BlinkDB: Queries with Bounded Errors and Bounded Response Times on Very Large Data

Sameer Agarwal†, Aurojit Panda†, Barzan Mozafari†, Samuel Madden†, Ion Stoica†

†UC Berkeley  ♠MIT CSAIL

ABSTRACT
In this paper, we present BlinkDB, a massively parallel, sampling-based approximate query engine for running ad-hoc, interactive SQL queries on large volumes of data. The key insight that BlinkDB builds on is that one can often make reasonable decisions in the absence of perfect answers. For example, reliably detecting a malfunctioning server using a distributed collection of system logs does not require analyzing every request processed by the system. Based on this insight, BlinkDB allows one to trade-off query accuracy for response time, enabling interactive queries over massive data by running queries on data samples and presenting results annotated with meaningful error bars. To achieve this, BlinkDB uses two key ideas that differentiate it from previous work in this area: (1) an adaptive optimization framework that builds and maintains a set of multi-dimensional, multi-resolution samples from original data over time, and (2) a dynamic sample selection strategy that selects an appropriately sized sample based on a query’s accuracy and/or response time requirements. We have built an open-source version of BlinkDB and validated its effectiveness using the well-known TPC-H benchmark as well as a real-world analytic workload derived from Conviva Inc [3]. Our experiments on a 100 node cluster show that BlinkDB can answer a wide range of queries from a real-world query trace on up to 17 TBs of data in less than 2 seconds (over 100× faster than Hive), within an error of 2 – 10%.

1. INTRODUCTION
Modern data analytics applications involve computing aggregates over a large number of records to “roll up” web clicks, online transactions, content downloads, phone calls, and other features along a variety of different dimensions, including demographics, content type, region, and so on. Traditionally, such queries have been answered via sequential scans of large fractions of a database to compute the appropriate statistics. Increasingly, however, these applications demand near real-time response rates. Examples include (i) in a search engine, recomputing what ad(s) on websites to show to particular classes of users as content and product popularity changes on a daily or hourly basis (e.g., based on trends on social networks like Twitter or real time search histories) (ii) in a financial trading firm, quickly comparing the prices of securities to fine-grained historical averages to determine items that are under or over valued, or (iii) in a web service, determining the subset of users who are affected by an outage or are experiencing poor quality of service based on the service provider or region.

In these and many other analytic applications, queries are unpredictable (because the exact problem, or query is not known in advance) and quick response time is essential as data is changing quickly, and the potential profit (or loss in profit in the case of service outages) is proportional to response time. Unfortunately, the conventional way of answering such queries requires scanning the entirety of several terabytes of data. This can be quite inefficient. For example, computing a simple average over 10 terabytes of data stored on 100 machines can take in the order of 30 – 45 minutes on Hadoop if the data is striped on disks, and up to 5 – 10 minutes even if the entire data is cached in memory. This is unacceptable for rapid problem diagnosis, and frustrating even for exploratory analysis. As a result, users often employ ad-hoc heuristics to obtain faster response times, such as selecting small slices of data (e.g., an hour) or arbitrarily sampling the data [12, 5]. These efforts suggest that, at least in many analytic applications, users are willing to forgo accuracy for achieving better response times.

In this paper, we introduce BlinkDB, a new distributed parallel approximate query-processing framework that runs on Hive/Hadoop [27] as well as Shark [16] (i.e., “Hive on Spark [28]”, which supports caching inputs and intermediate data). BlinkDB allows users to pose SQL-based aggregation queries over stored data, along with response time or error bound constraints. Queries over multiple terabytes of data can be answered in seconds, accompanied by meaningful error bounds relative to the answer that would be obtained if the query ran on the full data. The basic approach taken by BlinkDB is to precompute and maintain a carefully chosen set of random samples of the user’s data, and then select the best sample(s) at runtime, for answering the query while providing error bounds using statistical sampling theory.

While uniform samples provide a reasonable approximation for uniformly or near-uniformly distributed data, they work poorly for skewed distributions (e.g., exponen-
tial or zipfian). In particular, estimators over infrequent subgroups (e.g., smartphone users in Berkeley, CA compared to New York, NY) converge slower when using uniform samples, since a larger fraction of the data needs to be scanned to produce high-confidence approximations. Furthermore, uniform samples may not contain instances of certain subgroups, leading to missing rows in the final output of queries. Instead, stratified or biased samples [22], which over-represent the frequency of rare values in a sample, better represent rare subgroups in such skewed datasets. Therefore BlinkDB maintains both a set of uniform samples, and a set of stratified samples over different combinations of attributes. As a result, when querying rare subgroups, BlinkDB (i) provides faster-converging estimates (i.e., tighter approximation errors), and thus lower processing times, compared to uniform samples [15] and, (ii) significantly reduces the number of missing subgroups in the query results (i.e., subset error [26]), enabling a wider range of applications (e.g., more complex joins that would be not be possible otherwise [14]).

However, maintaining stratified samples over all combinations of attributes is impractical. Conversely, only computing stratified samples on columns used in past queries limits the ability to handle new ad-hoc queries. Therefore, we formulate the problem of sample creation as an optimization problem. Given a collection of past query templates (query templates contain the set of columns appearing in WHERE and GROUP BY clauses without specific values for constants) and their historical frequencies, we choose a collection of stratified samples with total storage costs below some user configurable storage threshold. These samples are designed to efficiently answer any instantiation of past query templates, and to provide good coverage for future queries and unseen query templates. In this paper, we refer to these stratified samples, constructed over different sets of columns (dimensions), as multi-dimensional samples.

In addition to multi-dimensional samples, BlinkDB also maintains multi-resolution samples. For each multi-dimensional sample, we maintain several samples of progressively larger sizes (that we call multi-resolution samples). Given a query, BlinkDB picks the best sample to use at runtime. Having samples of different sizes allows us to efficiently answer queries of varying complexity with different accuracy (or time) bounds, while minimizing the response-time (or error). A single sample, would hinder our ability to provide as fine-grained a trade-off between speed and accuracy. Finally, when the data distribution or the query load changes, BlinkDB refines the solution while minimizing the number of old samples that need to be discarded or new samples that need to be generated.

Our approach is substantially different from related sampling-based approximate query answering systems. One line of related work is Online Aggregation [19, 20, 18] (OLA) and its extensions [15, 21, 24]. Unlike OLA, pre-computation and maintenance of samples allows BlinkDB to store each sample on disk or memory in a way that facilitates efficient query processing (e.g., clustered by primary key and/or other attributes), whereas online aggregation has to access the data in random order to provide its statistical error guarantees. Additionally, unlike OLA, BlinkDB has prior knowledge of the sample size(s) on which the query runs (based on its response time or accuracy requirements). This additional information both helps us better assign cluster resources (i.e., degree of parallelism and input disk/memory locality), and better leverage a number of standard distributed query optimization techniques [10]. There is some related work that proposes pre-computing (sometimes stratified) samples of input data based on past query workload characteristics [13, 9, 25]. As noted above, BlinkDB computes both multi-dimensional (i.e., samples over multiple attributes) and multi-resolution sampling (i.e., samples at different granularities), which no prior system does. We discuss related work in more detail in §7.

In summary, we make the following contributions:

- We develop a multi-dimensional, multi-granular stratified sampling strategy that provides faster convergence, minimizes missing results in the output (i.e., subset error), and provides error/latency guarantees for ad-hoc workloads. (§3.1, §6.3.2)
- We cast the decision of what stratified samples to build as an optimization problem that takes into account: (i) the skew of the data distribution, (ii) query templates, and (iii) the storage overhead of each sample. (§3.2, §6.3.1)
- We develop a run-time dynamic sample selection strategy that uses multiple smaller samples to quickly estimate query selectivity and choose the best samples for satisfying the response time and error guarantees. (§4.1, §6.4)

BlinkDB is a massively parallel query processing system that incorporates these ideas. We validate the effectiveness of BlinkDB’s design and implementation on a 100 node cluster, using both the TPC-H benchmarks and a real-world workload derived from Conviva Inc [3]. Our experiments show that BlinkDB can answer a range of queries within 2 seconds on 17 TB of data within 90-98% accuracy. Our results show that our multi-dimensional sampling approach, versus just using single dimensional samples (as was done in previous work) can improve query response times by up to three orders of magnitude and are further a factor of 2× better than approaches that apply online sampling at query time. Finally, BlinkDB is open source\footnote{http://blinkdb.org} and several on-line service companies have expressed interest in using it.

Next, we describe the architecture and the major components of BlinkDB.

2. SYSTEM OVERVIEW

As it is built on top of Hive [27], BlinkDB supports a hybrid programming model that allows users to write SQL-
style declarative queries with custom user defined functions (UDFs). In addition, for aggregation queries (i.e., AVG, SUM, PERCENTILE etc.), users can annotate queries with either a maximum error or maximum execution time constraint. Based on these constraints, BlinkDB selects an appropriately sized data sample at runtime on which the query operates (see §2.3 below for an example). Specifically, to specify an error bound, the user supplies a bound of the form $(\epsilon, C)$, indicating that the query should return an answer that is within $\pm \epsilon$ of the true answer with a confidence $C$. As an example, suppose we have a table Sessions, storing the sessions of users browsing a media website with five columns: Session, Genre, OS (running on the user’s device), City, and URL (of the site visited by the user). Then the query:

```sql
SELECT COUNT(*), RELATIVE ERROR AT 95% CONFIDENCE
FROM Sessions
WHERE Genre = 'western'
GROUP BY OS
```

will return the number of sessions looking at media from the “western” Genre for each OS to within a relative error of $\pm 10\%$ within a 95% confidence interval. Users can also specify absolute errors. Alternatively, users can instead request a time bound. For example, the query:

```sql
SELECT COUNT(*), RELATIVE ERROR AT 95% CONFIDENCE
FROM Sessions
WHERE Genre = 'western'
GROUP BY OS
WITHIN 5 SECONDS
```

will return with the most accurate answer within 5 seconds, and will report the estimated count along with an estimate of the relative error at 95% confidence. This enables a user to perform rapid exploratory analysis on massive amounts of data, wherein she can progressively tweak the query bounds until the desired accuracy is achieved.

2.1 Settings and Assumptions

In this section, we discuss several assumptions we made in designing BlinkDB.

Queries with Joins. Currently, BlinkDB supports two types of joins. (i) Arbitrary joins \(^2\) are allowed (self-joins or joining two tables) as long as there is a stratified sample on one of the join tables that contains the join key in its column-set\(^3\). (ii) In the absence of any suitable stratified sample, the join is still allowed as long as one of the two tables fits in memory (since BlinkDB does not sample tables that fit in memory). The latter is, however, more common in practice as data warehouses typically consist of one large denormalized “fact” table (e.g., ad impressions, click streams, pages served) that may need to be joined with other “dimension” tables using foreign-keys. Dimension tables (e.g., representing customers, media, or locations) are often small enough to fit in the aggregate memory of cluster nodes.

Workload Characteristics. Since our workload is targeted at ad-hoc queries, rather than assuming that exact queries are known a priori, we assume that the query templates (i.e., the set of columns used in WHERE and GROUP-BY clauses) remain fairly stable over time. We make use of this assumption when choosing which samples to create. This assumption has been empirically observed in a variety of real-world production workloads \([7, 11]\) and is also true of the query trace we use for our primary evaluation (a 2-year query trace from Conviva Inc). We however do not assume any prior knowledge of the specific values or predicates used in these clauses. Note that, although BlinkDB creates a set of stratified samples based on past query templates, at runtime, it can still use the set of available samples to answer any query, even if it is not from one of the historical templates. In Section 3.2, we show that our optimization framework takes into account the distribution skew of the underlying data in addition to templates, allowing it to perform well even when presented with previously unseen templates.

Closed-Form Aggregates. In this paper, we focus on a small set of aggregation operators: COUNT, SUM, MEAN, MEDIAN/QUANTILE. We estimate error of these functions using standard estimates of closed-form error (see Table 2). However, using techniques proposed in \([30]\), closed-form estimates can be easily derived for any combination of these basic aggregates as well as any algebraic function that is mean-like and asymptotically normal (see \([30]\) for formal definitions).

Offline Sampling. BlinkDB computes samples of input data and reuses them across many queries. One challenge with any system like BlinkDB based on offline sampling is that there is a small but non-zero probability that a given sample may be non-representative of the true data, e.g., that it will substantially over- or under-represent the frequency of some value in an attribute compared to the actual distribution, such that a particular query $Q$ may not satisfy the user-specified error target. Furthermore, because we do not generate new samples for each query, no matter how many times $Q$ is asked, the error target will not be met, meaning the system can fail to meet user specified confidence bounds for $Q$. Were we to generate a new sample for every query (i.e., perform online sampling), our confidence bounds would hold, because our error estimates ensure that the probability of such non-representative events is proportional to the user-specified confidence bound. Unfortunately, such resampling is expensive and would significantly impact query latency. Instead, our solution is to periodically replace samples with new ones in the background, as described in §4.5.

2.2 Architecture

Fig. 1 shows the overall architecture of BlinkDB. BlinkDB
builds on the Apache Hive framework [27] and adds two major components to it: (1) an offline sampling module that creates and maintains samples over time, and (2) a run-time sample selection module that creates an **Error-Latency Profile (ELP)** for ad-hoc queries. The ELP characterizes the rate at which the error (or response time) decreases (or increases) as the size of the sample on which the query operates increases. This is used to select a sample that best satisfies the user’s constraints. BlinkDB augments the query parser, optimizer, and a number of aggregation operators to allow queries to specify constraints for accuracy, or execution time.

### 2.2.1 Offline Sample Creation and Maintenance

This component is responsible for creating and maintaining a set of uniform and stratified samples. We use uniform samples over the entire dataset to handle queries on groups of columns with relatively uniform distributions, and stratified samples (on one or more columns) to handle queries on groups of columns with less uniform distributions. This component consists of three sub-components:

1. **Offline Sample Creation.** Based on statistics collected from the data (e.g., average row sizes, key skews, column histograms etc.), and historic query templates, BlinkDB computes a set of uniform samples and multiple sets of stratified samples from the underlying data. We rely on an optimization framework described in §3.2. Intuitively, the optimization framework builds stratified samples over column(s) that are (a) most useful for the query templates in the workload, and (b) most skewed, i.e., they have long-tailed distributions where rare values are more likely to be excluded by a uniform sample.

2. **Sample Maintenance.** As new data arrives, we periodically update the initial set of samples. Our update strategy is designed to minimize performance overhead and avoid service interruption. A monitoring module observes overall system performance, detecting any significant changes in data distribution (or workload), and triggers periodic sample replacement, and updates, deletions, or creations of new samples.

3. **Storage optimization.** In addition to caching samples in memory, to maximize disk throughput, we partition each sample into many small files, and leverage the block distribution strategy of HDFS [1] to spread those files across the nodes in a cluster. Additionally, we optimize the storage overhead, by recursively building larger samples as a union of smaller samples that are built on the same set of columns.

#### 2.2.2 Run-time Sample Selection

Given a query, we select an optimal sample at runtime so as to meet its accuracy or response time constraints. We do this by dynamically running the query on smaller samples to estimate the query’s selectivity, error rate, and response time, and then extrapolate to a sample size that will satisfy user-specified error or response time goals. §4 describes this procedure in detail.

### 2.3 An Example

To illustrate how BlinkDB operates, consider a table derived from a log of downloads by users from a media website, as shown in Figure 2. The table consists of five columns: Session, Genre, OS, City, and URL.

Assume we know the query templates in the workload, and that 30% of the queries had **City** in their **WHERE/GROUP BY clause**, 25% of the queries had **Genre AND City** in their **WHERE/GROUP BY clause**, and so on.

Given a storage budget, BlinkDB creates several multi-dimensional and multi-resolution samples based on past query templates and the data distribution. These samples are organized in **sample families**, where each family contains multiple samples of different granularities. One family consists of uniform samples, while the other families consist of stratified samples biased on a given set of columns. In our example, BlinkDB decides to create two sample families of stratified samples: one on City, and another one on (OS, URL). Note that despite **Genre** being a frequently queried column, we do not create a stratified sample on this column. This could be due to storage constraint or because **Genre** is uniformly distributed, such that queries that only use this column are already well served by the uniform sample. Similarly, BlinkDB does not create stratified samples on columns (Genre, City), in this case because queries on these columns are well served by the stratified samples on the **City** column. BlinkDB also creates several instances of each sample family, each with a different size, or resolution. For instance, BlinkDB may build three biased samples on columns (OS, URL) with 1M, 2M, and 4M tuples respec-
3. SAMPLE CREATION

As described in §2.2.1, BlinkDB creates a set of multi-dimensional, multi-resolution samples to accurately and quickly answer ad-hoc queries. In this section, we describe sample creation in detail. First, in §3.1, we discuss the creation of a sample family, a set of stratified samples of different sizes, on the same set of columns. In particular, we show how the choice of stratified samples impact the query’s accuracy and response time, and evaluate the overhead for skewed distributions. Next, in §3.2 we formulate and solve an optimization problem to decide on the sets of columns on which sample families are built.

3.1 Multi-resolution Stratified Samples

In this section, we describe our techniques for constructing a family of stratified samples from input tables. We describe how we maintain these samples in §4.5. Table 1 contains the notation used in the rest of this section.

| Notation | Description |
|----------|-------------|
| $T$ | fact (original) table |
| $\phi$ | set of columns in $T$ |
| $R(p)$ | random sample of $T$, where each row in $T$ is selected with probability $p$ |
| $S(\phi, K)$ | stratified sample associated to $\phi$, where frequency of every value $x$ in $\phi$ is capped by $K$ |
| $SFam(\phi)$ | family (sequence) of multi-dimensional multi-resolution stratified samples associated with $\phi$ |
| $F(\phi, S, x)$ | frequency of value $x$ in set of columns $\phi$ in sample/table $S$ |

Table 1: Notation in §3.1

Tightly. In §3.2, we present an algorithm for optimally picking these sample families.

For every query, at run time, BlinkDB selects the appropriate sample family and the appropriate sample resolution to answer the query based on the user specified error or response time bounds. In general, the columns in the WHERE/GROUP BY of a query may not exactly match any of the existing stratified samples. For example, consider a query, $Q$, whose WHERE clause is $(OS='Win7'$ AND $City='NY'$ AND $URL='www.cnn.com')$. In this case, it is not clear which sample family to use. To get around this problem, BlinkDB runs $Q$ on the smallest resolutions of other candidate sample families, and uses these results to select the appropriate sample, as described in detail in §4.

A stratified sample $S(\phi, K_i)$ on the set of columns, $\phi$, caps the frequency of every value $x$ in $\phi$ to $K_i$. More precisely, consider tuple $x = \langle x_1, x_2, \ldots, x_k \rangle$, where $x_j$ is a value in column $c_i$, and let $F(\phi, T, x)$ be the frequency of $x$ in column set $\phi$ in the original table, $T$. If $F(\phi, T, x) \leq K_i$, then $S(\phi, K_i)$ contains all rows containing $x$ in $T$. Otherwise, if $F(\phi, T, x) > K_i$, then $S(\phi, K_i)$ contains $K_i$ randomly chosen rows from $T$ that contain $x$.

Figure 3 shows a sample family associated with column set $\phi$. There are three stratified samples $S(\phi, K_1)$, $S(\phi, K_2)$, and $S(\phi, K_3)$, respectively, where $K_1$ is the largest sample, and $K_3$ the smallest. Note that since each sample is a subset of a bigger sample, in practice there is no need to independently allocate storage for each sample. Instead, we can construct smaller samples from the larger ones, and thus need an amount of storage equivalent to maintaining only the largest sample. This way, in our example we only need storage for the sample corresponding to $K_1$, modulo the metadata required to maintain the smaller samples.

Each stratified sample $S(\phi, K_i)$ is stored sequentially sorted according to the order of columns in $\phi$. Thus, the records with the same or consecutive $x$ values are stored

\[ SFam(\phi) = \{ S(\phi, K_i) \mid 0 \leq i < m \} \]
contiguously on the disk, which, as we will see, significantly improves the execution times or range of the queries on the set of columns $\phi$.

Consider query $Q$ whose \texttt{WHERE} or \texttt{GROUP BY} clause contains $\phi = x$, and assume we use $S(\phi, K)$ to answer this query. If $F(\phi, S(\phi, K), x) < K$, the answer is exact as the sample contains all rows from the original table. On the other hand, if $F(\phi, S(\phi, K), x) > K$, we answer $Q$ based on $K$ random rows in the original table. For the basic aggregate operators $\text{AVG}$, $\text{SUM}$, $\text{COUNT}$, and $\text{QUANTILE}$, $K$ directly determines the error of $Q$’s result. In particular, for these aggregate operators, the standard deviation is inversely proportional to $\sqrt{K}$, as shown in Table 2.

In this paper, we choose the samples in a family so that they have exponentially decreasing sizes. In particular, $K_i = [K_1/c^i]$ for $1 \leq i \leq m$, and $m = \lceil \log_c K_1 \rceil$. Thus, the cap of samples in the sequence decreases by factor $c$.

\textbf{Properties.} A natural question is how “good” is a sample family, $SFam(\phi)$, given a specific query, $Q$, that executes on column set $\phi$. In particular, let $S(\phi, K^{opt})$ be the smallest possible stratified sample on $\phi$ that satisfies the error or response time constraints of $Q$. Since $SFam(\phi)$ contains only a finite number of samples, $S(\phi, K^{opt})$ is guaranteed to be among those samples. Assume $K_1 \geq K^{opt} \geq [K_1/c^m]$, and let $S(\phi, K')$ be the closest sample in $SFam(\phi)$ that satisfies $Q$’s constraints. Then we would like that the $Q$’s performance when running on $S(\phi, K')$ to be as close as possible to $Q$’s performance when running on the optimal-sized sample, $S(\phi, K^{opt})$. Then, for $K^{opt} \gg c$ the following two properties hold (see Appendix A for proofs):

1. For a query with response time constraints, the response time of the query running on $S(\phi, K')$ is within a factor of $c$ of the response time of the query running on the optimal-sized sample, $S(\phi, K^{opt})$.
2. For a query with error constraints, the standard deviation of the query running on $S(\phi, K')$ is within a factor of $\sqrt{c}$ of the response time of the query running on $S(\phi, K^{opt})$.

\textbf{Storage overhead.} Another consideration is the overhead associated with maintaining these samples, especially for heavy-tailed distributions. In Appendix A we provide numerical results for a Zipf distribution, one of the most common heavy-tailed distributions. Consider a table with 1 billion tuples and a column set with a Zipf distribution with an exponent of 1.5. Then, the storage required by a family of samples $S(\phi, K)$ is only 2.4% of the original table for $K_0 = 10^4$, 5.2% for $K_0 = 10^5$, and 11.4% for $K_0 = 10^6$.

These results are consistent with real-world data from Conviva Inc, where for $K_0 = 10^5$, the overhead incurred for sample families on popular columns like city, customer, autonomous system number (ASN) are all less than 10%.

\section{Optimization Framework}

We now describe the optimization framework we developed to select subsets of columns on which to build sample families. Unlike prior work which focuses on single-column stratified samples \cite{9}, BlinkDB creates multi-dimensional (i.e., multi-column) stratified samples. Having stratified samples on multiple columns that are frequently queried together can lead to significant improvements in both query accuracy and latency, especially when the set of columns have a skewed joint distribution. However, these samples lead to an increase in the storage overhead because (1) samples on multiple columns can be larger than single-column samples since multiple columns often contains more unique values than individual columns, and (2) there are an exponential number of subsets of columns, all of which may not fit in our storage budget. As a result, we need to be careful in choosing the set of columns on which to build stratified samples. Hence, we formulate the trade off between storage and query accuracy/performance as an optimization problem, described next.

\subsection{Problem Formulation}

The optimization problem takes three factors into account in determining the sets of columns on which stratified samples should be built: the non-uniformity/skew of the data, workload characteristics, and the storage cost of samples.

\textbf{Non-uniformity (skew) of the data.} Intuitively, the greater the skew for a set of columns, the more important it is to have a stratified sample on those columns. If there is no skew, the uniform sample and stratified sample will be identical. Formally, for a subset of columns $\phi$ in table $T$, let $D(\phi)$ denote the set of all distinct values appearing in $\phi$. Recall from Table 1 that $F(\phi, T, v)$ is the frequency of value $v$ in $\phi$. Let $\Delta(\phi)$ be a non-uniformity metric on the distribution of the values in $\phi$. The higher the non-uniformity in $\phi$’s distribution the higher the value of $\Delta(\phi)$. When $\phi$’s distribution is uniform (i.e., when $F(\phi, T, v) = \frac{|D(\phi)|}{|T|}$ for $v \in D(\phi)$), $\Delta(\phi) = 0$. In general, $\Delta$ could be any metric of the distribution’s skew (e.g., kurtosis). In this paper, for the sake of simplicity, we use a more intuitive notion of non-uniformity, defined as:

$$\Delta(\phi) = |\{v \in D(\phi) | F(\phi, T, v) < K\}|$$

where $K$ represents the cap corresponding to the largest sample in the family, $S(\phi, K)$ (see §3.1). Intuitively, this metric captures the length of $\phi$’s tail, i.e., the number of unique values in $\phi$ whose frequencies are less than $K$. While the rest of this paper uses this metric, our framework allows other metrics to be used.

\textbf{Workload.} The utility of a stratified sample increases if the set of columns it is biased on occur together frequently in queries. One way to estimate such co-occurrence is to use the frequency with which columns have appeared together in past queries. However, we wish to avoid over-fitting to a particular set of queries since future queries may use different columns. Hence, we use a \textit{query workload} defined as a
set of $m$ query templates and their weights:
$$\langle \phi_1^T, w_1 \rangle, \ldots, \langle \phi_m^T, w_m \rangle$$

where $0 < w_i \leq 1$ is the weight (normalized frequency or importance) of the $i$'th query template and $\phi_i^T$ is the set of columns appearing in the $i$'th template's WHERE and GROUP BY clauses$^3$.

**Storage cost.** Storage is the main constraint against building too many multi-dimensional sample families, and thus, our optimization framework takes the storage cost of different samples into account. We use $\text{Store}(\phi)$ to denote the storage cost (say, in MB) of building a sample family on a set of columns $\phi$.

Given these three factors defined above, we now introduce our optimization formulation. Let the overall storage budget be $S$. Consider the set of $\alpha$ column combinations that are candidates for building sample families on, say $\phi_1, \ldots, \phi_\alpha$. For example, this set can include all column combinations that co-appeared at least in one of the query templates. Our goal is to select $\beta$ subsets among these candidates, say $\phi_{i_1}, \ldots, \phi_{i_\beta}$, such that

$$\sum_{k=1}^\beta \text{Store}(\phi_{i_k}) \leq S$$

and these subsets can “best” answer our queries.

Specifically, in BlinkDB, we maximize the following mixed linear integer program (MILP):

$$G = \sum_{i=1}^m w_i \cdot \Delta(\phi_i^T)$$

subject to

$$\sum_{j=1}^\alpha \text{Store}(\phi_j) \cdot z_j \leq S$$

and

$$\forall 1 \leq i \leq m : \ y_i \leq \max_{\phi_j \subseteq \phi_i^T} \left| \frac{D(\phi_j)}{D(\phi_i^T)} \right| \cdot z_j$$

where $0 \leq y_i \leq 1$ and $z_j \in \{0, 1\}$.

Here, $z_j$ variables determines whether a sample family is built or not, i.e., when $z_j = 1$, we build a sample family on $\phi_j$; otherwise, when $z_j = 0$, we do not.

The goal function (2) aims to maximize the weighted sum of the coverage of the query templates. The degree of coverage of query template $\phi_i^T$ with a set of columns $\phi_j \subseteq \phi_i^T$, is the probability that a given value in $\phi_i^T$ is also present in the stratified sample associated with $\phi_j$, i.e., $S(\phi_j, K)$. Since this probability is hard to compute in practice, in this paper we approximate it by $y_i$ value which is determined by constraint (4). The $y_i$ value is in $[0, 1]$, with 0 meaning no coverage, and 1 meaning full coverage. The intuition behind (4) is that when we build a stratified sample on a subset

$^3$Here, HAVING clauses are treated as columns in the WHERE clauses.
of sample families are still effective or if the optimization problem needs to be re-solved based on the new input parameters. When re-solving the optimization, BlinkDB tries to find a solution that is robust to workload changes by favoring sample families that require fewer changes to the existing set of samples, as described below. Specifically, BlinkDB allows the administrator to decide what percentage of the sample families (in terms of storage cost) can be discarded/added to the system whenever BlinkDB triggers the sample creation module as a result of changes in data or workload distribution. The administrator makes this decision by manually setting a parameter $0 \leq r \leq 1$, which is incorporated into an extra constraint in our MILP formulation:

$$\sum_{j=1}^{\alpha} (\delta_j - z_j)^2 \cdot S(\phi_j) \leq r \cdot \sum_{j=1}^{\alpha} \delta_j \cdot S(\phi_j) $$

(5)

Here $\delta_j$’s are additional input parameters stating whether $\phi_j$ already exists in the system (when $\delta_j = 1$) or it does not ($\delta_j = 0$). In the extreme case, when the administrator chooses $r = 1$, the constraint (5) will trivially hold and thus, the sample creation module is free to create/discard any sample families, based on the other constraints discussed in §3.2.1. On the other hand, setting $r = 0$ will completely disable this module in BlinkDB, i.e., no new samples will be created/discarded because $\delta_j = z_j$ will be enforced for all $j$’s. For values of $0 < r < 1$, we ensure that the total size of the samples that need to be created/discarded is at most a fraction $r$ of the total size of existing samples in the system (note than we have to create a new sample when $z_j = 1$ but $\delta_j = 0$ and need to delete an existing sample when $z_j = 0$ but $\delta_j = 1$). When BlinkDB runs the optimization problem for the first time $r$ is always set to 1.

4. BLINKDB RUNTIME

In this section, we provide an overview of query execution in BlinkDB, and our approach for online sample selection. Given a query $Q$, the goal is to select one (or more) sample(s) at run-time that meet the specified time or error constraints and then compute answers over them. Selecting a sample involves first selecting a sample family (i.e., dimension), and then selecting a sample resolution within that family. The selection of a sample family depends on the set of columns in $Q$’s clauses, the selectivity of its selection predicates, and the data distribution. In turn, the selection of the resolution within a sample family depends on $Q$’s time/accuracy constraints, its computation complexity, and the physical distribution of data in the cluster.

As with traditional query processing, accurately predicting the selectivity is hard, especially for complex WHERE and GROUP-BY clauses. This problem is compounded by the fact that the underlying data distribution can change with the arrival of new data. Accurately estimating the query response time is even harder, especially when the query is executed in a distributed fashion. This is (in part) due to variations in machine load, network throughput, as well as a variety of non-deterministic (sometimes time-dependent) factors that can cause wide performance fluctuations.

Rather than try to model selectivity and response time, our sample selection strategy takes advantage of the large variety of non-overlapping samples in BlinkDB to estimate the query error and response time at run-time. In particular, upon receiving a query, BlinkDB "probes" the smaller samples of one or more sample families in order to gather statistics about the query’s selectivity, complexity and the underlying distribution of its inputs. Based on these results, BlinkDB identifies an optimal sample family and resolution to run the query on.

In the rest of this section, we explain our query execution, by first discussing our mechanism for selecting a sample family (§4.1), and a sample size (§4.2). We then discuss how to produce unbiased results from stratified samples (§4.3), followed by re-using intermediate data in BlinkDB (§4.4).

4.1 Selecting the Sample Family

Choosing an appropriate sample family for a query primarily depends on the set of columns used for filtering and/or grouping. The WHERE clause itself may either consist of conjunctive predicates (condition1 AND condition2), disjunctive predicates (condition1 OR condition2) or a combination of the two. Based on this, BlinkDB selects one or more suitable sample families for the query as described in §4.1.1 and §4.1.2.

4.1.1 Queries with Conjunctive Predicates

Consider a query $Q$ whose WHERE clause contains only conjunctive predicates. Let $\phi$ be the set of columns that appear in these clause predicates. If $Q$ has multiple WHERE and/or GROUP BY clauses, then $\phi$ represents the union of the columns that appear in each of these predicates. If BlinkDB finds one or more stratified sample family on a set of columns $\phi_i$ such that $\phi \subseteq \phi_i$, we simply pick the $\phi_i$ with the smallest number of columns, and run the query on $SFam(\phi_i)$. However, if there is no stratified sample on a column set that is a superset of $\phi$, we run $Q$ in parallel on the smallest sample of all sample families currently maintained by the system. Then, out of these samples we select the one that corresponds to the highest ratio of (i) the number of rows selected by $Q$, to (ii) the number of rows read by $Q$ (i.e., number of rows in that sample). Let $SFam(\phi_i)$ be the family containing this sample. The intuition behind this choice is that the response time of $Q$ increases with the number of rows it reads, while the error decreases with the number of rows $Q$’s WHERE clause selects.

A natural question is why probe all sample families, instead of only those built on columns that are in $\phi$? The reason is simply because the columns in $\phi$ that are missing from a family’s column set, $\phi_i$, can be negatively correlated with the columns in $\phi_i$. In addition, we expect the smallest sample of each family to fit in the aggregate memory of the cluster, and thus running $Q$ on these samples is very fast.

4.1.2 Queries with Disjunctive Predicates
Consider a query \( Q \) with disjunctions in its \( WHERE \) clause. In this case, we rewrite \( Q \) as a union of queries \( \{Q_1, Q_2, \ldots, Q_p\} \), where each query \( Q_i \) contains only conjunctive predicates. Let \( \phi_j \) be the set of columns in \( Q_j \)'s predicates. Then, we associate with every query \( Q_i \) an error constraint (e.g., standard deviation \( s_i \)) or time constraint, such that we can still satisfy \( Q \)'s error/time constraints when aggregating the results over \( Q_i \) (\( 1 \leq i \leq p \)) in parallel. Since each of the queries, \( Q_i \), consists of only conjunctive predicates, we select their corresponding sample families using the selection procedure described in §4.1.1.

### 4.2 Selecting the Sample Size

Once a sample family is decided, BlinkDB needs to select an appropriately sized sample in that family based on the query’s response time or error constraints. We accomplish this by constructing an Error-Latency Profile (ELP) for the query. The ELP characterizes the rate at which the error decreases (and the query response time increases) with increasing sample sizes, and is built simply by running the query on smaller samples to estimate the selectivity and project latency and error for larger samples. For a distributed query, its runtime scales with sample size, with the scaling rate depending on the exact query structure (JOINS, GROUP BYs etc.), physical placement of its inputs and the underlying data distribution [7]. As shown in Table 2, the variation of error (or the variance of the estimator) primarily depends on the variance of the underlying data distribution and the actual number of tuples processed in the sample, which in turn depends on the selectivity of a query’s predicates.

**Error Profile:** An error profile is created for all queries with error constraints. If \( Q \) specifies an error (e.g., standard deviation \( s \)) or time constraint, the BlinkDB error profile tries to predict the size of the smallest sample that satisfies \( Q \)'s error constraint. Table 2 shows the formulas of the variances for the most common aggregate operators. Note that in all these examples, the variance is proportional to \( 1/n \), and thus the standard deviation (or the statistical error) is proportional to \( 1/\sqrt{n} \), where \( n \) is the number of rows from a sample of size \( N \) that match \( Q \)’s filter predicates. The ratio \( n/N \) is called the selectivity \( s_q \) of the query.

Let \( n_{i,m} \) be the number of rows selected by \( Q \) when running on the smallest sample of the selected family, \( S(\phi_i, K_m) \). Furthermore, BlinkDB estimates the query selectivity \( s_q \), sample variance \( S_n \) (for \( \text{Avg}/\text{Sum} \)) and the input data distribution \( f \) (for \( \text{Quantile} \)) as it runs on this sample. Using these parameter estimates, we calculate the number of rows \( n = n_{i,m} \) required to meet \( Q \)'s error constraints using the equations in Table 2. Then we select the sample \( S(\phi_i, K_q) \) where \( K_q \) is the smallest value in \( SFam(\phi) \) that is larger than \( n * (K_m/n_{i,m}) \). This ensures that the expected number of rows selected by \( Q \) when running on sample \( S(\phi_i, K_q) \) is \( \geq n \). As a result, the answer of \( Q \) on \( S(\phi_i, K_q) \) is expected to meet \( Q \)'s error constraint.

**Latency Profile:** Similarly, a latency profile is created for all queries with response time constraints. If \( Q \) specifies a response time constraint, we select the sample family on which \( Q \) reads the same way as above. Again, let \( SFam(\phi_i) \) be the selected family and let \( n_{i,m} \) be the number of rows that \( Q \) reads when running on \( S(\phi_i, K_m) \). In addition, \( n \) be the maximum number of rows that \( Q \) can read without exceeding its response time constraint.

\( n \) depends on the physical placement of input data (disk vs. memory), the query structure and complexity, and the degree of parallelism (or the resources available to the query). As a simplification, BlinkDB simply predicts \( n \) by assuming latency scales linearly with input size, as is commonly done in parallel distributed execution environments [8, 29]. To avoid non-linearities that may arise when running on very small in-memory samples, BlinkDB runs a few smaller samples until performance seems to grow linearly and then estimates appropriate linear scaling constants (i.e., data processing rate(s), disk/memory I/O rates etc.) for the model. These constants are used to estimate a value of \( n \) that is just below what is allowed by the time constraints. Once \( n \) is estimated, BlinkDB picks sample \( S(\phi_i, K_q) \) where \( K_q \) is the largest value in \( SFam(\phi) \) that is smaller than \( n * (K_m/n_{i,m}) \) and executes \( Q \) on it in parallel.

![Figure 4: Mapping of BlinkDB’s non-overlapping samples to HDFS blocks](image-url)

| Operator | Calculation | Variance |
|----------|-------------|----------|
| Avg      | \[ \sum_{i=1}^{n} X_i \] \[ X_i \text{; observed values; } n \text{; sample size} \] | \[ \frac{s^2}{n} \] \[ S_n^2 \text{; sample variance} \] |
| Count    | \[ \frac{1}{N} \sum_{i=1}^{n} I_K \] \[ I_K \text{; matching tuple indicator; } N \text{; Total Rows} \] | \[ \frac{c}{n} \] \[ c \text{; fraction of items which meet the criterion} \] |
| Sum      | \[ \frac{1}{N} \sum_{i=1}^{n} I_K \] \[ X \] | \[ N^2 \frac{s^2}{n} c(1-c) \] |
| Quantile | \[ x_{i|h} + (h - [h])(x_{i|h} - x_{i|K}) \] \[ x_i \text{; } h \text{th ordered element in sample; } p \text{; specified quantile; } h \text{; } p \times n \] | \[ \frac{1}{n} \sum_{i=1}^{n} f(x_i) \] \[ f \text{; pdf for data} \] |

Table 2: Error estimation formulas for common aggregate operators.
4.3 Query Answers from Stratified Samples

Consider the Sessions table, shown in Table 3, and the following query against this table.

```sql
SELECT City, SUM(SessionTime) FROM Sessions GROUP BY City WITHIN 5 SECONDS
```

If we have a uniform sample of this table, estimating the query answer is straightforward. For instance, suppose we take a uniform sample with 40% of the rows of the original Sessions table. In this case, we simply scale the final sums of the session times by $1/0.4 = 2.5$ in order to produce an unbiased estimate of the true answer.

Using the same approach on a stratified sample may produce a biased estimate of the answer for this query. For instance, consider a stratified sample of the Sessions table on the Browser column, as shown in Table 4. Here, we have a cap value of $K = 1$, meaning we keep all rows whose Browser only appears once in the original Sessions table (e.g., Safari and IE), but when a browser has more than one row (i.e., Firefox), only one of its rows is chosen, uniformly at random. In this example we have choose the row that corresponds to Yahoo.com. Here, we cannot simply scale the final sums of the session times because different values were sampled with different rates. Therefore, to produce unbiased answers, BlinkDB keeps track of the effective sampling rate applied to each row, e.g. in Table 4, this rate is 0.33 for Firefox row, while it is 1.0 for Safari and IE rows since they have not been sampled at all. Given these per-row sample rates, obtaining an unbiased estimates of the final answer is straightforward, e.g., in this case the sum of sessions times is estimated as $\frac{1}{0.33} \times 20 + \frac{1}{1} \times 82$ for New York and as $\frac{1}{1} \times 22$ for Cambridge. Note that here we will not produce any output for Berkeley (this would not happen if we had access to a stratified sample over City, for example). In general, the query processor in BlinkDB performs a similar correction when operating on stratified samples.

### Table 3: Sessions Table.

| URL    | City    | Browser | SessionTime |
|--------|---------|---------|-------------|
| cnn.com | New York| Firefox | 15          |
| yahoo.com | New York| Firefox | 20          |
| google.com | Berkeley| Firefox | 85          |
| google.com | New York| Safari  | 82          |
| bing.com   | Cambridge| IE      | 22          |

### Table 4: A sample of Sessions Table stratified on Browser column.

| URL    | City    | Browser | SessionTime | SampleRate |
|--------|---------|---------|-------------|------------|
| yahoo.com | New York| Firefox | 20          | 0.33       |
| google.com | New York| Safari  | 82          | 1.0        |
| bing.com   | Cambridge| IE      | 22          | 1.0        |

Here we use the terms biased and unbiased in a statistical sense, meaning that although the estimate might vary from the actual answer, its expected value will be the same as the actual answer.

4.4 Re-using Intermediate Data

Although BlinkDB requires a query to operate on smaller samples to construct its ELP, the intermediate data produced in the process is effectively utilized when the query runs on larger samples. Fig. 4 decouples the logical and physical view of the non-overlapping samples maintained by BlinkDB as described in §3.1. Physically, each progressively bigger logical sample (A, B or C) consists of all data blocks of the smaller samples in the same family. BlinkDB maintains a transparent mapping between logical samples and data blocks, i.e., A maps to (I), B maps to (I, II) and C maps to (I, II, III). Now, consider a query $Q$ on this data. First, BlinkDB creates an ELP for $Q$ by running it on the smallest sample $A$, i.e., it operates on the first two data blocks to estimate various query parameters described above and caches all intermediate data in this process. Subsequently, if sample $C$ is chosen based on the $Q$’s error/latency requirements, BlinkDB only operates on the additional data blocks, utilizing the previously cached intermediate data.

4.5 Sample Maintenance

BlinkDB’s reliance on offline sampling can result in situations where a sample is not representative of the underlying data. Since statistical guarantees are given across repeated resamplings, such unrepresentative samples can adversely effect decisions made using BlinkDB. Such problems are unavoidable when using offline sampling, and affect all systems relying on such techniques.

As explained in §5, BlinkDB uses a parallel binomial sampling framework to generate samples when data is first added. We rely on the same framework for sample replacement, reapplying the process to existing data, and replacing samples when the process is complete.

To minimize the overhead of such recomputation, BlinkDB uses a low-priority, background task to compute new samples from existing data. The task is designed to run when the cluster is underutilized, and is designed to be suspended at other times. Furthermore, the task utilizes no more than a small fraction of unutilized scheduling slots, thus ensuring that any other jobs observe little or no overhead.

5. IMPLEMENTATION

Fig. 5 describes the entire BlinkDB ecosystem. BlinkDB is built on top of the Hive Query Engine [27], supports both Hadoop MapReduce [2] and Spark [28] (via Shark [16]) at the execution layer and uses the Hadoop Distributed File System [1] at the storage layer.

Our implementation required changes in a few key components. We added a shim layer of BlinkDB Query Interface to the HiveQL parser that enables queries with response time and error bounds. Furthermore, it detects data input, which causes the Sample Creation and Maintenance module to create or update the set of random and multi-dimensional samples at multiple granularities as described in §3. We further extend the HiveQL parser to implement a Sample Selection
Figure 5: BlinkDB’s Implementation Stack

module that re-writes the query and iteratively assigns it an appropriately sized biased or random sample as described in §4. We also added an Uncertainty Propagation module to modify the pre-existing aggregation functions summarized in Table 2 to return errors bars and confidence intervals in addition to the result. Finally, we extended the SQLite based Hive Metastore to create BlinkDB Metastore that maintains a transparent mapping between the non-overlapping logical samples and physical HDFS data blocks as shown in Fig. 4.

We also extend Hive to add support for sampling from tables. This allows us to leverage Hive’s parallel execution engine for sample creation in a distributed environment. Furthermore, our sample creation module optimizes block size and data placement for samples in HDFS.

In BlinkDB, uniform samples are generally created in a few hundred seconds. This is because the time taken to create them only depends on the disk/memory bandwidth and the degree of parallelism. On the other hand, creating stratified samples on a set of columns takes anywhere between a 5 – 30 minutes depending on the number of unique values to stratify on, which decides the number of reducers and the amount of data shuffled.

6. EVALUATION

In this section, we evaluate BlinkDB’s performance on a 100 node EC2 cluster using two workloads: a workload from Conviva Inc. [3] and the well-known TPC-H benchmark [6]. First, we compare BlinkDB to query execution on full-sized datasets to demonstrate how even a small trade-off in the accuracy of final answers can result in orders-of-magnitude improvements in query response times. Second, we evaluate the accuracy and convergence properties of our optimal multi-dimensional, multi-granular stratified-sampling approach against both random sampling and single-column stratified-sampling approaches. Third, we evaluate the effectiveness of our cost models and error projections at meeting the user’s accuracy/response time requirements. Finally, we demonstrate BlinkDB’s ability to scale gracefully with increasing cluster size.

6.1 Evaluation Setting

The Conviva and the TPC-H datasets were 17 TB and 1 TB (i.e., a scale factor of 1000) in size, respectively, and were both stored across 100 Amazon EC2 extra large instances (each with 8 CPU cores (2.66 GHz), 68.4 GB of RAM, and 800 GB of disk). The cluster was configured to utilize 75 TB of distributed disk storage and 6 TB of distributed RAM cache.

Conviva Workload. The Conviva data represents information about video streams viewed by Internet users. We use query traces from their SQL-based ad-hoc querying system which is used for problem diagnosis and data analytics on a log of media accesses by Conviva users. These access logs are 1.7 TB in size and constitute a small fraction of data collected across 30 days. Based on their underlying data distribution, we generated a 17 TB dataset for our experiments and partitioned it across 100 nodes. The data consists of a single large fact table with 104 columns, such as, customer ID, city, media URL, genre, date, time, user OS, browser type, request response time, etc. The 17 TB dataset has about 5.5 billion rows.

The raw query log consists of 19,296 queries, from which we selected different subsets for each of our experiments. We ran our optimization function on a sample of about 200 queries representing 42 query templates. We repeated the experiments with different storage budgets for the stratified samples—50%, 100%, and 200%. A storage budget of $x\%$ indicates that the cumulative size of all the samples will not exceed $\frac{x}{100}$ times the original data. So, for example, a budget of 100% indicates that the total size of all the samples should be less than or equal to the original data. Fig. 6(a) shows the set of sample families that were selected by our optimization program for the storage budgets of 50%, 100% and 200% respectively, along with their cumulative storage costs. Note that each stratified sample family has a different size due to variable number of distinct keys in the columns on which the sample is biased. Within each sample family, each successive resolution is twice as large than the previous one and the value of $K$ in the stratified sampling is set to 100,000.

TPC-H Workload. We also ran a smaller number of experiments on TPC-H to demonstrate the generality of our results, with respect to a standard benchmark. All the TPC-H experiments ran on the same 100 node cluster, on 1 TB of data (i.e., a scale factor of 1000). The 22 benchmark queries in TPC-H were mapped to 6 unique query templates. Fig. 6(b) shows the set of sample families selected by our optimization problem for the storage budgets of 50%, 100% and 200%, along with their cumulative storage costs.

Unless otherwise specified, all the experiments in this paper are done with a 50% additional storage budget (i.e., samples could use an additional storage of up to 50% of the original data size).

6.2 BlinkDB vs. No Sampling

We first compare the performance of BlinkDB versus frameworks that execute queries on complete data. In this experiment, we ran on two subsets of the Conviva data, with 7.5 TB and 2.5 TB respectively, spread across 100 machines. We chose these two subsets to demonstrate some key aspects of
the interaction between data-parallel frameworks and modern clusters with high-memory servers. While the smaller 2.5 TB dataset can be completely cached in memory, datasets larger than 6 TB in size have to be (at least partially) spilled to disk. To demonstrate the significance of sampling even for the simplest analytical queries, we ran a simple query that computed average user session times with a filtering predicate on the date column (\(dt\)) and a GROUP BY on the city column. We compared the response time of the full (accurate) execution of this query on Hive [27] on Hadoop MapReduce [2], Hive on Spark (called Shark [16]) – both with and without caching, against its (approximate) execution on BlinkDB with a 1% error bound for each GROUP BY key at 95% confidence. We ran this query on both data sizes (i.e., corresponding to 5 and 15 days worth of logs, respectively) on the aforementioned 100-node cluster. We repeated each query 10 times, and report the average response time in Figure 6(c). Note that the Y axis is log scale. In all cases, BlinkDB significantly outperforms its counterparts (by a factor of \(10 - 100\times\)), because it is able to read far less data to compute a fairly accurate answer. For both data sizes, BlinkDB returned the answers in a few seconds as compared to thousands of seconds for others. In the 2.5 TB run, Shark’s caching capabilities considerably help, bringing the query runtime down to about 112 seconds. However, with 7.5 TB data size, a considerable portion of data is spilled to disk and the overall query response time is considerably longer.

### 6.3 Multi-Dimensional Stratified Sampling

Next, we ran a set of experiments to evaluate the error (§6.3.1) and convergence (§6.3.2) properties of our optimal multi-dimensional, multi-granular stratified-sampling approach against both simple random sampling, and one-dimensional stratified sampling (i.e., stratified samples over a single column). For these experiments we constructed three sets of samples on both Conviva and TPC-H data with a 50% storage constraint:

1. **Multi-Dimensional Stratified Samples.** The sets of columns to stratify on were chosen using BlinkDB’s optimization framework (§3.2), restricted so that samples could be stratified on no more than 3 columns (considering four or more column combinations caused our optimizer to take more than a minute to complete).

2. **Single-Dimensional Stratified Samples.** The column to stratify on was chosen using the same optimization framework, restricted so a sample is stratified on exactly one column.

3. **Uniform Samples.** A sample containing 50% of the entire data, chosen uniformly at random.

#### 6.3.1 Error Properties

In order to illustrate the advantages of our multi-dimensional stratified sampling strategy, we compared the average statistical error at 95% confidence while running a query for 10 seconds over the three sets of samples, all of which were constrained to be of the same size.

For our evaluation using Conviva’s data we used a set of 40 queries (with 5 unique query templates) and 17 TB of uncompressed data on 100 nodes. We ran a similar set of experiments on the standard TPC-H queries. The queries we chose were on the `lineitem` table, and were modified to conform with HiveQL syntax.

In Figures 7(a), and 7(b), we report results per-query template, with numbers in parentheses indicating the percentage of queries with a given template. For common query templates, multi-dimensional samples produce smaller statistical errors than either one-dimensional or random samples. The optimization framework attempts to minimize expected error, rather than per-query errors, and therefore for some specific query templates single-dimensional stratified samples behave better than multi-dimensional samples. Overall, however, our optimization framework significantly improves performance versus single column samples.

#### 6.3.2 Convergence Properties

We also ran experiments to demonstrate the convergence properties of multi-dimensional stratified samples used by BlinkDB. We use the same set of three samples as §6.3, taken over 17 TB of Conviva data. Over this data, we ran multiple queries to calculate average session time for a particular ISP’s customers in 5 US Cities and determined the latency for achieving a particular error bound with 95% confidence. Results from this experiment (Figure 7(c)) show that error bars from running queries over multi-dimensional samples converge orders-of-magnitude faster than random sam-

Figure 6: (a) and (b) show the relative sizes of the set of stratified sample(s) created for 50%, 100% and 200% storage budget for Conviva and TPC-H workloads respectively. (c) compares the response times (in log scale) incurred by Hive on Hadoop, Shark (Hive on Spark) – both with and without input data caching, and BlinkDB, on simple aggregation.

(a) Sample Families (Conviva)  
(b) Sample Families (TPC-H)  
(c) BlinkDB Vs. No Sampling
| Query | Multi-Column | Single Column | Random Samples |
|-------|--------------|---------------|----------------|
| T1(39%) |               |               |                |
| T2(24.5%) |              |               |                |
| T3(2.4%)  |               |               |                |
| T4(31.7%) |               |               |                |
| T5(2.4%)  |               |               |                |
| T6(4.5%)  |               |               |                |

Figure 7: (a) and (b) compare the average statistical error per template when running a query with fixed time budget for various sets of samples. (c) compares the rates of error convergence with respect to time for various sets of samples.

**6.4 Time/Accuracy Guarantees**

In this set of experiments, we evaluate BlinkDB’s effectiveness at meeting different time/error bounds requested by the user. For each workload suite, we evaluate our ability to meet specified error constraints. To test time-bound queries, we picked a sample of 20 Conviva queries, and ran each of them 10 times, with a time bound from 1 to 10 seconds. Figure 8(a) shows the results run on the same 17 TB data set, where each bar represents the maximum and average response times of the 20 queries, averaged over 10 runs. From these results we can see that BlinkDB is able to accurately select a sample to satisfy a target response time.

Figure 8(b) shows results from the same set of queries, also on the 17 TB data set, evaluating our ability to meet specified error constraints. In this case, we varied the requested error bound from 2% to 32%. The bars again represent the minimum, maximum and average errors across different runs of the queries. Note that the measured error is almost always at or less than the requested error. However, as we increase the error bound, the measured error becomes closer to the bound. This is because at higher error rates the sample size is quite small and error bounds are wider.

**6.5 Scaling Up**

Finally, in order to evaluate the scalability properties of BlinkDB as a function of cluster size, we created 2 different sets of query workload suites consisting of 40 unique Conviva queries each. The first set (marked as *selective*) consists of highly selective queries — i.e., those queries that only operate on a small fraction of input data. These queries occur frequently in production workloads and consist of one or more highly selective WHERE clauses. The second set (marked as *bulk*) consists of those queries that are intended to crunch huge amounts of data. While the former set’s input is generally striped across a small number of machines, the latter set of queries generally runs on data stored on a large number of machines, incurring a higher communication cost. Figure 8(c) plots the query latency for each of these workloads as a function of cluster size. Each query operates on 100n GB of data (where n is the cluster size). So for a 10 node cluster, each query operates on 1 TB of data and for a 100 node cluster each query operates on around 10 TB of data. Further, for each workload suite, we evaluate the query latency for the case when the required samples are completely cached in RAM or when they are stored entirely on disk. Since in reality any sample will likely partially reside both on disk and in memory these results indicate the min/max latency bounds for any query.

**7. RELATED WORK**

Prior work on interactive parallel query processing frameworks has broadly relied on two different sets of ideas.

One set of related work has focused on using additional resources (i.e., memory or CPU) to decrease query processing time. Examples include Spark [28], Dremel [23] and Shark [16]. While these systems deliver low-latency response times when each node has to process a relatively small amount of data (e.g., when the data can fit in the aggregate memory of the cluster), they become slower as the data grows unless new resources are constantly being added in proportion. Additionally, a significant portion of query execution time in these systems involves shuffling or repartitioning massive amounts of data over the network, which is often a bottleneck for queries. By using samples, BlinkDB is able to scale better as the quantity of data grows. Additionally, being built on Spark, BlinkDB is able to effectively leverage the benefits provided by these systems while using limited resources.

Another line of work has focused on providing approximate answers with low latency, particularly in database systems. Approximate Query Processing (AQP) for decision support in relational databases has been the subject of extensive research, and can either use samples, or other non-sampling based approaches, which we describe below.

**Sampling Approaches.** There has been substantial work on using sampling to provide approximate responses, including work on stratified sampling techniques similar to ours (see [17] for an overview). Especially relevant are:

1. **STRAT** [13] relies on a single stratified sample, chosen based on the exact tuples accessed by each query. In contrast BlinkDB uses a set of samples computed using query templates, and is thus more amenable to ad-hoc queries.

2. **SciBORQ** [25] is a data-analytics framework designed for scientific workloads, which uses special structures, called *impressions*. Impressions are biased samples where tuples are picked based on past query results. SciBORQ tar-
gets exploratory scientific analysis. In contrast to BlinkDB, SciBORQ only supports time-based constraints. SciBORQ also does not provide any guarantees on the error margin.

3. Babcock et al. [9] also describe a stratified sampling technique where biased samples are built on a single column, in contrast to our multi-column approach. In their approach, queries are executed on all biased samples whose biased column is present in the query and the union of results is returned as the final answer. Instead, BlinkDB runs on a single sample, chosen based on the current query.

**Online Aggregation.** Online Aggregation (OLA) [20] and its successors [15, 24] proposed the idea of providing approximate answers which are constantly refined during query execution. It provides users with an interface to stop execution once a sufficiently good answer is found. The main disadvantages of Online Aggregation is that it requires data to be streamed in a random order, which can be impractical in distributed systems. While [24] proposes some strategies for implementing OLA on Map-Reduce, their strategy involves significant changes to the query processor. Furthermore, BlinkDB, unlike OLA, can store data clustered by a primary key, or other attributes, and take advantage of this ordering during data processing. Additionally BlinkDB can use knowledge about sample sizes to better allocate cluster resources (parallelism/memory) and leverage standard distributed query optimization techniques [10].

**Non-Sampling Approaches.** There has been a great deal of work on “synopses” for answering specific types of queries (e.g., wavelets, histograms, sketches, etc.). Similarly materialized views and data cubes can be constructed to answer specific types efficiently. While offering fast responses, these techniques require specialized structures to be built for every operator, or in some cases for every type of query and are hence impractical when processing arbitrary queries. Furthermore, these techniques are orthogonal to our work, and BlinkDB could be modified to use any of these techniques for better accuracy on certain types of queries, while resorting to samples on others.

8. CONCLUSION

In this paper, we presented BlinkDB, a parallel, sampling-based approximate query engine that provides support for ad-hoc queries with error and response time constraints. BlinkDB is based on two key ideas: (i) a multi-dimensional, multi-granularity sampling strategy that builds and maintains a large variety of samples, and (ii) a run-time dynamic sample selection strategy that uses smaller samples to estimate query selectivity and choose the best samples for satisfying query constraints. Evaluation results on real data sets and on deployments of up to 100 nodes demonstrate the effectiveness of BlinkDB at handling a variety of queries with diverse error and time constraints, allowing us to answer a range of queries within 2 seconds on 17 TB of data with 90-98% accuracy.

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A. STRATIFIED SAMPLING PROPERTIES AND STORAGE OVERHEAD

In this section prove the two properties stated in Section 3.1 and give the storage overhead for Zipf distribution.

Performance properties. Recall that $S(\phi, K^{\text{opt}})$ represents the smallest possible stratified sample on $\phi$ that satisfies the error or response time constraints of query $Q$, while $S(\phi, K')$ is the closest sample in $SFam(\phi)$ that satisfies $Q$’s constraints. Then, we have the following results.

**Lemma A.1.** Assume an I/O-bound query $Q$ that specifies an error constraint. Let $r$ be the response time of $Q$ when running on the optimal-sized sample, $S(\phi, K^{\text{opt}})$. Then, the response time of $Q$ when using sample family $SFam(\phi) = \{ S(\phi, K_i) \}, (0 \leq i < m)$ is at most $c + 1/K^{\text{opt}}$ times larger than $r$.

**Proof.** Let $i$ be such that

$$\frac{K}{c^{i+1}} < K^{\text{opt}} \leq \frac{K}{c^i}.$$  \hfill (6)

Assuming that the error of $Q$ decreases monotonically with the increase in the sample size, $S(\phi, \lfloor K/c^i \rfloor)$ is the smallest sample in $SFam(\phi)$ that satisfies $Q$’s error constraint. Furthermore, from Eq. (6) it follows that

$$\frac{K}{c^{i+1}} < cK^{\text{opt}} + 1.$$  \hfill (7)

In other words, in the worst case, $Q$ may have to use a sample whose cap is at most $c + 1/K^{\text{opt}}$ times larger than $K^{\text{opt}}$.

Let $K' = cK^{\text{opt}} + 1$, and let $A = \{a_1, a_2, ..., a_k\}$ be the set of values in $\phi$ selected by $Q$. By construction, both samples $S(\phi, K')$ and $S(\phi, K^{\text{opt}})$ contain all values in the fact table, and therefore in set $A$. Then, from the definition of the stratified sample, it follows that the frequency of any $a_i \in A$ in sample $S(\phi, K')$ is at most $K'/K^{\text{opt}}$ times larger than the frequency of $a_i$ in $S(\phi, K^{\text{opt}})$. Since the tuples matching the same value $a_i$ are clustered together in both samples, they are accessed sequentially on the disk. Thus, the access time of all tuples matching $a_i$ in $S(\phi, K')$ is at most $c + 1/K^{\text{opt}}$ times larger than the access time of the same tuples in $S(\phi, K^{\text{opt}})$. Finally, since we assume that the $Q$’s execution is I/O-bound, it follows that $Q$’s response time is at most $c + 1/K^{\text{opt}}$ times worse than $Q$’s response time on the optimal sample, $S(\phi, K^{\text{opt}})$.

**Lemma A.2.** Assume a query, $Q$, that specifies a response time constraint, and let $S(\phi, K^{\text{opt}})$ be the largest stratified sample on column set $\phi$ that meets $Q$’s constraint. Assume standard deviation of $Q$ is $\sim 1/\sqrt{n}$, where $n$ is the number of tuples selected by $Q$ from $S(\phi, K^{\text{opt}})$. Then, the standard deviation of $Q$ when using sample family $SFam(\phi)$ increases by at most $1/\sqrt{1/c - 1/K^{\text{opt}}}$ times.

**Proof.** Let $i$ be such that

$$\frac{K}{c^i} \leq K^{\text{opt}} < \frac{K}{c^{i-1}}.$$  \hfill (8)

Assuming that the response time of $Q$ decreases monotonically with the sample size, $S(\phi, \lfloor K/c^i \rfloor)$ is the largest sample in $SFam(\phi)$ that satisfies $Q$’s response time. Furthermore, from Eq. (8) it follows that

$$\frac{K}{c^i} > \frac{K^{\text{opt}}}{c} - 1.$$  \hfill (9)

Assuming that the number of tuples selected by $Q$ is proportional to the sample size, the standard deviation of running $Q$
on $S(\phi, \lfloor K/c \rfloor)$ increases by at most $1/\sqrt{1/c - 1/K^{opt}}$ times.

**Storage Overhead for Zipf distribution.** We evaluate the storage overhead of maintaining a stratified sample, $S(\phi, K)$, for a Zipf distribution, one of the most popular heavy tail distributions for real-world datasets. Without loss of generality, assume $F(\phi, T, x) = M/rank(x)^s$, where $rank(x)$ represents the rank of $x$ in $F(\phi, T, x)$ (i.e., value $x$ with the highest frequency has rank 1), and $s \geq 1$. Table 5 shows the overhead of $S(\phi, K)$ as a percentage of the original table size for various values of Zipf’s exponent, $s$, and for various values of $K$. The number of unique values in the original table size is $M = 10^9$. For $s = 1.5$ the storage required by $S(\phi, K)$ is only $2.4\%$ of the original table for $K = 10^4$, $5.2\%$ for $K = 10^5$, and $11.4\%$ for $K = 10^6$.

| $s$ | $K = 10,000$ | $K = 100,000$ | $K = 1,000,000$ |
|-----|--------------|---------------|-----------------|
| 1.0 | 0.49         | 0.58          | 0.69            |
| 1.1 | 0.25         | 0.35          | 0.48            |
| 1.2 | 0.14         | 0.21          | 0.32            |
| 1.3 | 0.07         | 0.13          | 0.22            |
| 1.4 | 0.04         | 0.08          | 0.15            |
| 1.5 | 0.024        | 0.02          | 0.114           |
| 1.6 | 0.015        | 0.036         | 0.087           |
| 1.7 | 0.010        | 0.026         | 0.069           |
| 1.8 | 0.007        | 0.020         | 0.055           |
| 1.9 | 0.005        | 0.015         | 0.045           |
| 2.0 | 0.0038       | 0.012         | 0.038           |

Table 5: The storage required to maintain sample $S(\phi, K)$ as a fraction of the original table size. The distribution of $\phi$ is Zipf with exponent $s$, and the highest frequency ($M$) of $10^9$. 