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UpSizeR: Synthetically Scaling an Empirical Relational Database[☆]

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Abstract

The TPC benchmarks have helped users evaluate database system performance at different scales. Although each benchmark is domain-specific, it is not equally relevant to different applications in the same domain. The present proliferation of applications also leaves many of them uncovered by the very limited number of current TPC benchmarks.

There is therefore a need to develop tools for application-specific database benchmarking. This paper presents UpSizeR, a software that addresses the **Dataset Scaling Problem**: *Given an empirical set of relational tables $\mathcal{D}$ and a scale factor s, generate a database state $\widetilde{\mathcal{D}}$ that is similar to $\mathcal{D}$ but s times its size.* Such a tool can be useful for scaling up $\mathcal{D}$ for scalability testing ($s > 1$), scaling down for application testing ($s < 1$), or anonymization ($s = 1$).

Experiments with Flickr show that query results and response times on UpSizeR output match those on crawled data. They also accurately predict throughput degradation for a scale out test.

The UpSizeR version in this paper focuses on extracting and replicating the correlation induced by the primary and foreign keys. There are many other forms of correlation involving nonkey values. It is a large task to develop UpSizeR into a tool that can extract and replicate all important

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correlation, so community effort is required. The current UpSizeR code has therefore been released for open-source development. The ultimate objective is to replace TPC with UpSizeR, so database owners can generate benchmarks that are relevant to their applications.

Keywords: application-specific benchmarking, synthetic data generation, scale factor, empirical dataset, attribute value correlation, social networks

1. Introduction

A database managements system for an enterprise is a complicated collection of software and hardware. Its complexity and its critical role require that a different index design, a scale out of machines, a new business application, etc., be adequately tested before deployment. Such testing needs to use a dataset of an appropriate size.

One possibility is to use a TPC[1] benchmark for such tests. TPC datasets can be scaled to desired sizes, and are also domain-specific: TPC-C for online transaction processing, TPC-H for decision support, etc. Vendors have used these benchmarks to improve and compare their products, and researchers have used them to test and compare their algorithms and prototypes. The TPC benchmarks have thus played an important role in the growth of the database industry and the progress of database research.

However, while there are myriad database applications, there are only a few TPC benchmarks. There are therefore innumerable applications not covered by these benchmarks. A TPC benchmark is also not equally relevant to two different applications even when they belong in the same domain. This is why vendors never use TPC benchmarks when tuning the performance of their customers' systems.

The mismatch between applications and TPC can only get worse, as the proliferation of new database applications far outpaces the approval of new TPC benchmarks [1].

1.1. Problem Statement

There is thus a pressing need for a tool to help database owners generate application-specific datasets to specified size. We state this issue as the

[1]`http://www.tpc.org/`

Dataset Scaling Problem:

> *Given a set of relational tables $\mathcal{D}$ and a scale factor s, generate a database state $\widetilde{\mathcal{D}}$ that is similar to $\mathcal{D}$ but s times its size.*

This paper presents **UpSizeR**, a first-cut tool for solving the above problem.

One can define "s times its size" in various ways (number of tuples or bytes, etc.), and numerical precision is unnecessary — if $s = 3$, it would not matter if the generated $\widetilde{\mathcal{D}}$ were actually 3.14 times $\mathcal{D}$'s size (however defined).

Rather, the issue here is "similarity". One could define similarity measures that are based on graph properties [2] or information content [3], but we expect the database practitioner to be more interested in query results. For this paper, we assume the database owner has some set of queries $\mathcal{Q}$ on hand, and she will judge if $\widetilde{\mathcal{D}}$ is similar to $\mathcal{D}$ by running $\mathcal{Q}$ on both.

However, for this paper, we do not assume that UpSizeR has access to $\mathcal{Q}$ (the UpSizeR user may change $\mathcal{Q}$ anytime anyway). It follows that we cannot rely on using $\mathcal{Q}$ to help generate the data. Moreover, we believe no single similarity metric suffices.

The UpSizeR algorithms therefore aim to replicate the distribution of attribute values and correlations extracted from $\mathcal{D}$ alone. This fundamental approach is a surer way for UpSizeR to satisfy a changeable $\mathcal{Q}$ and multiple similarity metrics. In our experiments, we verify similarity with sizes of tables and query results (Table 1, Table 5), throughput (Table 2), execution time (Table 3) and aggregate values (Table 4).

1.2. Motivation for $s > 1$, $s = 1$, $s < 1$

There are various possibilities for why one might want to synthetically scale up ($s > 1$) an empirical dataset. Some web applications have user populations that grow at breakneck speed (one recent example being Animoto[2]), so a small but fast-growing service may need to test the scalability of their hardware and software architecture with larger versions of their datasets.

Another example is where an enterprise supplies a vendor with only a sample of its dataset (e.g. the entire dataset is too large for easy transfer), and the vendor needs to scale up the sample to an appropriate size.

[2]`http://animoto.com`

Taking a small sample of a large dataset is itself nontrivial. For example, if a dataset contains 2000000 buyers, and we want to extract a sample with 1000 buyers, it does not suffice to randomly pick 1000 buyers; e.g. we may need to add their suppliers' other buyers, and this recursive adding can grow the sample to an indeterminate size. Instead, one can use UpSizeR with $s < 1$ to downsize the dataset.

An enterprise may want to downsize its dataset, not just for a vendor, but for itself. For example, rather than test a new application by running it on a production dataset, one can use UpSizeR to get a small synthetic copy for testing.

In providing a vendor with just a small sample of its dataset, an enterprise may be motivated by privacy or proprietary considerations. UpSizeR also addresses such issues, since its output dataset is synthetic. Thus, for $s = 1$, UpSizeR can be viewed as making an anonymized copy of a dataset. Note, however, that some information leakage is inevitable since $\widetilde{\mathcal{D}}$ is, after all, similar to $\mathcal{D}$.

Such anonymization can be useful for, say, exploring different system configurations or implementations in the cloud (leveraging on its elasticity, and before investing in a particular configuration). Instead of exposing their real dataset (i.e. their crown jewels), an enterprise can use UpSizeR to upload a synthetic copy into the cloud.

1.3. Our Contribution

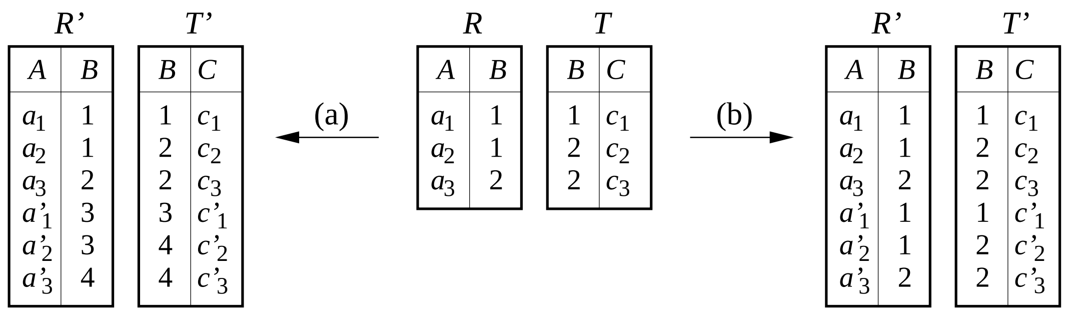
The TPC benchmarks have detailed scaling rules, and a table is generated by independently generating the required number of tuples. The decision to generate completely synthetic relations, instead of modeling empirical correlations, can be traced back to the Wisconsin benchmark [4]. Bitton et al. made that choice then because

(i) very large amounts of data are needed for the empirical values to reflect their underlying distribution;

(ii) synthetic data facilitates query design (for desired selectivity factors, join sizes, etc.); and

(iii) empirical datasets are hard to scale.

Nowadays, (i) is not an issue, since most datasets are big. In fact, gargantuan datasets are so common that the case for scale factor $s < 1$ may be



R' (a)

A	B
a_1	1
a_2	1
a_3	2
a'_1	3
a'_2	3
a'_3	4

T' (a)

B	C
1	c_1
2	c_2
2	c_3
3	c'_1
4	c'_2
4	c'_3

R

A	B
a_1	1
a_2	1
a_3	2

T

B	C
1	c_1
2	c_2
2	c_3

R' (b)

A	B
a_1	1
a_2	1
a_3	2
a'_1	1
a'_2	1
a'_3	2

T' (b)

B	C
1	c_1
2	c_2
2	c_3
1	c'_1
2	c'_2
2	c'_3

Figure 1: $\mathcal{D} = \{R, T\}$, $\mathcal{D}' = \{R', T'\}$, $s = 2$. **Naive copying does not work: For (a), creating new values may violate constraints on B (e.g. value range or number of distinct values). For (b), without creating new values, the scale up in join sizes may be wrong (for the natural join on B, $|R \bowtie T| = 4$ but $|R' \bowtie T'| = 16 \neq 4s$.)**

more important than $s > 1$. The task for UpSizeR is to scale a dataset; we assume the dataset owner already has an application-specific query set $\mathcal{Q}$, so we do not have to design the queries and (ii) is not a problem.

Issue (iii) remains true, i.e. the Dataset Scaling Problem is hard. However, thirty years have passed, so it is time to revisit the problem, and this paper's contribution lies in our UpSizeR solution. Note that although the UpSizeR *user* may have a query set $\mathcal{Q}$ on hand, UpSizeR *itself* may not have access to $\mathcal{Q}$.

To see why the Dataset Scaling Problem is hard, consider the toy $\mathcal{D}$ in Fig. 1. An obvious possibility for $s = 2$ is to scale $\mathcal{D}$ to $\widetilde{\mathcal{D}}$ by making a copy. However, as Fig. 1 illustrates:

Case (a) If new attribute values are created, then that may violate column constraints like value range or number of distinct values.

Case (b) If no new attribute values are created, then join sizes may scale by a wrong factor.

Besides, copying does not work for $s \leq 1$.

Our wish is that UpSizeR can work for any relational database. However, the UpSizeR version in this paper is far from solving the Dataset Scaling Problem. The algorithms here focus on replicating the correlation induced by primary/foreign keys. For inter- and intra-tuple correlation involving nonkey values, we only illustrate what can be done by presenting solutions for some special cases. To model and replicate all important correlations sufficiently (so UpSizeR can satisfactorily scale *any* application's dataset) requires more effort than any one research or development team can provide.

In other words, given the diversity of applications, the complexities in real data and the pressing need for a scaling tool, it will take a community effort to develop UpSizeR. As contribution to this task, we have released two implementations of UpSizeR for open-source development[3] — a single-server version and a parallelized Hadoop MapReduce[4] version.

Our UpSizeR release is the first step in our vision for a paradigm shift from top-down benchmark design by committee consensus to bottom-up collaborative development of tools and techniques for scaling empirical datasets[5].

Sec. 5 also identifies an **Attribute Value Correlation Problem for Social Networks**. This problem (not addressed in this paper) calls for the development of a database theory for how social interactions affect inter-column and inter-row correlations in relational databases. We believe this is a rich, new area for database research [5].

1.4. Paper Overview

We begin in Sec. 2 by introducing our notation and stating our assumptions. Sec. 3 then presents the UpSizeR algorithms. Sec. 4 describes how the assumptions can be relaxed, while Sec. 5 points out some limitations. Sec. 6 validates UpSizeR by comparing it to real data, and demonstrates how it can predict throughput degradation in a scale out test. Sec. 7 reviews related work, before Sec. 8 concludes with a summary and a proposal for extending UpSizeR into a broader program for the paradigm shift mentioned above.

2. UpSizeR Specification

We first fix our terminology and notation in Sec. 2.1 and list our assumptions in Sec. 2.2. We then describe the input and output for UpSizeR in Sec. 2.3.

[3]`http://www.comp.nus.edu.sg/∼upsizer`

[4]`http://hadoop.apache.org/`

[5]`http://www.vldb.org/2011/files/slides/cv1/cvSession1-3.pptx`

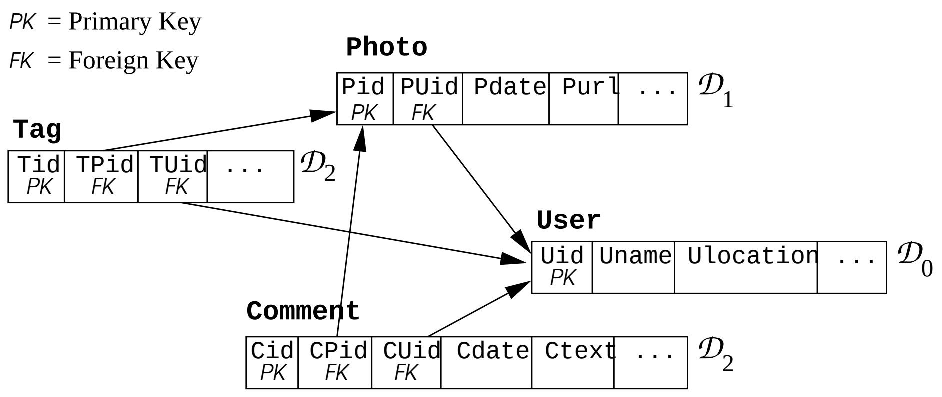


Figure 2: **A small schema graph for a photograph database $\mathcal{F}$. `Photo` records the owners (`PUid`) who uploaded the photographs, `Comment` records the comments on photographs (`CPid`) and their authors (`CUid`), and `Tag` records the tags on photographs (`TPid`) and the users who specified the tags (`TUid`). `User` records these owners, authors and taggers. Sorting this graph into $\mathcal{D}_i$ (Sec. 3) gives $\mathcal{D}_0 = \{\texttt{User}\}$, $\mathcal{D}_1 = \{\texttt{Photo}\}$ and $\mathcal{D}_2 = \{\texttt{Comment}, \texttt{Tag}\}$. $\mathcal{D}_1$ has one equivalence class $[\{\texttt{Uid}\}] = \{\texttt{Photo}\}$ and $\mathcal{D}_2$ also has one equivalence class $[\{\texttt{Pid}, \texttt{Uid}\}] = \{\texttt{Comment}, \texttt{Tag}\}$ (see [K] definition in Sec. 3).**

2.1. Terminology and Notation

We assume the reader is already familiar with the relevant definitions, and the following only serves to state our choice of terminology and notation.

A **database state** $\mathcal{D}$ consists of a set of **tables**. Each table has a **relation scheme**, a corresponding relation, and a **primary key**. The relation scheme is a set of **attributes**, including the primary key. The relation is a set of **tuples**, each of which assigns **values** to the attributes.

If a primary key K of table T appears as an attribute K' in another table T', K' is a **foreign key**. Such a K defines an **edge** from T' to T. These edges form a directed **schema graph** for the database state $\mathcal{D}$.

Fig. 2 gives an example of a schema graph for a database $\mathcal{F}$, like Flickr[6], that stores photographs uploaded by, commented upon and tagged by a community of users.

Each edge in the schema graph induces a bipartite graph between T and T', with bipartite edges between a tuple in T with K value v and the tuples in T' with K' value v. The number of such edges is denoted $deg(v, T')$. This

[6]`http://www.flickr.com`

is illustrated in Fig. 3 for $\mathcal{F}$.

For a positive number s, to **scale** $\mathcal{D}$ by s is to generate a synthetic database state $\widetilde{\mathcal{D}}$ such that:

(S1) $\widetilde{\mathcal{D}}$ has the same schema graph (or, simply, **schema**) as $\mathcal{D}$.

(S2) $\widetilde{\mathcal{D}}$ and $\mathcal{D}$ are similar in terms of query results.

(S3) For each table T_0 that has no foreign key, the number of T_0 tuples in $\widetilde{\mathcal{D}}$ should be s times that in $\mathcal{D}$; the sizes of tables with foreign keys are indirectly determined through their foreign key constraints.

How should one measure similarity of $\widetilde{\mathcal{D}}$ and $\mathcal{D}$? What counts as similar for one application may not be so for another. Since one motivation for UpSizeR lies in its use for scalability studies, UpSizeR should provide accurate forecasts of storage requirement, query time and retrieval results for larger datasets. The latter two are possible similarity measures, and they require some set $\mathcal{Q}$ of test queries.

We hence assume that the UpSizeR user has such a $\mathcal{Q}$ on hand (in addition to the database state $\mathcal{D}$) to measure the similarity of $\widetilde{\mathcal{D}}$ and $\mathcal{D}$, in terms of tuples retrieved, aggregates computed, response time, etc. This definition of dataset similarity, in terms of some user-specified $\mathcal{Q}$ and result similarity, makes (S2) application-specific.

For (S3), if $\mathcal{D}$ has the schema graph in Fig. 2, where `User` has no foreign keys, then the number of `User` tuples in $\widetilde{\mathcal{D}}$ should be s times the number of `User` tuples in $\mathcal{D}$. The number of `Photo` tuples in $\widetilde{\mathcal{D}}$ will be determined by $deg(\texttt{Uid}, \texttt{Photo})$, and the size of `Comment` then determined by the correlated values of $deg(\texttt{Pid}, \texttt{Comment})$ and $deg(\texttt{Uid}, \texttt{Comment})$.

One central issue in scaling up $\mathcal{D}$ lies in replicating its empirical inter-key correlations. For example, in the `Comment` table of $\mathcal{F}$, an author is more likely to comment on her own photographs. This implies that $deg(\texttt{Uid}, \texttt{Comment})$ and $deg(\texttt{Uid}, \texttt{Photo})$ are correlated. For each primary key K, let f_K be the joint degree distribution, i.e.

$$f_K(d_1, \dots, d_r) = \Pr(deg(v, T_1) = d_1, \dots, deg(v, T_r) = d_r),$$

where the random variable is K value v, and $T_1, \dots, T_r$ are the tables that contain K as foreign key.

Furthermore, if users are clustered into chefs, writers, etc., and photographs are clustered into cars, cakes, etc., then chefs are more likely to comment on photographs of cakes.

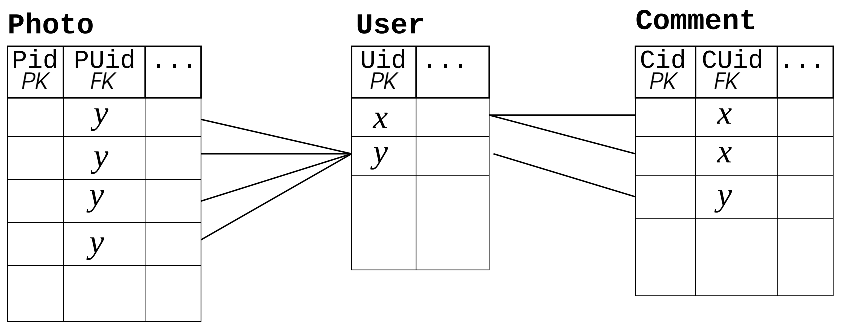


Figure 3: **A schema graph edge in Fig. 2 from `Photo` to `User` for the key `Uid` induces a bipartite graph between the tuples of `User` and `Photo`. Here,** $deg(x, \texttt{Photo}) = 0$ **and** $deg(y, \texttt{Photo}) = 4$**. Similarly,** $deg(x, \texttt{Comment}) = 2$ **and** $deg(y, \texttt{Comment}) = 1$**.**

For a table T with two foreign keys, let X be the random variable for a foreign key value, where these values are divided into clusters $c_1^X, \ldots, c_m^X$. Let random variable Y and clusters $c_1^Y, \ldots, c_n^Y$ be similarly defined for the other foreign key. Each $\langle c_i^X, c_j^Y \rangle$ is called a **co-cluster** [6], with joint distribution f_T^{cc} induced by T, i.e.

$$f_T^{cc}(c_i^X, c_j^Y) = \Pr(X \in c_i^X, Y \in c_j^Y).$$

Thus, in $\mathcal{F}$, `Comment` induces a co-clustering for photographs and users through a joint distribution $f_{\texttt{Comment}}^{cc}$.

Finally, we refer to generation of values for non-key attributes as **content generation**.

We will use v, T and $deg(v, T')$ to denote a value, table or degree in the given $\mathcal{D}$, and $\tilde{v}$, $\tilde{T}$ and $deg(\tilde{v}, \tilde{T}')$ to denote their synthetically generated counterparts in $\widetilde{\mathcal{D}}$.

2.2. Assumptions

To start, we assume the following:

(A1) Each primary key is a single attribute (i.e. no composite primary keys).
(A2) A table has at most two foreign keys.
(A3) The schema graph is acyclic.
(A4) The degree distribution is static. (E.g. the number of comments per user has the same distribution in $\mathcal{F}$ and $\widetilde{\mathcal{F}}$.)
(A5) Non-key attribute values for a tuple t only depends on t's key values.

(A6) Key values only depend on the joint degree and co-clustering distributions. (This is not true for $\mathcal{F}$ — see Sec. 5.)

These assumptions are mostly adopted as a tradeoff, giving up technical generality for expository clarity. In Sec. 4, we discuss how they can be relaxed.

2.3. Input and Output

The input to UpSizeR is given by an empirical dataset $\mathcal{D}$ and a positive number s that specifies the **scale factor**.

In response, UpSizeR will generate a synthetic database state $\widetilde{\mathcal{D}}$ satisfying (S1), (S2) and (S3) — see Sec. 2.1. The ratio in size of $\widetilde{\mathcal{D}}$ to $\mathcal{D}$ is only approximately s, since the exact size of $\widetilde{\mathcal{D}}$ is determined by key constraints, schema semantics (e.g. certain tables may have fixed sizes) and randomness in tuple generation.

The main issue in the Dataset Scaling Problem is similarity. For UpSizeR to be generally applicable, similarity must be application-specific. By defining dataset similarity in terms of query results (instead of, say, statistical distributions or graph properties), (S2) gives the UpSizeR user the final say.

3. UpSizeR Algorithms

We now describe the UpSizeR algorithms, using $\mathcal{F}$ as an example. The Appendix provides more details in pseudocode.

3.1. Extract probability distributions

For each table T in $\mathcal{D}$, UpSizeR processes T to extract the joint degree distribution f_K, where K is the primary key of T (see Sec. 2.1). This is done by normalizing the frequency distribution obtained from T. From f_K, UpSizeR can derive various marginal distributions, as needed, including that for $deg(v, T')$ where v is a K value and T' is any table with K as foreign key.

If T has more than one foreign key, UpSizeR then extracts the co-clustering distribution f_T^{cc} among the foreign keys. UpSizeR can work with any co-clustering algorithm (for the experiments, we use the one by Dhillon et al. [6]).

3.2. Sort the tables

Recall from (A3) that we assume the schema graph is acyclic. UpSizeR first groups the tables in $\mathcal{D}$ into subsets $\mathcal{D}_0, \mathcal{D}_1, \mathcal{D}_2, \ldots$ by sorting this graph, in the following sense:

• all tables in $\mathcal{D}_0$ have no foreign keys;
• for $i \geq 1$, $\mathcal{D}_i$ contains tables whose foreign keys are primary keys in $\mathcal{D}_0 \cup \mathcal{D}_1 \cup \cdots \cup \mathcal{D}_{i-1}$.

For $\mathcal{F}$, $\mathcal{D}_0 = \{\texttt{User}\}$, $\mathcal{D}_1 = \{\texttt{Photo}\}$ and $\mathcal{D}_2 = \{\texttt{Comment}, \texttt{Tag}\}$; here, the tables in $\mathcal{D}_i$ coincidentally have i foreign keys. This is not true in general. For the TPC-H example in the Appendix, the tables in $\mathcal{D}_2$ have just 1 foreign key each.

3.3. Partition $\mathcal{D}_i$ into equivalence classes $[\mathbf{K}]$

For each $\mathcal{D}_i$ and set of foreign keys $\mathbf{K}$, let $[\mathbf{K}]$ be the set of all tables in $\mathcal{D}_i$ with $\mathbf{K}$ as foreign keys. $[\mathbf{K}]$ is thus an equivalence class, and each $\mathcal{D}_i$ is partitioned by $[\mathbf{K}]$.

In the $\mathcal{F}$ example, $\mathcal{D}_1$ has one equivalence class $[\{\texttt{Uid}\}] = \{\texttt{Photo}\}$, and $\mathcal{D}_2$ also has one equivalence class $[\{\texttt{Pid}, \texttt{Uid}\}] = \{\texttt{Comment}, \texttt{Tag}\}$. In general, $\mathcal{D}_i$ may have more than 1 equivalence class. (For the TPC-H example in the Appendix, $\mathcal{D}_3$ has 2 equivalence classes.)

We need this definition because the tables in $[\mathbf{K}]$ are correlated through $\mathbf{K}$, so they are generated together.

3.4. Generate T in $\mathcal{D}_0$

Suppose T in $\mathcal{D}_0$ has h tuples. Since T has no foreign keys, UpSizeR simply generates sh primary key values for $\tilde{T}$. For example, the `User` table in $\widetilde{\mathcal{F}}$ has s times the number of `Uids` in $\mathcal{F}$.

Recall assumption (A5) that non-key values of a tuple depend only on its key values. For $\mathcal{D}_0$, this means the non-key attributes can be independently generated (without regard to the primary key values, which are arbitrary) by some content generator.

For example, values for `Uname` and `Ulocation` in $\widetilde{\mathcal{F}}$ can be picked from sets of names and locations, according to frequency distributions extracted from $\mathcal{F}$.

3.5. UpSizeR's main loop

A loop now generates tables in $\mathcal{D}_1, \mathcal{D}_2, \ldots$ in that order. The loop terminates when all tables are generated.

Each loop first generates $deg(\tilde{v}, \tilde{T}')$ before generating $\tilde{T}'$.

3.5.1. Generate $deg(\tilde{v}, \tilde{T}')$

In our $\mathcal{F}$ example, deg($\tilde{u}$, `Photo`) and $deg(\tilde{u}, \texttt{Comment})$ are correlated, since a user $\tilde{u}$ is likely to comment on her own photographs. With the $\mathcal{D}_i$ ordering, `Photo` is scaled before `Comment`, so we must compute the conditional probability to generate $deg(\tilde{u}, \texttt{Comment})$. Specifically, we use the joint degree distribution $f_{\texttt{Uid}}(deg(\texttt{u}, \texttt{Comment}), deg(\texttt{u}, \texttt{Photo}))$ to calculate

$$Pr(deg(\texttt{u}, \texttt{Comment}) = d' \mid deg(\texttt{u}, \texttt{Photo}) = d) = \frac{f_{\texttt{Uid}}(d', d)}{\sum_x f_{\texttt{Uid}}(x, d)}.$$

For a user $\tilde{u}$ with d tuples in `Photo`, we use this conditional probability to generate d' tuples in `Comment`.

In general, suppose $\tilde{T}'$ has the set of foreign keys $\mathbf{K}$, $K \in \mathbf{K}$ and K is the primary key of T. By the ordering $\mathcal{D}_0, \mathcal{D}_1, \mathcal{D}_2, \ldots$, $\tilde{T}$ would already have been generated, so the synthetic K values $\tilde{v}$ are ready to be used as foreign key values to generate $\tilde{T}'$.

Let $T_1', \ldots, T_n'$ be the tables that have $\mathbf{K}$ as foreign keys, i.e. $[\mathbf{K}] = \{T_1', \ldots, T_n'\}$. Earlier iterations of UpSizeR's main loop may have generated $deg(\tilde{x}, \tilde{T}_1''), \ldots, deg(\tilde{x}, \tilde{T}_m'')$ for all K values $\tilde{x}$ and some tables $\tilde{T}_1'', \ldots, \tilde{T}_m''$. Like the $f_{\texttt{Uid}}$ example above, UpSizeR now derives from the joint degree distribution f_K the conditional

$$Pr(deg(\tilde{v}, T_1') = d_1', \ldots, deg(\tilde{v}, T_n') = d_n' \mid deg(\tilde{v}, \tilde{T}_1'') = d_1, \ldots, deg(\tilde{v}, \tilde{T}_m'') = d_m).$$

This distribution is then used to compute the marginal distribution

$$Pr(deg(\tilde{v}, T_i') = d_1' \mid deg(\tilde{v}, \tilde{T}_1'') = d_1, \ldots, deg(\tilde{v}, \tilde{T}_m'') = d_m)$$

for $i = 1, \ldots, n$.

3.5.2. Generate $\tilde{T}'$ in $\mathcal{D}_i$ for $i \geq 1$

By (A2), each T' in $\mathcal{D}_i$ ($i \geq 1$) has 1 or 2 foreign keys.

Case T' has 1 foreign key:

Suppose T' has foreign key set $\mathbf{K} = \{K\}$, where K is primary key of T. In the $\mathcal{F}$ example, `Photo` has $\mathbf{K} = \{\texttt{Uid}\}$ and `User` is generated first; for each `Uid` $\tilde{v}$, we then generate $deg(\tilde{v}, \texttt{Photo})$ tuples for `Photo`.

In general, for each $\tilde{v}$, we generate $deg(\tilde{v}, \tilde{T}')$ tuples of $\tilde{T}'$, using $\tilde{v}$ for their K value and arbitrary (but unique) values for their primary key. Each tuple's non-key values are then assigned by content generation.

Case T' has 2 foreign keys:

Suppose T' has foreign key set $\mathbf{K} = \{K_1, K_2\}$ and K_i is the primary key of T_i for $i = 1, 2$. For $\mathcal{F}$, `Comment` has $\mathbf{K} = \{\texttt{Pid}, \texttt{Uid}\}$, so we need to use the distribution $f^{cc}_{\texttt{Comment}}$ that co-clusters `Pid`s and `Uid`s.

For $i = 1, 2$, UpSizeR first assigns every previously generated K_i value $\tilde{v}_i$ to a cluster cc_i, then assigns $deg(\tilde{v}_i, \tilde{T}')$ according to the degree distribution. We then force $\sum_{\tilde{v}_1} deg(\tilde{v}_1, \tilde{T}') = \sum_{\tilde{v}_2} deg(\tilde{v}_2, \tilde{T}')$ by randomly incrementing nonzero degrees in the smaller sum.

To generate a new tuple t for $\tilde{T}'$, UpSizeR generates a new primary key value $\tilde{v}'$ for $\tilde{T}'$ and assigns $\tilde{v}'$ to a random $\langle cc_1, cc_2 \rangle$ according to $f^{cc}_{T'}$. Within this co-cluster, UpSizeR picks $\tilde{v}_i$ in cc_i with probability proportional to $deg(\tilde{v}_i, \tilde{T}')$.

The key values $\tilde{v}, \tilde{v}_1, \tilde{v}_2$ now suffice to generate the rest of t. $deg(\tilde{v}_1, \tilde{T}')$ and $deg(\tilde{v}_2, \tilde{T}')$ are then decremented before generating the next tuple. This loop terminates when all $deg(\tilde{v}_i, \tilde{T}')$ are 0.

4. Relaxing the Assumptions

We adopted the strong assumptions above to help simplify the presentation. We now explain how (A1)–(A5) can be relaxed.

4.1. Composite primary keys

We can relax the assumption (A1) that primary keys are not composite by adding new attributes. If a table T has, say, attributes B_1 and B_2 that together act as the primary key, we add a new attribute C to take over as primary key. This is what we do for the TPC-H example in the Appendix.

To do so, we must ensure that $\langle B_1, B_2 \rangle$ values are unique in $\tilde{T}'$. If B_1 and B_2 are foreign keys and there are degree constraints $deg(\tilde{v}_1, \tilde{T}')$ and $deg(\tilde{v}_2, \tilde{T}')$ from B_1 and B_2 values $\tilde{v}_1$ and $\tilde{v}_2$ that are generated first, then we have to check for repetitions and resample when they occur.

4.2. More than two foreign keys

Assumption (A2) states that a table should have at most two foreign keys. UpSizeR can generate a table $\tilde{T}'$ with d foreign keys for $d \geq 3$, as long as there is an algorithm for co-clustering in d dimensions,

For example, if $d = 3$, we use any 3-dimensional co-clustering algorithm to generate the clusters, then use the degree distributions to assign $deg(\tilde{v}, \tilde{T}')$.

A new tuple is then assigned a co-cluster $\langle cc_1, cc_2, cc_3 \rangle$, using the co-clustering distribution $f^{cc}_{T'}(cc_1, cc_2, cc_3)$. The foreign key values $\tilde{v}_i$ in cc_i are then chosen according to $deg(\tilde{v}_i, \tilde{T}')$.

In the case of two foreign keys, the time complexity for the algorithm used in our experiments [6] is $O(NCL)$ where N is the number of key values, C is the number of clusters and L is the number of loops before convergence. The convergence is fast if the clustering is strong, but one can control the co-clustering time by pre-specifying C and tweaking the convergence threshold. For big datasets, one could use sampling instead.

4.3. Cyclic schemas

UpSizeR uses the acyclicity assumption (A3) to sort the tables into $\mathcal{D}_0, \mathcal{D}_1, \ldots$ and generate them in that order. The simplest violation of (A3) is where the schema graph has a self-loop. The most important example of this is where a table T has employee number `Eid` as primary key and manager `Mid` as foreign key (since every manager is also an employee), and the $\langle$`Eid`, `Mid`$\rangle$ pairs define a forest of management trees.

Here, we have to scale not just the number of nodes in the forest, but also maintain the "shape" of the trees. We describe the "shape" by

- r_i^{node}, which is the number of nodes at level i divided by the total number of nodes, and
- r_i^{leaf}, which is the number of leaves at level i divided by the total number of nodes at level i.

We use $i = 1$ for the roots, so r_1^{node} also specifies the number of trees.

Given a table T, we first obtain the empirical distributions for r_i^{node} and r_i^{leaf} by regression against i. We then use the regression equations for extrapolation, if necessary (for $s > 1$), and for generating the appropriate number of nodes and leaves at each level. After generating the trees, we then assign `Eid` to the nodes, and each parent's `Eid` becomes `Mid` for her children.

Sec. 9.3 in the Appendix presents an experimental evaluation of this idea for a Twitter[7] dataset.

[7]`http://twitter.com`

4.4. Nonstatic degree distribution

UpSizeR first scales by s all tables in $\mathcal{D}_0$ (see Sec. 3.4), and the other table sizes are then indirectly determined by the degree distributions. It follows from the static degree distribution assumption (A4) that all tables are scaled by s approximately. This may not be the right thing to do.

Some datasets may have fixed-size tables (e.g. `NATION` in TPC-H), thus changing the degree distribution in $\widetilde{\mathcal{D}}$. Suppose T has a primary key that appears as foreign key in T'. If T is static, then UpSizeR uses $s \times deg(v, T')$ for scaling. If T' is static, then UpSizeR can use $deg(v, T')/s$ but, in practice, it is unlikely that a foreign key is unaffected by a scaling in the primary key.

Another reason for a change in degree distribution when a dataset grows lies in the passage of time. For example, one expects the number of comments posted by a user to increase over time, possibly shifting the $deg(\texttt{Uid}, \texttt{Photo})$ distribution. We can further relax (A4) by having UpSizeR extract the degree growth function by mining the dates in the data (e.g. `Cdate` in `Comment`, `Tdate` in `Tag`, etc.).

4.5. Content generation for non-key attributes

This paper focuses on replicating key value correlation. There are many ways of generating non-key attribute values.

For example, one could extract from $\mathcal{D}$ relevant probability distributions (e.g. for `Ulocation`, `Psize` or `Clanguage`) and use them for content generation. The UpSizeR user can also supply a method for, say, generating fake `Comment` text (e.g. TEXTURE [7]).

Non-key attributes may also induce tuple correlation, thus violating assumption (A5). For example, there is some distribution for how many photographs an $\mathcal{F}$ user uploads per day. UpSizeR can replicate such correlation with $deg(d, \texttt{Photo})$ where d is a value for `Pdate` (which is not a key).

A more difficult form of tuple correlation for a non-key attribute in $\mathcal{F}$ is tag value ("bird", "car", etc.). The tags used by a bird watcher are likely to have a coherence that makes them recognizably different from those used by a car enthusiast. One must take such coherence into account when generating synthetic tags.

For the experiments in Sec. 6, we use the following algorithm to generate the taglist for a user $\tilde{u}$ in $\widetilde{\mathcal{F}}$, by perturbing the taglist ℓ of a random real user in $\mathcal{F}$: determine $\|\ell_{\tilde{u}}\|$, i.e. how many tags $\tilde{u}$ uses, from `Tag` in $\widetilde{\mathcal{F}}$; if $\|\ell\| > \|\ell_{\tilde{u}}\|$, randomly remove excess tags from ℓ; else if $\|\ell\| < \|\ell_{\tilde{u}}\|$, use the

Photo

Pid	PUid	...
Px	*x*	
Py	*y*	

Comment

Cid	CPid	CUid	...
	Px	*y*	
	Py	*x*	

Figure 4: **Users x and y comment on each other's photographs. Such interactions induce inter-column and inter-row correlations in the tables above.**

joint tag distribution to add tags to ℓ; we thus get $\|\ell\| = \|\ell_{\tilde{u}}\|$, and can assign ℓ to $\ell_{\tilde{u}}$.

5. Limitations

The main issue in scaling an empirical dataset lies in the correlations, but it is computationally intractable to replicate all of them. For example, extracting pairwise correlation in tag values from $\mathcal{F}$ (Sec. 4.5) takes far longer than the rest of UpSizeR. One must therefore judiciously choose which correlations to replicate. This choice can be made by the UpSizeR user, or by examining the queries (Sec. 7).

While the algorithms described so far may suffice for classical commercial datasets (in banking, telecom, etc.), social network data require more. For example, Flickr friends are more likely to comment on each other's photographs. Such an interaction appears in $\mathcal{F}$ as inter-column and inter-row correlation as illustrated in Fig. 4. Such correlations that are induced by social interactions go beyond assumption (A6). How can UpSizeR replicate such correlations?

Fig. 5 illustrates one possibility: First extract a graph $\langle V, E\rangle$ from $\mathcal{D}$, where the nodes in V represent members of the social network, and each edge in E represents a social interaction. This graph is then scaled by s to $\langle \tilde{V}, \tilde{E}\rangle$, and "injected" into $\widetilde{\mathcal{D}}$ (constructed under assumption (A6)) by modifying the values in $\widetilde{\mathcal{D}}$.

Recall from Sec. 1.1 that the UpSizeR approach to achieving similarity in query results is to extract statistics from $\mathcal{D}$ and reproduce them in $\widetilde{\mathcal{D}}$. In scaling $\langle V, E\rangle$, this necessarily means that UpSizeR must replicate the graph topology — number of triangles (a friend of a friend is likely to be a friend), path lengths (6 degrees of separation), etc. The purpose here is not to achieve graph similarity, but to capture the data correlation induced by the topology. This is not easy, but the techniques will rely on graph theory.

$$\begin{tikzcd}
\mathcal{D} \arrow[r, "\text{scale by } s", "\text{assumption (A6)}"'] \arrow[d, "\text{extract}"'] & \tilde{\mathcal{D}} \\
<V,E> \arrow[r, "\text{scale by } s"] & <\tilde{V},\tilde{E}> \arrow[u, "\text{inject}"']
\end{tikzcd}$$

Figure 5: **How UpSizeR can replicate correlation in a social network dataset $\mathcal{D}$ by extracting and scaling the social interaction graph $\langle V, E\rangle$.**

From the database perspective, the real difficulty lies in the graph extraction/injection, which may require some database theory for social network data. Given a relational dataset $\widetilde{\mathcal{D}}$ from a social network, how does one extract a social interaction graph? Conversely, what data dependencies are induced in the relations by, say, the triangles in the graph? We state this issue as the **Attribute Value Correlation Problem for Social Networks ($\mathbf{AVC_{SN}}$)**:

> *Suppose a database state $\mathcal{D}$ records data from a social network. How do the social interactions affect the correlation among attribute values in $\mathcal{D}$?*

There are many papers on online social networks, but we found none that translates that literature into relational database theory. We believe this Attribute Value Correlation Problem points to a rich, new area for database research.

6. Experiments

The TPC benchmarks are well-established, so the reader may expect us to compare UpSizeR to one of them; on the other hand, TPC datasets are purely synthetic. We therefore postpone a comparison to Sec. 9.1 in the Appendix.

To validate UpSizeR, we need to compare its results against real datasets for various values of s. We therefore use crawled data from Flickr for comparison in Sec. 6.1 below.

One motivation for UpSizeR is in scalability testing, so we also validate UpSizeR with a scale out test in Sec. 6.2.

#tuples	User	Photo	Comment	Tag	F1	F2	F3	F4	F5	F6
$\mathcal{F}_{1.00}$	146374	529926	1505267	3343964	945	85137	2654	1	2075	120
UpSizeR($\mathcal{F}_{1.00}, 1.00$)	146374	581069	1654678	3765474	906	71080	2896	0	3081	161
$\mathcal{F}_{2.81}$	410892	1557856	4234147	9198476	2398	219499	9717	3	8448	255
UpSizeR($\mathcal{F}_{1.00}, 2.81$)	411305	1557650	4410086	10377427	2687	205334	8119	1	9973	474
$\mathcal{F}_{5.35}$	783821	2803603	7709470	16299952	4369	401464	15671	4	15513	485
UpSizeR($\mathcal{F}_{1.00}, 5.35$)	783090	2823268	8093519	17813587	5063	406099	15751	5	17306	972
$\mathcal{F}_{9.11}$	1332796	4474956	18136861	27743408	8258	734766	27491	15	32619	1513
UpSizeR($\mathcal{F}_{1.00}, 9.11$)	1333448	4693496	13702306	29637029	8673	717454	26686	13	31640	1746

Table 1: Comparing table sizes and query results (number of tuples) for real $\mathcal{F}_s$ and synthetic UpSizeR($\mathcal{F}_{1.00}, s$).

6.1. UpSizeR Validation with Flickr

We downloaded four datasets from Flickr for $\mathcal{F}$. These datasets were then combined to give different sizes.

The downloads were at different times. Since $deg(x, \texttt{Photo})$, $deg(x, \texttt{Comment})$ and $deg(x, \texttt{Tag})$ generally increase over time for any user x,, the static degree assumption (A4) does not hold. Although we can extend UpSizeR to model this effect of time (Sec. 4.4), we impose (A4) in this validation exercise by keeping each pair of datasets disjoint through renaming. In other words, if two downloaded datasets $\mathcal{E}_1$ and $\mathcal{E}_2$ have some common `Uid`s (say), we rename the `Uid`s in one of them so that $\mathcal{E}_1$ and $\mathcal{E}_2$ have no common `Uid`s.

Rather than try to control the scale factor for the real datasets, we let them decide the s value for UpSizeR. Specifically, since the scaling up starts with $\mathcal{D}_0 = \{\texttt{User}\}$, we obtain s by $s = t_1/t_2$, where t_i is the number of `Uid`s in an $\mathcal{F}$ dataset. The baseline size is given by a fixed dataset $\mathcal{F}_{1.00}$ and, in general, $\mathcal{F}$ datasets are denoted $\mathcal{F}_s$ according to their s value when compared to $\mathcal{F}_{1.00}$. For example, $\mathcal{F}_{2.81}$ has a number of `Uid`s that is 2.81 times that in $\mathcal{F}_{1.00}$.

Hence, the validation is a comparison between a real $\mathcal{F}_s$ and a synthetic UpSizeR($\mathcal{F}_{1.00}, s$), as shown in Table 1

Since the s value given to UpSizeR is calculated from the real dataset $\mathcal{F}_s$, and the scaling up starts with $\mathcal{D}_0 = \{\texttt{User}\}$, the close agreement in Table 1 between real and synthetic `User` is expected.

For $\mathcal{D}_1 = \{\texttt{Photo}\}$, UpSizeR uses the degree distribution to generate the table. The efficacy of doing so cannot be taken for granted, since the difference between $\mathcal{F}_{1.00}$ and UpSizeR($\mathcal{F}_{1.00}, 1.00$) is about 10% for `Photo` in Table 1. The agreement is better for the other s values.

For $\mathcal{D}_2 = \{\texttt{Comment}, \texttt{Tag}\}$, Table 1 shows that UpSizeR's use of co-clustering produces table sizes that are in good agreement, considering the vagaries of empirical data in $\mathcal{F}_s$.

However, merely matching table sizes does not suffice. We have argued that dataset similarity should be judged with queries. Since the UpSizeR version in this paper does not replicate social interactions, we avoid querying the social network below. We start with the following queries:
F1: Retrieve users who uploaded photographs (0 joins).
F2: Retrieve photographs that are commented on by their owners (1 join).
F3: Retrieve users who tagged others' photographs (1 join).
F4: Retrieve users who uploaded photographs but made no comments (2 joins).

F1 tests UpSizeR's ability to reproduce selectivity, while F2, F3 and F4 test for correct join sizes. The number of tuples retrieved by these queries for the real $\mathcal{F}_s$ and UpSizeR($\mathcal{F}_{1.00}, s$) are also shown in Table 1.

Agreement in query results is harder to achieve than table sizes, since the datasets must also have similar data correlation. It is hence not surprising that discrepancy is now larger. Still, agreement is generally good. Note in particular that the UpSizeR datasets accurately return a very small number of tuples for F4 from among the millions of tuples for photographs and comments.

Although F3 tests the join of `Tag` and `Photo`, it does not query the (non-key) tag values. To test the taglist generation described in Sec. 4.5, we use the following:
F5: Retrieve photographs tagged with "bird".
F6: Retrieve photographs tagged with "bird" and "sky".
In particular, F6 tests our algorithm for replicating tag coherence. (Recall that our taglist generation only tries to maintain coherence for the tags used by a user.)

Table 1 shows that the number of tuples retrieved by F5 and F6 from the synthetic datasets, although inaccurate, are in the right ball park. Surely, there is room for improvement (e.g. associate "bird" and "birds"), but the F5 and F6 results already show how inter-tuple correlation induced by non-key attributes can be captured through content generation, like what we have done through taglist generation by sampling and perturbation.

6.2. UpSizeR Validation with Scale Out Test

Every system must encounter, sooner or later, some hardware or software bottleneck that causes performance to saturate. Beyond the saturation

concurrency C	1	4	8	10	12	16	20		
$\mathcal{F}_{1.00}$	0.040	0.125	0.172	*0.186*	0.175	0.167	0.142		
UpSizeR($\mathcal{F}_{1.00}$, 1.00)	0.043	0.131	0.164	*0.185*	0.169	0.167	0.145		
concurrency C	1	4	8	12	16	20	24	28	32
$\mathcal{F}_{2.81}$	0.039	0.153	0.271	0.312	0.339	0.355	*0.378*	0.358	0.356
UpSizeR($\mathcal{F}_{1.00}$, 2.81)	0.041	0.147	0.273	0.304	0.348	0.362	*0.389*	0.355	0.348
concurrency C	1	4	8	12	16	20	24	28	32
$\mathcal{F}_{5.35}$	0.038	0.149	0.253	0.276	0.313	0.326	*0.354*	0.342	0.336
UpSizeR($\mathcal{F}_{1.00}$, 5.35)	0.039	0.141	0.273	0.301	0.327	0.333	*0.359*	0.347	0.341
concurrency C	1	4	8	12	16	20	24	28	32
$\mathcal{F}_{9.11}$	0.040	0.154	0.296	0.323	0.377	0.384	0.401	*0.422*	0.418
UpSizeR($\mathcal{F}_{1.00}$, 9.11)	0.043	0.154	0.275	0.343	0.354	0.386	0.423	*0.435*	0.424

Table 2: **A scale out test that compares throughput (queries per second) when concurrent queries retrieve blobs from the real and synthetic datasets. The underlined numbers indicate where throughputs are maximum; note that the synthetic data accurately predict where throughput begins to degrade.**

point, resource contention usually causes inefficiencies that result in performance degradation. We now validate UpSizeR's accuracy in locating where performance begins to degrade as a system is scaled out.

For this experiment, we include synthetic blobs (binary large objects) in place of photographs. These blobs are stored in Hadoop Object Store [8], a storage system — similar to Facebook's custom-built Haystack [9] — that we built on top of Hadoop.

We use the same Awan cluster as in the TPC-H experiments (Sec. 9.1). We run C concurrent queries, where each query retrieves all photographs uploaded by a user who is randomly selected by name. (On average, each user in our Flickr data uploads 550 photographs.) We fix C by replacing each terminating query with a new query.

For each s, there is a concurrency C_s where throughput is maximum: as C increases, throughput is increasing for $C < C_s$ and decreasing for $C > C_s$. Our experiment tests if UpSizeR data can accurately predict the saturation point C_s for each s.

For validation, we use the real non-blob data (in particular, `User` and `Photo`) for $s = 1.00, 2.81, 5.35$ and 9.11. With the blobs included, the total dataset sizes are approximately 50GBytes for $\mathcal{F}_{1.00}$, 132GBytes for $\mathcal{F}_{2.81}$, 271GBytes for $\mathcal{F}_{5.35}$ and 426GBytes for $\mathcal{F}_{9.11}$.

We are limited by the size of our machine cluster, so the number of nodes used in the scale out test is set to 2, 6, 10 and 18 for $s = 1.00, 2.81, 5.35$ and 9.11 respectively.

Table 2 shows that throughput (queries per second) measured when the queries run on UpSizeR data is close to that for real Flickr non-blob data. More important, the synthetic dataset correctly identifies the concurrency C_s at which throughput begins to degrade.

One would hope that, as a system scales out, it can support higher concurrency; in particular, C_s should scale linearly with s. However, for this workload, Table 2 shows $C_{1.00} = 10$, $C_{2.81} = 24$, $C_{5.35} = 24$ and $C_{9.11} = 28$. Such a prediction of weak scalability with UpSizeR data would suggest a need for performance debugging or system redesign.

7. Related Work

Scalability engineering [10] requires an exploration of the design space for load balancing [11], query plans [12], power budgeting [13], etc. For example, the designers of SCOPE (a SQL-like scripting language for parallel processing of massive data [14]) exercised it with scalability tests that use TPC-H.

The TPC approach is being adopted by a new generation of benchmarks [15, 16]. However, Seltzer et al. [17] have observed how standard benchmarks can be irrelevant for particular applications, and argued for application-specific benchmarking. For database systems, this alternative approach must start with application-specific datasets [5].

So far, the use of empirical data is very limited. For example, MUDD only extracts names and addresses from a real dataset [18], while TEXTURE [7] extracts word distribution, document lengths, etc. from “seed” documents and use them to *independently* generate synthetic documents (like how TPC generates tuples).

Bruno and Chaudhuri’s Data Generation Language [19] can specify value distributions and generate data tuples, while Hoag and Thompson’s Synthetic Data Description Language [20] has a construct for specifying foreign keys, but data generation by both languages do not replicate correlation between foreign keys (like UpSizeR does with joint degree and co-clustering distributions).

Houkjær et al. have described a data generating tool [21] that processes the schema graph in the opposite order to UpSizeR. (For the Flickr example of Fig. 2, they would generate `Comment` and `Tag` before `Photo` and `User`.) This necessitates the use of temporary foreign key values that are replaced after primary key values are generated later. The tool also uses cardinalities and value (not correlation) distributions extracted from real data.

For $s = 1$, related work on anonymization (k-anonymity, etc.) mostly focused on a single table, or allowed at most one foreign key per table [22]. There is recent work on anonymization that preserves semantic constraints [23] or query plans [24]; UpSizeR can adopt some of their techniques to address those issues for $s \neq 1$.

Recall that the UpSizeR version presented here does not make use of the application queries. Binnig et al.'s reverse query processing [25] uses query results to generate a *smallest* dataset to test the application, whereas QAGen uses a given query plan with size constraints to generate a corresponding dataset [26], without requiring similarity to real data.

CORDS is a tool that uses the application queries to select columns whose correlations are important for query optimization [27]. It also uses the correlation to generate synthetic data, but this purely valued-based generation (e.g. humidity and temperature) is different from the entity-based correlation (e.g. gardeners and flowers) described in Sec. 3.5.2. CORADD is another tool that discovers attribute correlations that are important to the queries, and use them to design materialized views and indexes [28]. Although the current UpSizeR does not rely on the application queries for data generation, it can follow CORDS and CORADD in using the queries to select the attributes for correlation replication.

8. Conclusion

We believe that the TPC benchmarking paradigm cannot sufficiently cover, in timely fashion, the diverse applications in the ballooning number of data-centric systems [1]. (A recent empirical analysis of Hadoop MapReduce workloads shows that this is an issue for schema-less key-value stores as well [29].)

After a summary on UpSizeR in Sec. 8.1, we therefore propose in Sec. 8.2 a program to develop tools and techniques for application-specific benchmarking of such systems [5]. Unlike TPC's top-down approach to benchmark design by committee consensus, we expect this program will be driven bottom-up by application developers. Such a community effort must grow from some seed, and UpSizeR can possibly play such a role.

8.1. Paper Summary

We have presented UpSizeR, a software that addresses the Dataset Scaling Problem. UpSizeR's ability to synthetically scale an empirical dataset makes it a tool for generating application-specific benchmarks.

Table 1 confirms that UpSizeR can accurately scale table sizes for the Flickr dataset, and the query results show good agreement with crawled data, considering the intractable complexities of real data. Table 2 also shows that the datasets produced by UpSizeR can accurately predict where throughput degrades when scaling out a system.

These results suggest that UpSizeR has the basic techniques for scaling up traditional datasets (in retail, logistics, etc.). Indeed, Sec. 9.1 in the Appendix shows that UpSizeR gives an excellent match for TPC-H query results and response time.

Given the proliferation of relational databases, and the heterogeneity among them, an attack on the Dataset Scaling Problem is now overdue. UpSizeR is only a *first-cut* solution, and much remains to be done. We have therefore released a single-server version and a Hadoop MapReduce version for open-source development by the database community.

Although UpSizeR is intended for scaling real data, its accuracy for TPC-H is so good that one can use it to get around the difficulties in generating large TPC datasets [30]. Specifically: use TPC's DBGen to generate a small (1GB, say) TPC-H dataset $\mathcal{H}$, then use our MapReduce version of UpSizeR to scale up $\mathcal{H}$ on some — e.g. cloud-resident — cluster of commodity machines; i.e. no need for a large database server nor special parallel algorithms. We have verified that this works for a 200GB dataset.

8.2. A Program Proposal: Application-Specific Benchmarking of Data-Centric Systems

Our experience with UpSizeR shows that, for data system benchmarking to break away from the TPC paradigm, there is much to be done in the development of tools and techniques.

Currently, UpSizeR does not replicate correlations induced by **social interactions** (so Sec. 6.1 avoids querying the social network). The extension sketched in Fig. 5 would require graph-theoretic techniques that properly scale the degrees, triangles, paths, etc. It also requires a database-theoretic understanding of inter-column and inter-row correlations generated by social interactions (a probabilistic dependency theory for $\mathbf{AVC_{SN}}$, say). We see CORDS and CORADD as early signs of a growing interest in research on attribute value correlation and we believe, in particular, that $\mathbf{AVC_{SN}}$ is a very promising area for future work.

For example, what attributes make one Flickr user more likely to comment on another user's photographs? What events (e.g. birthdays) can induce temporal tuple correlations (e.g. writing on Facebook walls) in the tables? Without understanding how social interactions induce tuple correlations, one cannot replicate them, and the synthetic dataset will produce inaccurate results for queries that touch on the social network.

Online social networks are now major generators of data, and a better understanding of such data is necessary if one is to extract value from these networks. This is why we highlight $\mathbf{AVC_{SN}}$ here. The only related work we found in this area is by Qin et al. [31], who present an algorithm (no theory) for extracting communities of authors that are induced by keyword queries on the DBLP relational dataset.

The Web is driving the growth of **XML** databases. To generate a set of synthetic XML documents, it is particularly important that one starts with an empirical collection, since real documents are usually more restrictive than their DTD specifications. Where an XML dataset is exported from a relational database, the synthetic documents are probably best generated by first scaling the relations. However, there is a growing body of native XML fragments (e.g. generated by RSS feeds) that are not stored in relational format, so a scaling tool for XML may be necessary.

As a dataset grows, its **applications** may grow with it. For example, an insert transaction may generate more tuples, where the values inserted follow the correlation in the database. For a scalability study to exercise the indexes, locks, etc., the applications must also be scaled to match the dataset. This suggests the need for a tool that will, say, take as input a set of transactions, as well as the dataset they use, and scale up both.

The query **log** will also scale with a database. In fact, for Internet services, much of the value may lie in their click logs, so a log scaling tool may have corresponding commercial value. One particular difficulty here is the correlation among the clicks. For example, a log records an interleaving of multiple click streams, where the data returned by one click probabilistically determines the next click in its stream.

Two clicks from *different* **streams** that are close in time in a log may also have correlated data, so log scaling will be harder than stream scaling. Despite the intense interest in data streaming in recent years, there are very few benchmarks in this area [32]. Perhaps there is insufficient commercial motivation for a TPC-like effort to define streaming benchmarks. Since there is an abundance of stream data in finance, surveillance, traffic, e-commerce, etc., but many are jealously guarded, the development of a tool to anonymize and synthetically scale a recorded data stream may be a way of overcoming the dearth in streaming benchmarks.

References

[1] M. Stonebraker, A new direction for TPC?, in: TPCTC 2009, pp. 11–17.

[2] V. D. Blondel, A. Gajardo, M. Heymans, P. Senellart, P. V. Dooren, A measure of similarity between graph vertices: Applications to synonym extraction and web searching, SIAM Rev. 46 (2004) 647–666.

[3] D. Srivastava, S. Venkatasubramanian, Information theory for data management, in: SIGMOD 2010, pp. 1255–1256.

[4] D. J. DeWitt, The Wisconsin Benchmark: Past, present, and future, in: The Benchmark Handbook, Morgan Kaufmann Publishers Inc., 1993.

[5] Y. C. Tay, Data generation for application-specific benchmarking, PVLDB 4 (2011) 1470–1473.

[6] I. S. Dhillon, S. Mallela, D. S. Modha, Information-theoretic co-clustering, in: KDD 2003, pp. 89–98.

[7] V. Ercegovac, D. J. DeWitt, R. Ramakrishnan, The TEXTURE benchmark: measuring performance of text queries on a relational DBMS, in: VLDB 2005, pp. 313–324.

[8] D. T. Wang, Data Storage and Retrieval for Social Network Services, Master's thesis, National University of Singapore, Singapore, 2010.

[9] D. Beaver, S. Kumar, H. C. Li, J. Sobel, P. Vajgel, Finding a needle in Haystack: Facebook's photo storage, in: OSDI 2010, pp. 47–60.

[10] A. Jacobs, The pathologies of big data, Commun. ACM 52 (2009) 36–44.

[11] G. DeCandia, D. Hastorun, M. Jampani, G. Kakulapati, A. Lakshman, A. Pilchin, S. Sivasubramanian, P. Vosshall, W. Vogels, Dynamo: Amazon's highly available key-value store, SIGOPS Oper. Syst. Rev. 41 (2007) 205–220.

[12] M. Isard, M. Budiu, Y. Yu, A. Birrell, D. Fetterly, Dryad: distributed data-parallel programs from sequential building blocks, in: EuroSys 2007, pp. 59–72.

[13] K. Birman, G. Chockler, R. van Renesse, Toward a cloud computing research agenda, SIGACT News 40 (2009) 68–80.

[14] R. Chaiken, B. Jenkins, P.-A. Larson, B. Ramsey, D. Shakib, S. Weaver, J. Zhou, SCOPE: easy and efficient parallel processing of massive data sets, PVLDB 1 (2008) 1265–1276.

[15] C. Binnig, D. Kossmann, T. Kraska, S. Loesing, How is the weather tomorrow?: towards a benchmark for the cloud, in: DBTest 2009, pp. 1–6.

[16] B. F. Cooper, A. Silberstein, E. Tam, R. Ramakrishnan, R. Sears, Benchmarking cloud serving systems with YCSB, in: SoCC 2010, pp. 143–154.

[17] M. Seltzer, D. Krinsky, K. Smith, X. Zhang, The case for application-specific benchmarking, in: HOTOS 1999, pp. 102–109.

[18] J. M. Stephens, M. Poess, MUDD: a multi-dimensional data generator, in: WOSP 2004, pp. 104–109.

[19] N. Bruno, S. Chaudhuri, Flexible database generators, in: VLDB 2005, pp. 1097–1107.

[20] J. E. Hoag, C. W. Thompson, A parallel general-purpose synthetic data generator, SIGMOD Rec. 36 (2007) 19–24.

[21] K. Houkjær, K. Torp, R. Wind, Simple and realistic data generation, in: VLDB 2006, pp. 1243–1246.

[22] M. E. Nergiz, C. Clifton, A. E. Nergiz, Multirelational k-anonymity, IEEE Trans. on Knowl. and Data Eng. 21 (2009) 1104–1117.

[23] R. Yahalom, E. Shmueli, T. Zrihen, Constrained anonymization of production data: a constraint satisfaction problem approach, in: SDM 2010, pp. 41–53.

[24] M. Castellanos, B. Zhang, I. Jimenez, P. Ruiz, M. Durazo, U. Dayal, L. Jow, Data desensitization of customer data for use in optimizer performance experiments, in: ICDE 2010, pp. 1081–1092.

[25] C. Binnig, D. Kossmann, E. Lo, Reverse query processing, in: ICDE 2007, pp. 506–515.

[26] C. Binnig, D. Kossmann, E. Lo, M. T. Özsu, QAGen: generating query-aware test databases, in: SIGMOD 2007, pp. 341–352.

[27] I. F. Ilyas, V. Markl, P. Haas, P. Brown, A. Aboulnaga, CORDS: automatic discovery of correlations and soft functional dependencies, in: SIGMOD 2004, pp. 647–658.

[28] H. Kimura, G. Huo, A. Rasin, S. Madden, S. Zdonik, CORADD: Correlation aware database designer for materialized views and indexes, PVLDB 3 (2010) 1103–1113.

[29] Y. Chen, We don't know enough to make a big data benchmark suite - an academia-industry view, in: Workshop on Big Data Benchmarking 2012.

[30] J. Gray, P. Sundaresan, S. Englert, K. Baclawski, P. J. Weinberger, Quickly generating billion-record synthetic databases, in: SIGMOD 1994, pp. 243–252.

[31] L. Qin, J. X. Yu, L. Chang, Y. Tao, Querying communities in relational databases, in: ICDE 2009, pp. 724–735.

[32] A. Arasu, M. Cherniack, E. F. Galvez, D. Maier, A. Maskey, E. Ryvkina, M. Stonebraker, R. Tibbetts, Linear Road: A stream data management benchmark, in: VLDB 2004, pp. 480–491.

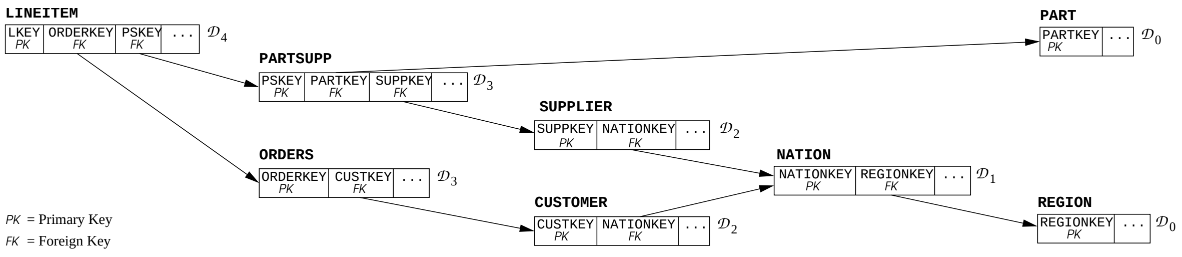


Figure 6: **Schema $\mathcal{H}$ for the TPC-H benchmark that is used for UpSizeR comparison in Sec. 9.1. Sorting this graph into $\mathcal{D}_i$ (Sec. 3) gives $\mathcal{D}_0 = \{\texttt{PART}, \texttt{REGION}\}$, $\mathcal{D}_1 = \{\texttt{NATION}\}$, $\mathcal{D}_2 = \{\texttt{SUPPLIER}, \texttt{CUSTOMER}\}$, $\mathcal{D}_3 = \{\texttt{PARTSUPP}, \texttt{ORDERS}\}$ and $\mathcal{D}_4 = \{\texttt{LINEITEM}\}$. $\mathcal{D}_1$, $\mathcal{D}_2$ and $\mathcal{D}_4$ have one equivalence class each, namely $[\{\texttt{REGIONKEY}\}] = \{\texttt{NATION}\}$ for $\mathcal{D}_1$, $[\{\texttt{NATIONKEY}\}] = \{\texttt{SUPPLIER}, \texttt{CUSTOMER}\}$ for $\mathcal{D}_2$ and $[\{\texttt{PSKEY}, \texttt{ORDERKEY}\}] = \{\texttt{LINEITEM}\}$ for $\mathcal{D}_4$. However, $\mathcal{D}_3$ has two equivalence classes: $[\{\texttt{PARTKEY}, \texttt{SUPPKEY}\}] = \{\texttt{PARTSUPP}\}$ and $[\{\texttt{CUSTKEY}\}] = \{\texttt{ORDERS}\}$.**

9. Appendix

This appendix presents more experimental results and UpSizeR details. Sec. 9.1 compares results of queries that are run on data generated by DBGen and UpSizeR for the TPC-H schema graph in Fig. 6. Sec. 9.2 further describes UpSizeR in pseudocode.

9.1. Comparing UpSizeR and TPC-H

One can view UpSizeR as generating datasets for benchmarking. The TPC benchmarks are *de rigueur* for database systems, and they also generate datasets to specified scale. Since the TPC benchmarks are widely accepted, the reader may reasonably expect a comparison between UpSizeR and a TPC benchmark. We do that here, and also demonstrate the use of UpSizeR for scaling down.

The latest TPC benchmarks are TPC-E for online transaction processing and TPC-H for decision support. TPC-E has tables that contain three or more foreign keys, thus requiring the use of compute-intensive high-dimensional co-clustering. We therefore choose to validate with TPC-H.

TPC-H datasets are generated by DBGen and specified by size. The 1GB, 2GB, 10GB and 40GB DBGen datasets are denoted $\mathcal{H}_1$, $\mathcal{H}_2$, $\mathcal{H}_{10}$ and $\mathcal{H}_{40}$, respectively. We use UpSizeR to scale down $\mathcal{H}_{40}$ with $s = 0.025, 0.05$ and 0.25. Thus, UpSizeR($\mathcal{H}_{40}$,0.025) is a dataset that is similar in size to $\mathcal{H}_1$, and replicates data correlation extracted from $\mathcal{H}_{40}$.

The correlation in DBGen data lies in the key values, and this correlation is replicated by UpSizeR through the use of joint degree and co-clustering distributions. For the generation of non-key values, UpSizeR uses the same techniques as DBGen when scaling down $\mathcal{H}_{40}$.

The experiments here use our single-server UpSizeR version on a machine with a 64GB RAM. This puts a constraint on the input size $\mathcal{D}$ for UpSizeR, which is why we did not scale down from a bigger H_s.

The queries we use to compare DBGen data and UpSizeR output are simplified versions of TPC-H queries, as shown in Fig. 7. The comparison is in terms of number of tuples retrieved, the aggregates computed, and the response time.

The run times are measured on a cluster — called Awan[8] — of 14 commodity machines, each having an Intel Xeon Quad Core, (2.4GHz, 8MB cache), 2×4GB ECC RAM and 2×500GB hard disk (SATA II, 3.5 inches). They run 64-bit Linux CentOS (release 5.5), the files are stored with Hadoop 0.20.2 and the queries executed with Hive 0.5.0. (Hadoop[9] is an open-source variant of MapReduce; Hive[10] is a data warehouse infrastructure built on Hadoop.) We use default values for the parameters (e.g. 3 replicas).

Table 3 shows good agreement in the number of tuples returned by the queries. Table 3 shows weaker agreement for response times. We expected this since even the same dataset, when loaded into Hive on separate occasions, can generate different query response times.

Query H1 computes `ave()` and `count()` and H4 computes `sum()`, so the appropriate comparison is in the returned values. Table 4 shows that the aggregates computed with UpSizeR output agrees well with those from DBGen.

[8] "Awan" is "cloud" in Malay and Bahasa Indonesia; "wan" is also "cloud" in Cantonese, and "Awan" is a common name for girls in Guangdong and Hong Kong.

[9] `http://hadoop.apache.org/`

[10] `http://hadoop.apache.org/hive/`

```
H1:

select
        l_returnflag,
        avg(l_extendedprice) as avg_price,
        count(*) as count_order
from
        lineitem
where
        l_shipdate <= ’1998−12−01’
group by
        l_returnflag
order by
        l_returnflag
```

```
H2:
select
        s_acctbal,
        s_name,
        n_name,
        p_partkey
from
        part,
        supplier,
        partsupp,
        nation,
        region
where
        p_partkey = ps_partkey
        and s_suppkey = ps_suppkey
        and s_nationkey = n_nationkey
        and n_regionkey = r_regionkey
        and p_size > 21
        and p_type like ’%BRASS’
order by
        s_acctbal desc,
        n_name,
        s_name,
        p_partkey
```

```
H3:

select
        l_orderkey,
        o_orderdate
from
        customer,
        orders,
        lineitem
where
        c_mktsegment = ’AUTOMOBILE’
        and c_custkey = o_custkey
        and l_orderkey = o_orderkey
group by
        l_orderkey,
        o_orderdate
order by
        o_orderdate
```

```
H4:

select
        sum(l_extendedprice*(1 − 1_discount) as revenue
from
        lineitem,
        partsupp,
        part
where
        ( l_ps_id = ps_id
          and ps_partkey = p_partkey
          and p_brand = ’Brand#13’
          and l_shipinstruct like ’DELIVER IN PERSON’
        )
        or
        ( l_ps_id = ps_id
          and ps_partkey = p_partkey
          and p_brand = ’Brand#25’
          and l_shipinstruct like ’DELIVER IN PERSON’
        )
        or
        ( l_ps_id = ps_id
          and ps_partkey = p_partkey
          and p_brand = ’Brand#35’
          and l_shipinstruct like ’DELIVER IN PERSON’
        )
```

```
H5:

select
        ps_partkey,
        sum(ps_supplycost*ps_availqty) as value
from
        lineitem,
        partsupp,
        supplier
where
        l_ps_id = ps_id
        and ps_suppkey = s_suppkey
        and l_quantity < 20
group by
        ps.ps_partkey
order by
        value desc
```

Figure 7: **Queries used to compare DBGen data and UpSizeR output.**

#tuples(time)		H1	H2	H3	H4	H5
1GB	DBGen $\mathcal{H}_1$	3 (52s)	92196(192s)	297453(173s)	1(138s)	199998(135s)
	UpSizeR($\mathcal{H}_{40}, 0.025$)	3 (50s)	92667(194s)	302264(177s)	1(150s)	199999(141s)
2GB	DBGen $\mathcal{H}_2$	3 (77s)	184156(203s)	597099(206s)	1(188s)	399995(156s)
	UpSizeR($\mathcal{H}_{40}, 0.05$)	3 (78s)	185693(196s)	595398(212s)	1(188s)	399998(155s)
10GB	DBGen $\mathcal{H}_{10}$	3(131s)	927140(265s)	3000540(297s)	1(356s)	1999983(235s)
	UpSizeR($\mathcal{H}_{40}, 0.25$)	3(168s)	928464(280s)	3006459(352s)	1(346s)	1999980(239s)

Table 3: **A comparison of resulting number of tuples and execution time (in brackets) when the queries H1,...,H5 in Fig. 7 are run over TPC-H data generated with DBGen and UpSizeR. Table 4 shows the aggregates computed by H1 and H4.**

H1 `avg(count)`					H4
`l_returnflag`		A	N	R	`sum`
1GB	DBGen $\mathcal{H}_1$	38273 (1478493)	38248 (3043852)	38250 (1478870)	6.586E09
	UpSizeR($\mathcal{H}_{40}, 0.025$)	38252 (1482196)	38246 (3042663)	38216 (1483192)	6.550E09
2GB	DBGen $\mathcal{H}_2$	38252 (2959267)	38234 (6076312)	38263 (2962417)	1.306E10
	UpSizeR($\mathcal{H}_{40}, 0.05$)	38246 (2963035)	38245 (6083163)	38239 (2965648)	1.304E10
10GB	DBGen $\mathcal{H}_{10}$	38237(14804077)	38234(30373792)	38251(14808183)	6.554E10
	UpSizeR($\mathcal{H}_{40}, 0.25$)	38236(14802818)	38237(30387309)	38243(14808265)	6.556E10

Table 4: **A comparison of returned aggregate values: `ave()` and `count()` for H1, `sum()` for H4. (A, N and R are values of `l_returnflag`.)**

9.2. UpSizeR's pseudocode

This section presents pseudocode for the UpSizeR algorithm in Sec. 3, *without* the extensions in Sec. 4.

Algo. 1:UpSizeR($\mathcal{D}, x$) starts with the extraction of probability distributions (Sec. 3.1), sorting of tables into $\mathcal{D}_i$ (Sec. 3.2), partitioning of $\mathcal{D}_i$ into equivalence classes [**K**] (Sec. 3.3), and table generation for $\mathcal{D}_0$ (Sec. 3.4 and Algo. 2:gen0FKTable(T, s)). Algo. 1 then enters the main loop (Sec. 3.5).

To generate a table $\tilde{T}'$ with foreign key(s), Algo. 3:genTables(**K**) first generates $deg(\tilde{v}, \tilde{T}')$ (Sec. 3.5.1 and Algo. 4:genDegree($\tilde{v}$, [**K**])). The two cases in Sec. 3.5.2 correspond to Algo. 5:gen1FKTable(K) and Algo. 6:gen2FKTable(K_1, K_2).

Algorithm 1 UpSizeR($\mathcal{D}, s$)

```
Input:  database state $\mathcal{D}$ and a scale factor $s$
Output: a synthetic database state that scales up $\mathcal{D}$ by $s$

get joint degree distribution $f_K$ from $\mathcal{D}$ for each key $K$
get co-clustering distribution $f_T^{cc}$ for each table $T$
use the schema graph to sort $\mathcal{D}$ into $\mathcal{D}_0, \mathcal{D}_1, \ldots$
partition each $\mathcal{D}_i$ into equivalence classes $[\mathbf{K}]$
for all $T \in \mathcal{D}_0$ do
  gen0FKTable($T, s$)
end for
$i \leftarrow 0$
repeat
  $i \leftarrow i + 1$
  for all $T \in \mathcal{D}_i$ do
    flag($T$) ←false
  end for
  for all $T \in \mathcal{D}_i$ and flag($T$) =false do
    Let $\mathbf{K}$ be the set of foreign keys in $T$
    genTables($\mathbf{K}$)
    for all $T' \in [\mathbf{K}]$ do
      flag($T$) ←true
    end for
  end for
until all tables are generated
```

Algorithm 2 gen0FKTable(T, s)

```
Input:  table $T$ with no foreign keys and scale factor $s$
Output: a synthetic $\tilde{T}$ that is $s$ times the size of $T$

let $t$ be the number of $T$ tuples in the given $\mathcal{D}$
for $i = 1$ to $st$ do
  generate a unique primary key value $\tilde{v}$
  genContent($\tilde{T}, \tilde{v}$)
end for
```

Algorithm 3 genTables($\mathbf{K}$)

Input: a set of keys $\mathbf{K}$
Output: a synthetic $\tilde{T}$ for each $T \in [\mathbf{K}]$

```
for all $K \in \mathbf{K}$ do
  for all $K$ value $\tilde{v}$ do
    genDegree($\tilde{v}$, $[\mathbf{K}]$)
  end for
end for
if $\mathbf{K} = \{K\}$ then
  gen1FKTable($K$)
end if
if $\mathbf{K} = \{K_1, K_2\}$ then
  gen2FKTable($K$)
end if
```

Algorithm 4 genDegree($\tilde{v}$, $[\mathbf{K}]$)

Input: a value $\tilde{v}$ for key $K \in \mathbf{K}$ where
$[\mathbf{K}]$ is the set of tables with $\mathbf{K}$ as foreign keys
Output: $deg(\tilde{v}, \tilde{T}')$ for each $\tilde{T} \in [\mathbf{K}]$

```
let $T''_1, T''_2, \ldots, T''_m$ be the tables for which
  earlier calls on genDegree has generated
  $deg(\tilde{x}, \tilde{T}''_1), \ldots, deg(\tilde{x}, \tilde{T}''_m)$ for all $K$ value $\tilde{x}$
let $[\mathbf{K}] = \{T'_1, \ldots, T'_n\}$
derive from the joint degree distribution $f_K$
  the conditional distribution
$\Pr(deg(\tilde{v}, T'_1) = d'_1, \ldots deg(\tilde{v}, T'_n) = d'_n$
      $\mid deg(\tilde{v}, T''_1) = d_1, \ldots deg(\tilde{v}, T''_m) = d_m)$
for all $T'_i$ do
  use the conditional distribution to choose $deg(\tilde{v}, \tilde{T}'_i)$
end for
```

Algorithm 5 gen1FKTable(K)

```
Input:  primary key $K$
Output: a table for each $T' \in [\{K\}]$
for all $T' \in [\{K\}]$ do
  for all $K$ value $\tilde{v}$ do
    choose $deg(\tilde{v}, \tilde{T}')$ according to degree distribution
  end for
  repeat
    generate a new value $\tilde{v}'$ for primary key of $T'$
    choose $\tilde{v}$ with probability proportional to $deg(\tilde{v}, \tilde{T}')$
    decrement $deg(\tilde{v}, \tilde{T}')$
    genContent($\tilde{T}', \tilde{v}'$)
  until $\sum_{\tilde{v}} deg(\tilde{v}, \tilde{T}') = 0$
end for
```

9.3. Scaling a self-loop

Sec. 4.3 describes how UpSizeR can be modified for a schema graph that has a self-loop, namely one where there is an employee table with a manager column. Since we have no sizeable real employee-manager data for testing, we use Twitter[11] data instead.

To test the scaling algorithm for a self-loop, we use just one table T with two attributes:

- a primary key `Tid` that identifies the tweet (a short message);
- a foreign key that identifies an earlier tweet `Tid′` if `Tid` retweets (i.e. forwards) `Tid′`, or is NULL if `Tid` is not a retweet.

This tweet table T thus has a self-loop. It can be represented as a forest of tweet trees, in which `Tid` is a root if `Tid′` is NULL; otherwise, it has `Tid′` as parent.

We collected our tweets through Palanteer[12], a service that allows users to search for socio-political tweets generated by a set of Twitter users in

[11]http://twitter.com/

[12]http://research.larc.smu.edu.sg/palanteer/, developed by Living Analytics Research Centre at the Singapore Management University.

Algorithm 6 gen2FKTable(K_1, K_2)

Input: primary keys K_1 and K_2
Output: a table for each $T' \in [\{K_1, K_2\}]$

```
for all $T' \in [\{K_1, K_2\}]$ do
  for all $K_1$ value $\tilde{v}_1$ and $K_2$ value $\tilde{v}_2$ do
    assign $\tilde{v}_1$ and $\tilde{v}_2$ to clusters $cc_1$ and $cc_2$
      according to marginal distributions of $f^{cc}_{T'}$
    randomly choose $deg(\tilde{v}_1, \tilde{T}')$ and $deg(\tilde{v}_2, \tilde{T}')$
      according to the degree distributions
  end for
  make $\sum_{\tilde{v}_1} deg(\tilde{v}_1, \tilde{T}')$ and $\sum_{\tilde{v}_2} deg(\tilde{v}_2, \tilde{T}')$ equal
  repeat
    generate a new value $\tilde{v}'$ for primary key of $T'$
    assign $\tilde{v}'$ to a random $\langle cc_1, cc_2 \rangle$ according to $f^{cc}_{T'}$
    randomly choose $\tilde{v}_1$ in $cc_1$ with probability
      proportional to $deg(\tilde{v}_1, \tilde{T}')$
    randomly choose $\tilde{v}_2$ in $cc_2$ with probability
      proportional to $deg(\tilde{v}_2, \tilde{T}')$
    create a $\tilde{T}'$ tuple with key values $\tilde{v}'$, $\tilde{v}'_1$, $\tilde{v}'_2$
      for primary key, $K_1$ and $K_2$
    decrement $deg(\tilde{v}_1, \tilde{T}')$ and $deg(\tilde{v}_2, \tilde{T}')$
    genContent($\tilde{T}', \tilde{v}'$)
  until $\sum_{\tilde{v}_1} deg(\tilde{v}, \tilde{T}') = 0 = \sum_{\tilde{v}_2} deg(\tilde{v}_2, \tilde{T}')$
end for
```

Algorithm 7 genContent($\tilde{T}', \tilde{v}'$)

Input: a synthetic table $\tilde{T}'$ and key value $\tilde{v}'$
Output: tuple for $\tilde{v}'$ acquires non-key values

```
for an attribute $A$ that is not a primary or foreign key,
  this paper assumes that $A$'s value is a function of the
  key values, and is generated through sampling from $\mathcal{D}$,
  data mining or user-supplied methods etc.
```

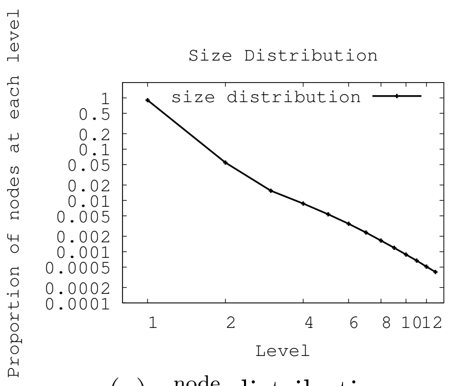
Singapore. Palanteer starts from 69 seed Twitter users who are interested in current affairs, including political candidates, political parties or organizations, journalists, and bloggers. The set of Twitter users is further expanded by following the incoming and outgoing follow-links from the seed users. This expansion is done for two times, i.e., all users are within 2-hops away from the 69 seed users. Note that only users who explicitly specify their location as Singapore in their profiles are included. In this experiment, we used the data collected by Palanteer in April 2011. We then recursively removed retweets whose reference tweet is not inside this set. The final dataset has some 2,352,000 tweets and 15,000 users.

Recall from Sec. 4.3 that we get the empirical distributions for nodes (r_i^{node}) and leaves (r_i^{leaf}) by regression. Fig. 8 shows that the data points in the log-log plots are approximately linear. Since the number of nodes have variances that depend on i, we use the number of nodes at each level to weight the linear regression, and thus get linear equations for extrapolating (r_i^{node}) and (r_i^{leaf}).

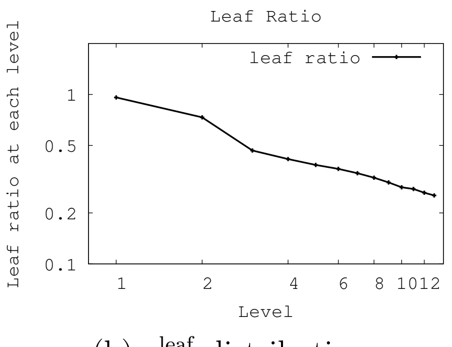
For experimental validation, we use the following queries:
C1: Count the number of nodes.
C2: Count the number of trees.
C3: Count the number of parents.
C4: Count the number of leaves.
C5: Count the number of level 2 nodes.
C6: Count the number of paths of length 2 (2-hop retweets).
C7: Count the number of paths of length 3 (3-hop retweets).

Each of these queries can be interpreted for both the tweet trees here and the management trees in Sec. 4.3. We have 4 real tweet datasets: $\mathcal{C}_s$ for $s = 1, 3, 5, 9$, where $\mathcal{C}_s$ has s times the number of tweets in $\mathcal{C}_1$. We then scale $\mathcal{C}_1$ by $s = 3, 5, 9$ and compare the result of running the above queries on $\mathcal{C}_s$ and UpSizeR($\mathcal{C}_1$, s).

Table 5 shows good agreement in query results between the empirical datasets and UpSizeR's synthetic versions. We plan to continue this work on self-loops in two directions: (1) extend the solution to more general cyclic schemas, and (2) adding correlation between tweets and users (thus taking a crack at $\mathbf{AVC_{SN}}$).



(a) r_i^{node} distribution



(b) r_i^{leaf} distribution

Figure 8: **Log-log regression of node and leaf distributions across levels.**

	C1	C2	C3	C4	C5	C6	C7
$\mathcal{C}_3$	705637	635988	54009	651628	39137	30512	19425
UpSizeR($\mathcal{C}_1, 3$)	705636	635324	54766	650870	39414	30898	19489
$\mathcal{C}_5$	1176062	1061902	88953	1087109	64236	49924	31713
UpSizeR($\mathcal{C}_1, 5$)	1176060	1058857	91864	1084196	64690	51513	32498
$\mathcal{C}_9$	2116912	1910213	161224	1955688	116196	90503	57792
UpSizeR($\mathcal{C}_1, 9$)	2116908	1905965	164929	1951979	118242	92701	58474

Table 5: Comparing query results for real $\mathcal{C}_s$ and UpSizeR($\mathcal{C}_1$, s).