# NoSQL Schema Design for Time-Dependent Workloads

Yusuke Wakuta

CyberAgent, Inc.

Tokyo, Japan

wakuta\_yusuke@cyberagent.co.jp

Michael Mior
Department of Computer Science
Rochester Institute of Technology
Rochester, NY, USA
mmior@mail.rit.edu

Teruyoshi Zenmyo

CyberAgent, Inc.

Tokyo, Japan
zenmyo\_teruyoshi@cyberagent.co.jp

Yuya Sasaki

Graduate School of Information Science and Technology

Osaka University

Osaka, Japan

sasaki@ist.osaka-u.ac.jp

Makoto Onizuka

Graduate School of Information Science and Technology

Osaka University

Osaka, Japan

onizuka@ist.osaka-u.ac.jp

Abstract—In this paper, we propose a schema optimization method for time-dependent workloads for NoSQL databases. In our proposed method, we migrate schema according to changing workloads, and the estimated cost of execution and migration are formulated and minimized as a single integer linear programming problem. Furthermore, we propose a method to reduce the number of optimization candidates by iterating over the time dimension abstraction and optimizing the workload while updating constraints.

Index Terms—NoSQL, Schema evolution, time-dependent workload, Integer Linear Programming

## I. INTRODUCTION

Frameworks for big data management are widely used in many applications, such as Web services, IoT applications, and scientific analysis. These applications need to manage petabyte-scale data. In particular, NoSQL databases are one of the important frameworks for such large-scale big data management. Historically, many NoSQL databases have their roots in systems such as BigTable [7], Amazon Dynamo [10], and Yahoo! PNUTS [8]. Some recent examples of NoSQL databases are Google F1 [23] and Spanner [9]: most of these systems are classified as wide-column store (or extensible record store), a general type of NoSQL databases.

In most of the above applications, workloads follow common time-dependent patterns, such as cycles, growth and spikes, or workload evolution [18]. We focus on predictable or pre-scheduled patterns that are common features in automated IoT applications and scientific analysis. Specifically, we describe two such examples:

• **IoT applications.** An electric power company utilizes an analytic pipeline to collect power usage from 7.5 million smart meters, put them into a distributed database system, aggregate the power usage, compute its total cost, and then notify electrical power retailers in a timely fashion [22].

Astronomical data analysis. Astronomers use an analytic pipeline to capture images, transform data, calibrate parameters, identify objects, and detect transients and variables [25]. The National Astronomical Observatory of Japan provides a database service on the Web to support such pipelines for astronomers. The database stores 436 million objects and works on a distributed database system [1]. A large number of different queries are executed on the database depending on the type of analysis tasks.

An important feature of those automated analysis pipelines is that they form predictable patterns: workloads are scheduled in advance and they are repeated for a certain time period, such as every day or every week. So, we can significantly improve the performance of database systems by appropriately designing database schema based on such predictable patterns.

Technical trend and Major issues: Schema design on NoSQL is crucial for achieving high performance for largescale big data management. There has been significant research on automated schema design on relational databases [3], [4], [16], [26], NoSQL [19], [20], [24], and cloud-scale environment [12], [15]. Since our target is a large-scale big data management, we focus on the technical trend of schema design techniques for NoSQL (see Section V for relational databases). Most existing work assumes that the workload is static (does not change dynamically). That is, they use an average workload aggregated from a dynamic time-dependent workload. As an example, NoSOL Schema Evaluator (NoSE) [19] leverages integer linear programming (ILP) for schema design to optimize the execution cost of static workload. However, NoSE is not effective for a timedependent workload because its average workload may not be a good approximation for the whole workload. Also, there is another type of research that adaptively changes schemas as workload changes. CONST [20] is one such example, which heuristically changes schema design over time. However, it ignores the cost of database migration when schema changes so it does not generate optimal schema designs for timedepended workloads.

Technical challenges: To tackle the above weaknesses of existing techniques, we take an approach for optimizing timeseries schema of taking both the execution cost of time-dependent workload and database migrations into account. However, if we naively extend existing techniques designed for static workloads to dynamic time-dependent ones, we have three obstacles for finding optimal answers using ILP: 1) we need to handle the trade-off between the cost of time-dependent workload execution and database migration, 2) the number of schema candidates blows up depending on the number of migration plan candidates also blows up depending on the number of schema candidates. Here, a migration plan indicates a database transformation from old schema to new schema.

Contributions: We propose new techniques for optimizing time-series schema by effectively reducing the number of schema candidates and the number of migration plan candidates. The novelty of our proposal is three-fold.

First, we formulate the optimization problem of time-series schema with a single integer linear program for minimizing the total cost of time-dependent workload execution and database migration. Second, we propose an efficient schema candidate pruning technique by introducing a new data structure which we call a workload summary tree. We decompose the ILP of the original time-dependent workload via approximation into hierarchical local ILPs of smaller sub-workloads. This technique is scalable by effectively pruning uninteresting schema candidates, since each local ILP works efficiently with a small number of time steps while capturing the global feature of its parent workload. Finally, we propose an effective technique that reduces the number of migration plan candidates. We notice that workload changes cause optimized query plan changes, which necessitate a database migration. So, we can effectively reduce the number of migration plan candidates by restricting them according to how optimized query plans are changed instead of considering arbitrary migration plans.

Paper organization: The rest of this paper is organized as follows. We describe the problem statement and the challenges of schema design problem for time-dependent workload (Section II) and then formulate it with a single integer linear program (Section III). We describe the detail of our approach (Section IV). We finally position our proposal with respect to the state of the art (Section V) and give concluding remarks (Section VI).

## II. PRELIMINARY

In this section, we describe a schema optimization problem for time-dependent workloads on NoSQL databases, in particular on extensible record stores [6].

# A. Extensible Record Store

An extensible record store, such as Apache Cassandra, is a general type of NoSQL databases that achieves high scalability by partitioning database in distributed multiple nodes. Extensible record stores utilize column families (CFs) for expressing database schema. We treat CFs as physical schema, which is derived from conceptual schema expressed with an entity graph [19] (simplified ER model). CFs contain three types of columns, partition key, clustering key, and value. partition key is a key used for database (range or hash) partitioning over multiple nodes. clustering key is a sorting key used inside for each node. Other columns are treated as values. CF is expressed in the following notation:

$$[partition \ keys][clustering \ keys] \rightarrow [values]$$

The notation indicates a functional dependency from (partition keys, clustering keys) pair to values.

## B. Time-dependent Workloads

We focus on predictable or pre-scheduled time-dependent workload patterns, such as cycles, growth and spikes, and workload evolution [18], which are common patterns in automated IoT applications and scientific analysis. In such workloads, all the queries and update operations are often known or predictable beforehand. A time-depended workload W denotes a collection of SQL statements, queries Q and update operations U, on a conceptual (relational) schema and only the frequency of each query/update operation changes over time<sup>1</sup>. Since the frequencies of queries/update change, we may need database migrations for reducing the total cost of the workload execution and the migration. For example, a more denormalized schema should be chosen when the workload is read-intensive. This motivates us to optimize time-series physical schema over time-dependent workloads on extensible record stores.

# C. Problem statement

Given a time-dependent workload, a conceptual schema, and a maximum storage size as a constraint, we identify an optimized time-series physical schema (set of column families) by minimizing the total cost of the workload execution and database migration. As a result of schema optimization, we also output optimized query plans using the physical schema at each time step and migration plans between the schemas of different time steps. A query plan is expressed on a physical schema, which is generated from a SQL statement in a workload W: it consists of multiple steps using filtering, sorting, and aggregation. A migration plan transforms old column families into a new column family, which is generated from a migration query. Notice that we generate migration queries from workload queries Q, since database migration is usually made for reducing query cost by materializing query results (See migration plan enumeration in Section IV-D for more detail). In addition, new column families are incrementally maintained and workload continues execution during database migration.

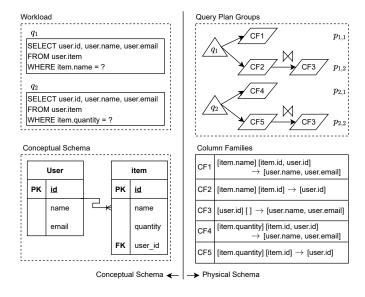


Fig. 1. An example of schema design obtained from a conceptual schema for two queries,  $q_1, q_2$ . A query plan group is generated on the column families enumerated from the columns used in each query.

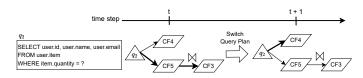


Fig. 2. An example of changing query plans (the orange arrows indicate the chosen plan). The workload execution cost is reduced by changing the query plan according to the query frequency changes at each time step.

## D. Query/migration plan group

We introduce query plan groups, a collection of query plans that are transformed from each SQL query in the workload<sup>2</sup>. We choose a single optimized query plan in a query plan group at every time step by schema optimization. We express a query plan as a path of steps (serialized from a typical query plan tree) where each step represents an operation, Get which fetches data from a column family. We call these steps Get steps for simplicity. Query plans in prior work [19] not only have Get steps but also has an ORDER BY step on column families at the server side additionally with join/filtering/sort steps that are executed at the application side. We also express a query plan group using a tree structure which nodes with the same parent share a prefix of their query plans. We call a query plan with a single Get step a materialized view (MV) plan and also call one with multiple Get steps a join plan. MV plans are efficient for query processing since they don't need join operations between column families. In contrast, join plans use multiple normalized column families so they are efficient for update processing and saving storage size. However, they require expensive join operations between the column families, since extensible record stores do not support join operations at the server side so the join operations need to be made at the application side.

Next, we introduce migration plan groups, a collection of migration plans that are transformed from a migration query. A migration plan generates a new column family at the next time step using schema at the current time step. We choose a single optimized migration plan among multiple migration plan groups obtained from migration queries by schema optimization.

## E. Examples of optimizing time-series schema

Figure 1 depicts an example of schema design obtained from a conceptual schema for two queries,  $q_1, q_2$ . A query plan group is generated on the column families enumerated from the columns used in each query. In Figure 1,  $p_{1,1}$  and  $p_{2,1}$  are MV plans, and  $p_{1,2}$  and  $p_{2,2}$  are join plans. For example, query plan  $p_{1,2}$  first extracts records from CF2 using an equality predicate on item.name in query q1 and then extracts records from CF3 using user.id as the join key from CF2 to CF3. Since join operations need to be made at the application side, the join plan  $p_{1,2}$  is significantly slower than the MV plan  $p_{1,1}$ . However, the join plan  $p_{1,2}$  requires less storage size than the MV plan  $p_{1,1}$ , since  $p_{1,2}$  uses denormalized schema, CF2, CF3.

Next, Figure 2 depicts an example of changing query plans for a time-dependent workload. We assume that 1) MV plans cannot be chosen both for  $q_1$  and  $q_2$  because of insufficient storage size, and 2)  $q_1$ 's frequency is larger than  $q_2$ 's at time t and they are reversed at time t+1;  $q_1$ 's frequency becomes smaller than  $q_2$ 's. In this case, a join plan is chosen for  $q_2$  at time t and it is switched to a MV plan at time t+1 due to the query frequency change. Such query plan changes reduce the workload execution cost at every time step, however they require the additional cost of database migrations. Therefore, we need to choose an optimized time-series schema by considering the trade-off between workload execution cost and migration cost.

## III. PROPOSED OPTIMIZATION FORMULA

We formulate the problem of time-series workload optimization using a single integer linear program (ILP) and output an optimized time-series schema, query plans at every time step, and migration plans between adjacent time steps. The benefit of this approach is that it formulates the total cost of time-dependent workload execution and database migration using a single ILP, so it can handle the trade-off between the cost of time-dependent workload and database migration.

For a given time-dependent workload consisting of queries Q and update operations U, we obtain an optimized time-series schema  $(S_1,...,S_T)$  from time step t=1 to T by minimizing the following objective function using three constraints for query plans, migration plans, and storage size.

**Objective function:** The objective of optimizing time-series

<sup>&</sup>lt;sup>1</sup>A new query appears if its frequency is changed from zero.

<sup>&</sup>lt;sup>2</sup>We similarly treat update operations as queries in the workload.

physical schema  $(S_1, \ldots, S_T)$  is to minimize the total cost of time-dependent workload execution and database migration.

$$\min_{S_1,\dots,S_T} \sum_{t=1}^T workload(S_t) + \sum_{t=1}^{T-1} migrate(S_t, S_{t+1})$$
 (1)

where  $workload(S_t)$  indicates the workload execution cost on schema  $S_t$  at time step t, and  $migrate(S_t, S_{t+1})$  indicates the migration cost from schema  $S_t$  to  $S_{t+1}$ . If there is no migration  $(S_t = S_{t+1})$ , then  $migrate(S_t, S_{t+1}) = 0$ .

## A. Workload execution cost

Workload execution cost is defined as the total cost of all queries and update operations in the workload; each query/update operation cost is computed as the product of its frequency and its estimated execution cost. In detail, we define the workload execution cost at time step t as follows:

$$workload(S_t) = \sum_{q_i \in Q} \sum_{cf_j \in CF(P(q_i))} f_i(t)C_{ij}\delta_{ijt} + \sum_{u_u \in U} \sum_{cf_n \in S(t)} f_u(t)C'_{un}\delta_{nt}$$

$$(2)$$

where  $P(q_i)$  is a query plan group enumerated from  $q_i$  and  $CF(P(q_i))$  is a set of column families enumerated from  $q_i$ used in query plan group  $P(q_i)^3$ . The first and the second terms on the right-hand side express query cost and update operation cost, respectively. The first term,  $f_i(t)$  is the frequency of query i at time step t and  $C_{ij}$  is the coefficient that represents the cost of query i using column family  $cf_i$ .  $\delta_{ijt}$ is a binary decision variable which expresses whether query  $q_i$  uses column family  $cf_j$  at time step t. Thus, the query cost is the summation of  $f_i(t)C_{ij}\delta_{ijt}$  for all combinations of queries and column families. The second term,  $f_u(t)$  is the frequency of update operation u at time step t and  $C'_{un}$  is the coefficient that represents the cost of update operation ufor column family  $cf_n$ .  $\delta_{nt}$  is a binary decision variable which expresses whether column family n exists in schema  $S_t$  at time step t. Thus, the update cost is the summation of  $f_u(t)C'_{un}\delta_{nt}$ for all combinations of update operation u and column family n.

#### B. Migration cost

Remember that we choose a single optimized migration plan among multiple migration plan groups obtained from migration queries. We define the database migration cost from old schema  $S_t$  to new schema  $S_{t+1}$  using multiple migration queries as follows:

$$migrate(S_{t}, S_{t+1}) = \sum_{cf_{g} \in S_{t+1}} \sum_{cf_{h} \in CF(P(q'_{o})), q'_{o} \in M(cf_{g})} C_{h}^{E} \delta_{goht}^{E} + \sum_{cf_{g} \in S_{t+1}} C_{g}^{L} \delta_{g(t+1)}^{L}$$

$$+ \sum_{u_{u} \in U} \sum_{cf_{g} \in S_{t+1}} C_{ug}^{U} \delta_{g(t+1)}^{L}$$
(3)

where  $M(cf_g)$  is migration queries for target column family  $cf_g \in S_{t+1}$ , migration plan group  $P(q'_o)$  and set of column families  $CF(P(q'_o))$  for migration query  $q'_o$  are similarly defined in the workload execution cost (Equation (2)).

The first term on the right-hand side expresses the cost of collecting records from old schema using migration plans.  $C_h^E$  is the coefficient that represents the cost of data collection from each column family  $cf_h$ .  $\delta_{goht}^E$  is a binary decision variable that expresses whether migration query  $q_o'$  uses old column family  $cf_h$  for generating new column family  $cf_g$  at time step t. Thus, the cost of collecting records from the old schema is the summation of  $C_h^E \delta_{goht}^E$  for all combinations of column family  $cf_g$ , migration query  $q_o'$ , and column family  $cf_h$ .

The second term expresses the cost of inserting the collected records into a new schema.  $C_g^L$  is the coefficient that represents the cost of inserting the collected records into new column family  $cf_g$ .  $\delta_{g(t+1)}^L$  is a binary decision variable that expresses whether database migration to column family  $cf_g$  is made between time step t and t+1. If  $\delta_{g(t+1)}^L=1$  then column family  $cf_g$  does not exist at time step t and exists at t+1, so we introduce the following constraint (4):

$$\delta_{q(t+1)} - \delta_{qt} \le \delta_{q(t+1)}^L \tag{4}$$

The third term expresses the cost of maintaining the new schema for ongoing update operations U in workload.  $C_{ug}^U$  is the coefficient that represents the cost of update operation  $u \in U$  for new column family  $cf_q$  during the migration process.

## C. Constraints

We introduce three constraints for query plans, migration plans, and storage size in order to choose column families required for optimized query/migration plans and avoid generating unused column families.

1) Constraints for query plans: Constraints for query plans ensure that for each query  $q_i \in Q$  at every time step t, 1) we choose a single optimized query plan  $p_t$  among query plan group  $P(q_i)$  (constraint (5, 6)), and 2) all column families used in optimized query plan  $p_t$  should exist in schema  $S_t$  (constraint (7)). A decision variable is appropriately assigned to each  $\delta_{ijt}$  and  $\delta_{nt}$  in Equation (2) using these constraints.

The first constraint (5) ensures that if column family  $cf_j$  is used in query plan  $p_t$ , any other column family  $cf_l$  that precedes  $(\prec)$   $cf_j$  in the same query plan needs to be chosen.

$$\forall cf_j, cf_l \in CF(P(q_i)). \ cf_l \prec_{p_t} cf_j \rightarrow \delta_{ilt} \geq \delta_{ijt}$$
 (5)

where  $\delta_{ijt}$  expresses whether query  $q_i$  uses column family  $cf_j$  at time step t (introduced in Equation (2)).

The second constraint (6) ensures that we produce a single unique query plan that joins all adjacent entities in a query graph.

$$\forall e, e' \in Entity(q_i).$$

$$\sum_{\{cf_j \in CF(P(q_i)) | e, e' \in Entity(cf_j)\}} \delta_{ijt} = 1$$
(6)

<sup>&</sup>lt;sup>3</sup>See Section IV for the detail of column family enumeration.

 $<sup>{}^{4}\</sup>delta^{E}_{goht} = 0$  when  $cf_g$  is not newly generated at time step t for all  $cf_h$ .

where  $Entity(q_i)$  is an entity set used in query  $q_i$ , e and e' are entities that are adjacent in  $q_i$ 's query graph<sup>5</sup> [19], and  $Entity(cf_j)$  is a entity set from which column family  $cf_j$  is generated. The constraint (6) ensures that only single column family  $cf_j$  is chosen from  $CF(P(q_i))$  for partial columns of each adjacent entity pair e, e' used in  $q_i$  at every time step t (specified by  $\sum \delta_{ijt} = 1$ )<sup>6</sup>.

The third constraint (7) ensures that if query plan  $p_t$  is chosen as the optimized plan for  $q_i$  at time step t, all column families  $(cf_j)$  used in  $p_t$  should exist at the same time step.

$$\forall cf_i \in CF(P(q_i)). \ \delta_{it} \ge \delta_{ijt}$$
 (7)

That is, if  $\delta_{ijt} = 1$  then  $\delta_{jt} = 1$  (remember that  $\delta_{jt}$  was introduced in Equation (2)).

As an example, we give the following constraints for  $q_2$  at time step t in Figure 2.

$$\delta_{2,5,t} \ge \delta_{2,3,t} \tag{8a}$$

$$\delta_{2,4,t} + \delta_{2,5,t} = 1, \delta_{2,3,t} + \delta_{2,4,t} = 1$$
 (8b)

$$\delta_{j,t} \ge \delta_{2,j,t} \quad \forall j \in \{3,4,5\} \tag{8c}$$

where (8a), (8b), and (8c) are instantiated from general constraints (5), (6), and (7), respectively. Constraint (8a) ensures that CF5 is chosen whenever CF3 is used. The left-hand side of Constraint (8b) specifies choosing either CF4 or CF5 for partial columns of an adjacent entity pair (*Item* and *User*), and the right-hand side specifies choosing either CF3 or CF4 for partial columns of a leaf entity (*User*, see footnote<sup>6</sup>). Finally, constraint (8c) ensures that  $S_t$  contains CF3, CF4, CF5 if they are used in the optimized query plan of  $q_2$ .

2) Constraints for migration plans: Constraints for migration plans ensure that for each target column family  $cf_g \in S_{t+1}$  (specified by  $\delta^L_{g(t+1)} = 1$ ), 1) we choose a single migration plan based on the migration queries for the target column family  $cf_g$  (constraints (9),(10),(11)) and 2) all column families used in the chosen migration plan should exist in  $S_t$  (constraint (12)). A decision variable is appropriately assigned to each  $\delta^E_{goht}$  and  $\delta^L_{g(t+1)}$  in Equation (3) using theses constraints.

Similarly to the constraint (5) for query plans, the first constraint (9) ensures that if the previous column family  $cf_h$  is used in a migration plan, any other column family  $cf_l$  that precedes  $(\prec)$   $cf_h$  in the same migration plan needs to be chosen.

$$\forall q_o' \in M(cf_g), \ \forall cf_h, cf_l \in CF(P(q_o')).$$

$$cf_l \prec cf_h \to \delta_{aolt}^E \ge \delta_{aoht}^E$$
(9)

where  $\delta^E_{golt}$  and  $\delta^E_{goht}$  express whether old column family  $cf_l$  and  $cf_h$  exists in schema  $S_t$ , respectively.

We choose a single migration plan from migration queries for target column family  $cf_q$  in two steps as follows. In

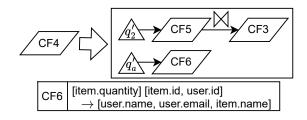


Fig. 3. An example of enumerated migration plans for collecting data of CF3 in Fig. 2. In order to collect data for CF3, we generate migration query  $q_1'$ ,  $q_2'$  and  $q_a'$  and enumerate their migration plan groups using our proposed method (described in Section IV-D).

the first step, we choose single migration query  $q_o'$  from the migration queries  $M(cf_g)$  (specified by  $\sum \delta_{got}^T = 1$ ) when target column family  $cf_g$  is generated at time step t+1 (specified by  $\delta_{g(t+1)}^L = 1$ ) using the second constraint (10).

$$\sum_{q_o' \in M(cf_g)} \delta_{got}^T = \delta_{g(t+1)}^L \tag{10}$$

In the second step, we choose a single migration plan for the migration query chosen in the first step. Similarly to the constraint (6) for query plans, the third constraint (11) ensures that only a single column family is chosen (specified by  $\sum \delta^E_{gomt} = \delta^T_{got}$ ) for partial columns of adjacent entity pair e,e' in the migration query graph from each migration plan group transformed from  $q'_o$  at every time step t.

$$\forall e, e' \in Entity(cf_g).$$

$$\sum_{\{cf_m \in CF(M(cf_g)) | e, e' \in Entity(cf_m)\}} \delta_{gomt}^E = \delta_{got}^T \quad (11)$$

where  $\delta^T_{got}$  is a binary decision variable that expresses whether an optimized migration plan for the target column family  $cf_g$  is chosen from migration plan group  $P^M_o$  at time step t.

Similarly to the constraint (7), the fourth constraint (12) ensures that if a migration plan is chosen as the optimized plan for generating  $cf_g$  at time step t, all column families  $(cf_h)$  used in the optimized migration plan should exist at the same time step.

$$\forall q'_o \in M(cf_g), \forall cf_h \in CF(P(q'_o)). \ \delta_{ht} \ge \delta^E_{goh(t+1)}$$
 (12)

Figure 3 depicts an example of a migration plan that generates a new column family CF4 in Figure 2. The constraints to generate a single migration plan for CF4 are described as follows.

$$\delta_{4,2,5,t}^E \ge \delta_{4,2,3,t}^E \tag{13a}$$

$$\delta_{4,a,t}^T + \delta_{4,2,t}^T = \delta_{4,t}^L \tag{13b}$$

$$\delta_{4,2,5,t}^E = \delta_{4,2,t}^T, \ \delta_{4,2,3,t}^E = \delta_{4,2,t}^T, \ \delta_{4,a,6,t}^E = \delta_{4,a,t}^T$$
 (13c)

$$\delta_{3,t} \ge \delta_{4,2,3,t}^E, \, \delta_{5,t} \ge \delta_{4,2,5,t}^E, \, \delta_{6,t} \ge \delta_{4,a,6,t}^E$$
 (13d)

where (13a), (13b), (13c), (13d), are instantiated from general constraints (9), (10), (11), (12), respectively. Constraint (13a) ensures that the preceding CF5 is also chosen when CF3

<sup>&</sup>lt;sup>5</sup>The query graph expresses a partial schema relating to a given query extracted from the entity graph. Our current implementation is restricted to acyclic query graphs as in the implementation of NoSE [19].

<sup>&</sup>lt;sup>6</sup>We permit generating a single column family for a leaf entity in the query graph.

is used in migration plan group 2. Constraint (13b) ensures that a single migration query is chosen among migration queries ( $q_a'$  and  $q_2'$ ). Constraint (13c) ensures that a single migration plan is chosen for  $q_a'$  and  $q_2'$ , respectively. Finally, constraint (13d) ensures that  $S_t$  contains all column families used in the optimized migration plan.

3) Constraint for storage size: The storage size constraint (14) ensures that the storage size of all column families should be smaller than B at every time step t.

$$\forall t \in [1, T]. \ \sum_{j} size(cf_j)\delta_{jt} \le B$$
 (14)

where size(cf) is the storage size of column family cf. We ignore the size change of column families even when workload contains update operations, since the change in size is usually quite small compared to the whole database size.

#### IV. PROPOSED SYSTEM

The optimization problem for time-series schema described in Section III does not scale due to the large size of decision variables ( $\delta_{jt}$  and  $\delta_{goht}^E$ ). For example, the size of  $\delta_{jt}$  is the product of the number of column families and the number of time steps. This is caused by the fact that the number of schema candidates blows up depending on the number of time steps, and the number of migration plan candidates also blows up depending on the number of queries and schema candidates. To overcome these obstacles, we propose a system for optimizing time-series schema by effectively reducing the number of schema (column family) candidates as well as the number of migration plan candidates.

First, we propose a novel column family pruning technique for time-dependent workload by introducing workload summary tree. The workload summary tree approximates the ILP for the original workload using multi-level of workload summaries and the pruning technique effectively identifies uninteresting column families by leveraging the workload summary tree. The novel idea is that we identify uninteresting column families that are never chosen as ILP answers at any nodes in the tree. This approach is scalable because each summarized sub-workload at each node consists only of three time steps so we can largely reduce the size of decision variables for the ILP of each summarized sub-workload.

Second, we propose an effective technique that reduces the number of migration plan candidates. Notice that workload changes cause optimized query plan changes, which necessitate database migration. Our idea is that we can effectively reduce the number of migration plan candidates by restricting them according to how optimized query plans are changed instead of enumerating all possible candidates.

## A. System Overview

Figure 4 depicts an overview of our system. Our system identifies an optimized time-series schema and outputs optimized query plans and migration plans using the following procedures: column family pruning (Section IV-B), column family and query plan enumeration (Section IV-C), migration

plan enumeration (Section IV-D), cost estimation (Section IV-E), and optimization (Section IV-F).

## B. Column family pruning using workload summary tree

The objective function described in Section III indicates that the decision variable size increases linearly to the time step size used in a time-dependent workload. So, the optimization problem by ILP does not scale to a large number of time steps. To tackle this issue, we propose a novel column family pruning technique for time-dependent workload by introducing novel hierarchical data structure, workload summary tree. The workload summary tree approximates ILP of the original workload in multi-level of workload summaries and the pruning technique effectively identifies uninteresting column families by leveraging the multi-level of workload summaries.

- 1) Workload summary tree: We introduce workload summary tree in order to approximate ILP of the original workload. We design the workload summary tree to have the following features, 1) every child node represents a sub-workload split in time-scale from the workload of its parent node, and 2) every parent node's workload is summarized from its children's sub-workload. Therefore, the root node represents a highly summarized whole workload with small time steps and each leaf node represents an unsummarized sub-workload split. Each intermediate node represents a summarized subworkload split. In detail, we design the workload summary tree as a binary tree<sup>7</sup>. Each node manages sub-workload with three time steps (minimum, median, maximum). The workload managed at each parent node represents the summary of the workloads of its child nodes: the left child manages the left half of the parent workload (between the minimum and median time steps) and the right child manages the right half (between median and maximum time steps).
- 2) Column Family Pruning Algorithm: By leveraging the novel workload summary tree, our pruning technique effectively identifies uninteresting column families using the multilevel of workload summaries: the upper level captures global aspects and the lower level captures more local aspect of the workload. Moreover, in order to take the global aspect from the upper level into account at the lower level, we propose a novel algorithm that recursively constructs an ILP for the summarized workload assigned to each node starting from the root and translates its answer as the ILP constraint of its child sub-workload. In detail, the constraint enforces the ILP of child workloads to inherit optimized column families found at the parent workload: a child node solves local ILP so that the optimized column families at min/max time steps should be identical with the ones found at the same time steps (e.g. min and median for the left child node) at the parent workload. After computing the portion of the ILP for each node throughout the tree, we can identify uninteresting column families that are never chosen as ILP answers at any nodes in the tree. This approach is efficient, because the time step size

 $<sup>^{7}</sup>$ To make the discussion simple, we assume the time step size in the workload is  $2^{n}$ . If not, we can add additional leaf nodes for the remainder time steps.

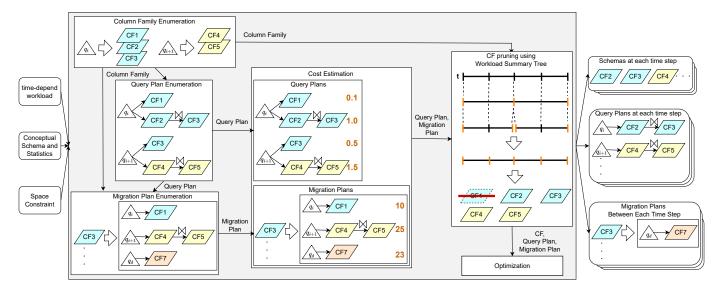


Fig. 4. An overview of proposed method.

**Algorithm 1:** Obtaining interesting column families from subtree of workload summary tree

Input: w (workload), const (ILP constraint)Output: column families chosen at least by one node of workload summary tree

```
1 Function get_subtree_cfs(w, const) is
      if min_ts + 1 is max_ts then
2
          return Ø
3
      end if
4
      // get solution of current workload
      S \leftarrow solve\_ILP(w, const)
5
       // get used CFs in the solution
      C \leftarrow S.cfs
       /* get middle time step of current
           workload
      mid\ ts \leftarrow (w.min\ ts + w.max\ ts)/2
7
       /* translate solution to the constraint
8
      const \leftarrow const()translate\_to\_const(S)
      l\_child\_w \leftarrow
        get\ child\ workload(w, w.min\ ts, mid\ ts)
      C \leftarrow C \bigcup get\_subtree\_cfs(l\_child\_w, const)
10
11
      r \ child \ w \leftarrow
        get\_child\_workload(w, mid\_ts, w.max\_ts)
12
      C \leftarrow C \bigcup get\_subtree\_cfs(r\_child\_w, const)
      return C
14 end
```

of the (sub-)workload at every node is limited to only three (minimum/median/maximum), which is significantly smaller than that of the original workload.

The detailed algorithm is given in 1.  $solve\_ILP()$  function (line 5) optimizes ILP for each node in the workload summary

tree. translate\_to\_const() function (line 8) translates the ILP answer of a current node into the constraint for its child node in order to share the optimized column families found at min\_ts, mid\_ts, max\_ts time steps. get\_child\_workload() function (line 9, 11) constructs workload for a child node for given min/max time steps. We recursively invoke get\_subtree\_cfs() function (line 10, 12) by splitting the current workload into two child sub-workloads. After the recursion (line 3, 13), the identified interesting column families are returned. We remove column families that are not contained in these interesting column families from candidates of the optimization.

# C. Column Family And Query Plan Enumeration

1) Column Family Enumeration: The purpose of this step is to enumerate column family candidates used for the optimization problem of time-series schema (Section III). Since arbitrary query plans can be chosen as optimized plans at any time step, we enumerate all possible column family candidates. To this end, we take the same approach used in existing systems [19] for column family enumeration; We decompose each query and materialize the whole query or its sub-queries as column families. Thus, we can answer a query with a single column family (query efficient MV plan) or multiple column families by joining them (update efficient join plan). In detail, we employ a query graph, which is a sub-graph of the entity graph in a conceptual schema and expresses a partial schema referred from a given query. We enumerate column family candidates by recursively decomposing query graphs; a query graph is decomposed at every node into two sub-queries that are materialized as column families. In addition, in order to increase the utilization of column families for answering queries, we employ relaxed queries [19] that are transformed from original queries by moving arbitrary attributes used in

WHERE/ORDER BY clauses to SELECT clause<sup>8</sup>. The column families materialized from relaxed queries can be used to answer more queries, because they can answer queries with fewer conditions in WHERE/ORDER BY clauses. However, the number of such column families increases exponentially with the number of query graph edges, because column families are materialized from sub-queries recursively decomposed at every edge. Moreover, it increases relative to the factorial of the number of attributes used in WHERE/ORDER BY clauses, because column family variants are sensitive to attribute order.

To overcome such significant growth in the number of enumerated column families, we propose two pruning techniques. First, we restrict the number of recursive decompositions of query graphs only to a single time for enumerating column families. Thus, we only need to enumerate MV plans and two-CF join plans for all queries. The enumerated query plans require at most a single join between column families. The number of the original queries and decomposed sub-queries becomes  $N_k = 1 + 2k$ , which is linear to the number of edges (k) in a query graph. Second, we reduce the variants of clustering keys in column families by following the features of extensible record stores: the prefix of clustering keys should contain attributes used in GROUP BY/ORDER BY clauses so that GROUP BY/ORDER BY operations can be executed on the server side. Notice that we ignore the order of the remaining part of clustering keys if they do not appear in WHERE/GROUP BY/ORDER BY clauses. Thus, we can reduce the number of column families by treating the remaining part of clustering keys to be order-insensitive.

2) Query Plan Enumeration: This step transforms each SQL query in the workload to query plans. We take the same approach proposed by Mior and Salem [19] as follows. We enumerate query plans that join column family candidates enumerated in the column family enumeration step (Section IV-C1) from all queries. Here, each query plan corresponds to reconstructing the original query graph from its decomposed subqueries. The enumerated query plans consist of three types of operations, 1) Get/Put operations for column families, 2) ORDER BY/GROUP BY at the server side, and 3) join/selection/ORDER BY/GROUP BY at the application side.

## D. Migration Plan Enumeration

The purpose of this step is to enumerate migration plan candidates used for the optimization problem of time-series schema (Section III). That is, we enumerate all possible migration plans that migrate schema from  $S_t$  to  $S_{t+1}$  at any time step t. However, column families in  $S_t$  are not decided before the schema optimization, so we enumerate migration plan candidates that generate each target column family enumerated in the column family enumeration (Section IV-C). We introduce two techniques for migration plan enumeration. The first one utilizes query plans as migration plans based on the fact that workload changes cause optimized query plan

changes, which necessitate database migration. The second one enumerates additional migration plans to complement the first one.

1) Migration plan enumeration by reusing query plans: Optimized query plan changes require generating the target column families in  $S_{t+1}$  that are used by the optimized query plans at time step t+1. We observe that if the optimized query plans at time step t and t+1 are produced from the same query, they use column families (physical schema elements) produced from the same tables (conceptual schema elements), so the former plan outputs similar target column families in  $S_{t+1}$  as those of the latter plan. Based on this observation, we can utilize query plans at time step t as migration plans from  $S_t$  to  $S_{t+1}$ . However, since optimized query plans are not decided before the schema optimization, we treat all enumerated query plans at time step t as migration plan candidates in order to permit those query plans to become optimized query plans.

In detail, we identify source queries from workload queries Q for each target column family in the enumerated column families (Section IV-C). A source query is a query whose query plans use the target column family. Then, we modify the source queries to migration queries by making the following modifications: 1) we simplify query plans by removing aggregation/ORDER BY operations that are not necessary for migration plans, and 2) we adjust the projections of the query plans to include the required columns of the target column family. Finally, we enumerate query plans for the migration queries and treat them as migration plans.

Figure 3 depicts migration plan examples generated using CF4 in Figure 1 as the target column family. Since CF4 is used in  $q_2$  query plan group, we choose this as the source query for CF4. Then, we modify  $q_2$  to migration query  $q_2'$  as follows:

SELECT item.id, user.id, user.name, user.email
FROM user.item WHERE item.quantity = ?

- $q_2'$  shares the same FROM/WHERE clauses as  $q_2$ 's but with a different SELECT clause which contains the necessary columns of CF4. Finally, we generate migration plans using  $q_2'$  and CF3 and CF5 (excluding the target column family, CF4). We obtain  $p_{2,2}$  as a migration plan which uses CF3 and CF5.
- 2) Complementary migration plan enumeration: The above enumeration technique may not enumerate appropriate migration plans when the number of query plans in each query is small. To complement this, the second technique enumerates additional migration plans using a simple migration query, which specifies the partition key and columns of the target column family in WHERE clause and SELECT clause, respectively. In Fig. 3,  $q'_a$  is simple migration query of CF4 and the second technique enumerates its migration plan uses CF6.

# E. Cost Estimation

In order to optimize the objective of Equation 1, we need to estimate the coefficients used in the workload execution cost

<sup>&</sup>lt;sup>8</sup>We keep at least a single equality predicate in WHERE clause in the same way as NoSE in order to construct a valid Get request for the column family.

(Equation 2) and migration cost (Equation 3).

Remember that  $C_{ij}$  in Equation 2 is defined as the coefficient that represents the cost of query i processing using column family  $cf_i$ . We estimate it using linear regression with the function  $T(n, w, s)^9$  where n is the number of Get operations, w is the query-cardinality (the expected number of records in the result), and s is the record size of column family j. n is computed as the sum of Get operations in the query plan tree: a single Get operation is required for the first step in the tree, and we use the query-cardinality of this node as the required number of Get operations for later steps, because we need to invoke a Get operation for each record returned from this node. w is computed using the cardinality of attributes in equality conditions and using the number of records of each entity in the conceptual schema. When query i uses a GROUP BY clause, w is computed using the number of expected groups by pushing down the GROUP BY clause at the server side. Since linear regression function T(n, w, s) depends on the instance of extensible record stores and its computing environment, we train T(n, w, s) using performance profiles as the training datasets collected by changing queries (attributes used in SELECT/WHERE clauses) and the number of records in column families. Next,  $C_{un}^{\prime}$  in Equation 2 is defined as the coefficient that represents the cost of update operation ufor column family  $cf_n$ . We estimate it using linear regression function T'(w) where w is the number of expected updated records. Similar to the above  $C_{ij}$  estimation, we train T'(w)using performance profiles.

As for the migration cost, we need to estimate the coefficients  $C^E, C^L, C^U$  used in Equation 3. First,  $C_h^E$  is the coefficient that represents the cost of data collection from each column family  $cf_h$ , which depends on the size of  $cf_h$ . So, we estimate  $C_h^E$  using linear regression with the function  $T''(s_h)$  where  $s_h$  is the size of  $cf_h$ . Second,  $C_g^L$  is the coefficient that represents the cost of inserting the collected records into new column family  $cf_g$ , which depends on the size of  $s_g$ . So, we estimate  $C_g^L$  using linear regression with the function  $T'''(s_g)$  where  $s_g$  is the size of  $cf_g$ . Finally,  $C_{ug}^U$  is the coefficient that represents the cost of the update operation  $u \in U$  for new column family  $cf_g$  during the migration process. We estimate it using Equation (15):

$$C_{ug}^{U} = f_{u(t-1)}C_{ug}^{\prime} \frac{C_g^L}{(interval)}$$
 (15)

where  $C_g^L/(interval)$  is the time ratio of column family g generation to the interval between time steps, and  $f_u(t-1)$  is the frequency of update operation u at time step t-1.

Similar to the coefficient estimation for workload cost, we train the above regression models using performance profiles from collecting and inserting records as the training datasets: the profiles are collected by changing the number of records in column families.

## F. Optimization

Finally, we obtain the optimal design for the time-series schema by minimizing the total cost of the time-dependent workload execution and database migrations for enumerated column families, query plans, and migration plans. In addition, we additionally minimize the number of column families and their storage size with three steps as follows.

First, we identify the optimal design for the time-series schema using Equation (1) and keep its minimum cost. Second, we additionally minimize the number of column families using (16) while keeping the cost of Equation (1) as the minimum cost.

$$\min \sum_{t=1}^{T} \sum_{j} \delta_{jt} \tag{16}$$

Finally, we also minimize the size of column families using (17) while keeping the number of column families as the minimum.

$$\min \sum_{t=1}^{T} \sum_{j} s_j \delta_{jt} \tag{17}$$

This approach is especially effective when the workload does not have update operations, because the approach ensures the minimality of the number of column families and their size.

## V. RELATED WORK

We summarize research trends in schema design for query workload on relational databases and NoSQL databases.

Since relational databases and NoSQL databases have different characteristics, we categorize existing methods designed for relational and NoSQL databases.

a) Schema design on relational databases: Schema design methods for time-depended workload were proposed [13]–[15], [17], [21]. Pavlo et al. [21] proposed Peloton, a self-driving database framework for in-memory databases. Peloton introduces recending-horizon control model (RHCM) to predict workload changes and also proposes a method that adaptively changes schema according to the workload changes. Kossmann et al. [17] proposed a dynamic optimization method for self-managing database systems. Their method uses linear programming to determine an efficient order to tune multiple dependent features, such as index selection, compression schemes, and data placement.

In addition, there are other works [27], [28] that dynamically change various tuning parameters in database systems. In Wiese et al. [28], the database administrator registers a tuning procedure, and the procedure is automatically triggered when a given condition is met, such as when deadlocks occur more frequently than a given threshold. Aken et al. [27] proposed OtterTune, which automatically tunes the memory size, cache size, etc. by leveraging past experiences: it combines supervised and unsupervised learning methods to choose the most impactful tuning knobs.

However, those methods are difficult to be applied to NoSQL databases, because there is no clear distinction between physical schema and logical schema in NoSQL databases.

<sup>&</sup>lt;sup>9</sup>We choose the simplest approach of using linear regression. We can utilize more recent techniques using deep learning for achieving higher accuracy.

b) Schema design on NoSQL databases: There are also studies on schema migration in NoSQL databases. NoSE [19] was proposed as a NoSQL schema design method for static workloads. NoSE estimates the execution cost of static workload query, and optimizes the schema design. However, since it does not support time-depended workloads, even if the schema is optimized once, the performance may deteriorate due to workload changes.

There are studies on schema migration for time-depended workloads [5], [11], [20]. Hillenbrand et al. [11] proposed a method that enumerates multiple data migration patterns using an input schema migration, and then chooses the optimized data migration method based on a rule-based manner.

Google Napa [2] guarantees robust query performance. Clients expect low query latency and low variance in latency regardless of the query/data ingestion load. It also provides users a flexibility to tune the system and meet their goals based on data freshness, resource costs, and query performance.

## VI. CONCLUSION

We proposed new techniques for optimizing time-series schema by effectively reducing the number of schema candidates and the number of migration plan candidates. First, we formulated the optimization problem of time-series schema with a single integer linear program for minimizing the total cost of time-dependent workload execution and database migration. Second, we proposed an efficient schema candidate pruning technique by decomposing the ILP of original time-dependent workload via approximation into hierarchical local ILPs of smaller sub-workloads. This technique is scalable by effectively pruning uninteresting schema candidates. Finally, we proposed an effective technique that reduces the number of migration plan candidates by restricting the candidates according to how optimized query plans are changed.

## ACKNOWLEDGMENT

This paper is based on results obtained from a project, JPNP16007, subsidized by the New Energy and Industrial Technology Development Organization (NEDO).

### REFERENCES

- [1] Hyper suprime-cam Subaru strategic program. https://hsc-release.mtk. nao.ac.jp/doc/index.php/database-2, 2021.
- [2] A. Agiwal, K. Lai, G. N. B. Manoharan, I. Roy, J. Sankaranarayanan, H. Zhang, T. Zou, J. Chen, M. Chen, M. Dai, T. Do, H. Gao, H. Geng, R. Grover, B. Huang, Y. Huang, A. Li, J. Liang, T. Lin, L. Liu, Y. Liu, X. Mao, M. Meng, P. Mishra, J. Patel, R. Sr, V. Raman, S. Roy, M. S. Shishodia, T. Sun, J. Tang, J. Tatemura, S. Trehan, R. Vadali, P. Venkatasubramanian, J. Zhang, K. Zhang, Y. Zhang, Z. Zhuang, G. Graefe, D. Agrawal, J. Naughton, S. Kosalge, and H. Hacigumus. Napa: Powering scalable data warehousing with robust query performance at google. Proc. VLDB Endow., 14(12):2986–2998,
- [3] S. Agrawal, S. Chaudhuri, and V. R. Narasayya. Automated Selection of Materialized Views and Indexes in SQL Databases. *VLDB*, (5):496–505, 2000.
- [4] R. Ahmed, R. Bello, and A. Witkowski. Automated Generation of Materialized Views in Oracle. VLDB, 2020.
- [5] p. boncz, s. manegold, a. ailamaki, a. deshpande, t. kraska, a. hillenbrand, m. levchenko, u. störl, s. scherzinger, and m. klettke. migcast: putting a price tag on data model evolution in nosql data stores. In SIGMOD, pages 1925–1928, 2019.

- [6] R. Cattell. Scalable SQL and NoSQL data stores. SIGMOD Record, 39:12–27, 2011.
- [7] F. Chang, J. Dean, S. Ghemawat, W. C. Hsieh, D. A. Wallach, M. Burrows, T. Chandra, A. Fikes, and R. E. Gruber. Bigtable: A distributed storage system for structured data. ACM Trans. Comput. Syst., 26(2):4:1–4:26, 2008.
- [8] B. F. Cooper, R. Ramakrishnan, U. Srivastava, A. Silberstein, P. Bohannon, H. Jacobsen, N. Puz, D. Weaver, and R. Yerneni. PNUTS: yahoo!'s hosted data serving platform. *Proc. VLDB Endow.*, 1(2):1277–1288, 2008.
- [9] J. C. Corbett, J. Dean, M. Epstein, A. Fikes, C. Frost, J. J. Furman, S. Ghemawat, A. Gubarev, C. Heiser, P. Hochschild, W. C. Hsieh, S. Kanthak, E. Kogan, H. Li, A. Lloyd, S. Melnik, D. Mwaura, D. Nagle, S. Quinlan, R. Rao, L. Rolig, Y. Saito, M. Szymaniak, C. Taylor, R. Wang, and D. Woodford. Spanner: Google's globally distributed database. ACM Trans. Comput. Syst., 31(3):8:1–8:22, 2013.
- [10] G. DeCandia, D. Hastorun, M. Jampani, G. Kakulapati, A. Lakshman, A. Pilchin, S. Sivasubramanian, P. Vosshall, and W. Vogels. Dynamo: amazon's highly available key-value store. In SOSP, pages 205–220. ACM, 2007.
- [11] A. Hillenbrand, U. Störl, M. Levchenko, S. Nabiyev, and M. Klettke. Towards Self-Adapting Data Migration in the Context of Schema Evolution in NoSQL Databases. In *ICDEW*, volume 00, pages 133– 138, 2020.
- [12] A. Jindal, H. Patel, A. Roy, S. Qiao, Z. Yin, R. Sen, and S. Krishnan. Peregrine: Workload optimization for cloud query engines. In SoCC, pages 416–427, 2019.
- [13] A. Jindal, H. Patel, A. Roy, S. Qiao, Z. Yin, R. Sen, and S. Krishnan. Peregrine: Workload optimization for cloud query engines. In *SoCC*, pages 416–427, 2019.
- [14] A. Jindal, S. Qiao, H. Patel, Z. Yin, J. Di, M. Bag, M. Friedman, Y. Lin, K. Karanasos, and S. Rao. Computation reuse in analytics job service at microsoft. In SIGMOD, pages 191–203, 2018.
- [15] A. Jindal Konstantinos Karanasos Sriram Rao Hiren Patel Microsoft, A. Jindal, K. Karanasos, S. Rao, H. Patel, and H. P. Microsoft. Selecting Subexpressions to Materialize at Datacenter Scale. *PVLDB*, 11(7):800– 812, 2018.
- [16] H. Kimura, G. Huo, A. Rasin, S. Madden, and S. Zdonik. Coradd: Correlation aware database designer for materialized views and indexes. *PVLDB*, 3:1103–1113, 09 2010.
- [17] J. Kossmann and R. Schlosser. A framework for self-managing database systems. In *ICDEW*, pages 100–106, 2019.
- [18] L. Ma, D. V. Aken, A. Hefny, G. Mezerhane, A. Pavlo, and G. J. Gordon. Query-based Workload Forecasting for Self-Driving Database Management Systems. In SIGMOD, page 15, 2018.
- [19] M. J. Mior, K. Salem, A. Aboulnaga, and R. Liu. NoSE: Schema design for NoSQL applications. TKDE, 29(10):2275–2289, 2017.
- [20] M. Mozaffari, E. Nazemi, and A. Eftekhari-Moghadam. CONST: Continuous online NoSQL schema tuning. Software: Practice and Experience, 2020.
- [21] A. Pavlo, G. Angulo, J. Arulraj, H. Lin, J. Lin, L. Ma, P. Menon, T. Mowry, M. Perron, I. Quah, S. Santurkar, A. Tomasic, S. Toor, D. V. Aken, Z. Wang, Y. Wu, R. Xian, and T. Zhang. Self-driving database management systems. In CIDR, 2017.
- [22] N. Sasaki. Large-scale high-speed processing of smart meter data following the deregulation of electrical power. https://www.global.toshiba/ ww/company/digitalsolution/articles/tsoul/22/004.html, Aug 2017.
- [23] J. Shute, M. Oancea, S. Ellner, B. Handy, E. Rollins, B. Samwel, R. Vingralek, C. Whipkey, X. Chen, B. Jegerlehner, K. Littlefield, and P. Tong. F1: the fault-tolerant distributed RDBMS supporting google's ad business. In SIGMOD Conference, pages 777–778. ACM, 2012.
- [24] K. F. T. Vajk, L. Deak and G. Mezei. Automatic NoSQL schema development: A case study. In PDCN, 2013.
- [25] T. Takata, H. Furusawa, Y. Okura, Y. Yamada, M. Onizuka, H. Suga, R. Kurosawa, and T. Kambayashi. Toward fast search and real-time inputs of big astronomical catalogs by the new generation relational database. In Astronomical Society of the Pacific Conference Series, number 527, page 717, 2020.
- [26] D. Tang, Z. Shang, A. J. Elmore, S. Krishnan, and M. J. Franklin. CrocodileDB in action: Resource-efficient query execution by exploiting time slackness. *Proc. VLDB Endow.*, 13(12):2937–2940, 2020.
- [27] D. Van Aken, A. Pavlo, G. J. Gordon, and B. Zhang. Automatic database management system tuning through large-scale machine learning. In SIGMOD, pages 1009–1024, 2017.

[28] D. Wiese, G. Rabinovitch, M. Reichert, and S. Arenswald. Autonomic tuning expert: a framework for best-practice oriented autonomic database tuning. In *CASCON*, 27-30, page 3, 2008.