A Taxonomy of Schema Changes for NoSQL Databases*,

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Abstract

Schema evolution is a crucial aspect in database management. The proposed taxonomies of schema changes have neglected the set of operations that involves relationships between entity types: aggregation and references, as well as the possible existence of structural variations for schema types, as most of NoSQL systems are schemaless. The distinction between entity types and relationship types, which is typical of graph schemas, is also not taken into account in the published works. Moreover, NoSQL schema evolution poses the challenge of having different data models, and no standard specification exists for them. In this paper, a generic approach for evolving NoSQL and relational schemas is presented, which is based on the U-Schema unified data model that includes aggregation and reference relationships, and structural variations. For this data model, we introduce a taxonomy of schema changes for all the U-Schema elements, which is implemented by creating the Orion database-independent language. We will show how Orion can be used to automatically generate evolution scripts for a set of NoSQL databases, and the feasibility of each schema operation will be analyzed through the performance results obtained. The taxonomy has been formally validated by means of Alloy, and two case studies show the application of Orion.

Keywords NoSQL databases · Schema evolution · Evolution management · Taxonomy of changes · Schema change operations

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1 Introduction

Database schemas have to be normally modified along the lifetime of databases. These schema changes may be caused due to new functional or non-functional requirements, or database refactoring, among other situations. When this happens, stored data and application code must be adapted to the new schema, as illustrated in Figure 1. Thus, the automation of schema changes is crucial to save effort and to avoid data and application errors. For relational databases, a great deal of research effort has been devoted to address the schema evolution problem, and a number of tools, from prototypes to workbenches, have been built to facilitate the schema change management [7, 16]. Also, schema evolution of object databases has been extensively studied [22]. In this paper, we will address concerns related to schema evolution for NoSQL (Not only SQL) stores.

Modern technologies as Web 2.0, smartphones and Internet of Things motivated the building of applications with requirements that relational systems could not meet. Then, NoSQL systems emerged to provide qualities as flexibility to frequently change the schema, horizontal scalability and availability, among others [27]. NoSQL systems are commonly classified in four kinds of data models: columnar, document, key-value and graph, but the lack of a standard or specification of the data model leads to systems of the same category having different features. Today, relational systems are still predominant but the idea of “one size does not fit all” is widely accepted and polyglot persistence [31] is considered the future trend, as the growth of multi-model systems suggests: the first eight databases in the DB-engines ranking\(^4\) are multi-model, and the main relational database vendors are including support of NoSQL systems in their products.

To provide flexibility to adapt to schema changes, most of NoSQL systems are “schema-on-read,” that is, the schema declaration is not required prior to storing data (i.e., they are schemaless). However, this does not mean that there is not a schema, but that it is implicit in data and code. Stored data always are structured conforming to a schema, and code that manipulates data is written according to that schema. To achieve results similar to those obtained in relational systems, schema evolution requires a larger research effort to overcome some limitations in published approaches [21, 17]. For example, schema change operations for relationships have not adequately been addressed, and the existence of structural variations or relationship types are not considered. Structural variation is possible for schemaless systems since schemas guarantee that data conforms to a particular structure, and relationship types are part of graph schemas. Moreover, the building of automated solutions should be tackled for each NoSQL system. The lack of a standard or specification for NoSQL data models makes this task difficult.

In this work, we present a generic approach aimed to offer automated support for NoSQL and relational systems. It is based on the U-Schema unified data model presented in [4]. U-Schema integrates data models for the four kinds of NoSQL systems and the relational model, and has more expressive power than other proposed generic data models in [11, 9], as discussed in detail in [4]. For example, U-Schema distinguishes between entity type and relationship type, includes aggregation and reference relationships, and allows to represent the structural variation of the schema types.

Our proposal consists of a taxonomy of schema change operations (SCOs) defined on U-Schema and a domain-specific language (DSL) that implements them. With this language, named Orion, database administrators and developers can write scripts that specify a set of SCOs. From these scripts, the inferred or declared schema and the database are automatically updated. The Orion engine has been built with data updaters for several database systems, in particular MongoDB (document data model), Cassandra (columnar), and Neo4j (graph). We have evaluated these data updaters for two non-trivial case studies with real datasets: a refactoring case to improve query performance, and an outlier migration problem. The taxonomy has been formally validated by using the Alloy language [19]. On the other hand, code updating is not addressed here.

Our work contributes to the state of the art as follow:

- We have defined a taxonomy for NoSQL logical schemas, which includes a set of operations richer than those previously proposed. Being based on U-Schema, we have considered changes on relationships, which are involved in frequent operations such as converting a particular reference into an

\(^4\)https://db-engines.com/en/ranking.
aggregate or vice versa [6], or copying features between schema types. Also, he has included changes related to variations, which could be very useful, e.g., joining all the variations in a single variation to remove outliers [20].

- As far as we know, NoSQL data model heterogeneity has only been addressed in [9, 18]. But taxonomies of these proposals do not include the changes above mentioned.

- Orion is a novel language to apply the operations of the taxonomy proposed. Orion data updaters have been built for three popular systems, and a study of the data updating cost for each operation has been performed.

- Non-trivial case studies of schema evolution have been carried out by using real datasets.

Orion was already presented in the “ER 2021–Conference on Conceptual Modeling” [15]. Here, we show how that initial work has been completed. An Orion data updater has been built for a graph store, in particular Neo4j, and performance results have been obtained for each schema change operation in our taxonomy. We have also used the Alloy formal language to check the consistency of the operations, and have performed a new case study. Below, the changes we have applied on the previous paper are indicated:

- The performance analysis has been completely rewritten as a new experiment has been designed, and results for graph stores were not included in the ER paper.

- A section has been added to describe the Alloy validation of the taxonomy.

- Related work has been extended to consider the most promising research approaches regarding evolution taxonomies. Several criteria to compare approaches are proposed, and a table summarizes the comparison we have carried out.

- A new case study is introduced to show the usefulness of our proposal: how outliers can be removed by changing the schema. The refactoring case study has been redesigned to be applied on a graph database instead of in a document database.

This paper has been organized in the following sections: The next Section is used to introduce our data model. In Section 3 we define our abstract taxonomy of changes. In Section 4 the Orion Language is described as a concrete implementation of that taxonomy. Next, in Section 5 two case studies are discussed. Section 6 shows a formal validation for the taxonomy and a measure of performance of Orion. Section 7 is used to discuss related work, tools and research, and to compare the most promising approaches. Finally, conclusions and future work are drawn in Section 8.

2 U-Schema: A Unified Data Model

U-Schema is a generic metamodel that integrates the relational model and data models for each of the four most common NoSQL paradigms: columnar, document, key-value, and graph. A detailed description of U-Schema is presented in [4], where some of its applications are also outlined. The use of different data models for different needs of persistence is a trend, and U-Schema was devised to build generic database solutions. Here, U-Schema is used to define a generic schema evolution approach.

In this section, we will introduce U-Schema through the Athena language [14], which has been built to provide a generic schema definition language with high expressive power. Although most NoSQL systems are schemaless, this language is useful, for example, when designing schemas from scratch, generating data for testing purposes, or schema manipulation when there is no database whose schema can be inferred.

Figure 2: The Sales department schema defined using Athena.
NoSQL data models can be classified in two categories [27]: aggregate-based systems where aggregations prevail over references to connect objects, and graph systems where only references are present. In graph systems, references are instances of relationship types, and aggregate-based systems only have entity types, and references are managed as identifier-based joins. U-Schema allows both kinds of NoSQL systems to be represented.

A schema is formed by a set of schemas types that can represent domain entities or relationship types to represent relationships between nodes in graph stores. In the Sales department example (Figure 2) there are five entity types: Salesperson, Sale, SeasonExercise, PersonalData, and SaleSummary. The three former are root entity types, that is, their variations and references to connect objects reference SaleSummary objects, whereas PersonalData, and Salesperson.personalData which include a set of features (id, teamCode, email, and personalData) while Variation 2 adds the sales and profits features.

A feature declaration specifies its name and type. There are four kinds of features: keys, attributes, aggregates, and references. Attributes and aggregates denote the features that hold the values of a database object. For attributes, the type can be either scalar (Number, String, Boolean, etc) or structured (Set, List, Map, and Tuple). In the case of aggregates, the type is a non-root entity type.

For example, Salesperson.email is an attribute of type String, and Salesperson.personalData specifies that PersonalData objects are embedded in Salesperson objects.

Keys and references are features that hold an object identifier. They are formed by one or more attributes. Keys are declared with the modifier "+", and references are associated to a root type. For example, Salesperson.id is a key, and Sale.exercises specifies that Sale objects reference SeasonExercise objects whose key is the id attribute.

A cardinality needs to be specified for references and aggregations, such as one to one or one to many. The features may also have modifiers as key ("*"+) or optional ("?"

3 Taxonomy of Changes for NoSQL Databases

In schema evolution approaches, the set of changes that can be applied on a particular data model are usually organized in form of a taxonomy [2, 17]. Several categories are established depending on the kind of schema element affected by a change. Here, we present a taxonomy for the U-Schema data model introduced in the previous section, which includes operations for all its elements. In this way, our taxonomy includes all the operations proposed in the studied taxonomies, and adds new operations, such as those related to aggregates, references, relationship types, and variations, as shown later.

Next, the terminology used to define the semantics of operations in our taxonomy is introduced. Let T be the set of schema types, and let E be the set of entity types E = \{E_i\}, i = 1 . . . n, T = E in the case of aggregate-based stores, while T = E ∪ R, where R = \{R_i\}, i = 1 . . . m denotes the set of relationship types, in the case of graph stores. Each schema type t ∈ T includes a set of structural variations V_t = \{v_1, v_2, . . . , v_n\}, with v_i.feature denoting the set of features of a variation v_i. Then, the set of features of a schema type t is F_t = \bigcup_{i=1}^{n} v_i.feature, which will include attributes, aggregates, and references, and C ∩ F denotes the set of common features of a type t. We will use dot notation to refer to parts of a schema element, e.g., given an entity type e, e.name and e.feature refer to the name and set of features (F_t), respectively, of the entity type.

The proposed taxonomy is shown in Table 1. In a similar way to [7], we have added operations taking into account a compromise between atomicity, usability, and reversibility. The case of changes affecting variations, usefulness and atomicity have prevailed on reversibility. Each SCO is defined by an identifying name, together with information regarding the gaining or loss of information the operation causes on the schema, denoted by a C^+ notation as follows:

- C^+ if an operation carries an additive change, e.g., Add Schema Type.
- C^− if a subtractive change occurs, e.g., Delete Feature.
- C^+− denotes an operation in which there is a gain and a loss of information, e.g., Move Feature.
- C^− means no change in information, e.g., Rename Schema Type.
- C^+− adds or subtracts information, depending on the operation parameters, e.g., casting a feature to boolean.

As noted in [7], a schema change operation can be considered a function whose input is a schema S and a database D conforming to it and produces as output a modified schema S’ and the database D’ that results of updating D to conform to S’. In this paper, the
schema operation semantics is defined in form of pre and postconditions, which appear in the second and third column. Note that the postconditions only specify the changes on the schema and not the changes on the database, because these depend on the concrete data model. Since the operations semantics would be expressed very similarly to specifying the database change, this semantics is not included here, but we have added a comment to the postcondition of the Adapt operation to show that its effect is different to the Delvar operation.

As Table 1 shows, taxonomy operations are classified in 6 categories that correspond to U-Schema elements: schema types, variations, features, attributes, references, and aggregates.

The Schema type category groups operations that can be applied indistinctly on entity and relationship types. In addition to the atomic operations: Add, Delete, and Rename, three complex operations are added to create new schema types. The Extract operation creates a new schema type by copying some of the features of an existing schema type, and leaving the original schema type unmodified. The Split operation divides an existing schema type into two new schema types by separating its features into two subsets, and the original schema type ceases to exist. The Merge operation can be understood as the inverse of the previous operation: a new schema type is created as the union of two existing ones, which are removed afterwards.

The Structural Variations category groups three operations defined to manipulate them. The Delvar operation deletes a given variation, Adapt deletes a given variation but also migrates data belonging to the deleted variation to a new variation, and Union joins all the variations of a schema type into a single one. The first two operations could be useful, for example, to remove outliers (i.e., variations with a small number of elements) [20]. Since Delvar and Adapt cause the same changes on the schema (a variation is deleted), a comment has been added in the Adapt postcondition to indicate the effect on the database. Similarly to the Schema Type category, the Feature category groups the operations with the same semantics for attributes, aggregates, and references. It includes operations to (i) copy a feature from a schema type to another one, either maintaining (Copy) or not (Move) the feature copied in the original schema type; and (ii) move a feature from/to an aggregate: Nest and Unnest.

The Attribute category includes operations to Add a new attribute, change its type (Cast), and add/remove an attribute to/from a key: Promote and Demote. The Reference category includes the Add and Cast operations commented for attributes, Mult to change the multiplicity, and the Morph operation to transform a reference to an aggregate. Finally the Aggregate category includes operations Add, Mult and Morph commented for references. Please note that there is not Key category because in U-Schema a Key is a logical feature that is always bound to an attribute, and therefore keys can be created and deleted by means of the attribute operations Add, Promote, and Demote.

All the listed SCOs, except for Split and Move, are atomic operations. This means that these basic SCOs cannot be implemented as a combination of two or more other SCOs. On the other hand, Split and Move are non-atomic operations because they can be implemented by using other SCOs (Movie is composed of a Copy and Delete feature operations, and Split can be defined as two Extract and a Delete schema type operations). These two operations have still been added to the taxonomy because they are recurrent operations in refactoring scenarios, and other approaches have considered them.

4 Implementing the Taxonomy in Orion

Orion is the language created to implement the taxonomy defined on U-Schema. With Orion, developers can declare and execute change operations in a system-independent way. Metamodeling has been applied to define the language: a metamodel expresses the abstract syntax, and notation or concrete syntax and semantics are defined on the metamodel [3]. The Orion metamodel specifies the Orion grammar as an Ecore model [30], i.e., an object-oriented domain model. Here, the metamodel is not shown because we consider the grammar notation is enough to understand the contribution of the language. The notation will be explained by showing examples for the running example, and, finally, semantics will be illustrated by indicating the generated code.

4.1 Concrete Syntax

SCOs can be easily expressed like commands of a command-line language. Therefore, the syntax of Orion is very simple as illustrated in Figure 3 in which an excerpt of its EBNF grammar is shown. Note that the general format for the majority of operations is a keyword denoting the change operation (e.g., Add or Delete) followed by another keyword to indicate the kind of schema element it affects (e.g., Entity or Relationship, Aggregate or Reference), and finally a list of arguments. The Orion syntax has been defined to let operations be written as concise as possible, e.g., it is possible to apply certain operations over all schema types by using the “*” wild-card, as in DELETE *::name, and operations can define a list of parameters as in DELETE Sales::types, isActive, description. Operations can also be applied to specific variations of a schema type, as in RENAME *(v1,v3)::phone TO newPhone. Differences between aggregate-based systems and graph systems are expressed through optional parameters in
some operation commands, e.g., ADD REF requires to indicate a target entity type and a join condition, and has two optional parameters: the primitive type of the references values in the case of an aggregated-based store, and a set of attributes for a graph store.

Figure 4 shows an Orion script that applies changes on the Sales department schema of Figure 2. An Orion script starts with a Using statement that indicates the schema on which the changes are applied. This declaration allows runtime checking of the validity of each operation on the current schema. Note that the schema has to be updated after the execution of each operation of the script, so that the checking can be correctly performed. The operations are therefore sequentially executed.

The script of Figure 4 shows changes on several entity types of the schema, illustrating most of the different changes in the taxonomy: casting on attributes (:profits, :PersonalData::postCode, and :SaleSummary::isCompleted), deleting attributes (:Sale::isActive), nesting attributes to an aggregate (:Salesperson::email and :PrivateData::city, postcode, street), morphing an aggregate to a reference (:Salesperson::personalData), renaming entity types (:Salesperson) and features (:SaleSummary::completedAt), and adapting a variation (:Salesperson::v1). Operations to create entity types and aggregates are also shown (:Company, :Company::media and :PersonalData::address).

### 4.2 Semantics: Schema and Data Update

The Orion semantics is determined by the changes that each operation causes in the existing schema and stored data. In our case, this semantics is implemented by the Orion engine that updates the U-Schema model and translates Orion scripts into database-specific operations for updating data according to the modified schema. The Orion engine has a component for each

| Table 1: Schema Change Operations of the Taxonomy. |
|---|---|---|
| **Precondition** | **Postcondition** |
| **Schema Type Operations** (Entity Type and Relationship Type) | |
| Add | (C+) | Let t be a new schema type, t \∉ T | t ∈ T |
| Delete | (C-) | Given a schema type t ∈ T | t \notin T |
| Rename | (C'-) | Given a schema type t ∈ T and a string value n, n \notin T.names | t.name = n |
| Extract | (C+o) | Given a schema type t ∈ T, a set of features fs \subset F^t and a string value n \notin T.names | t.T \setminus t_1 = T.\new \land t_1.name = n \land t_1.features = fs |
| Split* | (C-o) | Given a schema type t ∈ T, two sets of features fs_1 \subset F^t \land fs_2 \subset F^t and two string values n_1, n_2 \notin T.names | t.T \setminus t_1 = T.\new \land t_1.name = n_1 \land t_1.features = fs_1 \land t_2.name = n_2 \land t_2.features = fs_2 |
| Merge | (C-) | Given two schema types t_1, t_2 and a string value n \notin T.names | t_1, t_2 \notin T \land T.\new \land t_1.name = n \land t_1.features = t_1.features \cup t_2.features |

| Structural Variation Operations | |
| Delvar | (C-) | Given a schema type t ∈ T and a variation v^t \notin V^t | v^t \notin V^t |
| Adap | (C-) | Given a schema type t ∈ T and two variations v^t_1, v^t_2 \notin V^t | v^t \notin V^t |
| Union | (C-) | Given a schema type t ∈ T \land V^t \land \langle \rangle | V^t = \{v^t_1 \land v^t_2\} |

| Feature Operations (Attribute, Reference and Aggregate) | |
| Delete | (C-) | Given a schema type t ∈ T and a feature f \in F^t | f \notin F^t |
| Rename | (C-) | Given a schema type t ∈ T, a feature f \in F^t, and a string value n \notin t.features | f.name = n |
| Copy | (C-) | Given two schema types t_1, t_2 and a feature f \in F^t_1 \land f \in F^t_2 | f \in F^t_1 \land f \in F^t_2 |
| Move* | (C-) | Given two schema types t_1, t_2 and a feature f \in F^t_1 \land f \in F^t_2 | f \in F^t_1 \land f \in F^t_2 |
| Nest | (C+) | Given an entity type e \in E, a feature f \in F^e \land an aggregate ag \in F^1 \land ag.type = e_2 \land f \notin F^e_2 | f \in F^e_1 \land f \in F^e_2 |
| Unnest | (C-) | Given an entity type e \in E, an aggregate ag \in F^t_1 \land ag.type = e_2, and a feature f \notin F^e_1 \land f \in F^e_2 | f \in F^e_1 \land f \in F^e_2 |

| Attribute Operations | |
| Add | (C+) | Given a schema type t \in T, let at be an attribute, at \notin C^t | at \in C^t |
| Cast | (C+) | Given a schema type t \in T, an attribute at \in E^t, and a scalar type st | at.type = st |
| Promote | (C+) | Given an entity type e \in E and an attribute at \in F^e \land at.key = False | at.key = True |
| Demote | (C+) | Given an entity type e \in E and an attribute at \in F^e \land at.key = True | at.key = False |

| Reference Operations | |
| Add | (C+) | Given a schema type t \in T, let rf be a reference, rf \notin C^t | rf \in C^t |
| Cast | (C+) | Given a schema type t \in T, a reference rf \in F^t, and a scalar type st | rf.type = st |
| Mult | (C+) | Given a schema type t \in T, a tuple (l, u) \in \{(0, 1), (1, 0), (0, -1), (1, -1)\} | rf.lowerBound = l \land rf.upperBound = u |
| Morph | (C+) | Given a schema type t \in T and a reference rf \in F^t, let ag be a new aggregate, ag \notin F^t | rf \notin F^t \land ag \in F^t \land ag.name = rf.name \land ag.type = rf.type |

| Aggregate Operations | |
| Add | (C+) | Given an entity type e \in E, let ag be an aggregate, ag \notin C^e | ag \in C^e |
| Mult | (C+) | Given an entity type e \in E, an aggregate ag \in F^e \land a tuple (l, u) \in \{(0, 1), (1, 0), (0, -1), (1, -1)\} | ag.lowerBound = l \land ag.upperBound = u |
| Morph | (C+) | Given an entity type e \in E and an aggregate ag \in F^e, let rf be a new reference, rf \notin F^e | ag \notin F^t \land rf \in F^t \land rf.name = ag.name \land rf.type = ag.type |
The Schema Updater takes an Athena model (i.e., a schema) and an Orion model as input, and outputs the updated schema. To do so, the input schema is taken as a starting point, and each Orion operation is sequentially applied to that schema, with the semantics shown in Section 3. This process is implemented as a model to model transformation which assures platform-independence. It also has to be executed along with the Data Updater, to assure the correctness of the data adapting, or can be executed as a standalone process to study schema evolution.

While we implemented a single Schema Updater, as it is independent of any database and works at a logical level, the Data Updater is bound to a specific database, so a different data updater must be implemented for each supported system. In our case, we have developed data updaters for MongoDB, Cassandra, and Neo4j. With this choice, we covered document, columnar, and graph NoSQL data models, and we support three widely used NoSQL stores, which occupy the position 5, 11, and 20 in the DB-engines ranking as of March 2022.

A data updater receives an Athena and Orion model as input, and generates the piece of database-specific code that applies the necessary changes on the database according to the operations specified in the Orion script. Therefore, this process consists of a model to text transformation.

In the case of MongoDB, the data updater generates native MongoDB commands and stores them in a Javascript file. Since MongoDB does not have to declare an explicit schema, in order to apply changes, documents belonging to the desired entity type have to be selected. To improve performance, Orion analyzes the scripts and optimizes operations that can be applied sequentially on the same entity type, stacking them together into a single bulk write. Some complex operations, however, do not allow that optimization, and they must be executed in their own aggregation.
We injected the dataset into Neo4j but changed it slightly during injection to take advantage of relationship types. In StackOverflow, a Comment references its User and a Post in a 1..1 relation, so we injected this database transforming the Comment entity type as a relationship type named Rel_Comments between Users and Posts. After injecting the dataset into Neo4j, the schema inference strategy from [4] was applied. Figure 7 shows an excerpt of the schema inferred with two of the seven entity types discovered and the already mentioned new relationship type; the schema is visualized with the notation introduced in [12]. Here, Posts and Users are shown as union entity types listing their required and optional features. Users references Posts by rel_comments, a reference with attributes that belongs to Rel_Comments. Rel_Comments has four required features (ContentLicense, CreationDate, PostId and Score) and five structural variations each with a different set of additional features.

Analyzing the schema, we realized that the newly created relationship type could be improved by casting some types of attributes to specific Neo4j types, adding new fields or copying fields from Users and Posts to the relationship type. Also injecting an entity type as a relationship type caused that some attributes in Rel_Comments turned obsolete and could be deleted. In this way, by slightly changing the schema, query performance could be improved.

The proposed refactoring can be divided into two blocks: (i) Applying operations to some fields of Users and Posts to improve query performance over them, and (ii) applying operations over the newly created Rel_Comments to improve its expressiveness.

The Orion script to refactor the StackOverflow schema is shown in Figure 8. Firstly, some Cast operations are performed to convert certain fields stored as strings to timestamps. These casts are performed against every schema type containing the CreationDate and LastAccessDate (which are all three schema types

Figure 6: Example of two operations stacked together in MongoDB.

In Cassandra, CQL (Cassandra Query Language) instructions are generated to perform the data update. Due to Cassandra declaring an explicit schema, evolution changes are restricted. To implement some of these operations it is necessary to export the data to an external file, change the schema and import the data back.

The Neo4j data updater uses the Cypher language to generate code for updating data. Given its graph nature, Neo4j is also able to handle relationship types and therefore allows the full set of schema type operations to be implemented for relationships. The schemaless nature of Neo4j also allows the database to be updated in a similar way to MongoDB: (i) Selecting all nodes belonging to the entity type to be modified and (ii) applying the desired change. This also allows to stack changes to the same schema type, reducing the overhead of the change. Table 2 sums up how each data updater handles each operation. For each specific database, some keywords give insight of how each operation is implemented, and also which operations cannot be executed in a particular database.

5 Case Studies of Orion Applications

5.1 Case Study 1: A StackOverflow Refactoring

Database refactoring is an activity aimed to improve the database design and performance without changing its semantics [1]. A refactoring is a small change on the schema, and several refactorings can be applied to achieve a determined improvement. In our first case study, Orion was used to apply a refactoring to a Neo4j database that imported the StackOverflow\textsuperscript{4} dataset.

We injected the dataset into Neo4j but changed it slightly during injection to take advantage of relationship types. In StackOverflow, a Comment references its User and a Post in a 1..1 relation, so we

\begin{verbatim}
Sales_department.SaleSummary.bulkWrite(
    // RENAME SaleSummary::isCompleted TO isCompleted
    updateMany: {
        filter: [],
        update: {
            SaleSummary: {
                rename: {
                    isCompleted: "isCompleted",
                    completedAt: "completedAt"
                }
            }
        }
    }
)!
\end{verbatim}

Figure 6: Example of two operations stacked together in MongoDB.

Figure 7: Excerpt of the StackOverflow schema injected in Neo4j.

\begin{verbatim}
Figure 7: Excerpt of the StackOverflow schema injected in Neo4j.
\end{verbatim}
shown). Then a *Mult* operation to allow the possibility for a post to hold more than one tag and two *Copy* operations to move a couple of attributes from *Users* and *Posts* to each *Comment* between them, in order to get quick access to those fields. Operations regarding *Rel_Comment* include a *Union* in order to maintain only a single variation and make all the features mandatory, two *Add Attribute* operations to create new features, a *Cast* over a feature that should be of *double* type, and two *Delete* operations over the two *PostId* and *UserId* carried from the injection that now are useless since the relationship stores that information. Finally, we performed a *Rename Relationship* to change the *Rel_Comments* name to a more suitable *comments* name for a relationship. Given this script and the extracted schema, the Orion engine generates the updated schema and the Neo4j API code script to execute the changes on the data.

Figure 8: Operations to be applied to the StackOverflow schema and data.

5.2 Case Study 2: Outlier Migration in Reddit

In this second case study, we remove outliers in the Reddit dataset5. We injected this dataset into MongoDB, and inferred its schema by applying the process in [4]. Figure 9 shows the inferred *Comment* entity type, with more than 860 million comments distributed in 20 structural variations. We consider that outliers are those variation with a very small number of objects. We developed a process in which outliers could be detected by using the *count* property of the variations, that indicates how many instances belong to each variation, and then we proposed an approach to migrate those outlier instances to regular variations (i.e., variations that were not outliers). In Figure 10 we show a bar chart with logarithmic axes in which each variation is represented by its *count* property. There, few variations hold the majority of objects. By following our approach, we classified the top five most

5https://files.pushshift.io/reddit/comments/.

Figure 9: The *Comment* entity type from the Reddit schema.

Figure 10: *Comments* variations represented by their *count* property.

Using Orion, a developer can delete obsolete instances belonging to old variations, as well as adapt some variations to new ones, migrating the data accordingly. The developer can do so by using the *Delvar* and *Adapt* operations, as is shown in Figure 11. Here, adapting variation 11 (an outlier) to variation 5 (a regular variation) means that all instances matching variation 11 will be modified accordingly to fit variation 5, reducing the number of resulting variations. Each of these *Delvar* and *Adapt* operations will be translated into Javascript code and will remove or migrate instances from a certain variation. In Figure 12 an example of the code generated from one of the *Adapt* operations is shown, where a match that captures only instances of variation 11 is applied and then fields are removed and added with default values as needed. Once the script is executed against the

Figure 11: *Adapt* operation from variation 11 to variation 5.

Figure 12: Code generated from *Adapt* operation.
The U-Schema metamodel has been modeled in Alloy by using
operation. Each step will be detailed below.
Two kinds of evaluations have been carried out. The signatures
for contradictions have been implemented for each
taxonomy have been defined, and then (iii) checks
have been modeled, (ii) operations implementing the
taxonomy as Alloy operations, by using
implementing restrictions that any U-Schema model
must fulfill, such as: (i) A schema must contain at
least one entity type or one relationship type, (ii) there
cannot be two different entity types with the same
name, and (iii) each reference to a schema type must
belong to the same schema as that schema type. Once
the U-Schema specification is defined, Alloy is capable
of searching for scenarios that fulfill all the provided
restrictions.

```
// ADAPT ENTITY Comments::v10 TO v7
ADAPT ENTITY Comments::v11 TO v6
ADAPT ENTITY Comments::v12 TO v7
ADAPT ENTITY Comments::v13 TO v9
ADAPT ENTITY Comments::v14 TO v8
ADAPT ENTITY Comments::v15 TO v6
ADAPT ENTITY Comments::v16 TO v6
ADAPT ENTITY Comments::v17 TO v6
ADAPT ENTITY Comments::v18 TO v7
ADAPT ENTITY Comments::v19 TO v6
ADAPT ENTITY Comments::v20 TO v6
```

Figure 12: Orion script migrating Comments variation 11 to 5.

6 Evaluation
Two kinds of evaluations have been carried out. The
schema change semantics of each operation of the
proposed taxonomy has been formally validated by
using Alloy. Also, the feasibility or applicability of
the changes has been evaluated by measuring execution
times for the three currently supported NoSQL systems.

6.1 Validating the Taxonomy
Alloy 5 was used to implement each schema change
based on its pre and postconditions. This has been
achieved by applying a three step process in which (i) U-Schema concepts and their restrictions
have been modeled, (ii) operations implementing the
taxonomy have been defined, and then (iii) checks
for contradictions have been implemented for each operation. Each step will be detailed below.

The U-Schema metamodel has been modeled in Alloy by using signatures. In 13 an excerpt of U-Schema is
shown, consisting of two parts: (i) entities and relationships field declarations, which are a set of Entity
types and Relationship types, and (ii) a set of facts

```
Reddit_migration operations
Using reddit:
DELVAR ENTITY Comments::v1
DELVAR ENTITY Comments::v2
DELVAR ENTITY Comments::v3
DELVAR ENTITY Comments::v4
ADAPT ENTITY Comments::v10 TO v7
ADAPT ENTITY Comments::v11 TO v6
ADAPT ENTITY Comments::v12 TO v7
ADAPT ENTITY Comments::v13 TO v9
ADAPT ENTITY Comments::v14 TO v8
ADAPT ENTITY Comments::v15 TO v6
ADAPT ENTITY Comments::v16 TO v6
ADAPT ENTITY Comments::v17 TO v6
ADAPT ENTITY Comments::v18 TO v7
ADAPT ENTITY Comments::v19 TO v6
ADAPT ENTITY Comments::v20 TO v6
```

Figure 11: Orion script used to migrate variations on Reddit Comments.

database, data is migrated, variations are removed
and the complexity of the schema is reduced as a
result.

```
// ADAPT ENTITY Comments::11 TO 5
reddit.Comments.updateMany(
  "archived": $exists: true,
  "distinguished": $exists: true,
  "downs": $exists: true,
  "edited": $exists: true,
  "name": $exists: true,
  "score_hidden": $exists: true,
  "author_flair_css_class": $exists: false,
  "author_flair_text": $exists: false),
  )
)
```

Figure 13: The U-Schema definition excerpt in Alloy.

The next step is to model the change operations in the
taxonomy as Alloy operations, by using predicates
that may be applied over instances of U-Schema elements. Each operation shows the same structure: (i) it checks
that input parameters do meet the preconditions, and
then (ii) it matches the changes to be reflected on the
output parameters.

```
// Precondition check: m ∈ T.names
newName not in schemaI.entities.name
```

Figure 14: Alloy definition for the Rename Entity operation.

In Figure 14, the Rename Entity operation is implemented. Its precondition is declared in the same
way as it was defined in Table 1, newName not in schemaI.entities.name, and then several statements
are defined to be fulfilled by the output schema. When this operation is executed in Alloy to search
scenarios in which it is successfully applied, a scenario is found, which is shown in Figure 15. As can be seen, the input schema only has an entity type whose name changes in the output schema but its root and variations properties are the same.

**Figure 15:** One of the Rename Entity scenarios found.

We have defined Alloy Check operations to find contradictions, for instance, check operation for the Rename Entity operation is shown in Figure 16. When executing each check operation, no scenarios were found in which the implications (i.e., postconditions) of the operation are not true (counterexample).

**Figure 16:** Postcondition checking of the Rename Entity operation.

Therefore, we concluded that preconditions were consistent and postconditions were valid. The usage of Alloy also served to refine with additional preconditions certain operations, such as Extract/Split/Merge Entity, which were not consistent at the beginning of the process. It also showed the importance of including invariants in the metamodel.

### 6.2 Measuring performance of Orion operations

To evaluate the feasibility of each implemented operation we created the following scenario for each database system considered. First, we defined a schema with several root entity types: one entity type per group of operations (features, attributes, references, and aggregates), and one entity type per schema type operation, each one of them with the same number of features. Then by using the tool shown in [13], we generated a dataset of 150,000 instances per entity type conforming to that schema. After that, we defined a process to inject this dataset into a MongoDB, Cassandra, and Neo4j. Then we formulated an experiment, but first we applied several standard queries to warm up the database and let it fill its caches. In order to provide a meaningful expression of the feasibility of the implemented SCOs, we did not measure absolute times. Instead, we used a modification operation $\text{op}_{\text{mod}}$ to normalize the obtained times. This $\text{op}_{\text{mod}}$ operation modifies a field that is not indexed, so the database is not optimized for it and results are more reliable. In the third step, $\text{op}_{\text{mod}}$ is applied over all the instances of a certain entity type. Note that an update operation is preferred over a standard query because we are measuring operations modifying the database.

The final step consists on executing each operation independently to measure its execution time. To do so, we defined three blocks to execute: (i) Entity type operations, (ii) feature, attribute, reference, and aggregate operations, and (iii) relationship type operations, if applicable. Since operations are executed individually, it is not possible to take advantage of certain mechanisms such as stacking operations together, which is relevant in the case of, for example, MongoDB. This whole process was repeated five times to get a reliable mean time. Given the different nature of each database system considered, the $\text{op}_{\text{mod}}$ operation is slightly different for each one of them.

Table 2 shows the different execution times for each taxonomy operation performed over each of the considered NoSQL systems. The table includes two columns for each system, one shows a summary of the native code performed and the other the execution time multiplied by a factor that is the execution time for the $\text{op}_{\text{mod}}$ operation on MongoDB, Cassandra and Neo4J, which are denoted as $t_M$, $t_C$ and $t_N$, respectively.

MongoDB operations performed as expected because the majority of them scan over a single entity type ($\text{Delete}$, $\text{Unnest}$ or $\text{Cast}$), so their ratio is close to $1 \times t_M$ and only a couple of operations such as $\text{Copy}$ or $\text{Morph}$ do require additional scans (or an explicit join) and therefore are much more costly. As was explained in Section 3, although $\text{Delvar}$ and $\text{Adapt}$ are semantically equal, they are implemented differently.
because the former removes instances belonging to a variation and the latter transforms those instances to a new variation by adding and/or deleting fields. Cassandra operations do not show huge performance differences between them, although the ones with the COPY command are the most costly. As explained in Section 4, these operations are the ones that were implemented by means of an export/import to an external file. These tables were of only five fields, but it is foreseeable that their performance would drop if tables had more fields. It is also important to note that CSV manipulation on the most costly operations was not included in the measurement.

Finally, Neo4j operations behaved in a similar way as in MongoDB, although certain relationship operations (Split, Merge, and Union) performed worse than other relationship operations because they not only affect single relationships but also involve creating new relationships between nodes and filling their fields.

7 Related Work

In this section, we will contrast our proposal to some relevant schema evolution approaches presented for relational and object-oriented databases, and to most of research work done on NoSQL systems.

The works of Jean Luc Hainaut et al. [16, 10] and Carlo Curino et al. [8, 7] are some of more influential contributions on automating relational schema evolution. While the interest of Curino et al. was exclusively focused on relational systems in order to build the PRISM/PRISM++ tool, Hainaut et al. defined the DB-MAIN generic approach that involved the main data models existing at the end of the nineties. DB-Main was based on two main elements: (i) The Generic Entity/Relationship (GER) metamodel to achieve platform-independence; and (ii) a transformational approach to implement processes such as reverse and forward engineering, and schema mappings. Our proposal is also based on a generic metamodel and a transformational approach, but differs in two several significant aspects. Firstly, GER did not integrate data models supported by NoSQL systems, instead we used the U-Schema metamodel which was specially designed to support NoSQL and relational schemas. Secondly, we have taken advantage of Model-driven Engineering (MDE) technology incorporated in the EMF/Eclipse framework, as U-Schema data model is implemented in form of an Ecore metamodel [30]. A detailed comparison between GER and U-Schema data model is given in [4]. Also, it should be noted that no taxonomy was defined for DB-Main. Instead, the taxonomy shown in [26] is adopted.

The PRISM/PRISM++ tool is aimed at automating data migration tasks and rewriting legacy queries. PRISM/PRISM++ provides an evolution language based on Schema Modification Operators (SMOs) that preserve information and are reversible, and Integrity Constraint Modification Operators (ICMO). Given a schema, a new schema, and a set of mappings expressed through SMOs and ICMOs, queries can be rewritten and stored data are updated. Although much more mature and evolved than our work, this approach does not address the NoSQL database evolution.

In OO systems, schema evolution is a more complicated problem than in relational systems. This is because OO schemas are classes hierarchies of inheritance and aggregation, while relational schemas are sets of tables. In addition, classes have structure (attributes) and behavior (methods). OO schema evolution aroused great interest until the mid-1990s, when OO systems evidenced limitations to become an alternative to relational systems. A survey on that topic was presented in [25], and Bauerjee et al. [2] published a seminal paper proposing a schema changes taxonomy, and discussing the operations whose semantic impact was analyzed. Our proposal is inspired by that work: we have defined a taxonomy for NoSQL databases, the change operations are rigorously specified and its performance is measured.

To the best of our knowledge, most research efforts on NoSQL schema evolution are considered below. A proposal for different NoSQL databases is described in [21]. The main focus in this approach is on efficient data migration for different NoSQL databases. In this work, a 5-operation taxonomy is defined for a simple data model: schemas are a set of entities that are formed by attributes whose type can be a primitive or collection type or either another entity, but relationships between entities are not considered. In this work, the schema model serves as an abstraction layer on top of different NoSQL databases but do provide the additional constraints of a conceptual model. The five schema evolution operations are add/remove/re-name properties, and copy/move a set of properties from an entity type to another. This taxonomy was implemented in Darwin [33, 32], a data platform for schema evolution management and data migration. Darwin is also able to extract the implicit schema and version history of NoSQL databases, manage those versions, update data eager, lazily or with intelligent hybrid approaches and rewrite queries that try to retrieve data that is yet to be updated. It was also implemented on the Google Cloud Platform as part of the Cleaver tool [29]. This tool maps operations of the taxonomy to MapReduce functions. Our proposal is based on a more complex unified data model, and this results in a richer change taxonomy, which is applicable for NoSQL and relational data models.

As noted in [24], heterogeneous database systems are commonly implemented through a unified schema approach or a multi-database approach. Holubová et al. explored schema evolution for multi-database database systems in [17] and [35]. They proposed a layered architecture which consists of a model-independent layer and a model-specific layer. The former delegates to the corresponding model-specific
components by examining the prefix of the affected entities, thus providing a way to support both intra-model and inter-model operations. Since heterogeneous databases can store entities referencing others stored in a different data model, the proposal also provides the foundation for managing referential integrity between them when modifying the database. Regarding schema evolution, a taxonomy of 10 operations is defined: 5 for entity types (kinds) and 5 for properties. These latter correspond to those defined in [21], and the first 5 are add, drop, rename, split, and merge, which have the same meaning as in our taxonomy. The impact of operations is discussed classifying them as intra-model or inter-model, depending on how many models are affected by changes, and as global and local operations, depending on whether they may be specified over the global union schema, or only over a specific model. It is worth noting that we have not tackled the issues related to schema evolution in heterogeneous systems, but we are interested in offering automation for individual stores in a data model-independent way through a unified data model. Furthermore, our taxonomy includes operations related to relationships and variations, and we have defined a complete language to define and execute schema change operations.

In [9], a taxonomy is proposed as part of an approach to rewrite queries for polystore (i.e., heterogeneous databases) evolution. The taxonomy includes six operations applicable to entity types, four to attributes and four to relations. A generic language, called TyphonML, is used to define relational and NoSQL schemas, physical mapping and schema evolution operations. Like our approach, TyphonML is based on a generic metamodel also created with the Ecore metamodeling language. However, U-Schema is a richer data model as discussed in [4], which allowed us to define operations on (i) aggregates and references in a separate way, (ii) structural variations, and (iii) distinguish between entity and relationship types in graph stores.

Suárez-Otero et al. [34] have recently published a work-in-progress paper where they define a taxonomy of 7 schema changes and analyze how they affect to the schema and data in the case of Cassandra, but no automation is addressed. In our case, a unified model for logical schemas is considered, the taxonomy includes a larger number of operations, and the taxonomy is implemented for 3 popular NoSQL systems for different data models.

Some works have presented approaches for a particular NoSQL store. Loup Meurice and Anthony Cleve
presented a strategy for MongoDB [23]: queries are extracted from Java code, and queries are analyzed to find the database entities (i.e., collections of documents), entity properties and references between documents. A “historical database schema” is obtained from the set of variations of each collection, which is visualized through a table by using different colors and icons to indicate if a property can give rise to errors due to possible data corruption or warn developers of renamed properties or collections. As far as we know, this work is the only proposal that extracts schemas from code. The strategy of schema evolution is limited to consider existing entity variations as schema changes. We proposed a strategy for NoSQL and relational stores, and a operations definition language. Actually, the work of Meurice and Cleve is a reverse engineering strategy to extract schemas rather than a schema evolution approach. KVolve [28] is a library that allows for schema evolution in the Redis key-value store. It is restricted to key and value changes for entries sharing a common prefix, and accepts a previously-defined user function written in C with the actions to be performed. In this library, key changes must be done by unambiguous bijections, and value changes can only access the value to be updated. This library to operate on standalone Redis instances. It employs a lazy strategy that updates entries as they are accessed. This solution is limited to Redis, while our approach is applicable to the four most widely used NoSQL data models. In [4], a mapping of Redis to U-Schema is shown, so the approach here presented may be applied to Redis, but we have not built an Orion engine yet.

In short, the differences between our work and the existing ones can be summarized as follows. We suppose a NoSQL schema represented as a U-Schema model has been extracted from a existing store, this schema can then be changed by writing a Orion script, and the schema and data updates are automatically performed. Orion is a system-independent operation language because U-Schema is a unified data model that includes all the typical elements of logical NoSQL and relational schemas, even structural variations are considered, which allows a more complete taxonomy to be defined.

Table 3 summarizes the comparison carried out between our approach and other works. Several criteria are defined to compare the schema evolution approaches discussed above: changes operations in the taxonomies, supported database paradigms, schema representation, aim, if operation impact analysis has been performed, and if a tool is available.

8 Conclusions and Future Work

In this paper we have explored the NoSQL schema evolution by using a generic solution: a unified data model with which we have defined a taxonomy of schema changes. We presented the Orion schema operation language implementing this taxonomy. Thanks to the richness of the unified metamodel abstractions, we were able to define changes that affect aggregates, references and variations. The operations have been implemented for three widely used NoSQL stores, one based in documents and schemaless, other column-based that requires schema declarations and a third one based in graphs. The usefulness of our proposal has been validated through a refactoring of the StackOverflow dataset and an outlier migration on the Reddit dataset. Also note that this work presents an application of the unified metamodel presented in [4]. An implementation of Athena and Orion are publicly available on a GitHub repository.

Although the main purpose of the Orion language is to support schema changes in a platform-independent way, it can be used in other cases: (i) If no initial schema is provided, an Orion script can bootstrap a schema by itself; (ii) Differences between Athena schemas may be expressed as Orion specifications; and (iii) Orion specifications may be obtained from specifications of existing tools such as the PRISM++ operation language [7].

The future work considered includes: (i) Updating application code that makes use of the retrieved data as well as handling query rewriting. Some preliminary work has been done on [5], where code analysis is proposed to extract schemas, apply refactorings and provide suggestions of code modifications, and this functionality could be integrated in Orion. (ii) Investigating new operations to be added to the taxonomy, such as operations regarding schema inheritance and type hierarchies, and refining existing ones as needed. (iii) Extending Orion to generate code for specific programming languages, which will allow to implement operations on databases that are not supported natively. Finally, (iv) integrating Orion into a tool for agile migration.

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| Operation       | Curino et al. [8] | Hainaut et al. [11] | Störfl et al. [21] | Holubová et al. [17] | Fink et al. [9] | Hernández et al. |
|-----------------|-------------------|---------------------|--------------------|----------------------|----------------|-----------------|
| **Schema Types**| Create,Drop,Rename| Add,Delete,Rename   | Create,Drop,Rename | Add,Delete,Rename    | Add,Delete,Rename| Add,Delete,Rename|
|                 | Copy,Merge,Join   | Change to/from weak| Split,Partition,Join,Coalesce| Merge,Split,Migrate | Merge,Split,Migrate| Merge,Split,Migrate|
|                 | Partition,Decompose|                      |                     |                      |                |                 |
| **Variations**  | —                  | —                   | —                  | —                    | —              | Delvar,Adapt,Union|
| **Features**    | —                  | —                   | —                  | —                    | —              | —               |
| **Attribute**   | Add,Drop,Rename   | Add,Drop,Rename     | Add,Drop,Rename    | Add,Drop,Rename      | Add,Drop,Rename| Add,Drop,Rename|
|                 | Copy,Move         | Copy,Move           | Copy,Move          | Copy,Move            | Delete,Remove,| Delete,Remove,|
|                 |                   |                     |                    |                      | Rename,      | Rename,       |
|                 |                   |                     |                    |                      | Copy,Move    | Move, Nest, Unnest|
| **Reference**   | —                  | —                   | —                  | —                    | —              | —               |
| **Aggregate**   | —                  | —                   | —                  | —                    | —              | —               |
| **Supported Paradigms** | Relational | Relational, hierarchical | NoSQL | Multi-model | Multi-model | Relational, NoSQL |
| **Unified Schema Representation** | No | Yes (GER) | No (But a Generic Interface) | No | No | Yes (U-Schema) |
| **Data Update** | Yes | Yes | Yes (eager, lazy, hybrid) | Yes | Yes | Yes |
| **Code Update** | Query rewriting SQL Views | Program modification (hints) | Query adaptation | Query adaptation | Query adaptation | No |
| **Implementing Tool** | PRISM/PRISM++ | DB-Main | Darwin | MM-evolver | TyphonML | Orion |
| **Semantic Change Analysis** | No | No | Yes | Yes | Yes | Yes |