MTBase : Optimizing Cross-Tenant Database Queries

White Paper

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ABSTRACT

In the last decade, a lot of business applications have moved into the cloud and even database vendors have started to follow this trend, despite the numerous obstacles and the fact that many research questions are still open. While existing multi-tenant data management systems focus on single-tenant query processing, we believe that it is time to rethink how queries can be processed across multiple tenants in such a way that we do not only gain more valuable insights, but also at minimal costs. As we will argue in this paper, standard SQL semantics are insufficient to process cross-tenant queries in an unambiguous way, which is why existing systems use other, expensive means like ETL or data integration. We first propose MTSQL, a set of extensions to standard SQL, which fixes the ambiguity problem. Next, we present MTBase, a query processing middleware that efficiently processes MTSQL on top of SQL. As we will see, there is a canonical, provably correct, rewrite algorithm from MTSQL to SQL, which may however result in poor query execution performance, even on high-performance database products. We further show that with carefully-designed optimizations, execution times can be reduced in such ways that the difference to single-tenant queries becomes marginal.

1. INTRODUCTION

Indisputably, cloud computing is one of the fastest growing businesses related to the field of computer science. Cloud providers promise good elasticity, high availability, and a fair pay-as-you-go pricing model to their tenants. Moreover, corporations are no longer required to rely on on-promise infrastructure which is typically costly to acquire and maintain. While it is still an open research question whether and how these good promises can be kept with regard to databases [20, 33], all the big players, like Google [30], Amazon [43], Microsoft [4], and recently Oracle [16], have launched their own Database-as-a-Service (DaaS) cloud products. All these products host massive amounts of clients and are therefore *multi-tenant*.

As pointed out by Chong et al. [15], the term *multi-tenant database* is ambiguous and can refer to a variety of DaaS schemes with different degrees of logical data sharing between tenants. On the other hand, as argued by Aulbach et al. [10], multi-tenant databases not only differ in the way how they logically share information between tenants, but also how information is physically separated. We conclude that the *multi-tenancy spectrum* consists of four different schemes: First, there are DaaS products that offer each tenant her proper database while relying on physically-shared resources (*SR*), like CPU, network, and storage. Examples include *SAP HANA* [39], *SqlVM* [35], *RelationalCloud* [34], and *Snowflake* [19]. Next, there are systems that share databases (*SD*), but each tenant gets her own set of tables within such a database, as for in example *Azure SQL DB* [21]. Finally, there are the two schemes where tenants not only share a database, but also the table layout (schema). Either, as for example in *Apache Phoenix* [1], tenants still have their private tables, but these tables have the same schema (*SS*), or the data of different tenants is consolidated into shared tables (*ST*) which is hence the layout with the highest degree of physical and logical sharing. *SS* and *ST* layouts are not only used in DaaS, but also in Software-as-a-Service (SaaS) platforms, as for example in *Salesforce* [44] and *FlexScheme* [10, 11]. The main reason why these systems prefer *ST* over *SS* is cost [10]. Moreover, if the number of tenants exceeds the number of tables a database can hold (which is typically a number in the range of 10,000), *SS* becomes prohibitive. Conversely, *ST* databases can easily accommodate 100,000s to even millions of tenants.

An important use case for *multi-tenancy databases*, which as we believe did so far not get the attention it deserves, is *cross-tenant query processing*. In Switzerland, for instance, three big institutions, namely Swisscom (a telco provider), Ringier (a big media provider), and SRF (Swiss national TV) have recently joined into a strategic marketing allegiance [41]. This means nothing else than cross-tenant query processing to get better insights into how to drive their marketing campaigns. Another compelling use case is health care where many providers (and insurances) use the same integrated SaaS application. If the providers would agree to query their joint datasets of (properly anonymized) patient data with scientific institutions, this could enable medical research to advance much faster because the data can be queried as soon as it gets in.

There are several existing approaches to *cross-tenant query processing* which are summarized in Figure 1: The first approach is *data warehousing* [29] where data is *extracted*

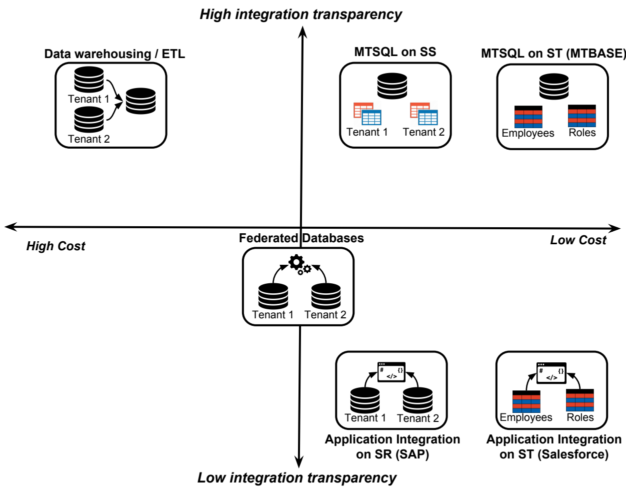


Figure 1: cross-tenant query processing systems

from several *data sources* (tenant databases / tables), *transformed* into one common format and finally *loaded* into a new database where it can be queried by the client. This approach has high integration transparency in the sense that once the data is loaded, it is in the right format as required by the client and she can ask any query she wants. Moreover, as all data is in a single place, queries can be optimized. On the down-side of this approach, as argued by [13, 36, 9], are costs in terms of both, developing and maintaining such *ETL* pipelines, and maintaining a separate copy of the data. Another disadvantage is *data staleness* in the presence of frequent updates.

Federated Databases [32, 26] reduce some of these costs by integrating data *on demand* (no copying). However, maintenance costs are still significant as for every new data source a new integrator / wrapper has to be developed. As data resides in different places (and different formats), queries can only be optimized to a very small extent (if at all), which is why the degree of integration transparency is considered sub-optimal. Finally, systems like *SAP HANA* [39] and *Salesforce* [44], which are mainly tailored towards single-tenant queries, offer some degree of *cross-tenant query processing*, but only through their application logic, which means that the set of queries that can be asked is limited.

The reason why none of these approaches tries to use SQL for *cross-tenant query processing* is that it is ambiguous. Consider, for instance the *ST* datbase in Figure 2, which we are going to use as a running example throught the paper: As soon as we want to query the joint dataset of tenants 0 and 1, and for instance join `Employees` with `Roles`, joining on `role_id` alone is not enough as this would also join `Patrick` with `researcher` and `Ed` with `professor`, which is clear nonsense. The obvious solution is to add the tenant-ID `ttid` to the join predicate. On the other hand, joining the `Employees` table with itself on `E1.age > E2.age` does not require `ttid` to be present in the join predicate because it actually makes sense to include results like `(Patrick, Alan)`. As `ttid` is an attriubte invisible to the end client, there is no way to distinguish the two cases (the one where `ttid` has to be included in the join and the one where it does not) in plain SQL. Another challenge arises from the fact that different tenants might store their employee's salaries in different currencies. If this is the case, computing the average salary across all tenants clearly involves some value conversions that should, ideally, happen without the end client noticing or even worrying about.

This paper presents *MTSQL* as a solution to all these ambiguity problems. MTSQL extends SQL with additional semantics specifically-suited for *cross-tenant query processing*. It enables high integration transparency because any client (with any desired data format) can ask any query at any time. Moreover, as data resides in a single database (*SS* or *ST*), queries can be aggressively optimized with respect to both, standard SQL semantics, and additional MTSQL semantics. As MTSQL adopts the single-database layout, it is also very cost-effective, especially if used on top of *ST*. Moreover, data conversion only happens as needed, which perfectly fits the cloud's *pay-as-you-go* cost model.

The paper makes the following contributions:

- It defines the syntax and semantics of *MTSQL*, a query language that extends SQL with additional semantics suitable for cross-tenant query processing.
- It presents the design and implementation of *MTBase*, a database middleware that executes *MTSQL* on top of any *ST* database.
- It studies MTSQL-specific optimizations for query execution in MTBase.
- It extends the well-known TPC-H benchmark to run and evaluate *MTSQL* workloads.
- It evaluates the performance and the implementation correctness of *MTBase* with this benchmark.

The rest of this paper is organized as follows: Section 2 defines *MTSQL* while Section 3 gives an overview on *MTBase*. Section 4 discusses the MTSQL-specific optimizations, which are validated in Section 6 using the benchmark presented in Section 5. Section 7 shortly summarizes lines of related work while the paper is concluded in Section 8.

E_ttid	**E_emp_id**	**E_name**	**E_role_id**	**E_reg_id**	**E_salary**	**E_age**
0	0	Patrick	1	3	50K	30
0	1	John	0	3	70K	28
0	2	Alice	2	3	150K	46
1	0	Allan	1	2	80K	25
1	1	Nancy	2	4	200K	72
1	2	Ed	0	4	1M	47

Employees (tenant-specific), `E_salary` of tenant 0 in USD, `E_salary` of tenant 1 in EUR

R_ttid	**R_role_id**	**R_name**
0	0	phD stud.
0	1	postdoc
0	2	professor
1	0	intern
1	1	researcher
1	2	executive

Roles (tenant-specific)

Re_reg_id	**Re_name**
0	AFRICA
1	ASIA
2	AUSTRALIA
3	EUROPE
4	N-AMERICA
5	S-AMERICA

Regions (global)

Figure 2: MTSQL database in *Basic Layout* (*ST*), *ttid*s not visible to clients

E_emp_id	E_name	E_role_id	E_reg_id	E_salary	E_age
0	Patrick	1	3	50K	30
1	John	0	3	70K	28
2	Alice	2	3	150K	46

Employees_0 (private), `E_salary` in USD

E_emp_id	E_name	E_role_id	E_reg_id	E_salary	E_age
0	Allan	1	2	80K	25
1	Nancy	2	4	200K	72
2	Ed	0	4	1M	47

Employees_1 (private), `E_salary` in EUR

R_role_id	R_name
0	phD stud.
1	postdoc
2	professor

Roles_0 (private)

R_role_id	R_name
0	intern
1	researcher
2	executive

Roles_1 (private)

Re_reg_id	Re_name
0	AFRICA
1	ASIA
2	AUSTRALIA
3	EUROPE
4	N-AMERICA
5	S-AMERICA

Regions (global)

Figure 3: MTSQL database in *Private Table Layout* (*SS*)

2. MTSQL

In order to model the specific aspects of *cross-tenant query processing* in *multi-tenant databases*, we developed *MTSQL*, which will be described in this section. MTSQL extends SQL in two ways: First, it extends the SQL interface with two additional parameters, C and D. C is the tenant ID (or *ttid* for short) of the client who submits a statement and hence determines the format in which the result must be presented. The data set, D, is a set of *ttids* that refer to the tenants whose data the client wants to query. Secondly, MTSQL extends the syntax and semantics of the SQL Query Language, Data Definition Language (DDL), Data Manipulation Language (DML), and Data Control Language (DCL, consists of `GRANT` and `REVOKE` statements).

As mentioned in the introduction, there are several ways how a multi-tenant database can be laid out: Figure 2 shows an example of the *ST* scheme, also referred to as *basic layout* in related work [10] where tenants's data is consolidated using the same tables. Meanwhile, Figure 3 illustrated the *SS* scheme, also referred to as *private table layout*, where every tenant has her own set of tables. In that scheme, *data ownership* is defines as part of the table name while in *ST*, records are explicitly annotated with the *ttid* of their *data owner*, using an extra meta column in the table which is invisible to the end client.

As these two approaches are semantically equivalent, the MTSQL semantics that we are about to define apply to both. In the case of the *SS*, applying a statement s with respect to D simply means to apply s to the logical union of all private tables owned by a tenant in D. In *SS*, s is applied to tables filtered according to D. In order to keep the presentation simple, the rest of this paper assumes an *ST* scheme, but sometimes defines semantics with respect to *SS* if that makes the presentation easier to understand.

2.1 MTSQL API

MTSQL needs a way to incorporate the additional parameters C and D. As C is the *ttid* of the tenant that issues a statement, we assume it is implicitly given by the SQL connection string. *ttids* are not only used for identification and access control, but also for data ownership (as shown in Figure 3). While this paper uses integers for simplicity reasons, *ttids* can have any data type, in particular they can also be database user names. D is explicitly defined using the MTSQL-specific `SCOPE` keyword. The `SCOPE` clause follows at the end of a MTSQL statement and comes in two flavours: Either, as shown in Listing 1, as *simple scope* with an `IN` list stating the set of *ttids* that should be queried, or as in Listing 2, with a sub-query with a `FROM` and a `WHERE` clause (*complex scope*). The semantics of the latter is that every tenant that owns at least one record in one of the tables mentioned in the `FROM` clause that satisfies the `WHERE` clause is part of D. If the `SCOPE` keyword is missing, this means that a client wants to query the entire database, resp. all the bits of the database she was granted access to.

```sql
SELECT AVG(E_age) FROM Employees GROUP BY region_id
SCOPE IN (1,3,42);
```

Listing 1: simple SCOPE expression using IN

```sql
SELECT R_name FROM Roles   -- complex scope
SCOPE FROM Employees WHERE MAX(E_salary) > 180K;
```

Listing 2: complex SCOPE expression with sub-query

2.2 Data Definition Language

DDL statements are issued by a special role called the *data modeller*. In a multi-tenancy application, this would be the SaaS provider (e.g. a Salesforce administrator) or the provider of a specific application. However, the data modeller can delegate this privilege to any tenant she trusts using a `GRANT` statement, as will be described in § 2.3.

There are two types of tables in MTSQL: tables that contain common knowledge shared by everybody (like `Regions`) and those that contain data of a specific tenant (like `Employees` and `Roles`). More formally, we define the *table generality* of `Regions` as *global* and the one of all other tables as *tenant-specific*. In order to process queries across tenants, MTSQL needs a way to distinguish whether an attribute is *comparable* (can be directly compared against attribute values of other tenants), *convertible* (can be compared against attribute values of other tenants after applying a well-defined *conversion function*), or *tenant-specific* (it does semantically not make sense to compare against attribute values of other tenants). An overview of these types of *attribute comparability*, together with examples from Figure 2, is shown in Table 1.

type	description	examples
comparable	can be directly compared to and aggregated with other values	E_region_id, E_age, Re_name, R_region_id, R_name
convertible	other values need to be converted to the format of the current tenant before comparison or aggregation	E_salary
tenant-specific	values of different tenants cannot be compared with each other	E_role_id, R.role_id

Table 1: Overview on Attribute Comparability in MTSQL

2.2.1 CREATE TABLE Statement

The MTSQL-specific keywords for creating (or altering) tables are `GLOBAL`, `SPECIFIC`, `COMPARABLE` and `CONVERTIBLE`. An example of how they can be used is shown in Listing 3. Note that `SPECIFIC` can be used for tables and attributes. Moreover, using these keywords is optional as we define that tables are global by default, attributes of tenant-specific tables default to *tenant-specific* and those of global tables to *comparable*[1].

```sql
CREATE TABLE Employees SPECIFIC (
  E_emp_id   INTEGER     NOT NULL SPECIFIC,
  E_name     VARCHAR(25) NOT NULL COMPARABLE,
  E_role_id  INTEGER     NOT NULL SPECIFIC,
  E_reg_id   INTEGER     NOT NULL COMPARABLE,
  E_salary   VARCHAR(17) NOT NULL CONVERTIBLE
     @currencyToUniversal @currencyFromUniversal,
  E_age      INTEGER     NOT NULL COMPARABLE,
  CONSTRAINT pk_emp PRIMARY KEY (E_emp_id),
  CONSTRAINT fk_emp FOREIGN KEY (E_role_id)
     REFERENCES Roles (R_role_id)
);
```

Listing 3: exemplary MTSQL CREATE TABLE statement, MT-specific keywords marked in red

2.2.2 Conversion Functions

Cross-tenant query processing requires the ability to execute comparison predicates on *comparable* and *convertible attribute*. While comparable attributes can be directly compared to each other, convertible attributes, as their name indicates, have to be converted first, using conversion functions. Each tenant has a pair of conversion functions for each attribute to translate from and to a well-defined universal format. More formally, a *conversion function pair* is defined as follows:

Definition 1 ($toUniversal : X \times T \to X, fromUniversal : X \times T \to X$) is a valid MTSQL conversion function pair for attribute A, where T is the set of tenants in the database and X is the domain of A, if and only if:

(i) There exists a *universal format* for attribute A: $image(toUniversal(\cdot, t_1)) = image(toUniversal(\cdot, t_2)) = ... = image(toUniversal(\cdot, t_{|T|}))$

(ii) For every tenant $t \in T$, the partial functions $toUniversal(x, t)$ and $fromUniversal(x, t)$ are well-defined, bijective functions.

(iii) $fromUniversal$ is the inverse of $toUniversal$: $\forall t \in T, x \in X : fromUniversal(toUniversal(x, t), t) = x$

(iv) $toUniversal$ and $fromUniversal$ are equality-preserving: $\forall t \in T : toUniversal(x, t) = toUniversal(y, t) \Leftrightarrow x = y \Leftrightarrow fromUniversal(x, t) = fromUniversal(y, t)$

An important corollary of Properties (iv) and (i) is that values from any tenant t_i can be converted into the representation of any other tenant t_j by first applying $toUniversal(\cdot, t_i)$, followed by $fromUniversal(\cdot, t_j)$ while equality is preserved:

$$\forall t_i, t_j \in T : x = y \Leftrightarrow fromUniversal(toUniversal(x, t_i), t_j) = fromUniversal(toUniversal(y, t_i), t_j)$$

[1] In fact, global tables, as they are shared between all tenants, can only have comparable attributes anyway.

The reason why we opted for a two-step conversion through universal format is that it allows each tenant t_i to define her share of the conversion function pair (i.e. $toUniversal(\cdot, t_i)$, $fromUniversal(\cdot, t_i)$) individually without the need of a central authority. Moreover, this design greatly reduces the overall number of partial conversion functions as we need at most $2 \cdot |T|$ partial function definitions, compared to $|T|^2$ functions in the case where we would define a direct conversion for every pair of tenants.

```sql
CREATE FUNCTION phoneToUniversal (VARCHAR(17),
    INTEGER) RETURNS VARCHAR(17)
    AS 'SELECT SUBSTRING($1, CHAR_LENGTH(PT_prefix)
    +1) FROM Tenant, PhoneTransform WHERE
    T_tenant_key = $2 AND T_phone_prefix_key =
    PT_phone_prefix_key;'
LANGUAGE SQL IMMUTABLE;
```

Listing 4: Converting a phone number to universal form (without prefix), postgreSQL syntax

```sql
CREATE FUNCTION phoneFromUniversal (VARCHAR(17),
    INTEGER) RETURNS VARCHAR(17)
    AS 'SELECT CONCAT(PT_prefix, $1) FROM Tenant,
    PhoneTransform WHERE T_tenant_key = $2 AND
    T_phone_prefix_key = PT_phone_prefix_key;'
LANGUAGE SQL IMMUTABLE;
```

Listing 5: Converting to a specific phone number format, postgreSQL syntax

Listings 4 and 5 show an example of such a conversion function pair. These functions are used to convert phone numbers with different prefixes (like "+", "00" or any other specific county exit code[2]) and the universal format is a phone number without prefix. In this example, converting phone numbers simply means to lookup the tenant's prefix and then either prepend or remove it, depending whether we convert from or to the universal format. Note that the exemplary code also contains the keyword `IMMUTABLE` to state that for a specific input the function always returns the same output, which is an important hint for the (PostgreSQL) query optimizer (other vendors have similar syntax).

It is important to mention that Property (iv) of Definition 1 is a minimal requirement for conversion functions to make sense in terms of producing coherent query results among different clients. There are, however conversion functions that exhibit additional properties, for example:

- order-preserving with respect to tenant t: $x < y \Leftrightarrow toUniversal(x, t) < toUniversal(y, t)$
- homomorphic with respect to tenant t and function h: $toUniversal(h(x_1, x_2, ...), t) = h(toUniversal(x_1, t), toUniversal(x_2, t), ...)$

We will call a conversion function pair *fully-order-preserving* if $toUniversal$ and $fromUniversal$ are order-preserving with respect to all tenants. Consequently, a conversion function pair can also be *fully*-h-*preserving*.

Listings 6 and 7 show an exemplary conversion function pair used to convert currencies (with USD as universal format). These functions are not only equality-preserving, but also fully-SUM-preserving: as the currency conversion is

[2] The country exit code is a sequence of digits that you have to dial in order to inform the telco system that you want to call a number abroad. A full list of country exit codes can be found on `http://www.howtocallabroad.com/codes.html`.

nothing but a multiplication with a constant factor[3] from CurrencyTransform, it does not matter in which format we sum up individual values (as long as they all have that same format). As we will see, such special properties of conversion functions are another crucial ingredient for query optimization.

```
CREATE FUNCTION currencyToUniversal (DECIMAL(15,2),
    INTEGER) RETURNS DECIMAL(15,2)
    AS 'SELECT CT_to_universal*$1 FROM Tenant,
    CurrencyTransform WHERE T_tenant_key = $2 AND
    T_currency_key = CT_currency_key;'
LANGUAGE SQL IMMUTABLE;
```

Listing 6: Converting a currency to universal form (USD), postgreSQL syntax

```
CREATE FUNCTION currencyFromUniversal (DECIMAL(15,2),
    INTEGER) RETURNS DECIMAL(15,2)
    AS 'SELECT CT_from_universal*$1 FROM Tenant,
    CurrencyTransform WHERE T_tenant_key = $2 AND
    T_currency_key = CT_currency_key;'
LANGUAGE SQL IMMUTABLE;
```

Listing 7: Converting from USD to a specific currency, postgreSQL syntax

The conversion function examples shown in Listings 4 to 7 assumes the existence of tables PhoneTransform and CurrencyTransmform holding additional conversion information as well as a Tenants table with references into these tables. The way how a tenant can define her portion of the conversion functions is then simply to choose a specific currency and phone format as part of an initial setup procedure. However, this is only one possible implementation. MTSQL does not make any assumptions (or restrictions) on the implementation of conversion function pairs themselves, as long as they satisfy the properties given in Definition 1.

MTSQL is not the first work that talks about conversion functions. In fact, there is an entire line of work that deals with data integration and in particular with schema mapping techniques [37, 24, 10]. These works mention and take into account conversion functions, like for example a multiplication or a division by a constant. More complex conversion functions, including regular-expression-based substitutions and other arithmetic operations, can be found in *Potter's Wheel* [38] where *conversion* is referred to as *value translation*. All these different conversion functions can potentially also be used in MTSQL which is, to the best of our knowledge, the first work that formally defines and categorizes conversion functions according to their properties.

2.2.3 Integrity Constraints

MTSQL allows for *global* integrity constraints that every tenant has to adhere to (with respect to entirety of her data) as well as *tenant-specific* integrity constraints (that tenants can additionally impose on their own data). An example of a *global* referential integrity constraint is shown in the end of Listing 3. This constraint means that for every tenant, for each entry of E_role_id, a corresponding entry R_role_id has to exist in Roles and must be owned by that same tenant. Consider for example employee *John* with R_role_id 0. The constraint implies that their must be a *role* 0 owned by tenant 0, which in that case is *PhD student*. If the constraint were only *tenant-specific* for tenant 1, John would not link to roles and E_role_id 0 would just be an arbitrary numerical value. In order to differentiate *global* from *tenant-specific* constraints, a tenant can simply use the scope (where an empty scope means *global*).

[3] We are aware of the fact that currency conversion is not at all constant, but depends on rapidly changing exchange rates. However, we want to keep the examples as simple as possible in order to illustrate the underlying concepts. However, the general ideas of this paper also apply to temporal databases.

2.2.4 Other DDL Statements

CREATE VIEW statements look the same as in plain SQL. As for the other DDL statements, anyone with the necessary privilege can define global views on *global* and *tenant-specific* tables. Tenants are allowed to create their own, tenant-specific views (using an appropriate scope). The SELECT clause of a CREATE VIEW statement needs to be handled as will be described in § 2.4. The selected data has to be presented in universal format if it is a *global* view and in the *tenant-specific* format otherwise. DROP VIEW, DROP TABLE, and ALTER TABLE work the same as in plain SQL.

2.3 Data Control Language

Let us have a look at the MTSQL GRANT statement:

```
GRANT <privileges> ON <database|table> TO <ttid>;
```

As in plain SQL, this grants some set of access privileges (READ / INSERT / UPDATE / DELETE) to the tenant identified by *ttid*. In the context of MTSQL, however, this means that the privileges are granted with respect to C. Consider the following statement:

```
GRANT READ ON Employees TO 42;
```

In the private table layout, if C is 0, then this would grant tenant 42 read access to Employees_0, but if C is 1, tenant 42 would get read access to Employees_1 instead. If a grant statement grants to ALL, then the grant semantics also depend on D, more concretely if $D = \{7, 11, 15\}$ the privileges would be granted to tenants 7, 11, and 15.

By default, a new tenant that joins an MTSQL system is granted the following privileges: READ access to global tables, READ / INSERT / UPDATE / DELETE / GRANT / REVOKE on his own instances of tenant-specific tables. In our example, this means that a new tenant 111 can read and modify data in Employees_111 and Roles_111. Next, a tenant can start asking around to get privileges on other tenants' tables or also on global tables. The REVOKE statement, as in plain SQL, simply revokes privileges that were granted with GRANT.

2.4 Query Language

Just as in FlexScheme [10, 11], queries themselves are written in plain SQL and have to be filtered according to D. Whereas in FlexScheme D always equals $\{C\}$ (a tenant can only query her own data), MTSQL allows cross-tenant query processing, which means that the data set can include other tenants than C and can in particular be bigger than one. As mentioned in the introduction, this creates some new challenges that have to be handled with special care.

2.4.1 Client Presentation

As soon as tenants can query other tenants' data, the MTSQL engine has to be make sure to deliver results in the proper format. For instance, looking again at Figure 2, if

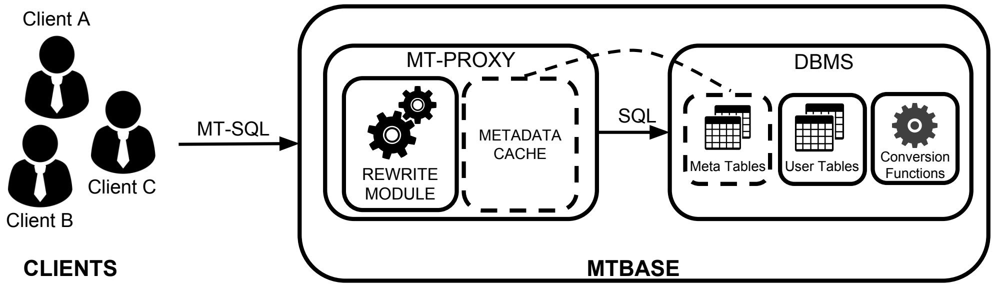


Figure 4: MTBase architecture

tenant 0 queries the average salary of all employees of tenant 1, then this should be presented in USD because tenant 0 stores her own data in USD and expects other data to be in USD as well. Consequently, if tenant 1 would ask that same query, the result would be returned as is, namely in EUR.

2.4.2 Comparisons

Consider a join of `Roles` and `Employees` on `reg_id`. As long as the dataset size is only one, such a join query has the same semantics as in plain SQL (or FlexScheme). However, as soon as tenant 1, for instance, asks this query with $D = \{0, 1\}$, the join has to take the *ttids* into account. The reason for this is that `reg_id` is a *tenant-specific* attribute and should hence only be joined within the same tenant in order to prevent semantically wrong results like John being an intern (although tenant 0 does not have such a role), or Nancy being a professor (despite the fact that tenant 1 only has roles *intern*, *researcher*, and *executive*).

Comparison or join predicates containing *comparable* and *convertible* attributes, on the other hand, just have to make sure that all data is brought into universal format before being compared. For instance, if tenant 0 wants to get the list of all employees (of both tenants) that earn more than 100K USD, all employee salaries have to be converted to USD before executing the comparison.

Finally, MTSQL does not allow to compare *tenant-specific* with other attributes. For instance, we see no way how it could make sense to compare `E_role_id` to something like `E_age` or `E_salary`.

2.5 Data Manipulation Language

As for the query language, MTSQL DML works the same way as in FlexScheme [10, 11] if $|D| = 1$. For `INSERT` statements, MTSQL does not allow scopes bigger than one either. However, it allows a tenant X to insert data on behalf of another tenant Y, in which case the engine needs to make sure to convert the data into Y's format before inserting it. `UPDATE` and `DELETE` statements, on the other hand can have a scope bigger than one, which means that these statements can update/delete records from several tuples as long as they qualify the `WHERE` clause. Again, updating `convertible` attributes involves value conversion to the proper tenant format(s). The semantics of a `WHERE` clause in an `UPDATE` or `DELETE` statement, as well as the semantics of a sub-query in an `INSERT` statement are the same as those for queries (see § 2.4).

3. MTBASE

Based on the concepts described in the previous section, we implemented MTBase, an open-source MTSQL engine [5]. As shown in Figure 4, the basic building block of MTBase is an MTSQL-to-SQL translation middleware sitting between a traditional DBMS and the client. In fact, as it communicates to the DBMS (and to the client) by the means of pure SQL, MTBase works in conjunction with any off-the-shelve DBMS. For performance reasons, the proxy maintains a cache of MT-specific meta data, which is persisted in the DBMS along with the actual user data. Conversion functions are implemented as UDFs that might involve additional meta tables, both of which are also persisted in the DBMS. MTBase implements the *basic data layout*, which means that *data ownership* is implemented as an additional (meta) *ttid* column in each *tenant-specific* table as illustrated in Figure 2). There are some dedicated meta tables: `Tenant` stores each tenant's privileges and conversion information and `Schema` stores information about table and attribute comparability. Additional meta tables can (but do not have to) be used to implement conversion function pairs, as for example `CurrencyTransform` and `PhoneTransform` shown in Listings 4 to 7.

While the rewrite module was implemented in Haskell and compiled with GHC [2], the connection handling and the meta data cache maintenance was written in Python (and run with the Python2 interpreter) [7]. Haskell is handy because we can make full use of pattern matching and additive data types to implement the rewrite algorithm in a quick and easy-to-verify way, but any other functional language, like e.g. Scala [8], would also do the job. Likewise, there is nothing fundamental in using Python, any other framework that has a good-enough abstraction of SQL connections, like e.g. JDBC [3], could be used.

Upon opening a connection at the middleware, the client's tenant ID, C, is derived from the connection string and used throughout the entire lifetime of that connection. Whenever a client sends a MTSQL statement s, first if s contains a complex scope, a SQL query q_s is derived from this scope and evaluated at the DBMS in order to determine the relevant dataset D. After, that D is compared against privileges of C in the `Tenant` table and *ttids* in D without the corresponding privilege are pruned, resulting in D'. Next, s, C and D' are input into the rewrite algorithm which produces a rewritten SQL statement s'. s' is then sent to the DBMS before relaying the result back to the client. Note that in order to guarantee correctness in the presence of updates, q_s and s' have to be executed within the same transaction and with a consistency level at least *repeatable-read* [12] (even if the client does not impose any transactional guarantees). If s is a DDL statement, the middleware also updates the MT-Specific meta information in the DBMS and the cache.

The rest of this section explains the MTSQL-to-SQL rewrite algorithm in its canonical form and proves its correctness with respect to § 2.4, while Section 4 shows how to optimize the rewritten queries such that they can be run on the DBMS with reasonable performance.

3.1 Canonical Query Rewrite Algorithm

Our proposed canonical MTSQL-to-SQL rewrite algorithm works top-down, starting with the outer-most SQL query and recursively rewriting sub-queries as they come along. For each sub-query, the SQL clauses are rewritten one-by-one. The algorithm makes sure that for each sub-query the following invariant holds: the result of the sub-query is filtered according to D' and presented in the format required by C.

In the following, we will look at the rewrite functions for the different SQL clauses. As explaining this in detail would take the space of an entire paper on its own, we only provide the high-level ideas and illustrate them with suitable minimal examples. However, we strongly encourage the interested reader to check-out the Haskell code [6], which in fact almost reads like a mathematical definition of the algorithm.

SELECT The rewritten `SELECT` clause has to present every attribute a in C's format, which, if a is convertible, is achieved by two calls to the conversion function pair of a as can be seen in the examples of Listing 8. If a is part of compound expression (as in line 6), it has to be converted before the functions (in that case AVG) are applied. Note that in order to make a potential super-query work correctly, we also rename the result of the conversion, either by the new name that it got anyway (as in line 6) or by the name that it had before (as in line 3). Rewriting a Star expression (line 9) in the uppermost query also needs special attention, in order not to provide the client with confusing information, like *ttid* (which should stay invisible).

```
1 -- Rewriting a simple select expression:
2 SELECT E_salary FROM Employees; -->
3 SELECT currencyFromUniversal(currencyToUniversal(
      E_salary, ttid), C) as salary FROM Employees;
4 -- Rewriting an aggregated select expression
5 SELECT AVG(E_salary) as avg_sal FROM Employees; -->
6 SELECT AVG(currencyFromUniversal(currencyToUniversal(
      E_salary, ttid), C)) as avg_sal FROM Employees;
7 -- Rewriting star expression, hiding irrelevant info
8 SELECT * FROM Employees; -->
9 SELECT E_name, E_reg_id, E_salary, E_age FROM
      Employees;
```

Listing 8: Examples for Rewriting SELECT clause

WHERE There are essentially three steps that the algorithm has to perform in order to create a correctly rewritten `WHERE` clause (as shown in Listing 9). First, conversion functions have to be added to each convertible attribute in each predicate in order make sure that comparisons are executed in the correct (client) format (lines 2 to 6). This happens the same way as for a `SELECT` clause. Notably, all constants are always in C's format because it is C who asks the query. Second, for every predicate involving two or more `tenant-specific` attributes, additional predicates on *ttid* have to be added (line 9), unless if the attributes are part of the same table, which means they are owned by the same tenant anyway. Predicates that contain `tenant-specific` together with other attributes have to be rejected as stated in § 2.4. Last, but not least, for every base table in the `FROM` clause, a so-called D-filter has to be added to the `WHERE` clause (line 12). This filter makes sure that only the relevant data (data that is owned by a tenant in D') gets processed.

```
1  -- Comparison with a constant:
2  .. FROM Employees WHERE E_salary > 50K  -->
3  .. WHERE currencyFromUniversal(currencyToUniversal(
       E_salary,ttid),C) > 50K) ..
4  -- General comparison:
5  .. FROM Employees E1, Employees E2 WHERE E1.E_salary
       > E2.E_salary -->
6  .. WHERE currencyFromUniversal(currencyToUniversal(E1
       .E_salary,E1.ttid),C) > currencyFromUniversal(
       currencyToUniversal(E1.E_salary,E1.ttid),C) ..
7  -- Extend with predicate on ttid
8  .. FROM Employees, Roles WHERE E_role_id = R_role_id
       -->
9  .. FROM Employees, Roles WHERE E_role_id = R_role_id
       AND Employees.ttid = Roles.ttid ..
10 -- Adding D-filters for D' = {3,7}
11 .. FROM Employees E, Roles R .. -->
12 .. WHERE E.ttid IN (3,7) AND R.ttid IN (3,7) ..
```

Listing 9: Examples for Rewriting WHERE clause

FROM All tables referred by the `FROM` clause are either base tables or temporary tables derived from a sub-query. Rewriting the `FROM` clause simply means to call the rewrite algorithm on each referenced sub-query as shown in Algorithm 1. A `FROM` table might also contain a `JOIN` of two tables (sub-queries). In that case, the two sub-queries are rewritten and then the join predicate is rewritten in the exact same way like any `WHERE`.

Notably, this algorithm preserves the desired invariant for (sub)-queries: the result of each sub-query is in client format and filtered according to D', and, due to the rewrite of the `SELECT` and the `WHERE` clause of the current query, base tables are also presented in client format and filtered by D. So are joins. We conclude that the result of the current query therefore also preserves the invariant.

function REWRITEFROM($C, D, FromClause$)
  $res \leftarrow$ getBaseTables ($FromClause$)
  for all $q \in$ getSubQueries ($FromClause$) **do**
    $res \leftarrow res \cup \{$ rewriteQuery (C, D, q)$\}$
  for all $(q_1, q_2, cond) \in$ getJoins ($FromClause$) **do**
    $q_1' \leftarrow$ rewriteQuery (C, D, q_1)
    $q_2' \leftarrow$ rewriteQuery (C, D, q_2)
    $cond' \leftarrow$ rewriteWhere ($C, D, cond$)
    $res \leftarrow res \cup \{$ createJoin $(q_1', q_2', cond')\}$
  return res

Algorithm 1: Rewrite Algorithm for `FROM` clause

GROUP-BY, ORDER-BY and HAVING `HAVING` and `GROUP-BY` clauses are basically rewritten the same way like the expressions in the `SELECT` clause. Some DBMSs might throw a warning stating that grouping by a comparable attribute a is ambiguous because the way we rewrite a in the WHERE clause and rename it back to a, we could actually group by the original or by the converted attribute a. However, the SQL standard clearly says that in such a case, the result should be grouped by the outer-more expression, which is exactly what we need. `ORDER-BY` clauses need not be rewritten at all.

SCOPE Simple scopes do not have to be rewritten at all. The `FROM` and `WHERE` clause of a complex scope are rewritten the same way as in a sub-query. In order to make it a valid SQL query, the rewrite algorithm adds a `SELECT` clause that projects on the respective *ttid*s as shown in Listing 10.

```
SCOPE FROM Employees WHERE MAX(E_salary) > 180K -->
SELECT ttid FROM Employees WHERE MAX(
    currencyFromUniversal(currencyToUniversal(
    E_salary,ttid),C)) > 180K;
```

Listing 10: Rewriting a comples SCOPE expression

3.2 Algorithm Correctness

We proof the correctness of the canonical rewrite algorithm with respect to § 2.4 by induction over the composable structure of SQL queries and by showing that the desired invariant (the result of each sub-query is filtered according to D' and presented in the format required by C) holds: First, as a base, we state that adding the D-filters in the `WHERE` clause and transforming the `SELECT clause` to client format for every base table in each lowest-level sub-query ensures that the invariant holds. Next, as an induction step, we state that the way how we rewrite the `FROM` clause, as it was described earlier, preserves that property. The top-most SQL query is nothing but a composition of sub-queries (and base tables) for which the invariant holds. This means that the invariant holds for the entire query, which is hence guaranteed to deliver the correct result. □

3.3 Rewriting DDL statements

The introduction of this section already explained how to execute `CREATE TABLE` statements. Rewriting *global* constraints is also straight-forward: for global constraints, the *ttids* have to be made part of the constraint. For instance, the foreign key constraint of Listing 3 just becomes:

```
CONSTRAINT fk_emp FOREIGN KEY (E_role_id, ttid)
  REFERENCES Roles (R_role_id, ttid)
```

Tenant-specific check constraints are rewritten just like queries, so they automatically include the *ttids* where needed. The tricky question is how to implement *tenant-specific* referential integrity constraints. The way MTBase implements this, is to rewrite these constraints as check constraints. Imagine, as an example, that there is no *global* foreign key constraint on the `Employees` table and only tenant 0 adds this constraint privately. The way to rewrite this to a SQL check constraint is to make sure that the set of distinct keys in `Employees_0` is a subset of the distinct keys in `Roles_0`:

```
CONSTRAINT fk_emp_0 CHECK (SELECT COUNT(E_role_id)
  FROM Employees WHERE ttid=0 AND E_role_id
    NOT IN (SELECT R_role_id FROM Roles
      WHERE ttid=0)) = 0
```

MTBase executes `CREATE VIEW` statements by rewriting their `WHERE` clause the same way it rewrites queries (including the proper scope, D). No other modifications are needed.

3.4 Rewriting DML statements

In general, DML statements are handled exactly as specified in § 2.5. `INSERT` statements that consist of a sub-query have to be executed in two steps: First, the sub-query is rewritten and executed on the DBMS on behalf of the only tenant in D. Second, the result (which does not include any *ttids*) is extended with the *ttid* in D before being sent back to the DBMS as a simple `INSERT` statement that contains a simple list of of `VALUES`. For instance, consider tenant 0 inserting data on behalf of tenant 1 ($C = 0, D = \{1\}$) with the following statement:

```
INSERT INTO Employees VALUES E_name, E_reg_id,
    E_salary, E_age (
    SELECT E_name, E_reg_id, E_salary, E_age
    FROM Employees WHERE E_age > 40 SCOPE IN (0)
) SCOPE IN (1);
```

Firs of all, tenant 0 uses a different scope for the sub-query than for the insert because the intension here is to actually copy records from tenant 0 to tenant 1. The result of the sub-query is `('Alice', 3, 135K, 46)` (remember that the salary is rendered for tenant 1). This tuple is then converted into the format of tenant 1 and extended with its *ttid*: `(1,'Alice', 3, 135K, 46)`, before being inserted into the `Employees` table. This examples already shows some of the difficulties of executing an insert statement on behalf of somebody else. First, as `E_emp_id` and `E_role_id` are `NOT NULL`, there must either be some default values or the statement fails. For tenant 0 to provide a useful `E_role_id` for tenant 1 is difficult because it is a *tenant-specific* attribute. MTBase does not prevent a tenant from inserting *tenant-specific* attributes, even on behalf of other tenants, but it throws a warning in order to notify that the value might not make sense. Luckily, these problems do not occur with `DELETE` and `UPDATE` statements because they are applied to every tenant in D separately.

4. OPTIMIZATIONS

As we have seen, there is a canonical rewrite algorithm that correctly rewrites MTSQL to SQL. However, we will show in Table 3 that the rewritten queries often execute very slowly on the underlying DBMS. The main reason for this is that the pure rewritten queries call two conversion functions on every transformable attribute of every record that is processed, which is extremely expensive. Luckily, the execution costs can be reduced dramatically when applying the optimization passes that we describe in this section. As we assume the underlying DBMS to optimize query execution anyway, we focus on optimizations that a DBMS query optimizer cannot do (because it needs MT-specific context) or does not do (because an optimization is not frequent enough outside the context of MTBase). We differentiate between *semantic optimizations*, which are always applied because they never make a query slower and *cost-based* optimizations which are only applied if the predicted costs are smaller than in the original query.

```
-- dropping D-filter if D is the default scope:
SELECT E_age FROM Employees WHERE E_ttid IN (1,2) -->
SELECT E_age FROM Employees
-- dropping ttid from join predicate if |D| = 1:
SELECT E_age, R_name FROM Employees, Roles WHERE
    E_role_id = R_role_id AND E_ttid = R_ttid AND
    E_ttid IN (2) AND R_ttid IN (2); -->
SELECT E_age, R_name FROM Employees, Roles WHERE
    E_role_id = R_role_id AND E_ttid IN (2) AND
    R_ttid IN (2);
-- dropping conversion functions if D = {C}:
SELECT currencyFromUniversal(currencyToUniversal(
    E_salary, E_ttid),0) AS E_salary FROM Employees;
    -->
SELECT E_salary FROM Employees;
```

Listing 11: Examples for trivial semantic optimizations

4.1 Trivial Semantic Optimizations

There are a couple of special cases for C and D that allow to save conversion function calls, join predicates, and/or D-filters. First, if D is the empty/default scope that means that we want to query all data and hence D-filters are no longer required as shown in line 3 of Listing 11. Second, as shown in line 6, if $|D| = 1$, we know that all data is from the same tenant, which means that including `ttid` in the join predicate is no longer necessary. Last, if we know that a client queries her own data, i.e. $D = \{C\}$, we know that even convertible attributes or already in the correct format and can hence remove the conversion function calls (line 9).

4.2 Other Semantic Optimizations

There are a couple of other semantic optimizations that can be applied to rewritten queries. While *client presentation push-up* and conversion push-up try to minimize the number of conversions by delaying conversion to the latest possible moment, *aggregation distribution* takes into account specific properties of conversion functions (as mentioned in § 2.2.2). If conversion functions are UDFs written in SQL it is also possible to inline them. This typically gives queries an additional speed up.

4.2.1 Client Presentation and Conversion Push-Up

As conversion function pairs are equality-preserving, it is possible in some cases to defer conversions to later, for e.g. to the outermost query in the case of nested queries. While *client presentation push-up* converts everything to universal format and defers conversion to client format to the outermost `SELECT` clause, *conversion push-up* pushes this idea even more by also delaying the conversion to universal format as much as possible. Both optimizations are beneficial if the delaying of conversions allows the query execution engine to evaluate other (less expensive) predicates first. This means that, once the data has to be converted, it is already more filtered and therefore the overall number of (expensive) conversion function calls becomes smaller (or, in the worst case, stays the same). Naturally, if we delay transformation, this also means that we have to propagate the necessary *ttids* to the outer-more queries and keep track of whether data is in original, universal or client format.

```
-- before optimization
SELECT Dom.name1, Dom.sal1 as sal, COUNT(*) as cnt
    FROM (
  SELECT E1.name as name1, currencyFromUniversal(
     currencyToUniversal(E1.E_salary, E1.E_ttid), C)
     as sal1
  FROM Employees E1, Employees E2
  WHERE currencyFromUniversal(currencyToUniversal(E1.
     E_salary, E1.E_ttid), C) >
  currencyFromUniversal(currencyToUniversal(E2.
     E_salary, E2.E_ttid), C)
) as Dom GROUP BY Dom.name1 ORDER BY cnt;
-- after optmimization
SELECT Dom.name1, currencyFromUniversal(Dom.sal1, C)
     as sal, COUNT(*) as cnt FROM (
  SELECT E1.name as name1, currencyToUniversal(E1.
     E_salary, E1.E_ttid) as sal1
  FROM Employees E1, Employees E2
  WHERE currencyToUniversal(E1.E_salary, E1.E_ttid) >
      currencyToUniversal(E2.E_salary, E2.E_ttid)
) as Dom GROUP BY Dom.name1 ORDER BY cnt;
```

Listing 12: example for client presentation push-up

Listing 12 shows a query that ranks employees according to the fact how many salaries of other employees their own salary dominates. With *client presentation push-up*, salaries are compared in universal instead of client format, which is correct because of the order-preserving property (s. Definition 1) and saves half of the function calls in the sub-query.

Conversion push-up, as shown in Listing 13, reduces the number of function calls dramatically: First, as it only converts salaries in the end, salaries of employees aged less than do not have to be considered at all. Second, the WHERE clause converts the constant (`100K`) instead of the attribute (`E_salary`). As the outcome of conversion functions is immutable (s. § 2.2.2) and C is also constant, the conversion functions have to be called only once per tenant and are then cached by the DBMS for the rest of the query execution, which becomes much faster as we will see in Section 6.

```
-- before optimization
SELECT AVG(X.sal) FROM (
  SELECT currencyFromUniversal(currencyToUniversal(
     E_salary, E_ttid), C) as sal
  FROM Employees WHERE E_age >= 45 AND
  currencyFromUniversal(currencyToUniversal(E_salary,
      E_ttid), C) > 100K) as X;
-- after optimization
SELECT AVG(currencyFromUniversal(currencyToUniversal(
     X.sal, X.sal_ttid),C)) FROM (
  SELECT E_salary as sal, E_ttid as sal_ttid
  FROM Employees WHERE E_age >= 45 AND
  E_salary > currencyFromUniversal(
     currencyToUniversal(100K, E_ttid), C) as X);
```

Listing 13: example for conversion push-up

4.2.2 Aggregation Distribution

Many analytical queries contain aggregation functions, some of which aggregate on *convertible* attributes. The idea of aggregation distribution is to aggregate in two steps: First, aggregate per tenant in that specific tenant format (requires no conversion) and second, convert intermediary to universal (one conversion per tenant), aggregate those and convert the final result to client format (one additional conversion). This simple idea reduces the number of conversion function calls for N records and T different data owners of these records from $(2N)$ to $(T + 1)$. This is significant because T is typically much smaller than N (and cannot be greater).

Unfortunately, computing total aggregates from partial aggregates (aggregation distribution) does not always work. Gray et al. [25] categorize numerical aggregation functions into three categories with regard to their ability to distribute: *distributive* functions, like `COUNT`, `SUM`, `MIN`, and `MAX` distribute with functions F (for partial) and G (for total aggregation). For `COUNT` for instance, F is `COUNT` and G is `SUM` as the total count is the sum of all partial counts. There are also *algebraic* aggregation functions, e.g. AVG, where the partial results are not scalar values, but tuples. In the case of AVG, this would be the pairs of a partial sums and partial counts because the total average can be computed from the sum of all sums, divided by the sum of all counts. Finally, *holistic* aggregation functions cannot be distributed at all.

	$to(x) = c \cdot x$	$to(x) = a \cdot x + b$	to = order-preserving	to = equality-preserving
COUNT	✓	✓	✓	✓
MIN	✓	✓	✓	×
MAX	✓	✓	✓	×
SUM	✓	[✓]	×	×
AVG	✓	✓	×	×
Holistic	×	×	×	×

Table 2: Distributability of different aggregation functions for some different categories of conversion functions

We would like to extend the notion of [25] and define the *distributability of an aggregation function a with respect to a conversion function pair* $(from, to)$. Table 2 shows some examples for different aggregation and conversion functions. First of all, we want to state that, as all conversion functions have scalar values as input and output, they are always fully-`COUNT`-preserving, which means that `COUNT` can be distributed over all sorts of conversion functions. Next, we observe that all *order-preserving functions* preserve the minimum and the maximum of a given set of numbers, which is why `MIN` and `MAX` distribute over all conversion functions displayed in Table 2. We further notice that if *to* (and consequently also $from$) is just a multiplication with a constant (first column of Table 2), *to* is fully- `MIN`-, fully-`MAX`-, and fully-`SUM`-preserving, which is why these aggregation functions distribute. As `SUM` and `COUNT` distribute, `AVG`, an algebraic function, distributes as well. Finally looking at the second column of Table 2 where $from$ is a linear function, we realize that such a function is no longer `SUM`-preserving. More formally, for the set of tenants T, their lists of values $X_1, ..., X_T$, and corresponding conversion functions $f_1(x) = a_1x + b_1, ..., f_T(x) = a_tx + b_t$, their aggregated sum in universal format is:

$$\begin{aligned}
\sum_{t \in T}\left(\sum_{x \in X_t} f_t(x)\right) &= \sum_{t \in T}\left(\sum_{x \in X_t} a_t x + b_t\right) \\
&= \sum_{t \in T}\left(a_t\left(\sum_{x \in X_t} x\right) + b_t \cdot |X_t|\right) \\
&\neq \sum_{t \in T}\left(a_t\left(\sum_{x \in X_t} x\right) + b_t\right) \\
&= \sum_{t \in T}\left(f_t\left(\sum_{x \in X_t} x\right)\right)
\end{aligned}$$

We see that the very first term is not equal to the very last term, which proves that distributing `SUM` directly does not work. However, looking at the last term before the unequal symbol, we encounter the partial sum and the partial count of tenant t. We conclude that if for every tenant t the constants a_t and b_t are known, we can still compute the total sum without having to convert every single value of every tenant.

Unlike `SUM`, `AVG` can be distributed over a liner function by computing the total average as the weighted average of the partial averages. This is proven by the following series of equations:

$$\begin{aligned}
\frac{\sum_{t \in T}\left(\sum_{x \in X_t} f_t(x)\right)}{\sum_{t \in T}|X_t|} &= \frac{\sum_{t \in T}\left(\sum_{x \in X_t} a_t x + b_t\right)}{\sum_{t \in T}|X_t|} \\
&= \frac{\sum_{t \in T}\left(a_t\left(\sum_{x \in X_t} x\right) + b_t \cdot |X_t|\right)}{\sum_{t \in T}|X_t|} \\
&= \frac{\sum_{t \in T}\left(\frac{|X_t|}{|X_t|}\left(a_t\left(\sum_{x \in X_t} x\right) + b_t \cdot |X_t|\right)\right)}{\sum_{t \in T}|X_t|} \\
&= \frac{\sum_{t \in T}\left(|X_t|\left(\frac{1}{|X_t|} \cdot a_t\left(\sum_{x \in X_t} x\right) + b_t\right)\right)}{\sum_{t \in T}|X_t|} \\
&= \frac{\sum_{t \in T}\left(|X_t| \cdot f\left(\frac{1}{|X_t|}\sum_{x \in X_t} x\right)\right)}{\sum_{t \in T}|X_t|}
\end{aligned}$$

We conclude this paragraph by observing that the conversion function pair for *phone format* (s. Listings 4 and 5) is not even *order-preserving* and does therefore not distribute while the pair for *currency format* (s. Listings 6 and 7) distributes over all standard SQL aggregation functions. An example of how this can be used is shown in Listing 14.

```
-- before optimization
SELECT SUM(currencyFromUniversal(currencyToUniversal(
     E_salary, E_ttid), C)) as sum_sal FROM Employees
-- after optimization
SELECT currencyFromUniversal(SUM(t.E_partial_salary),
      C) as sum_sal FROM (SELECT currencyToUniversal(
     SUM(E_salary), E_ttid) as E_partial_salary FROM
     Employees GROUP BY E_ttid) as t;
```

Listing 14: example for conversion function distribution

4.2.3 *Function Inlining*

As explained in § 2.2.2, there are several ways how to define conversion functions. However, if they are defined as a SQL statement (potentially including lookups into meta tables), they can be directly inlined into the rewritten query in order to save calls to UDFs. Function inlining typically also enables the query optimizer of the underlying DBMS to optimize much more aggressive. In `WHERE` clauses, conversion functions could simply be inlined as sub-queries, which, however often results in sub-optimal performance as calling a sub-query on each conversion is not much cheaper than calling the corresponding UDF. For `SELECT` clauses, the SQL standard does anyway not allow to inline as a sub-query as this can result in attributes not being contained in either aggregate function or the `GROUP BY` clause, which is why most commercial DBMS reject such queries (while PostgreSQL, for instance executes them anyway). This is why the proper way to inline functions is by using a join as shown in Listing 15. Our results in Section 6 suggest, function inlining, though producing complex-looking SQL queries, result in very good query execution performance.

```
-- before optimization
SELECT currencyFromUniversal(currencyToUniversal(
     E_salary, E_ttid), C)) as E_salary FROM Employees
-- after optimization
SELECT (C1.CT_from_universal * C2.CT_to_universal *
     E_salary) as E_salary
FROM Employees, Tenant T1, Tenant T2,
     CurrencyTransform1, CurrencyTransform2
WHERE T1.T_tenant_key = C AND T1.T_currency_key =
     CurrencyTransform1.CT_currency_key AND
T2.T_tenant_key = E_ttid AND T2.T_currency_key =
     CurrencyTransform2.CT_currency_key
```

Listing 15: example for function inlining

4.3 Cost-based optimizations

§ 4.2.1 proposed to rewrite predicates in such a way that comparisons between two attributes are always done in universal format. However, as conversion functions have to be *equality-preserving* (s. Definition 1), equality predicates could be executed in any (appropriate) format. Likewise, if a conversion function is known to be *order-preserving*, also inequality predicates could be executed in any format. The question which format to use for comparison predicates in order to execute a query with minimal cost depends on the following cost factors: First, there are the costs of tenants' partial conversion functions, which might not be uniform.

Second, we have to know which portion of the data is in which format. For instance if 90% of the data is in a specific tenant format, that format is a good candidate format for predicate evaluation. While knowing the format usage frequency requires access to the database statistics, more specifically histograms, good cost estimations for UDFs are a research topic on its own [31, 28].

Our current implementation of MTBase does not do cost-based optimizations. First, because we consider it still an open question whether such optimizations should be implemented in the MTBase optimizer or rather in the query optimizer of the underlying DMBS (by teaching it the notion of conversion function pairs). Also, as query optimizers become better and better in optimizing UDFs by analyzing their algebraic properties [28], doing cost-based optimizations in MTBase might become obsolete.

One idea that could be used if we assume a uniform cost model for conversion functions, is to minimize the total number of function calls among the entire query, thereby following the ideas for *expensive predicate evaluation* proposed by Hellerstein and Stonebreaker [27]: If the total amount of tuples to be process is N, it needs N conversion function calls to bring all these tuples into universal format. If there exists a tenant-specific format F (different from the universal format) that is used in more than 50% of the tuples to be compared, using that format becomes cheaper: tuples that are in format F do not have to converted at all and the other M tuples need two conversions (first to universal and then to F). Hence the total number of conversions is: $2 \cdot M < 2 \cdot (1/2N) = N$

5. MT-H BENCHMARK

As MTSQL is a novel language, their exists no benchmark to evaluate the performance on an engine that implements it, like for instance MTBase. So far, there exists no standard benchmark for *cross-tenant query processing*, only for *data integration* [17] which does not assume the data to be in shared tables. Transactions in MTBase are not much different from standard transactions. Analytical queries, however, typically involve a lot of conversions and therefore thousands of (potentially expensive) calls to UDFS. Studying the usefulness of different optimizations passes on different analytical queries was the primary desired property for a benchmark, which is why we decided to extend the well-known TPC-H database benchmark [18]. Our new benchmark, which we call *MT-H*, extends TPC-H in the following way:

- Each tenant represents a different company. The number of tenants T is a parameter of the benchmark. *ttids* go from t to T.
- We consider `Nation`, `Region`, `Supplier`, `Part`, and `Partsupp` common, publicly available knowledge. They are therefore *global* tables and need no modification.
- We consider `Customer`, `Orders`, and `Lineitem` *tenant-specific*. While the latter two are quite obviously *tenant-specific* (each company processes their own orders and line items), customers might actually make business with several companies. However, as customer information might be sensitive and the format how this information is stored might differ from tenant to tenant, it makes sense to have specific customers per tenant.
- All the primary keys of and foreign keys to tenant-specific tables (`C_custkey`, `O_orderkey`, `O_custkey`, `L_orderkey`) are tenant-specific. If not mentioned otherwise, the attributes in `Customer`, `Orders`, and `Lineitem` are *comparable*.
- We consider two domains for *convertible attributes* and corresponding functions: *currency* and *phone format*. *currency* refers to monetary values, i.e. `C_acctbal`, `O_totalprice`, and `L_extendedprice`, and uses the conversion functions shown in Listings 6 and 7. *phone format* is used in `C_phone` with the conversion function pair of Listings 4 and 5. We modified the data generator (dbgen) of TPC-H to take the specific currency and phone formats into account. Each tenant is assigned a random *currency* and *phone format*, except for tenant 1 who gets the universal format for both.
- The TPC-H scaling factor sf also applies to our benchmark and dictates the overall size of the tables. After creating all records with dbgen, each record in `Customer`, `Orders`, and `Lineitem` is assigned to a tenant in a way that foreign-key constraints are preserved (e.g. orders of a specific tenant link to a customer of that same tenant). There are two ways how this assignment happens, either uniform (each tenant gets the same amount of records), or zipf'schen (tenant 1 gets the biggest share and tenant T the smallest). This `tenant share distribution` ρ is another parameter of the benchmark.
- We use the same 22 queries and query parameters as TPC-H. Additionally, for each query run, we have to define the client C who runs the queries as well as the dataset / scope D she wants to query.
- For query validation, we simply set $C = 1$ and $D = \{1, 2..., T\}$. Like this, we make sure to process all data and that the result is presented in universal format and can therefore be compared to expected query results of the standard TPC-H. An exception are queries that contain joins on `O_custkey = C_custkey`. In MT-H, we make sure that each order links to a customer from the same tenant, thus the mapping between orders and customers is no longer the same as in TPC-H (where an order can potentially link to any customer). For such queries, we define the result from the canonical rewrite algorithm (without optimizations) to be the *gold standard* to validate against.

6. EXPERIMENTS AND RESULTS

This section presents the evaluation of MTBase using the MT-H benchmark. We first evaluated the benefits of different optimization steps from Section 4 and found that the combination of all of these steps brings the biggest benefit. Second, we analyzed how MTBase scales with an increasing number of tenants. With all optimizations applied and for a dataset of 100 GB on a single machine, MTBase scales up to thousands of tenants with very little overhead. We also validated result correctness as explained in Section 5 and can report only positive results.

6.1 Setup

In our experiments, we used the following two setups: The first setup is a PostgreSQL 9.6 Beta installation, running on Debian Linux 4.9.2-10 on a 4x16 Core AMD Opteron 6174 processor with 256 GB of main memory. The second installation runs a commercial database (which we will call *System C*) on a commercial operating system and on the same processor with 512 GB of main memory. Although both machines have enough secondary storage capacity available, we decided to configure both database management systems to use in-memory backed files in order to achieve the best performance possible. Moreover, we configured the systems to use all available threads, which enabled *intra-query parallelism*.

6.2 Workload and Methodology

As the MT-H benchmark has a lot of parameters and in order to make things more concrete, we worked with the following two scenarios, which were already sketched in the introduction:

Scenario 1 handles the data of a business allegiance of a couple of small to mid-sized enterprises, which means there are 10 tenants with $sf = 1$ and each of them owns more or less the same amount of data (ρ =uniform).

Scenario 2 is a huge database ($sf = 100$) of medical records coming from thousands of tenants, like hospitals and private practices. Some of these institutions have vast amounts of data while others only handle a couple of patients (ρ=zipf). A research institution wants to query the entire database (D={1,2,...,T}) in order to gather new insights for the development of a new treatment. We looked at this scenario for different numbers of T.

In order to evaluate the overhead of *cross-tenant query processing* in MTBase compared to a single-tenant query processing, we also measured the standard TPC-H queries with different scaling factors. When D was set to all tenants, we compared to TPC-H with the same scaling factor as MT-H. For the cases where D had only one tenant (out of ten), we compared with TPC-H with a scaling factor ten times smaller.

Every query run was repeated three times in order to ensure stable results. We noticed that three runs are needed for the response times to converge (within 2%). Thus we always report the last measured response time for each query (with two significant digits).

All experiments were executed with both setups (PostgreSQL and *System M*). Whereas the major findings where the same on both systems, PostgreSQL optimizes conversion functions (UDFs) much better by caching their results. *System M*, on the other hand does not allow UDFs to be defined as deterministic and hence cannot cache conversion results. This section reports the result on PostgreSQL, while the numbers on System M can be found in the appendix.

6.3 Benefit of Optimizations

In order to test the benefit of the different combinations of optimizations applied, we tested *Scenario 1* with different optimization levels as shown in Table 3. From *o1* to *o4* we added optimizations incrementally, while the last optimization level (*inl-only*) only applied trivial optimizations and function inlining in order to find out whether all the other optimizations are, after all, useful.

opt level	**optimization passes**
canonical	none
o1	trivial optimizations
o2	o1 + client presentation push-up + conversion push-up
o3	o2 + conversion function distribution
o4	o3 + conversion function inlining
inl-only	o1 + conversion function inlining

Table 3: different optimization levels for evaluation

Table 4 shows the MT-H queries for different optimization levels and *Scenario 1* ($sf = 1, T = 10$) where client 1 queries her own data. As we can see, in that case, applying trivial optimizations in *o1* is enough because these already eliminate all conversion functions and joins and only the D-filters remain. Executing these filters seems to be very inexpensive because most response times of the optimized queries are close to the baseline, TPC-H with $sf = 1$. Queries 2, 11, and 16 however, take roughly ten times longer than the baseline. This is not surprising when taken into account that these queries only operate on *shared tables* which have ten times more data than in TPC-H.

Table 5 shows similar results, but for $D = 2$, which means that now conversion functions can no longer be optimized away. While most of the queries show a similar behaviour than in the previous experiment, for the ones that involve a lot of conversion functions (i.e. queries 1, 6, and 22), we see how the performance becomes better with each optimization pass added. We also notice that while function inlining is very beneficial in general, it is even more so when combined with the other optimizations.

Table 6, finally shows the results where we look at all data ($D = \{1, 2, ..., 10\}$). This experiment involves even more conversion functions from all the different tenant formats into universal. In particular, when looking again at queries 1, 6, and 22, we observe the great benefit of *conversion function distribution* (added with *o3*), which, in turn, can only work as great in conjunction with *client and conversion function push-up* because aggregation typically happens in the outermost query while conversion happens in the subqueries. Overall, *o4*, which contains all optimization passes that MTBase offers, is the clear winner.

6.4 Cross-Tenant Query Processing at Large

In our final experiment, we evaluated the cost of *cross-tenant query processing* up to thousands of tenants. More concretely, we measured the response time of conversion-intensive MT-H queries (queries 1, 6 and 22) for a varying number of tenants between 1 and 100,000, for a large dataset where $sf = 100$, and for the best optimization level (*o4*) as well as for *inlining-only*. The obtained results were then compared to plain TPC-H with $sf = 100$, as shown in Figure 5. First of all, we notice that the cost overhead compared to *single-tenant query-processing* (TPC-H) stays below a factor of 2 and in general increases very moderately with the number of tenants. An interesting artifact can be observed for query 22 where MT-H for one tenant executes faster than plain TPC-H. The reason for this is a sub-optimal optimization decision in PostgreSQL: one of the most expensive parts of query 22, namely to find customers with a specific country code, is executed with a parallel scan in MT-H while no parallelism is used in the case of TPC-H.

Level	Q01	Q02	Q03	Q04	Q05	Q06	Q07	Q08	Q09	Q10	Q11	Q12	Q13	Q14	Q15	Q16	Q17	Q18	Q19	Q20	Q21	Q22
tpch-0.1G	2.6	0.11	0.27	0.35	0.15	0.29	0.18	0.14	0.59	0.36	0.081	0.37	0.26	0.27	0.77	0.12	0.081	0.89	0.12	0.13	0.57	0.081
canonical	84	1.0	0.55	0.65	0.32	1.0	0.29	0.36	4.9	0.91	0.37	0.55	0.63	0.98	3.1	1.2	0.49	1.7	0.3	2.8	0.66	2.0
o1	2.7	1.0	0.43	0.61	0.22	0.43	0.23	0.56	3.8	0.76	0.37	0.55	0.92	0.56	0.91	1.2	0.48	1.6	0.3	2.8	0.66	0.085
o2	2.7	1.0	0.42	0.61	0.22	0.43	0.22	0.57	3.9	0.76	0.38	0.55	0.89	0.56	0.96	1.2	0.5	1.7	0.3	2.8	0.67	0.085
o3	2.7	1.0	0.43	0.61	0.22	0.43	0.23	0.56	3.9	0.76	0.37	0.55	0.92	0.56	0.91	1.2	0.48	1.6	0.3	2.8	0.66	0.085
o4	2.7	1.0	0.43	0.62	0.22	0.43	0.23	0.61	4.1	0.78	0.39	0.56	0.9	0.57	1.0	1.2	0.51	1.7	0.31	3.1	0.67	0.085
inl-only	2.7	1.0	0.42	0.65	0.22	0.43	0.22	0.57	3.8	0.76	0.37	0.55	0.92	0.56	0.92	1.2	0.48	1.6	0.3	2.8	0.66	0.085

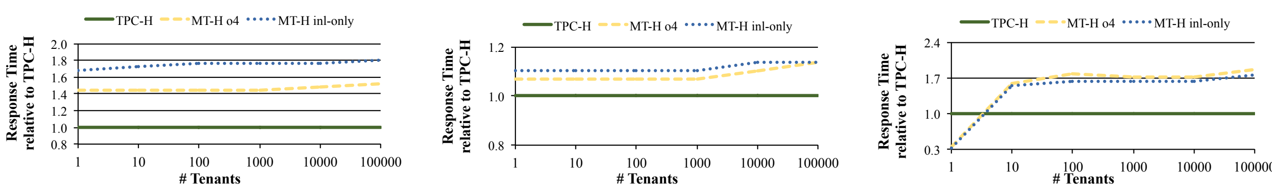
Table 4: response times [sec] of 22 TPC-H queries for MTBase-on-PostgreSQL with, $sf = 1$, $T = 10$, $\rho =$ uniform, $C = 1$, $\boldsymbol{D = \{1\}}$, for different levels of optimizations, versus TPC-H with $sf = 0.1$

Level	Q01	Q02	Q03	Q04	Q05	Q06	Q07	Q08	Q09	Q10	Q11	Q12	Q13	Q14	Q15	Q16	Q17	Q18	Q19	Q20	Q21	Q22
tpch-0.1G	2.6	0.11	0.27	0.35	0.15	0.29	0.18	0.14	0.59	0.36	0.081	0.37	0.26	0.27	0.77	0.12	0.081	0.89	0.12	0.13	0.57	0.081
canonical	87	1.0	0.5	0.6	0.28	1.0	0.26	0.37	4.9	0.89	0.37	0.56	0.65	1.0	3.2	1.2	0.49	1.6	0.31	2.8	0.66	2.0
o1	87	1.0	0.5	0.69	0.33	1.0	0.27	0.38	5.2	0.9	0.39	0.56	0.92	1.0	3.1	1.2	0.51	1.6	0.32	3.1	0.68	2.0
o2	87	1.0	0.5	0.61	0.28	1.0	0.27	0.38	5.2	0.9	0.39	0.57	0.91	1.0	3.1	1.2	0.51	1.6	0.32	3.1	0.67	1.3
o3	32	1.0	0.45	0.63	0.28	0.44	0.24	0.37	4.3	0.83	0.38	0.56	0.91	1.1	1.9	1.3	0.51	1.6	0.32	3.1	0.67	1.3
o4	14	1.0	0.48	0.62	0.22	0.44	0.23	0.57	3.9	0.93	0.38	0.56	0.89	0.73	1.3	1.2	0.49	1.6	0.3	2.8	0.66	0.27
inl-only	45	1.0	0.47	0.61	0.27	0.64	0.24	0.58	4.2	0.94	0.37	0.55	0.91	0.73	2.2	1.2	0.48	1.7	0.3	2.8	0.66	0.27

Table 5: response times [sec] of 22 TPC-H queries for MTBase-on-PostgreSQL with, $sf = 1$, $T = 10$, $\rho =$ uniform, $C = 1$, $\boldsymbol{D = \{2\}}$, for different levels of optimizations, versus TPC-H with $sf = 0.1$

Level	Q01	Q02	Q03	Q04	Q05	Q06	Q07	Q08	Q09	Q10	Q11	Q12	Q13	Q14	Q15	Q16	Q17	Q18	Q19	Q20	Q21	Q22
tpch-1G	26	1.2	4.5	1.4	1.5	2.9	3.7	1.3	9.5	2.2	0.38	3.9	8.4	2.7	5.9	1.2	0.54	10	0.3	2.4	4.8	0.47
canonical	870	1.1	6.5	1.5	3.4	8.7	3.7	1.7	19	11	0.36	4.1	4.9	7.3	28	1.2	0.57	12	0.32	2.6	5.8	20
o1	860	1.1	6.5	1.5	3.4	8.7	3.7	1.7	19	11	0.36	4.1	4.9	7.3	28	1.2	0.62	12	0.33	2.7	5.9	20
o2	870	1.1	6.5	1.5	3.4	8.6	3.7	1.7	19	11	0.35	4.1	4.9	7.2	28	1.2	0.57	12	0.32	2.6	5.8	13
o3	310	1.1	5.5	1.5	3.1	3.1	3.4	1.6	11	10	0.36	4.1	4.9	7.3	12	1.2	0.55	12	0.32	2.6	5.9	13
o4	130	1.1	3.7	1.5	1.7	3.1	3.4	1.4	11	4.6	0.38	4.1	4.9	4.4	9.1	1.2	0.59	12	0.32	2.6	5.7	2.2
inl-only	450	1.1	4	1.6	1.8	5.1	3.5	1.4	14	4.9	0.39	4.1	4.8	4.4	19	1.2	0.55	12	0.32	2.6	5.8	2.3

Table 6: response times [sec] of 22 TPC-H queries for MTBase-on-PostgreSQL with $sf = 1$, $T = 10$, $\rho =$ uniform, $C = 1$, $\boldsymbol{D = \{1, 2, ...10\}}$, for different levels of optimizations, versus TPC-H with $sf = 1$



(a) MT-H Query 1

(b) MT-H Query 6

(c) MT-H Query 22

Figure 5: response times (relative to TPC-H, $sf = 100$) of *o4* and *inlining-only* optimization levels for selected MT-H queries, T scaling from 1 to 100,000 on a log-scale, MTBase-on-PostgreSQL

7. RELATED WORK

MTBase builds heavily on and extends a lot of related work. This section gives a brief summary of the most prominent lines of work that influenced our design.

Shared-resources (SR) systems: In related work, this problem is also often called *database virtualization* or *database as a service (DaaS)* when it is used in the cloud context. Important lines of work in this domain include (but are not limited to) *SqlVM / Azure SQL DB* [35, 21], *RelationalCloud* [34], *SAP-HANA* [39], and Snowflake [19]. Most of this work is well summarized in [23]. This line of work is very important and very useful for bigger organizations. MTBase complements these systems by providing a platform that can accommodate more, but typically smaller tenants.

Shared-databases (SD) systems: This approach, while appearing in the *spectrum of multi-tenant databases* by Chong et al. [15], seems to be rare in practice. *Sql Azure DB* [21] seems to be the only product that has an implementation of this approach. However, even Microsoft strongly advises against using SD and instead recommends to either use SR or ST [4].

Shared-tables (ST) systems and schema evolution: work in that area includes Salesforce [44], Apache Phoenix [1], FlexScheme [10, 11], and Azure SQL Database [4]. Their common idea is to use an invisible tenant-identifier (ttid) to identify which records belong to which tenant and rewrite SQL queries in order to include filters on this ttid. MTBase extends these systems by first extending the SQL semantics and then extend the rewrite mechanism to account for these additional semantics, thereby providing the necessary features for cross-tenant query processing. [11] shows how FlexSchem handles extensible, evolving multi-tenant databases using a technique called *chunk folding*. By making sure that the MTSQL semantics are properly applied, MTBase could relatively easily be extended to work for chunk folding and hence provide *cross-tenant query processing* even in the presence of evolving databases.

Database Federation / Data Integration: The problem that data integration (DI) systems (like e.g. *CLIO* [37, 24] and *Potter's Wheel* [38]) try to solve is to find schema and data mappings between different schemata used by different data sources and a target schema specified by the client application. In order to relate DI to cross-tenant query processing, we could model each tenant as a data source. Consequently, MTBase in the case of *ST* solves the special sub-class of the DI problem that deals with data translation. DI is often combined with database federation [32, 26], which means that there exist small program modules (called *integrators*, *mediators*, or simply *wrappers*) to map data from different sources (possibly not all of them SQL databases) into one common format. As discussed in the introduction, maintaining such wrappers is expensive and they might have to change if a different tenant (with a different target format) wants to query the federated database. Moreover, as data is pulled from different sources and the wrappers are static, there is little or no potential for query optimization.

Data Warehousing: Another approach how data integration can happen is during extract-transform-load (ETL) operations from different (OLTP) databases into a data warehouse [29]. Data warehouses have the well-known drawbacks that there are costly to maintain and that the data is possibly outdated [13, 36, 9]. Meanwhile, MTBase was specifically designed to work well in the context of integrated OLTP/OLAP systems, also known as *hybrid transaction-analytical processing (HTAP)* systems, and could therefore be advocated as *in-situ* or *just-in-time* data integration.

Security: How to compose our proposed system with tenant data encryption as proposed in [15] is not obvious as this opens the question how tenants can process data for which they have permission to process but which is owned by another tenant (and is therefore encrypted with that other tenant's key). Obviously, simply sharing the key of tenant t with all tenants that were granted the privilege to process t's data is not a viable solution, as this allows them to impersonate t, which defeats the whole purpose of encryption. How to address this issue also depends a lot on the given attacker scenario: (Do we want to prevent tenants from each other? Do we trust the cloud provider? Do we expect honest-but-curious behaviour or active attacks?) as well as the granularity at which a tenant can share data with another tenant (schema- vs. table- vs. attribute- vs. row- vs. predicate-based, aggregations-only and possible combinations of these variants). For some of these granularities and attacker models, proposed solutions exist and can be found for example in [22, 14].

Query Optimization / Compilation: Using semantic optimizations to reduce conversion function costs comes at the possible drawback that the underlying DBMS might optimize for another cost metric, thereby possibly generating a sub-optimal overall plan in a small number of cases (as the two optimization steps happen independently from each other). A possible solution towards that end would be to integrate MTSQL directly into a query compiler / optimizer of a specific SQL-capable system instead of putting a rewrite engine on top. This would allow for multi-objective query optimization (for which an efficient algorithm exists [42]) where tuple conversion costs is just one metric among others. The challenge that query compilers are often monolythic code monsters and therefore hard to work with, could be mitigated by using a modern layered architecture with DSLs as proposed in [40].

8. CONCLUSION

This paper presented *MTSQL*, a novel paradigm to address *cross-tenant query processing* in multi-tenant databases. MTSQL extends SQL with multi-tenancy-aware syntax and semantics, which allows to efficiently optimize and execute cross-tenant queries in *MTBase*. *MTBase* is an open-source system that implements *MTSQL*. At its core, it is an MTSQL-to-SQL rewrite middleware sitting between a client and any DBMS of choice. The performance evaluation with a benchmark adapted from TPC-H showed that *MTBase* (on top of PostgeSQL) can scale to thousands of tenants at very low overhead and that our proposed optimizations to *cross-tenant queries* are highly effective.

In the future, we plan to further analyze the interplay between the *MTBase*- and the DBMS query optimizer in order to implement cost-based optimizations. We also want to study conversion functions that vary over time and investigate how MTSQL can be extended to temporal databases. Moreover, we would like to look more into the privacy issues of multi-tenant databases, in particular how to enable *cross-tenant query processing* if data is encrypted.

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APPENDIX

A. OPTIMIZATIONS ON SYSTEM M

As mentioned in Section 6, the performance numbers of MTBase on *System M* show, all in all, the similar trends for optimization functions than to the ones on PostgreSQL. The only difference is that executing conversion functions (which are implemented as UDFs) is much more expensive in *System M* because results cannot be cached. The results for *scenario 1* are shown in Tables 7 to 9.

B. TENANT SCALING ON SYSTEM M

An interesting picture can be seen for the tenant scaling experiment in Figure 6. While executing the queries for a small number of tenants (≤ 10) or a big one ($\geq 10,000$) seems to be reasonably expensive, executing queries for a mid-sized number of tenants seems to increase the costs dramatically. By looking at the query plans, we can observe that for this range of tenants the optimizer seems to do a couple of unfortunate decisions.

Level	Q01	Q02	Q03	Q04	Q05	Q06	Q07	Q08	Q09	Q10	Q11	Q12	Q13	Q14	Q15	Q16	Q17	Q18	Q19	Q20	Q21	Q22
tpch-1G	0.8	0.053	0.1	0.077	0.18	0.067	0.13	0.12	0.28	0.092	0.078	0.1	0.66	0.095	0.1	0.19	0.071	0.25	0.072	5.2	0.21	0.04
canonical	1000	0.12	230	0.17	1.7	8.7	2.6	3.0	29	10	0.3	0.25	0.66	8.0	18	1.3	2.4	26	29	0.099	0.2	79
o1	0.78	0.1	0.23	0.14	0.087	0.099	0.95	0.15	1.1	0.12	0.29	0.25	0.65	0.14	0.14	1.3	0.13	8.9	0.91	0.076	0.19	0.55
o2	0.77	0.1	0.23	0.14	0.087	0.098	0.97	0.15	1.0	0.12	0.28	0.25	0.66	0.14	0.14	1.3	0.13	8.9	0.94	0.077	0.2	3.0
o3	0.78	0.1	0.23	0.14	0.088	0.097	0.93	0.15	1.1	0.12	0.28	0.25	0.65	0.14	0.14	1.3	0.14	8.8	0.92	0.078	0.2	3.1
o4	0.78	0.1	0.3	0.14	0.089	0.099	1.0	0.15	1.0	0.12	0.29	0.25	0.66	0.14	0.14	1.3	0.14	8.9	0.92	0.078	0.2	0.59
inl-only	0.78	0.1	0.24	0.14	0.088	0.097	0.95	0.15	1.0	0.12	0.29	0.25	0.67	0.14	0.14	1.3	0.14	8.9	0.91	0.076	0.2	0.55

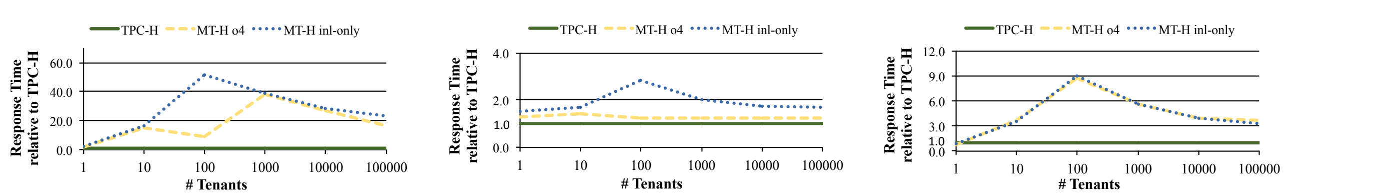
Table 7: response times [sec] of 22 TPC-H queries for MTBase-on-System-M with $sf = 10$, $T = 10$, $\rho = \text{uniform}$, $C = 1$, $\boldsymbol{D = \{1\}}$, for different levels of optimizations, versus TPC-H with $sf = 1$

Level	Q01	Q02	Q03	Q04	Q05	Q06	Q07	Q08	Q09	Q10	Q11	Q12	Q13	Q14	Q15	Q16	Q17	Q18	Q19	Q20	Q21	Q22
tpch-1G	0.8	0.053	0.1	0.077	0.18	0.067	0.13	0.12	0.28	0.092	0.078	0.1	0.66	0.095	0.1	0.19	0.071	0.25	0.072	5.2	0.21	0.04
canonical	1100	0.13	240	0.18	1.6	9.0	1.8	2.7	29	10	0.29	0.25	0.66	7.9	18	1.3	2.3	26	28	0.12	0.2	80
o1	1100	0.12	250	0.16	1.6	9.0	1.8	2.9	30	11	0.29	0.25	0.68	7.9	18	1.3	2.4	26	29	0.13	0.19	80
o2	1100	0.11	240	0.18	1.6	8.9	14	2.9	40	10	0.29	0.25	0.67	7.8	18	1.3	2.2	26	28	0.11	0.2	80
o3	240	0.12	4.2	0.18	1.1	1.0	3.2	3.0	17	3.4	0.3	0.25	0.66	8.1	9.2	1.3	2.4	26	28	0.11	0.2	79
o4	1.1	0.1	0.17	0.14	0.15	0.099	0.91	0.16	0.94	2.1	0.31	0.25	0.67	0.34	0.29	1.3	0.15	1.5	1.1	0.089	0.2	1.2
inl-only	1.7	0.13	0.2	0.14	0.15	0.1	0.78	0.17	1.1	0.19	0.28	0.25	0.61	0.33	0.21	1.3	0.15	1.5	12	0.099	0.2	1.1

Table 8: response times [sec] of 22 TPC-H queries for MTBase-on-System-M with $sf = 10$, $T = 10$, $\rho = \text{uniform}$, $C = 1$, $\boldsymbol{D = \{2\}}$, for different levels of optimizations, versus TPC-H with $sf = 1$

Level	Q01	Q02	Q03	Q04	Q05	Q06	Q07	Q08	Q09	Q10	Q11	Q12	Q13	Q14	Q15	Q16	Q17	Q18	Q19	Q20	Q21	Q22
tpch-10G	7.9	0.097	0.94	0.81	1.6	0.83	0.92	0.68	2.5	0.85	0.27	1.1	5.5	0.92	0.9	1.3	0.7	2.6	0.76	0.14	2.0	0.32
canonical	11000	0.14	2500	1.7	28	90	20	38	200	1100	0.3	1.2	6.3	73	180	1.3	2.1	69	29	0.17	3.3	800
o1	11000	0.13	2500	1.6	28	90	21	37	190	1100	0.3	1.2	6.2	74	180	1.3	2.0	69	29	0.16	3.3	800
o2	11000	0.15	2400	1.7	29	90	24	39	310	1100	0.3	1.2	6.2	74	180	1.4	2.1	69	30	0.17	3.4	790
o3	2400	0.12	43	1.7	22	9.8	18	35	64	52	0.31	1.2	6.3	74	65	1.3	1.9	69	30	0.16	3.4	790
o4	38	0.13	1.1	1.6	0.59	0.97	1.6	1.2	5.3	29	0.31	1.2	6.2	1.1	2.4	1.3	0.83	11	1.3	0.14	3.4	0.75
inl-only	42	0.13	1.8	1.7	1.6	1.2	9.8	1.2	5.5	13	0.3	1.2	6.3	1.1	1.6	1.3	0.84	11	17	0.18	3.4	0.53

Table 9: response times [sec] of 22 TPC-H queries for MTBase-on-System-M with $sf = 10$, $T = 10$, $\rho = \text{uniform}$, $C = 1$, $\boldsymbol{D = \{1, 2, ...10\}}$, for different levels of optimizations, versus TPC-H with $sf = 10$



(a) MT-H Query 1

(b) MT-H Query 6

(c) MT-H Query 22

Figure 6: response times (relative to TPC-H, $sf = 100$) of *o4* and *inlining-only* optimization levels for selected MT-H queries, T scaling from 1 to 100,000 on a log-scale, MTBase-on-System M