Multi-Tenant Databases for Software as a Service: Schema-Mapping Techniques

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ABSTRACT

In the implementation of hosted business services, multiple tenants are often consolidated into the same database to reduce total cost of ownership. Common practice is to map multiple single-tenant logical schemas in the application to one multi-tenant physical schema in the database. Such mappings are challenging to create because enterprise applications allow tenants to extend the base schema, e.g., for vertical industries or geographic regions. Assuming the workload stays within bounds, the fundamental limitation on scalability for this approach is the number of tables the database can handle. To get good consolidation, certain tables must be shared among tenants and certain tables must be mapped into fixed generic structures such as Universal and Pivot Tables, which can degrade performance.

This paper describes a new schema-mapping technique for multi-tenancy called *Chunk Folding*, where the logical tables are vertically partitioned into chunks that are folded together into different physical multi-tenant tables and joined as needed. The database's "meta-data budget" is divided between application-specific conventional tables and a large fixed set of generic structures called *Chunk Tables*. Good performance is obtained by mapping the most heavily-utilized parts of the logical schemas into the conventional tables and the remaining parts into Chunk Tables that match their structure as closely as possible. We present the results of several experiments designed to measure the efficacy of Chunk Folding and describe the multi-tenant database testbed in which these experiments were performed.

Categories and Subject Descriptors

H.4 [**Information Systems Applications**]: Miscellaneous; H.2.1 [**Information Systems**]: Database Management—*Logical Design*

General Terms

Design, Performance

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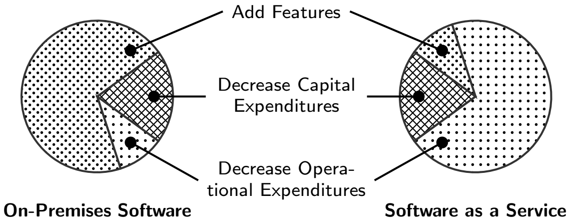

Add Features
Decrease Capital Expenditures
Decrease Operational Expenditures
On-Premises Software
Software as a Service

Figure 1: Software Development Priorities

1. INTRODUCTION

In the traditional on-premises model for software, a business buys applications and deploys them in a data center that it owns and operates. The Internet has enabled an alternative model – Software as a Service (SaaS) – where ownership and management of applications are outsourced to a service provider. Businesses subscribe to a hosted service and access it remotely using a Web browser and/or Web Service clients. Hosted services have appeared for a wide variety of business applications, including Customer Relationship Management (CRM), Supplier Relationship Management (SRM), Human Capital Management (HCM), and Business Intelligence (BI). IDC estimates that the worldwide revenue associated with SaaS reached $3.98 billion in 2006 and that it will reach $14.5 billion in 2011, representing a compound annual growth rate (CAGR) of 30% [24].

Design and development priorities for SaaS differ greatly from those for on-premises software, as illustrated in Figure 1. The focus of on-premises software is generally on adding features, often at the expense of reducing total cost of ownership. In contrast, the focus of SaaS is generally on reducing total cost of ownership, often at the expense of adding features. The primary reason for this is, of course, that the service provider rather than the customer has to bear the cost of operating the system. In addition, the recurring revenue model of SaaS makes it unnecessary to add features in order to drive purchases of upgrades.

A well-designed hosted service reduces total cost of ownership by leveraging economy of scale. The greatest improvements in this regard are provided by a *multi-tenant architecture*, where multiple businesses are consolidated onto the same operational system. Multi-tenancy invariably occurs at the database layer of a service; indeed this may be the only place it occurs since application servers for highly-scalable Web applications are often stateless [14].

The amount of consolidation that can be achieved in a multi-tenant database depends on the complexity of the ap-

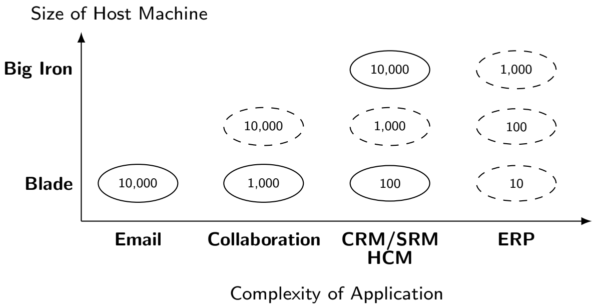


Figure 2: Number of Tenants per Database (Solid circles denote existing applications, dashed circles denote estimates)

plication and the size of the host machine, as illustrated in Figure 2. In this context, a tenant denotes an organization with multiple users, commonly around 10 for a small to mid-sized business. For simple Web applications like business email, a single blade server can support up to 10,000 tenants. For mid-sized enterprise applications like CRM, a blade server can support 100 tenants while a large cluster database can go up to 10,000. While the total cost of ownership of a database may vary greatly, consolidating hundreds of databases into one will save millions of dollars per year.

One downside of multi-tenancy is that it can introduce contention for shared resources [19], which is often alleviated by forbidding long-running operations. Another downside is that it can weaken security, since access control must be performed at the application level rather than the infrastructure level. Finally, multi-tenancy makes it harder to support application extensibility, since shared structures are harder to individually modify. Extensibility is required to build specialized versions of enterprise applications, e.g., for particular vertical industries or geographic regions. Many hosted business services offer platforms for building and sharing such extensions [21, 22, 26].

In general, multi-tenancy becomes less attractive as application complexity increases. More complex applications like Enterprise Resource Planning (ERP) and Financials require more computational resources, as illustrated in Figure 2, have longer-running operations, require more sophisticated extensibility, and maintain more sensitive data. Moreover, businesses generally prefer to maintain more administrative control over such applications, e.g., determining when backups, restores, and upgrades occur. More complex applications are of course suitable for single-tenant hosting.

1.1 Implementing Multi-Tenant Databases

In order to implement multi-tenancy, most hosted services use query transformation to map multiple single-tenant logical schemas in the application to one multi-tenant physical schema in the database. Assuming the workload stays within bounds, the fundamental limitation on scalability for this approach is the number of tables the database can handle, which is itself dependent on the amount of available memory. As an example, IBM DB2 V9.1 [15] allocates 4 KB of memory for each table, so 100,000 tables consume 400 MB of memory up front. In addition, buffer pool pages are allocated on a per-table basis so there is great competition for the remaining cache space. As a result, the performance on a blade server begins to degrade beyond about 50,000 tables.

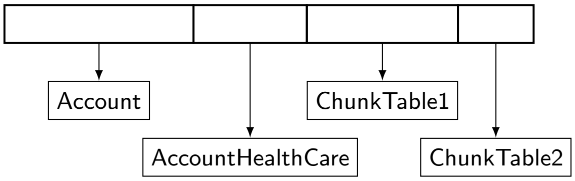


Figure 3: Chunk Folding

The natural way to ameliorate this problem is to share tables among tenants. However this technique can interfere with a tenant's ability to extend the application, as discussed above. The most flexible solution is to map the logical tables into fixed generic structures, such as Universal and Pivot Tables [11]. Such structures allow the creation of an arbitrary number of tables with arbitrary shapes and thus do not place limitations on consolidation or extensibility. In addition, they allow the logical schemas to be modified without changing the physical schema, which is important because many databases cannot perform DDL operations while they are on-line. However generic structures can degrade performance and, if they are not hidden behind the query transformation layer, complicate application development.

Our experience is that the mapping techniques used by most hosted services today provide only limited support for extensibility and/or achieve only limited amounts of consolidation. In particular, simpler services on the left side of Figure 2 tend to favor consolidation while more complex services on the right side tend to favor extensibility.

1.2 Contributions of this Paper

This paper describes a new schema-mapping technique for multi-tenancy called *Chunk Folding*, where the logical tables are vertically partitioned into chunks that are folded together into different physical multi-tenant tables and joined as needed. The database's "meta-data budget" is divided between application-specific conventional tables and a large fixed set of generic structures called *Chunk Tables*. As an example, Figure 3 illustrates a case where the first chunk of a row is stored in a conventional table associated with the base entity Account, the second chunk is stored in a conventional table associated with an extension for health care, and the remaining chunks are stored in differently-shaped Chunk Tables. Because Chunk Folding has a generic component, it does not place limitations on consolidation or extensibility and it allows logical schema changes to occur while the database is on-line. At the same time, and in contrast to generic structures that use only a small, fixed number of tables, Chunk Folding attempts to exploit the database's entire meta-data budget in as effective a way as possible. Good performance is obtained by mapping the most heavily-utilized parts of the logical schemas into the conventional tables and the remaining parts into Chunk Tables that match their structure as closely as possible.

This paper presents the results of several experiments designed to measure the efficacy of Chunk Folding. First, we characterize the performance degradation that results as a standard relational database handles more and more tables. This experiment is based on a multi-tenant database testbed we have developed that simulates a simple hosted CRM service. The workload contains daily create, read, update, and delete (CRUD) operations, simple reporting tasks, and administrative operations such as modifying tenant schemas.

The experiment fixes the number of tenants, the amount of data per tenant, and the load on the system, and varies the number of tables into which tenants are consolidated.

Our second experiment studies the performance of standard relational databases on OLTP queries formulated over Chunk Tables. These queries can be large but have a simple, regular structure. We compare a commercial database with an open source database and conclude that, due to differences in the sophistication of their query optimizers, considerably more care has to be taken in generating queries for the latter. The less-sophisticated optimizer complicates the implementation of the query-transformation layer and forces developers to manually inspect plans for queries with new shapes. In any case, with enough care, query optimizers can generate plans for these queries that are efficiently processed. A goal of our on-going work is to compare the penalty of reconstructing rows introduced by Chunk Folding with the penalty for additional paging introduced by managing lots of tables.

This paper is organized as follows. To underscore the importance of application extensibility, Section 2 presents a case study of a hosted service for project management. Section 3 outlines some common schema-mapping techniques for multi-tenancy, introduces Chunk Folding, and surveys related work. Section 4 outlines our multi-tenant database testbed. Section 5 describes our experiments with managing many tables. Section 6 describes our experiments with queries over Chunk Tables. Section 7 summarizes the paper and discusses future work.

2. THE CASE FOR EXTENSIBILITY

Extensibility is clearly essential for core enterprise applications like CRM and ERP. But it can also add tremendous value to simpler business applications, like email and project management, particularly in the collaborative environment of the Web. To underscore this point, this section presents a case study of a hosted business service called Conject [6].

Conject is a collaborative project-management environment designed for the construction and real estate industries. Users of the system include architects, contractors, building owners, and building managers. Participants interact in *project workspaces*, which contain the data and processes associated with building projects. Within a project workspace, participants can communicate using email, instant messaging, white boards, and desktop sharing. All discussions are archived for reference and to resolve any subsequent legal disputes. Documents such as drawings can be uploaded into a project workspace, sorted, selectively shared among participants, and referenced in discussions. Tasks may be defined and assigned to participants and the progress of the project is tracked as tasks are completed. Integrated reports can be issued for the control and documentation of a project. Requests for bids can be created and bids can be submitted, viewed, and accepted.

At present, Conject has about 6000 projects shared by 15,000 registered participants across 400 organizations. The system maintains 2 TB of documents in a file-based store and 20 GB of structured data in a commercial database. Data is maintained in conventional, application-specific tables that are shared across projects, participants, and their organizations. A single database instance on a 2.4 GHz dual-core AMD Opteron 250 machine with 8 GB of memory manages the full load of 50 million transactions per year.

In the future, Conject will support more sophisticated business processes such as claim management, defect management, issue management, and decision tracking. Such processes can vary greatly across projects and must be specifically designed by the participants. Current plans are to allow participants to associate an object with additional attributes, a set of states, and allowable transitions between those states. Participants will be able to save, reuse, and share these configurations. To implement these features, the current fixed database schema will have to be enhanced to support extensibility using techniques such as the ones discussed in this paper.

3. SCHEMA-MAPPING TECHNIQUES

This section outlines some common schema-mapping techniques for multi-tenancy, introduces Chunk Folding, and surveys related work. Figure 4 illustrates a running example that shows various layouts for Account tables of three tenants with IDs 17, 35, and 42. Tenant 17 has an extension for the health care industry while tenant 42 has an extension for the automotive industry.

Basic Layout. The most basic technique for implementing multi-tenancy is to add a tenant ID column (Tenant) to each table and share tables among tenants. This approach provides very good consolidation but no extensibility. As a result of the latter, it cannot represent the schema of our running example and is not shown in Figure 4. This approach is taken by conventional Web applications, which view the data as being owned by the service provider rather than the individual tenants, and is used by many simpler services on the left side of Figure 2.

Private Table Layout – Figure 4(a). The most basic way to support extensibility is to give each tenant their own private tables. In this approach, the query-transformation layer needs only to rename tables and is very simple. Since the meta-data is entirely managed by the database, there is no overhead for meta-data in the data itself (the gray columns in Figure 4). However only moderate consolidation is provided since many tables are required. This approach is used by some larger services on the right side of Figure 2 when a small number of tenants can produce sufficient load to fully utilize the host machine.

Extension Table Layout – Figure 4(b). The above two layouts can be combined by splitting off the extensions into separate tables. Because multiple tenants may use the same extensions, the extension tables as well as the base tables should be given a Tenant column. A Row column must also be added so the logical source tables can be reconstructed. The two gray columns in Figure 4(b) represent the overhead for meta-data in the data itself.

At run-time, reconstructing the logical source tables carries the overhead of additional joins as well as additional I/O if the row fragments are not clustered together. On the other hand, if a query does not reference one of the tables, then there is no need to read it in, which can improve performance. This approach provides better consolidation than the Private Table Layout, however the number of tables will still grow in proportion to the number of tenants since more tenants will have a wider variety of basic requirements.

This approach has its origins in the Decomposed Storage Model [7], where an n-column table is broken up into n 2-column tables that are joined through surrogate values. This model has then been adopted by column-oriented

Account$_{17}$

Aid	Name	Hospital	Beds
1	*Acme*	*St. Mary*	135
2	*Gump*	*State*	1042

Account$_{35}$

Aid	Name
1	*Ball*

Account$_{42}$

Aid	Name	Dealers
1	*Big*	65

(a) Private Table Layout

Account$_{\text{Ext}}$

Tenant	Row	Aid	Name
17	0	1	*Acme*
17	1	2	*Gump*
35	0	1	*Ball*
42	0	1	*Big*

Healthcare$_{\text{Account}}$

Tenant	Row	Hospital	Beds
17	0	*St. Mary*	135
17	1	*State*	1042

Automotive$_{\text{Account}}$

Tenant	Row	Dealers
42	0	65

(b) Extension Table Layout

Universal

Tenant	Table	Col1	Col2	Col3	Col4	Col5	Col6
17	0	*1*	*Acme*	*St. Mary*	*135*	–	–
17	0	*2*	*Gump*	*State*	*1042*	–	–
35	1	*1*	*Ball*	–	–	–	–
42	2	*1*	*Big*	*65*	–	–	–

(c) Universal Table Layout

Pivot$_{\text{int}}$

Tenant	Table	Col	Row	Int
17	0	0	0	1
17	0	3	0	135
17	0	0	1	2
17	0	3	1	1042
35	1	0	0	1
42	2	0	0	1
42	2	2	0	65

Pivot$_{\text{str}}$

Tenant	Table	Col	Row	Str
17	0	1	0	*Acme*
17	0	2	0	*St. Mary*
17	0	1	1	*Gump*
17	0	2	1	*State*
35	1	1	0	*Ball*
42	2	1	0	*Big*

(d) Pivot Table Layout

Chunk$_{\text{int}|\text{str}}$

Tenant	Table	Chunk	Row	Int1	Str1
17	0	0	0	1	*Acme*
17	0	1	0	135	*St. Mary*
17	0	0	1	2	*Gump*
17	0	1	1	1042	*State*
35	1	0	0	1	*Ball*
42	2	0	0	1	*Big*
42	2	1	0	65	–

(e) Chunk Table Layout

Account$_{\text{Row}}$

Tenant	Row	Aid	Name
17	0	1	*Acme*
17	1	2	*Gump*
35	0	1	*Ball*
42	0	1	*Big*

Chunk$_{\text{Row}}$

Tenant	Table	Chunk	Row	Int1	Str1
17	0	0	0	135	*St. Mary*
17	0	0	1	1042	*State*
42	2	0	0	65	–

(f) Chunk Folding

Figure 4: Account table and its extensions in different layouts. (Gray columns represent meta-data.)

databases [4, 23], which leverage the ability to selectively read in columns to improve the performance of analytics [23] and RDF data [1]. The Extension Table Layout does not partition tables all the way down to individual columns, but rather leaves them in naturally-occurring groups. This approach has been used to map object-oriented schemas with inheritance into the relational model [9].

Universal Table Layout – Figure 4(c). Generic structures allow the creation of an arbitrary number of tables with arbitrary shapes. A Universal Table is a generic structure with a Tenant column, a Table column, and a large number of generic data columns. The data columns have a flexible type, such as VARCHAR, into which other types can be converted. The n-th column of each logical source table for each tenant is mapped into the n-th data column of the Universal Table. As a result, different tenants can extend the same table in different ways. By keeping all of the values for a row together, this approach obviates the need to reconstruct the logical source tables. However it has the obvious disadvantage that the rows need to be very wide, even for narrow source tables, and the database has to handle many *null* values. While commercial relational databases handle *nulls* fairly efficiently, they nevertheless use some additional memory. Perhaps more significantly, fine-grained support for indexing is not possible: either all tenants get an index on a column or none of them do. As a result of these issues, additional structures must be added to this approach to make it feasible.

This approach has its origins in the Universal Relation [18], which holds the data for all tables and has every column of every table. The Universal Relation was proposed as a conceptual tool for developing queries and was not intended to be directly implemented. The Universal Table described in this paper is narrower, and thus feasible to implement, because it circumvents typing and uses each physical column to represent multiple logical columns.

There have been extensive studies of the use of generic structures to represent semi-structured data. Florescu et al. [11] describe a variety of relational representations for XML data including Universal and Pivot Tables. Our work uses generic structures to represent irregularities between pieces of schema rather than pieces of data.

Pivot Table Layout – Figure 4(d). A Pivot Table is an alternative generic structure in which each field of each row in a logical source table is given its own row. In addition to Tenant, Table, and Row columns as described above, a Pivot Table has a Col column that specifies which source field a row represents and a single data-bearing column for the value of that field. The data column can be given a flexible type, such as VARCHAR, into which other types are converted, in which case the Pivot Table becomes a Universal Table for the Decomposed Storage Model. A better approach however, in that it does not circumvent typing, is to have multiple Pivot Tables with different types for the data column. To efficiently support indexing, two Pivot Tables can be created for each type: one with indexes and one without. Each value is placed in exactly one of these tables depending on whether it needs to be indexed.

This approach eliminates the need to handle many *null* values. However it has more columns of meta-data than actual data and reconstructing an n-column logical source table requires $(n - 1)$ aligning joins along the Row column. This leads to a much higher runtime overhead for interpreting the meta-data than the relatively small number of joins needed in the Extension Table Layout. Of course, like the Decomposed Storage Model, the performance can benefit from selectively reading in a small number of columns.

The Pathfinder query compiler maps XML into relations using Pivot-like Tables [13]. Closer to our work is the research on sparse relational data sets, which have thousands of attributes, only a few of which are used by any object. Agrawal et al. [2] compare the performance of Pivot Tables (called vertical tables) and conventional horizontal tables in this context and conclude that the former perform better because they allow columns to be selectively read in. Our use case differs in that the data is partitioned by tenant into well-known dense subsets, which provides both a more challenging baseline for comparison as well as more opportunities for optimization. Beckman et al. [3] also present a technique for handling sparse data sets using a Pivot Table Layout. In comparison to our explicit storage of meta-data columns, they chose an "intrusive" approach which manages the additional runtime operations in the database kernel. Cunningham et al. [8] present an "intrusive" technique for supporting general-purpose pivot and unpivot operations.

Chunk Table Layout – Figure 4(e). We propose a third generic structure, called a *Chunk Table*, that is particularly effective when the base data can be partitioned into well-known dense subsets. A Chunk Table is like a Pivot Table except that it has a set of data columns of various types, with and without indexes, and the Col column is replaced by a Chunk column. A logical source table is partitioned into groups of columns, each of which is assigned a chunk ID and mapped into an appropriate Chunk Table. In comparison to Pivot Tables, this approach reduces the ratio of stored meta-data to actual data as well as the overhead for reconstructing the logical source tables. In comparison to Universal Tables, this approach provides a well-defined way of adding indexes, breaking up overly-wide columns, and supporting typing. By varying the width of the Chunk Tables, it is possible to find a middle ground between these extremes. On the other hand, this flexibility comes at the price of a more complex query-transformation layer.

Chunk Folding – Figure 4(f). We propose a technique called *Chunk Folding* where the logical source tables are vertically partitioned into chunks that are folded together into different physical multi-tenant tables and joined as needed. The database's "meta-data budget" is divided between application-specific conventional tables and a large fixed set of Chunk Tables. For example, Figure 4(f) illustrates a case where base Accounts are stored in a conventional table and all extensions are placed in a single Chunk Table. In contrast to generic structures that use only a small, fixed number of tables, Chunk Folding attempts to exploit the database's entire meta-data budget in as effective a way as possible. Good performance is obtained by mapping the most heavily-utilized parts of the logical schemas into the conventional tables and the remaining parts into Chunk Tables that match their structure as closely as possible.

A goal of our on-going work is to develop Chunk Folding algorithms that take into account the logical schemas of tenants, the distribution of data within those schemas, and the associated application queries. Because these factors can vary over time, it should be possible to migrate data from one representation to another on-the-fly.

4. THE MTD TESTBED

This section describes the configurable testbed we have developed for experimenting with multi-tenant database implementations. The testbed simulates the OLTP component of a hosted CRM service. Conceptually, users interact with the service through browser and Web Service clients. The testbed does not actually include the associated application servers, rather the testbed clients simulate the behavior of those servers. The application is itself of interest because it characterizes a standard multi-tenant workload and thus could be used as the basis for a multi-tenant database benchmark.

The testbed is composed of several processes. The System Under Test is a multi-tenant database running on a private host. It can be configured for various schema-mapping layouts and usage scenarios. A Worker process engages in multiple client sessions, each of which simulates the activities of a single connection from an application server's database connection pool. Each session runs in its own thread and gets its own connection to the target database. Multiple Workers are distributed over multiple hosts.

The Controller task assigns actions and tenants to Workers. Following the TPC-C benchmark [25], the Controller creates a deck of "action cards" with a particular distribution, shuffles it, and deals cards to the Workers. The Controller also randomly selects tenants, with an equal distribution, and assigns one to each card. Finally, the Controller collects response times and stores them in a Result Database. The timing of an action starts when a Worker sends the first request and ends when it receives the last response.

4.1 Database Layout

The base schema for the CRM application contains ten tables as depicted in Figure 5. It is a classic DAG-structured OLTP schema with one-to-many relationships from child to parent. Individual users within a business (a tenant) are not modeled, but the same tenant may engage in several simultaneous sessions so data may be concurrently accessed. Every table in the schema has a tenant-id column so that it can be shared by multiple tenants.

Each of the tables contains about 20 columns, one of which is the entity's ID. Every table has a primary index on the entity ID and a unique compound index on the tenant ID and the entity ID. In addition, there are twelve indexes on selected columns for reporting queries and update tasks. All data for the testbed is synthetically generated.

In order to programmatically increase the overall number of tables without making them too synthetic, multiple copies of the 10-table CRM schema are created. Each copy should be viewed as representing a logically different set of entities. Thus, the more instances of the schema there are in the database, the more *schema variability* there is for a given amount of data.

In its present form, the testbed models the Extension Table Layout with many base tables but no extension tables. This is sufficient for the experiments on schema variability presented in the next section. The testbed will eventually offer a set of possible extensions for each base table.

4.2 Worker Actions

Worker actions include CRUD operations and reporting tasks that simulate the daily activities of individual users. The reporting tasks model fixed business activity monitor-

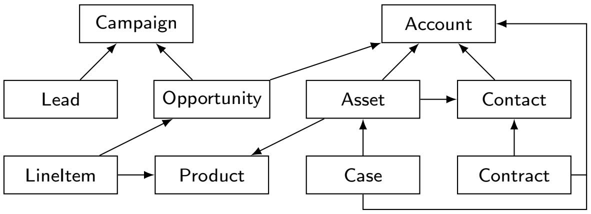


Figure 5: CRM Application Schema

Select Light (50%) Selects all attributes of a single entity or a small set of entities as if they were to be displayed on an entity detail page in the browser.
Select Heavy (15%) Runs one of five reporting queries that perform aggregation and/or parent-child-rollup.
Insert Light (9.59%) Inserts one new entity instance into the database as if it had been manually entered into the browser.
Insert Heavy (0.3%) Inserts several hundred entity instances into the database in a batch as if they had been imported via a Web Service interface.
Update Light (17.6%) Updates a single entity or a small set of entities as if they had been modified in an edit page in the browser. The set of entities is specified by a filter condition that relies on a database index.
Update Heavy (7.5%) Updates several hundred entity instances that are selected by the entity ID using the primary key index.
Administrative Tasks (0.01%) Creates a new instance of the 10-table CRM schema by issuing DDL statements.

Figure 6: Worker Action Classes

ing queries, rather than ad-hoc business intelligence queries, and are simple enough to run against an operational OLTP system. Worker actions also include administrative operations for the business as a whole, in particular, adding and deleting tenants. Depending on the configuration, such operations may entail executing DDL statements while the system is on-line, which may result in decreased performance or even deadlocks for some databases. The testbed does not model long-running operations because they should not occur in an OLTP system, particularly one that is multi-tenant.

To facilitate the analysis of experimental results, Worker actions are grouped into classes with particular access characteristics and expected response times. Lightweight actions perform simple operations on a single entity or a small set of entities. Heavyweight actions perform more complex operations, such as those involving grouping, sorting, or aggregation, on larger sets of entities. The list of action classes (see Figure 6) specifies the distribution of actions in the Controller's card deck.

The testbed adopts a strategy for transactions that is consistent with best practices for highly-scalable Web applications [16, 17]. The testbed assumes that neither browser nor Web Service clients can demarcate transactions and that the maximum granularity for a transaction is therefore the duration of a single user request. Furthermore, since long-running operations are not permitted, large write requests such as cascading deletes are broken up into smaller independent operations. Any temporary inconsistencies that result from the visibility of intermediate states must be eliminated at the application level. Finally, read requests are always performed with a weak isolation level that permits unrepeatable reads.

Schema Variability	Number of instances	Tenants per instance	Total tables
0.0	1	10,000	10
0.5	5,000	2	50,000
0.65	6,500	1 – 2	65,000
0.8	8,000	1 – 2	80,000
1.0	10,000	1	100,000

Table 1: Schema Variability and Data Distribution

5. HANDLING MANY TABLES

The following section describes an experiment with our multi-tenant database testbed which measures the performance of a standard relational database as it handles more and more tables. Conventional on-line benchmarks such as TPC-C [25] increase the load on the database until response time goals for various request classes are violated. In the same spirit, our experiment varies the number of tables in the database and measures the response time for various request classes. The testbed is configured with a fixed number of tenants – 10,000 – a fixed amount of data per tenant – about 1.4 MB – and a fixed workload – 40 client sessions. The variable for the experiment is the number of instances of the CRM schema in the database, which we called the schema variability in Section 4.1.

The schema variability takes values from 0 (least variability) to 1 (most variability) as shown in Table 1. For the value 0, there is only one schema instance and it is shared by all tenants, resulting in 10 total tables. At the other extreme, the value 1 denotes a setup where all tenants have their own private instance of the schema, resulting in 100,000 tables. Between these two extremes, tenants are distributed as evenly as possible among the schema instances. For example, with schema variability 0.65, the first 3,500 schema instances have two tenants while the rest have only one.

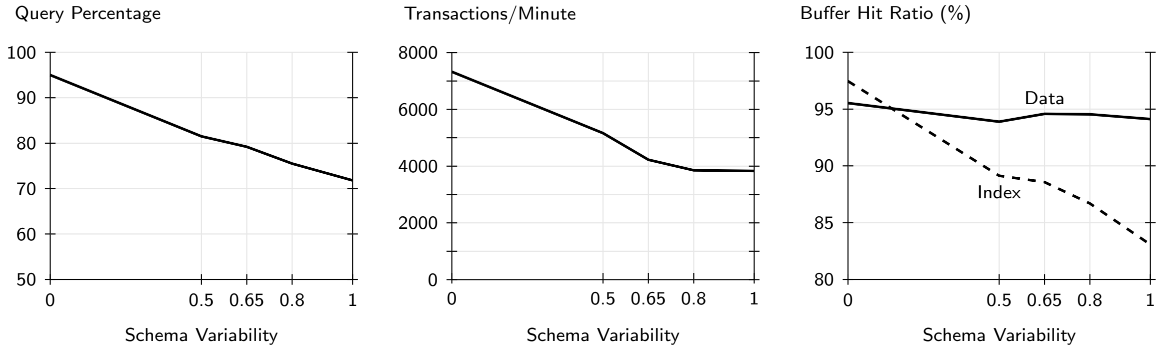
The experiment was run on a DB2 database server with a 2.8 GHz Intel Xeon processor and 1 GB of memory. The database server was running a recent enterprise-grade Linux operating system. The data was stored on an NFS appliance that was connected with dedicated 2 GBit/s Ethernet trunks. The Workers were placed on 20 blade servers with a 1 GBit/s private interconnect.

The experiment was designed in a manner that increasing the schema variability beyond 0.5 taxes the ability of the database to keep the primary key index root nodes in memory. Schema variability 0.5 has 50,000 tables, which at 4 KB per table for DB2 consumes about 200 MB of memory. The operating system consumes about 100 MB, leaving about 700 MB for the database buffer pool. The page size for all user data, including indexes, is 8 KB. The root nodes of the 50,000 primary key indexes therefore require 400 MB of buffer pool space. The buffer pool must also accommodate the actual user data and any additional index pages, and the dataset for a tenant was chosen so that most of the tables need more than one index page.

The raw data collected by the Controller was processed as follows. First, the ramp-up phase during which the system reached steady state was stripped off. Then rollups of the results were taken across 30 minute periods for an hour, producing two runs. This process was repeated three times, resulting in a total of six runs. The results of the runs were consistent and so only the first run is reported for each value of the schema variability; see Table 2.

Metric			Schema Variability				
			0.0	0.5	0.65	0.8	1.0
Baseline Compliance		[%]	95.0	81.5	79.2	75.5	71.8
Throughput		[1/min]	7,325.60	5,162.30	4,225.17	3,852.70	3,829.40
95% Response Time	Select Light	[ms]	370	766	747	846	1,000
	Select Heavy	[ms]	2,226	1,677	1,665	1,959	2,375
	Insert Light	[ms]	4,508	2,031	2,620	3,020	2,005
	Insert Heavy	[ms]	8,530	10,128	13,383	16,681	9,718
	Update Light	[ms]	428	1,160	1,403	1,719	2,049
	Update Heavy	[ms]	679	1,393	1,524	1,777	2,096
Bufferpool Hit Ratio	Data	[%]	95.53	93.89	94.58	94.54	94.12
	Index	[%]	97.46	89.13	88.57	86.69	83.07

Table 2: Experimental Results



(a) Baseline Compliance (b) Database Throughput (c) Buffer Hit Ratios

Figure 7: Results for Various Schema Variability

The first line of this table shows the *Baseline Compliance*, which was computed as follows. The 95% quantiles were computed for each query class of the schema variability 0.0 configuration: this is the baseline. Then for each configuration, the percentage of queries within the baseline were computed. The lower the baseline compliance, the higher the percentage of queries whose response time is above the baseline. Per definition, the baseline compliance of the schema variability 0.0 configuration is 95%. Starting around schema variability 0.65 the high response times are no longer tolerable. The baseline compliance is also depicted in Figure 7(a). The second line of Table 2 is the database throughput in actions per minute, computed as an average over the 30 minute period. The throughput is also depicted in Figure 7(b).

The middle part of Table 2 shows the 95% quantiles for each query class. For the most part, the response times grow with increasing schema variability. We hypothesize that the exceptions occur for the following reasons. First, for low schema variability, there is more sharing among tenants and therefore more contention for longer running queries and tuple inserts. Since the heavyweight select queries do aggregation, sorting, or grouping, multiple parallel query instances have impact on each other. The query execution plans show that these queries do a partial table scan with some locking, so the performance for this class degrades. For insert operations, the database locks the pages where the tuples are inserted, so concurrently running insert operations have to wait for the release of these locks. This effect can be seen especially for the lightweight insert operations. Second, there is a visible performance improvement for the insert operations at schema variability 1.0, where the database outperforms all previous configurations. We hypothesize that this behavior is due to the fact that DB2 is switching between the two insert methods it provides. The first method finds the most suitable page for the new tuple, producing a compactly stored relation. The second method just appends the tuple to the end of the last page, producing a sparsely stored relation.

The last two lines of Table 2 show the buffer pool hit ratio for the data and the indexes. As the schema variability increases, the hit ratio for indexes decreases while the hit ratio for data remains fairly constant. Inspection of the query plans shows that the queries primarily use the indexes for processing. The hit ratios are also depicted in Figure 7(c).

These experimental results are consistent with anecdotal practical experience using MySQL and the InnoDB storage engine. The hosted email service Zimbra [27] initially experimented with a design in which each mailbox was given its own tables [5]. When thousands of mailboxes were loaded on a blade server, performance became unacceptably slow because pages kept getting swapped out of the buffer pool. In addition, when a table is first accessed, InnoDB runs a set of random queries to determine the cardinality of each index, which resulted in a large amount of data flowing through the system. The performance problems disappeared when tables were shared among tenants.

6. QUERYING CHUNK TABLES

This section describes the transformations needed to produce queries over Chunk Tables by considering the simpler case of Pivot Tables. The generalization to Chunk Tables is straight-forward. This section also discusses the behavior of commercial and open-source databases on those queries.

6.1 Transforming Queries

In the running example of Figure 4, consider the following query from Tenant 17 over the Private Table Layout:

```
SELECT Beds
  FROM Account_17                                   (Q1)
 WHERE Hospital='State'.
```

The most generic approach to formulating this query over the Pivot Tables Pivot$_{\text{int}}$ and Pivot$_{\text{str}}$ is to reconstruct the original Account$_{17}$ table in the FROM clause and then patch it into the selection. Such table reconstruction queries generally consists of multiple equi-joins on the column Row. In the case of Account$_{17}$, three aligning self-joins on the Pivot table are needed to construct the four-column wide relation. However in Query Q1, the columns Aid and Name do not appear and evaluation of two of the three mapping joins would be wasted effort.

We therefore devise the following systematic compilation scheme that proceeds in four steps.

1. All table names and their corresponding columns in the logical source query are collected.
2. For each table name, the Chunk Tables and the meta-data identifiers that represent the used columns are obtained.
3. For each table, a query is generated that filters the correct columns (based on the meta-data identifiers from the previous step) and aligns the different chunk relations on their Row columns. The resulting queries are all flat and consist of conjunctive predicates only.
4. Each table reference in the logical source query is extended by its generated *table definition* query.

Query Q1 uses the columns Hospital and Beds of table Account$_{17}$. The two columns can be found in relations Pivot$_{\text{str}}$ and Pivot$_{\text{int}}$, respectively. For both columns, we know the values of the Tenant, Table, and Col columns. The query to reconstruct Account$_{17}$ checks all these constraints and aligns the two columns on their rows:

```
(SELECT s.Str as Hospital, i.Int as Beds
   FROM Pivot_str s, Pivot_int i
  WHERE s.Tenant = 17
    AND i.Tenant = 17                               (Q1_Account17)
    AND s.Table = 0 AND s.Col = 2
    AND i.Table = 0 AND i.Col = 3
    AND s.Row = i.Row).
```

To complete the transformation, Query $Q1_{\text{Account}_{17}}$ is then patched into the FROM clause of Query Q1 as a nested subquery.

When using Chunk Tables instead of Pivot Tables, the reconstruction of the logical Account$_{17}$ table is nearly identical to the Pivot Table case. In our example, the resulting FROM clause is particularly simple because both requested columns reside in the same chunk (Chunk = 1):

```
SELECT Beds
  FROM (SELECT Str1 as Hospital,
               Int1 as Beds
          FROM Chunk_int|str
         WHERE Tenant = 17                          (Q1_Chunk)
           AND Table = 0
           AND Chunk = 1) AS Account_17
 WHERE Hospital='State'.
```

The structural changes to the original query can be summarized as follows.

- An additional nesting due to the expansion of the table definitions is introduced.
- All table references are expanded into join chains on the base tables to construct the references.
- All base table accesses refer to the columns Tenant, Table, Chunk, and in case of aligning joins, to column Row.

We argue in the following that these changes do not necessarily need to affect the query response time.

Additional Nesting. Fegaras and Maier proved in [10] (Rule N8) that the nesting we introduced in the FROM clause – queries with only conjunctive predicates – can always be flattened by a query optimizer. If a query optimizer does not implement such a rewrite (as we will see in Section 6.2) it will first generate the full relation before applying any filtering predicates – a clear performance penalty. For such databases, we must directly generate the flattened queries. For more complex queries (with e.g., GROUP BY clauses) the transformation is however not as clean as the technique described above.

Join Chains. Replacing the table references by chains of joins on base tables may be beneficial as long as the costs for loading the chunks and applying the index-supported (see below) join are cheaper than reading the wider conventional relations. The observation that different chunks are often stored in the same relation (as in Figure 4(e)) makes this scenario even more likely as the joins would then turn into self-joins and we may benefit from a higher buffer pool hit ratio.

Base Table Access. As all table accesses refer to the meta-data columns Tenant, Table, Chunk, and Row we should construct indexes on these columns. This turns every data access into an index-supported one. Note that a B-tree index look up in a (Tenant, Table, Chunk, Row) index is basically a partitioned B-tree lookup [12]. The leading B-tree columns (here Tenant and Table) are highly redundant and only partition the B-tree into separate smaller B-trees (partitions). Prefix compression makes sure that these indexes stay small despite the redundant values.

6.2 Evaluating Queries

To assess the query performance of standard databases on queries over Chunk Tables, we devised a simple experiment that compares a conventional layout with equivalent Chunk Table layouts of various widths. The first part of this section will describe the schema and the query we used, the second part outlines the experiments we conducted.

Test Schema. The schema for the conventional layout consists of two tables Parent and Child:

Parent
id col1 col2 . . . col90
Child
id parent col1 col2 . . . col90 (Conventional)

Both tables have an id column and 90 data columns that are evenly distributed between the types `INTEGER`, `DATE`, and `VARCHAR(100)`. In addition, table Child has a foreign key reference to Parent in column parent.

The Chunk Table layouts each have two tables: Chunk$_{\text{Data}}$ storing the grouped data columns and Chunk$_{\text{Index}}$ storing the key id and foreign key parent columns of the conventional tables. In the different Chunk Table layouts, the Chunk$_{\text{Data}}$ table varied in width from 3 data columns (resulting in 30 groups) to 90 data columns (resulting in a single group) in 3 column increments. Each set of three columns had types `INTEGER`, `DATE`, and `VARCHAR(100)` allowing groups from the conventional table to be tightly packed into the Chunk Table. In general, the packing may not be this tight and a Chunk Table may have *nulls*, although not as many as a Universal Table. The Chunk$_{\text{Index}}$ table always had a single `INTEGER` column.

As an example, Chunk$_6$ shows a Chunk Table instance of width 6 where each row of a conventional table is split into 15 rows in Chunk$_{\text{Data}}$ and 1 (for parents) or 2 (for children) rows in Chunk$_{\text{Index}}$.

Chunk$_{\text{Data}}$
table chunk row int1 int2 date1 date2 str1 str2
Chunk$_{\text{Index}}$
table chunk row int1 (Chunk$_6$)

For the conventional tables, we created indexes on the primary keys (id) and the foreign key (parent, id) in the Child table. For the chunked tables, we created (table, chunk, row) indexes on all tables (see previous section for the reasons) as well as an (int1, table, chunk, row) index on Chunk$_{\text{Index}}$ to mimic the foreign key index on the Child table.

The tests used synthetically generated data for the individual schema layouts. For the conventional layout, the Parent table was loaded with 10,000 tuples and the Child table was loaded with 100 tuples per parent (1,000,000 tuples in total). The Chunk Table Layouts were loaded with equivalent data in fragmented form.

Test Query. Our experiments used the following simple selection query.

```
SELECT p.id, ...
  FROM parent p, child c
 WHERE p.id = c.parent
   AND p.id = ?.
```
(Q2)

Query Q2 has two parameters: (a) the ellipsis (`...`) representing a selection of data columns and (b) the question mark (`?`) representing a random parent id. Parameter (b) ensures that a test run touches different parts of the data. Parameter (a) – the *Q2 scale factor* – specifies the width of the result. As an example, Query Q2$_3$ is Query Q2 with a scale factor of 3: the ellipsis is replaced by 3 data columns each for parent and child.

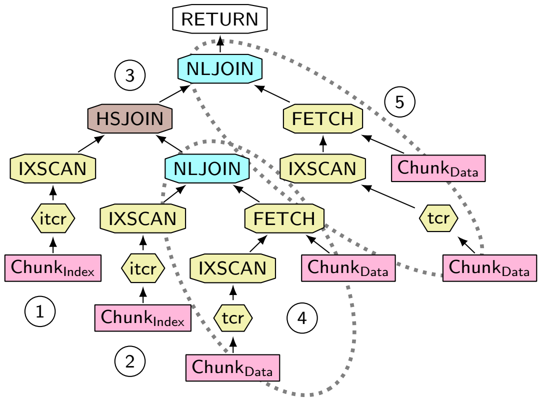


Figure 8: Join plan for simple fragment query

```
SELECT p.id, p.col1, p.col2, p.col3,
       c.col1, c.col2, c.col3
  FROM parent p, child c
 WHERE p.id = c.parent
   AND p.id = ?.
```
(Q2$_3$)

Higher Q2 scale factors (ranging up to 90) are more challenging for the chunked representation because they require more aligning joins.

Test 1 (Transformation and Nesting). In our first test, we transformed Query Q2 using the methods described in Section 6.1 and fed the resulting queries into the open-source database MySQL [20] and the commercial database DB2. We then used the database debug/explain facilities to look at the compiled query plans. The MySQL optimizer was unable to unnest the nesting introduced by our query transformation. DB2 on the other hand presented a totally unnested plan where the selective predicate on `p.id` was even pushed into the chunk representing the foreign key of the child relation. DB2's evaluation plan is discussed in more detail in the next test.

We then flattened the queries in advance and studied whether the predicate order on the SQL level would influence the query evaluation time. We produced an ordering where all predicates on the meta-data columns preceded the predicates of the original query and compared it with the ordering that mimics DB2's evaluation plan. For MySQL, the latter ordering outperformed the former ordering by a factor of 5.

After adjusting the query transformation to produce flattened queries with predicates in the correct order, we reran the experiment on both databases. DB2 produced the same execution plan and MySQL was able to produce a plan that started with the most selective predicate (`p.id = ?`). As one would expect, the query evaluation times for MySQL showed an improvement.

Test 2 (Transformation and Scaling). To understand how queries on Chunk Tables behave with an increasing number of columns (output columns as well as columns used in predicates) we analyzed the plans for a number of queries. The pattern is similar for most queries and we will discuss the characteristics based on Query Q2$_3$, which was designed for the Chunk Table Layout in Chunk$_6$.

The query plan is shown in Figure 8. The leaf operators all access base tables. If the base tables are accessed via

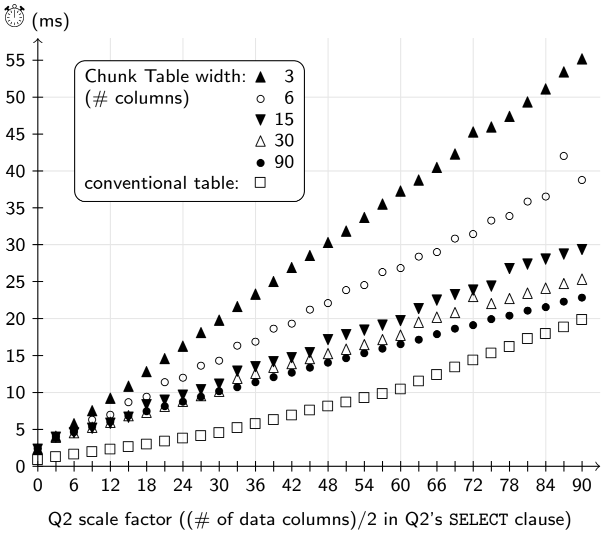


Figure 9: Response Times with Warm Cache

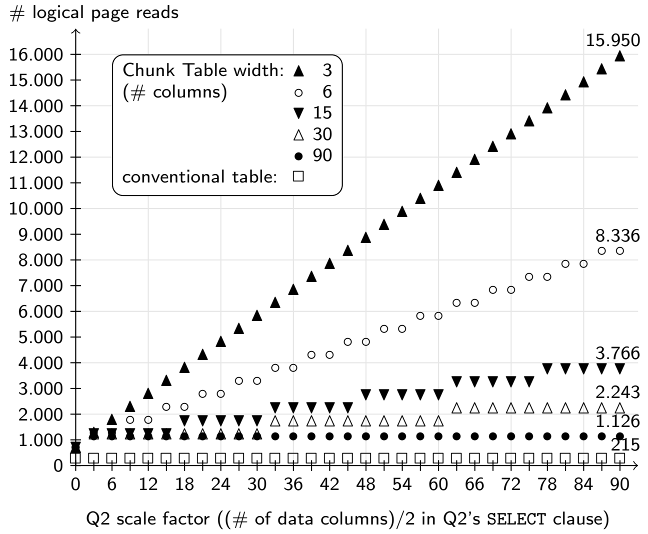


Figure 10: Number of logical page reads.

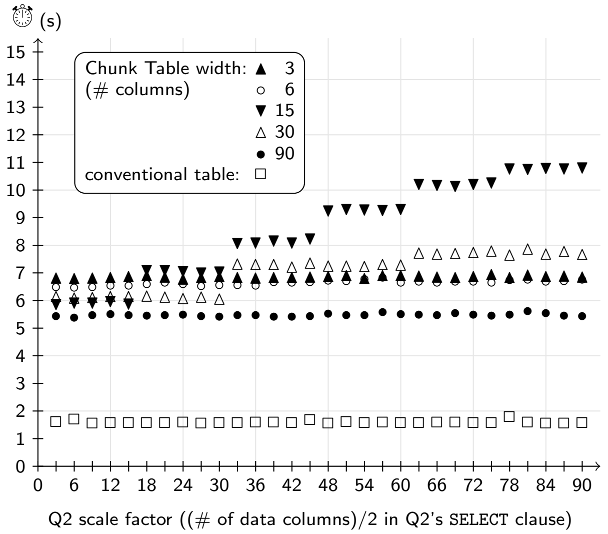


Figure 11: Response Times with Cold Cache

an index, an IXSCAN operator sits on top of the base table with a node in between that refers to the used index. Here, the meta-data index is called tcr (abbreviating the columns table, chunk, and row) and the value index is called itcr. If a base table access cannot be completely answered by an index (e.g., if data columns are accessed) an additional FETCH operator (with a link to the base table) is added to the plan. Figure 8 contains two different join operators: a hash join (HSJOIN) and an index nested-loop join (NLJOIN).

The plan in Figure 8 can be grouped into 5 regions. In region ①, the foreign key for the child relation is looked up. The index access furthermore applies the aforementioned selection on the ? parameter. In region ②, the id column of the parent relation is accessed and the same selection as for the foreign key is applied. The hash join in region ③ implements the foreign key join p.id = c.parent. But before this value-based join is applied in region ④, all data columns for the parent table are looked up. Note that region ④ expands to a chain of aligning joins where the join column row is looked up using the meta-data index tcr if parent columns in different chunks are accessed in the query. A similar join chain is built for the columns of the child table in region ⑤.

Test 3 (Response Times with Warm Cache). Figure 9 shows the average execution times *with warm caches* on DB2 V9, with the same database server setup described in Section 5. We conducted 10 runs; for all of them, we used the same values for parameter ? so the data was in memory. In this setting, the overhead compared to conventional tables is entirely due to computing the aligning joins. The queries based on narrow chunks have to perform up to 60 more joins (layout Chunk_3 with Q2 scale factor 90) than the queries on the conventional tables which results in a 35 ms slower response time. Another important observation is that already for 15-column wide chunks, the response time is cut in half in comparison to 3-column wide chunks and is at most 10 ms slower than conventional tables.

Test 4 (Logical Page Reads). Figure 10 shows the number of logical data and index page reads requested when executing Query Q2. For all chunked representations, 74% to 80% of the reads were issued by index accesses. Figure 10 clearly shows that every join with an additional base table increases the number of logical page reads. Thus this graph shows the trade-off between conventional tables, where most meta-data is interpreted at compile time, and Chunk Tables, where the meta-data must be interpreted at runtime.

Test 5 (Response Times with Cold Cache). Figure 11 shows the average execution times *with cold caches*. For this test, the database buffer pool and the disk cache were flushed between every run. For wider Chunk Tables, i.e. 15 to 90 colums, the response times look similar to the page read graph (Figure 10). For narrower Chunk Tables, cache locality starts to have an effect. For example, a single physical page access reads in 2 90 column-wide tuples and 26 6 column-wide tuples. Thus the response times for the narrower Chunk Tables are lower than for some of the wider Chunk Tables. For a realistic application, the response times would fall between the cold cache case and the warm cache case.

Test 6 (Cache Locality Benefits). The effects of cache locality are further clarified in Figure 12, which shows the

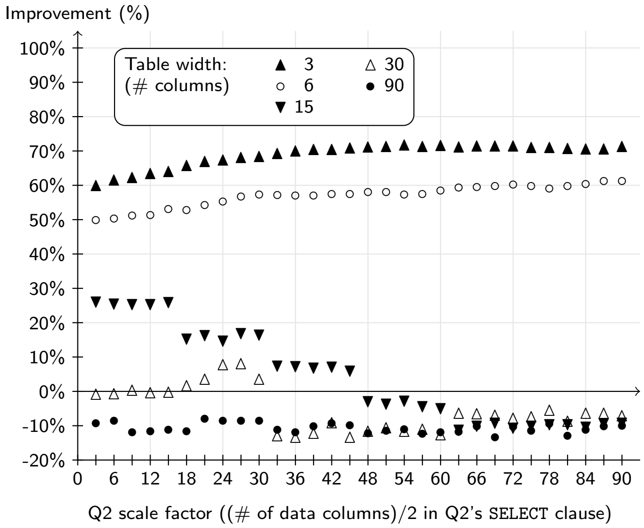


Figure 12: Response Time Improvements for Chunk Tables Compared to Vertical Partitioning

relative difference in response times between Chunk Folding and more conventional vertical partitioning. In the latter case, the source tables are partitioned as before, but the chunks are kept in separate tables rather than being folded into the same tables. For configurations with 3 and 6 columns, Chunk Folding exhibits a response time improvement of more than 50 percent. In the configuration with 90 columns, Chunk Folding and vertical partitioning have nearly identical physical layouts. The only difference is that Chunk Folding has an additional column Chunk to identify the chunk for realigning the rows, whereas in the vertical partitioning case, this identification is done via the physical table name. Since the Chunk column is part of the primary index in the Chunk Folding case, there is overhead for fetching this column into the index buffer pools. This overhead produces up to 25% more physical data reads and a response time degradation of 10%.

Additional Tests. We also ran some initial experiments on more complex queries (such as grouping queries). In this case, queries on the narrowest chunks could be as much as an order of magnitude slower than queries on the conventional tables, with queries on the wider chunks filling the range in between.

The overall result of these experiments is that very narrow Chunk Tables, such as Pivot Tables, carry considerable overhead for reconstruction of rows. As Chunk Tables get wider however, the performance improves considerably and becomes competitive with conventional tables well before the width of the Universal Table is reached.

6.3 Transforming Statements

Section 6.1 presented a systematic compilation scheme for generating queries over Chunk Tables. This section briefly describes how to cope with `UPDATE`, `DELETE`, and `INSERT` statements.

In SQL, data manipulation operations are restricted to single tables or updateable selections/views which the SQL query compiler can break into separate DML statements. For update and delete statements, predicates can filter the tuples affected by the manipulation. As insert and delete operations also require the modification of meta-data values, we devised a consistent DML query transformation logic based on single table manipulations.

Since multiple chunked tables are required for a single source table, a single source DML statement generally has to be mapped into multiple statements over Chunk Tables. Following common practice, we transform delete operations into updates that mark the tuples as invisible instead of physically deleting them, in order to provide mechanisms like a Trashcan. Such an update naturally has to mark all chunk tables as deleted in comparison to normal updates that only have to manipulate the chunks where at least one cell is affected.

Our DML transformation logic for updates (and thus also for deletes) divides the manipulation into two phases: (a) a query phase that collects all rows that are affected by an update and (b) an update phase that applies the update for each affected chunk with *local* conditions on the meta-data columns and especially column row only. Phase (a) transforms the incoming query with the query transformation scheme from Section 6.1 into a query that collects the set of affected row values. One possibility to implement the updates in Phase (b) is to nest the transformed query from Phase (a) into a nested sub-query using an `IN` predicate on column row. This approach lets the database execute all the work. For updates with multiple affected chunks (e.g., deletes) the database however has to evaluate the query from Phase (a) for each chunk relation. An alternative approach would be to first evaluate the transformed predicate query, let the application then buffer the result and issue an atomic update for each resulted row value and every affected Chunk Table.

We turn now to insert statements. For any insert, the application logic has to look up all related chunks, collect the meta-data for tables and chunks, and assign each inserted new row a unique row identifier. With the complete set of meta-data in hand, an insert statement for any chunk can be issued.

Other operations like `DROP` or `ALTER` statements can be evaluated on-line as well. They however require no access to the database. Instead only the application logic has to do the respective bookkeeping.

6.4 Chunk Tables vs. Chunk Folding

Chunk Folding mixes Extension and Chunk Tables. The inclusion of Extension Tables does not affect the query part of the previous section at all. The reason is that the only interface between the different tables is the meta-column Row, which is also available in the Extension Table Layout.

The only important change necessary to make Chunk Folding work is a refinement of the transformation logic in the second bullet of Section 6.1 that enables also the meta-data lookup for Extension Tables.

7. CONCLUSION

This paper has presented *Chunk Folding*, a new schema-mapping technique for implementing multi-tenancy on top of a standard relational database. In this technique, the logical tables are vertically partitioned into chunks that are folded together into application-specific conventional tables and a fixed set of generic *Chunk Tables*. Chunk Tables can vary in width, from very narrow Pivot-like Tables to very wide Universal Tables.

This paper presented the results of several experiments designed to measure the efficacy of Chunk Folding. We studied the performance of standard relational databases on OLTP queries formulated over Chunk Tables. Very narrow Chunk Tables can carry considerable overhead for reconstruction of rows, but wider Chunk Tables become competitive in performance with conventional tables well before the width of the Universal Table is reached.

Finally, this paper described a multi-tenant database testbed that simulates a simple hosted CRM service. We used this testbed to characterize the performance degradation that results as a standard relational database handles more and more tables. A goal of our on-going work is to compare the penalty of reconstructing rows introduced by Chunk Folding with the penalty for additional paging introduced by managing lots of tables.

More generally, our on-going work entails enhancing the testbed to include extension tables as well as base tables. This framework will allow us to study Chunk Folding in a more complete setting. In particular, our goal is to develop algorithms that take into account the logical schemas of tenants, the distribution of data within those schemas, and the associated application queries, and then create a suitable Chunk Table Layout. Because these factors can vary over time, it should be possible to migrate data from one representation to another on-the-fly.

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