be stored in persistent storage. Any database schemas, compression, indices or other configuration or optimization should be reported. All writes must be durable, with data flushed to persistent storage before the operation completes so that the data can be recovered in the event of a crash. Any update operations should be atomic and ensure consistency. For example, in our MySQL benchmark implementation, a separate edge count is updated in the same atomic transaction as an edge insertion or deletion. Any weaker ACID properties should be disclosed.

4.2 Benchmark Client Design

In designing the benchmark we kept a balance between the realism of the workload and the simplicity of the implementation. We avoid requiring communication between concurrent requesting threads, which makes scaling the benchmark client trivial. We also minimize the amount of state required in the benchmark client: with one exception, no state is tracked in the benchmark client. In particular, we avoided any approaches that would have required storing a significant volume of data about a full multi-terabyte graph in memory. This means that, in order to generate a workload that is influenced with graph structure, we had to rely on knowledge of how the initial graph was generated. The statelessness contrasts with real-world clients, where navigation patterns of users induce some spatial locality, with bursts of activity in sections of the graph. We believe that the locality effects will be limited and unpredictable due to the aggressive caching, so we will not sacrifice much realism.

4.3 Workload Generator Building Blocks

LinkBench uses a range of configurable and extensible building blocks so that the benchmark can be tweaked and customized. The benchmark configuration file contains many modifiable parameters, and allows different implementations of these building blocks for graph creation and workload generation to be swapped in.

LinkBench has a framework for *probability distributions*, which are used in many places in the benchmark to generate random data. Distributions are implemented as Java classes and include the uniform distribution, the Zipf distribution, and the log-normal distribution. Wherever a distribution is used in LinkBench, the implementation and parameters can be configured. A distribution provides two functions: a quantile function that allows, for example, calculation of outdegree of the graph node with the kth highest outdegree out of n nodes; and a choose function that selects integers in a range $[1, n]$ with probability weighted by the distribution.

The weighting works such that the lowest keys are most popular, meaning that popular database rows would be clustered together if the values are used directly as database row keys. In real data sets, popular data is scattered throughput the key space. Other benchmarks shuffle popular data throughout the key space by permuting each key i within the range of valid keys $[1, n]$ using a permutation function $p(i)$. Gray suggests multiplying the index by a prime modulo n to obtain the new key [25]. YCSB [17] generates keys within a much larger range then shrinks the range by hashing.

In LinkBench, we want correlated distributions for access frequency and node outdegree, while generating data in bulk in primary key order. In order to achieve this the inverse of the prior permutation, $p^{-1}(i)$, needs to be efficiently computable. Both permutation functions mentioned previously are difficult to invert, so LinkBench uses a different, invertible, *permutation function*. It can be given different parameters to alter the permutation, and has low CPU and memory overhead. If there are n items in the keyspace, we choose a number k, for example $k = 1024$. We then fill an array A with k pseudorandom integers (using a known seed for reproducibility). If n is divisible by k, then the permutation is computed as $p(i) = ((i + k \cdot A[i \bmod k]) \bmod n)$, which rotates each set of indices with the same remainder modulo k in the keyspace. The inverse is easily computable using the same formula with $A[i \bmod k]$ negated. For LinkBench, we generalized the formula for the case where n is not divisible by k. This method of permuting data can key distribution sufficiently with limited memory overhead.

LinkBench also has a framework for *data generators*, which can fill byte buffers with randomly generated data, useful to generate payload data for graph nodes and edges that has similar compressibility to real data. By default, LinkBench uses the *motif data generator*, which generates a configurable mix of random bytes and repeated multi-byte motifs.

4.4 Generative Model for Social Graph

In this section we describe the generative model used to construct a social graph. Generating random graphs with structure close to real social networks is challenging and an active area of research. For the purposes of the benchmark, we do not need full fidelity to the original graph structure. Rather, we want a simple, configurable, and fast graph generator that gives results close to the real social graph in the right dimensions so that it places similar stresses on the database. The degree distribution of the generated data must be realistic, so that similar numbers of records are scanned by range queries. However, the community structure of the generated graph (e.g. the probability of two friends having another mutual friend) is unimportant, as this does not directly affect the performance of any queries in the workload.

4.4.1 Graph Size

LinkBench can be run with different graph sizes by specifying the *initial node ID range*. For example, if a range of $[1..1,000,001]$ is specified, then $1,000,000$ nodes and corresponding edges will be bulk loaded. The graph will continue to expand in the later benchmark phase.

For full-scale benchmarking we use graphs with around 1 billion nodes occupying approximately 1TB using InnoDB without compression. A social graph of this size can be generated and loaded by LinkBench in around 12 hours on a high-end servers with solid state drives thanks to bulk-loading optimizations such as batch insertions.

4.4.2 Generating Graph Nodes

The simpler part of generating a synthetic social graph is generating graph nodes (also referred to as objects). We have simplified the benchmark by only having a single node type in the graph. The major downside of this is that we cannot have different types of nodes with different workload characteristics. The simplification of the benchmark implementation is considerable, as without this simplification, to select a random node ID of a given type to query would require the benchmark client to track which parts of the ID space are of which type. This is challenging and memory-intensive when new IDs are being allocated during the benchmark. This is a good compromise, since node queries are a small portion of the workload compared to edge queries and much of the variation in access patterns is captured by the access distributions used for node queries.

Node payload data is generated using the *motif generator* with parameters chosen to get a compression ratio of approximately 60%, similar to the measured compression ratio in Table 2. The size of the payload is chosen from a configured probability distribution. We use a log-normal distribution with a median of 128 bytes.

4.4.3 Generating Graph Edges

Given the varying access patterns for different association types seen in Section 3.6, we explored the possibility of a benchmark that incorporated a range of distinct edge types. However, in the end we decided against attempting to faithfully replicate this diversity, mainly because we could not justify the additional complexity when it was possible to capture much variation with a homogenous model of edges. We support a configurable number of association types, but all use the same data and workload generator.

Graph edges (or associations) are generated concurrently with graph nodes during bulk loading. We divide the node ID space into chunks based on the ID of the source node. The chunks are processed in parallel to speed loading. The chunks are processed in approximate order of ID and within each chunk strictly in order of ID. Loading in primary key order can speeds up loading greatly for many database systems. As an aside, we have encountered a phenomenon with MySQL's InnoDB B-tree-based tables where, after a table is loaded in primary key order, insertion and deletion can cause fragmentation over time. This leads to increased storage usage and somewhat degraded performance. Database benchmarkers should be aware of such phenomena, particularly when examining storage efficiency.

For each node the steps to generate edges are:

1. Choose the outdegree deterministically using a probability distribution and shuffler. We use the measured outdegree distribution from Section 3.3.3 directly.
2. Divide the out-edges between the different association types in a round robin fashion, in such a way that the ith type always has at least as many edges as the $i+1$th type.
3. Select the ID of target nodes for the jth edge of each type to be source_id $+ j$. This makes it simple to determine during later workload generation which graph edges are likely to exist.
4. Generate payload data for each edge using the motif data generator with settings tuned to produce data that can be compressed to approximately 30% of its original size, in line with Table 2.

4.5 Generating Workload

Our workload generator comprises many threads of execution, all of which execute a randomized workload generated with the same parameters but a different random seed. Statistics are collected by each thread and then aggregated at the end of the benchmark.

4.5.1 Node Selection

As discussed previously, some of the most important features of the benchmark workload are the access patterns for different data types and operations: the distribution of reads and writes between graph nodes and edges. In this section we discuss the approaches used to select the IDs for nodes used for operations.

The access patterns for node reads, node writes, edge reads and edge writes are separately configurable using the previously described probability distribution framework. We use the algorithm described by Gray et al. [25] to implement a Zipf probability distribution that is used for node accesses, with parameters calculated based on the fitted pareto distributions in Section 3.5.

The most straightforward access patterns are for node queries, where only the node ID must be chosen. Since we observed that node query frequency was uncorrelated with the number of out-edges, we use a different shuffler to that used to generate outdegree.

For edge queries, we saw a loose correlation between row hotness and outdegree in the real workload. In order to simulate this loose correlation two access distributions are combined: one with the same shuffler as the outdegree distribution, giving a perfect correlation between access frequency and outdegree, and another with a different shuffler and no correlation. The distributions are blended by selecting from the correlated distribution with probability p_{corr} and the uncorrelated with probability $1 - p_{\text{corr}}$ p_{corr} is selected such that the mean range scan size approximately matched the empirical observations.

Some edge operations (multiget, add, delete, update) require the the IDs of the edge ends be selected. Some operations (delete, update) require the edge to be present, while others (add) require the edge to be absent. In the synthetic benchmark we want to select present or absent edges as the operation requires. It is not practical for the client to track which potential edges exist for a large database, so we exploit the knowledge that edges from node i to nodes $[i..i + \text{outdegree}(id) - 1]$ were in the initial graph to choose target nodes with a given probability of the edge existing. Edges are added or removed during benchmarking, so to handle the cases of inserting existing edges and updating non-existing edges, a single combined insert/update operation is used that inserts if not present or updates if present.

4.5.2 Arrival Rate

In order to generate latency/throughput curves, we want to be able to control the arrival rate of new operations. We assume that the average arrival rate (a configurable parameter) remains constant during the benchmark and choose the interval between arrivals from an exponential distribution.

4.5.3 Operation Mix

Given the timing of an operation, we then need to select the operation to execute and then the parameters of that operation. We do not attempt to capture any temporal correlation between different operation types. The steps for all operations are the same:

1. An operation from Table 3 is selected. The measurements of the operation mix in Section 3.4 are used to select which operation to execute.
2. The ID (ID of the node or ID1 of the edge) is chosen as described previously
3. For edge queries, a association type is selected uniformly.
4. For non-range edge queries, the number of edges is selected using a geometric distribution with $p = 0.382$, yielding the same mean as observed (2.615 IDs per query).
5. Any required target node IDs of edges are chosen as described previously.
6. For data modification, node or edge fields are filled in with the same method as the load phase.
7. For edge range queries, a fixed result limit of $10,000$ is used. By default, the queries return the most recent rows, but a small fraction are *history queries* that specify a maximum timestamp.

The decision to generate node/payload data from scratch for every operation is an imperfect approximation of the real workload, since the workload characterization in Section 3.8 revealed that many updates only made a small change to data size or did not change some fields at all. This inaccuracy may slightly hurt update performance on storage layers that perform in-place modification of data, since the additional churn in data size and values may result in more fragmentation, page splitting, and dirty pages.

The fixed range result limit of $10,000$ should be reasonably reflective of the real workload: 90% of queries used that limit, while very few queries return more than $1,000$ rows. The client generates range history queries by maintaining a fixed-size cache of (id1, association_type, timestamp) records which are added whenever a range query returns $10,000$ rows (which indicates there is likely more history past the oldest timestamp). This simulates a process where a client, after retrieving the first $10,000$ entries in a list of edges, may later retrieve further history. This is the only stateful element of the LinkBench client.

4.6 Metrics

There are a number of key metrics that we want LinkBench to measure. The most important metrics for speed are operation latency and throughput. We measure latency in LinkBench from the time when the operation to be executed is selected in the Linkbench client until the time when the client receives all result data for a read operation or receives confirmation of durable completion for a write operation.

The mean operation throughput should be reported, along with the latency statistics for each operation type that are reported by LinkBench: latency at 50th, 75th, 95th, 99th percentiles, maximum latency, and mean latency.

Latency versus throughput curves can be obtained by varying the arrival rate of operations. A complete comparison of two systems will show a complete curve. Latency for specific operation types at the given level of throughput can also be reported.

Price/performance is also important, so for comparison of commercial systems, peak throughput per dollar for the full system (hardware and software) should be reported.

Several measures of resource utilization by the database system under test should be collected at regular intervals:

- CPU usage: user, system, idle, and wait.
- Read and write I/O operations per second.
- Read and write I/O rate in MB/s.
- Resident memory size.
- Persistent storage size, including temporary indices, tables, and logs.

All of these metrics are useful for understanding system performance and efficiency. Storage size has become increasingly important as the bottleneck for systems with solid state disks is often capacity rather than I/O.

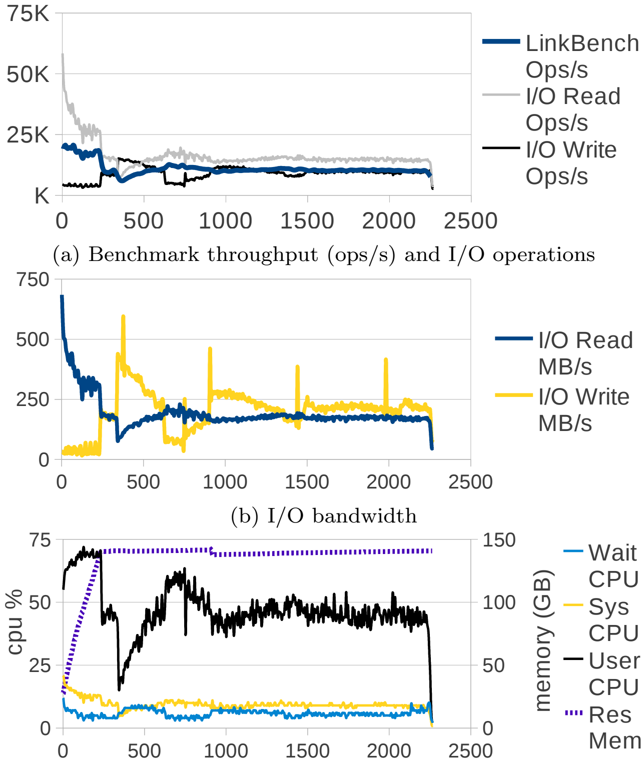
4.7 Validating Benchmark Configuration

Although LinkBench is customizable, we also focused on creating a workload configuration that would closely match the workload characterized earlier in this paper. This section summarizes how the match between LinkBench and our real workload can be validated in certain important dimensions.

The generated graph matches in several dimensions by construction: the outdegree distribution exactly matches the empirical outdegree distribution, while node and edge payload data sizes follow a similar log-normal distribution and have the same compression ratios.

The workload generated also matches in several dimensions by construction. The mix of different operation types is the same and the distributions of reads and writes to nodes follow power-law distribution with empirically derived exponents. The mean number of keys per multiget is the same and has a similar skewed distribution.

One important property of the workload that we could not guarantee by construction was the mean number of result rows for range queries, which was measured at approximately 21 rows. Our first attempted configuration lead to an average result size of several hundred rows, which markedly affected results. We brought this down to $20 - 30$ rows by modifying the configuration in several ways. Edges were split into two different association types, halving average length. We limited edge history queries, which tend to have



(a) Benchmark throughput (ops/s) and I/O operations

(b) I/O bandwidth

(c) CPU and memory utilization

Figure 13: Operation throughput and system resource utilization over time (in secs)

larger results, to 0.3% of range queries, less than the 0.96% observed. We finally set $p_{\text{corr}} = 0.005$ for edge reads, so the outdegree-correlated distribution is used only 0.5% of the time.

5. MYSQL BENCHMARK RESULTS

In this section we present results of benchmarking MySQL with LinkBench. The system under test is MySQL 5.1.53 with the Facebook patch. MySQL was configured with a 120GB InnoDB buffer pool and the association table partitioned 32 ways to reduce mutex contention. Full durability was enabled with logs flushed to disk at transaction commit and a binary log for replication generated. Separate hosts were used for the LinkBench client and MySQL server. The MySQL host had 2 CPU sockets, 8+ cores/socket, 144GB of RAM and solid-state storage with read latency at 16kB less than 500μs.

In order to ensure that benchmark performance was not bottlenecked by the LinkBench client, we did several runs while monitoring the client. The MySQL server was saturated using only a fraction of client CPU and network capacity. To double-check this result, we ran two LinkBench clients concurrently on different hosts and confirmed that this did not increase overall operation throughput.

A graph with 1.2 billion nodes and approximately 5 billion edges was generated, which occupied 1.4TB on disk.

We ran a benchmark with 50 concurrent requesting threads performing 25 million requests in total. Figure 13 shows benchmark throughput and resource utilization and Table 6 reports operation latencies at different percentiles. The benchmark took 2,266 seconds, for an average throughput of 11,029 requests a second. The system goes through a warm-up phase as the InnoDB buffer pool is populated with pages from disk and those pages are dirtied with writes. After a period it enters a steady-state phase. During the steady-state phase I/O read utilization remains high, indicating that the working set of the benchmark is larger than main memory. The high rates of I/O operations and I/O throughput highlight the benefit that MySQL/InnoDB can derive from solid-state storage.

	mean	p25	p50	p75	p95	p99	max
object_get	1.6	0.4	0.6	1	9	13	191
object_insert	4.2	1	3	5	12	20	142
object_delete	5.2	2	3	6	14	21	142
object_update	5.3	2	3	6	14	21	143
assoc_count	1.3	0.3	0.5	0.9	8	12	65
assoc_range	2.4	0.7	1	1	10	15	2064
assoc_multiget	1.7	0.5	0.8	1	9	14	53
assoc_insert	10.4	4	7	14	25	38	554
assoc_delete	5.1	0.5	1	7	19	31	468
assoc_update	10.3	4	7	14	25	38	554

Table 6: MySQL LinkBench operation latencies in ms

6. CONCLUSION

We have presented the motivation and design of LinkBench, a database benchmark that reflects real-world database workloads for social applications. We characterized the social graph data and accompanying database workload for Facebook's social network, extracting key statistical distributions and showing how power law distributions occur in several places. We then described the design and construction of a benchmark that mimics the key aspects of the database workload and presented a performance profile of the MySQL database system under this workload.

The benchmark software has been released as open source and we hope can be used by others to profile and experiment with other database systems. We will extend LinkBench with adapters for further database systems as we continue to evaluate new database technology for use at Facebook.

7. ACKNOWLEDGMENTS

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APPENDIX

A. HBASE/MYSQL EXPERIMENT

The HBase/MySQL comparison was begun in 2011 with the goal of reducing total cost of storing massive amounts of data in MySQL. HBase was already in production deployment for Facebook Messages. In addition it supports high write throughput and maintains replicas for quick failover.

A MySQL and a HBase cluster both received a portion of production requests. The HBase cluster had five machines: a HDFS NameNode, a HBase master and three nodes running both HDFS Datanode and HBase Region Server. Facebook's internal branches of HBase (roughly corresponding to HBase release 0.94) and HDFS were used. A native C++ client for HBase was developed and used for benchmarking. LZO compression was used. The MySQL cluster had three machines each running one MySQL server. Zlib compression was used. Both MySQL and HBase servers had 8GB of memory available for data caching (the OS buffer cache was disabled). In-house experts for both MySQL and HBase were involved in tuning and optimizing both systems, leading to HBase enhancements for latency and I/O.

We measured the 99th percentile latencies of several operations. Latencies were similar or markedly lower on MySQL.

	MySQL p99 Latency	HBase p99 Latency
assoc_range	25.3ms	54.8ms
assoc_get	21.9ms	39.0ms
assoc_insert	39.2ms	56.3ms
assoc_delete	49.9ms	52.3ms

System resource utilization was markedly different between MySQL and HBase processing the same workload. CPU utilization for HBase servers fluctuated between 20% and 35%, while it remained steady at around 5% for the MySQL servers. I/O operations per second varied greatly with HBase, varying sharply from 1000 up to above 2000, while MySQL consistently used 1200-1400.

This experiment showed that HBase consumed more CPU and incurred more I/O operations for the Facebook Graph workload. It also demonstrated the challenges in building custom tools to shadow production load onto test systems.