Logical Unified Modeling for NoSQL Databases

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Abstract: NoSQL data stores are becoming widely used to handle Big Data; these systems operate on schema-less data model enabling users to incorporate new data into their applications without using a predefined schema. But, there is still a need for a conceptual model to define how data will be structured in the database. In this paper, we show how to store Big Data described by conceptual model within NoSQL systems. For this, we use the Model Driven Architecture (MDA) that provides a framework for models automatic transformation. Starting from a conceptual model describing a set of complex objects, we propose transformation rules formalized with QVT to generate NoSQL physical models. To ensure efficient automatic transformation and to limit the impacts related to technical aspects of NoSQL systems, we propose a generic logical model that is compatible with the three types of NoSQL systems (column, document and graph). We provide experiments of our approach using a case study related to the health care field. The results of our experiments show that the proposed logical model can be effectively transformed into different NoSQL physical models independently of their specific details.

1 INTRODUCTION

Company digital transformation is accompanied by an exponential growth in data collected which is known as Big Data. Generally, we describe Big Data according to three vectors (Gartner, 2001): Volume (many terabytes of data that need to be processed), Variety (different data type including factors such as format, structure, and sources) and Velocity (speed of data loading and processing). Relational systems representing the majority of DBMS, prove to be inadequate for all applications, especially these involving Big Data (Abello, 2015). As a result, new kind of DBMS, known as "NoSQL" (Cattell, 2011), has appeared. These systems, with flexible schemas, are well suited for managing large volume of data. They also offer good performance when scaling up (Angadi, 2013). NoSQL encompasses a wide variety of different systems that were developed to meet specific needs. They can be classified into four basic types: key-value, column-oriented, document and graph-oriented. In this paper, we exclude the key-value because column-oriented, document-oriented and graph-oriented systems extend the concepts of key-value systems (Abadi, 2008).

Big Data applications developers are faced with the problem of storing data in NoSQL systems. To address this problem, some solutions dealing with model transformation have been proposed. Li et al. (Li, 2014) propose MDA-based process to transform UML class diagram into column-oriented physical HBase model. Daniel et al. (Daniel, 2016) describe mapping between an UML conceptual model and a NoSQL physical model compatible only with graph-oriented systems. In these works, the adopted processes depend only on one type of NoSQL systems (column-oriented in (Li, 2014) and graph-oriented in (Daniel, 2016)). However, users need to choose the system type most suited to their needs. For example, processing operations require access to hierarchically structured data, document-oriented is the most adapted solution.

The main purpose of our work is to assist developers in implementing Big Data on NoSQL systems. For this, we propose a new MDA-based process that transforms a conceptual data model describing Big Data into several NoSQL physical models. This automatic process allows developer to choose the system type he wants to use.

The rest of the paper is structured as follows:

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Section 2 motivates our work using a case study in the healthcare field, Section 3 introduces our MDA-based approach, Section 4 presents a first transformation that creates a NoSQL logical model starting from UML class diagram, Section 5 presents a second transformation that generates NoSQL physical models from the logical model, Section 6 details our experiments and Section 7 reviews previous work on models transformation. Finally, Section 8 ends up with the conclusion and future work.

2 MOTIVATION

To motivate and illustrate our work, we present a case study in healthcare filed. This case study concerns national or international scientific programs for monitoring patients having serious diseases. The main goal of this program is (1) to collect data about disease development over time, (2) to study interactions between different diseases (3) to evaluate the short and medium-term effects of their treatments. The medical program can last up to 3 years. Data collected from establishments involved in such a program have the characteristics of Big Data (the 3 V): **Volume:** The amount of data collected from all the establishments in three years can reach several terabytes. **Variety:** Data created while monitoring patients come in different types ; they can be (1) structured like patient's vital signs (respiratory rate, blood pressure, temperature, etc.), patient name, diagnosis codes, etc. (2) unstructured such as patient histories, consultation summaries, paper prescriptions, radiology reports, and (3) semi-structured document such as the package leaflets of medicinal products that provide a set of comprehensible information enabling the use of the medicinal product safely and appropriately. **Velocity:** Some data are produced in continuous flow by sensors; it must be processed in near real time because it can be integrated into time-sensitive processes (for example, some measurements, like temperature, require an emergency medical treatment if they cross a given threshold).

3 UMLtoNoSQL APPROACH

Our purpose in this paper is to define, specify and automate a process for storing Big Data in NoSQL systems. For this, we propose the process called UMLtoNoSQL that automatically transforms a conceptual model (UML class diagram) provided by the developer into the physical model of the NoSQL system he wants to use. In UMLtoNoSQL process, we introduce a logical level between conceptual (business description) and physical (technical description) levels in which a generic model is developed. This generic logical model has a double interest: (1) compatible with the three NoSQL systems, which allow developers to choose the NoSQL system type that best meets their needs. (2) independent of the technical aspects of NoSQL systems that can evolve and create new versions. To formalize and automate our process, we use the Model Driven Architecture proposed by OMG.

One of the main aims of MDA is to separate the functional specification of a system from the details of its implementation in a specific platform (Hutchinson, 2011). This architecture defines a hierarchy of models from three points of view: Computation Independent Model (CIM), Platform Independent Model (PIM), and Platform Specific Model (PSM) (Bézivin, 2001). Among this proposed models, we use PIM and PSM.

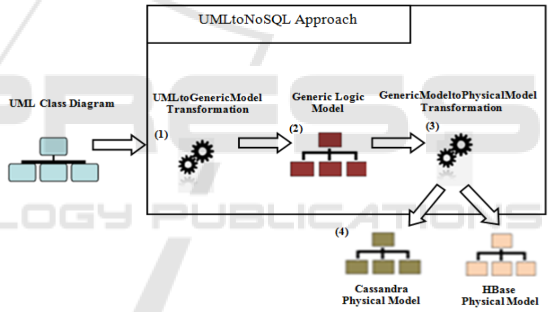


Figure 1: Overview of UMLtoNoSQL process.

In our scenario, the UML and generic models would conform to the PIM level. UMLtoNoSQL process takes care of generating the generic model (logical PIM) from the UML class diagram (conceptual PIM). At the PSM level, we consider three physical models that correspond to Cassandra (column-oriented system), MongoDB (document-oriented system) and Neo4J (graph-oriented system). Figure 1 presents the different component of UMLtoNoSQL process. UMLtoGenericModel (1) is the first transformation (section 4) in UMLtoNoSQL process. It is in charge of converting the input UML class diagram (conceptual PIM) into the generic logical model (2) conforming to the generic logical metamodel proposed in Section 4; this metamodel describes a data structure compatible with the three types of NoSQL systems. GenericModeltoPhysicalModel (3) is the second transformation (section 5) in UMLtoNoSQL. It is in charge of transforming the generic logical model into NoSQL physical models (PSMs) (4).

We note that UMLtoNoSQL process generates several NoSQL physical models from a UML class diagram. In order to do this, it’s necessary to register, for each physical model, its specific parameters (transformation rules). To illustrate our work, we have taken as example three physical models that correspond to: Cassandra, MongoDB and Neo4j systems. If the developer chooses to use another system, the process must be completed by adding new parameters specific to this system.

4 UML TO GENERIC MODEL TRANSFORMATION

In this section we present the UMLtoGenericModel transformation, which is the initial transformation in our approach presented in Figure 2. We first define the source (UML Class Diagram) and the target (Generic Logical Model), and then we focus on the transformation itself.

4.1 Source: UML Class Diagram (Conceptual PIM)

UML is widely accepted as a standard modelling language for describing data. Therefore, we model Big Data using UML class diagram. A Class Diagram (CD) is defined as a tuple (N, C, L), where:
N is the CD name,

C is a set of classes. Classes are composed from structural and behavioural constituents. In this paper, we consider only the structural part; since the operations are linked to the behaviour, we will not take them into account. The schema of each class c ∈ C is a tuple (N, A, IdentO), where:

- c.N is the class name,
- c. A = $\{a_1^c, \dots, a_q^c\}$ is a set of q attributes. The schema of each attribute a^c ∈ A is a pair (N,C) where “a^c.N” is the attribute name and “a^c.C” the attribute type; C can be a predefined class, i.e. a standard data type (String, Integer, Date, etc.) or a business class (class defined by user),
- c.IdentO is a special attribute of c; it has a name IdentO^c.N and a type called “Oid”. In this paper, an attribute whose type is “Oid” represents a unique object identifier, i.e. an attribute whose value distinguishes an object from all other objects of the same class,

L is a set of links. Each link l between n classes, with n>=2, is defined as a tuple (N, Ty, Pr^l), where:

- l.N is the link name.
- l.Ty is the link type : Association, Composition or Generalization.
- l.Pr^l = $\{pr_1^l, \dots, pr_n^l\}$ is a set of n pairs. ∀ i ∈ {1,..,n}, pr_i^l = (c,cr), where pr_i^l.c is a linked class and pr_i^l.cr is the cardinality placed next to c. Note that pr_i^l.cr can contain a null value if no cardinality is indicated next to c (like in generalization link).

Class diagram metamodel is shown in figure 2. This metamodel is adapted from the one proposed by OMG.

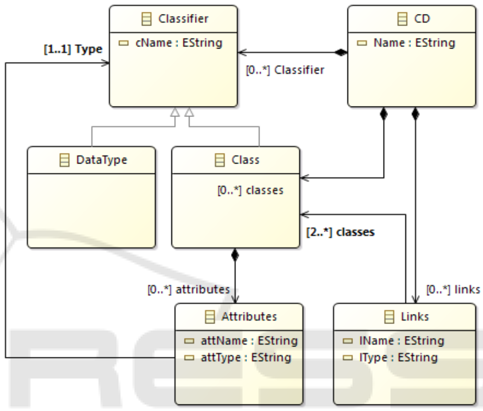


Figure 2: Source Metamodel.

4.2 Target: Generic Logical Model (Logical PIM)

This section aims to define a generic logical model that describes data according to the common characteristics to the three types of NoSQL systems: column-oriented, document-oriented and graph-oriented. In the generic logical model, DataBase (DB) is defined as a tuple (N, T, R), where:
N is the database name,

T is a set of tables. The schema of each table t ∈ T is a tuple (N, A, IdentL), where:

- t.N is the table name,
- t.A = $\{a_1^t, \dots, a_q^t\}$ is a set of q attributes that will be used to define rows of t; each row can have a variable number of attributes. The schema of each attribute a^t ∈ A is a pair (N,Ty) where “a^t.N” is the attribute name and “a^t.Ty” the attribute type.
- t.IdentL is a special attribute of t; it has a name IdentL^t.N and a type called “row-key”. In this paper, an attribute whose type is “row-key” represents a unique row identifier, i.e. an

attribute whose value distinguishes a row from all other rows of the same table,

R is a set of relationships. A relationship is a link between two tables. In the generic logical model there are only binary relationships between tables. Each relationship r ∈ R between t_1 and t_2 is defined as a tuple (N, Ty, Pr^r), where:

- r.N is the relationship name.
- r.Ty is the relationship type : Association, Composition or Generalization.
- $r.Pr^r = \{pr_1^r, pr_2^r\}$ is a set of two pairs. ∀ i ∈ {1,2}, pr_i^r = (t,cr), where pr_i^r.t is a related table and pr_i^r.cr is the cardinality placed next to t.

Metamodel of the proposed generic logical model is shown in figure 3.

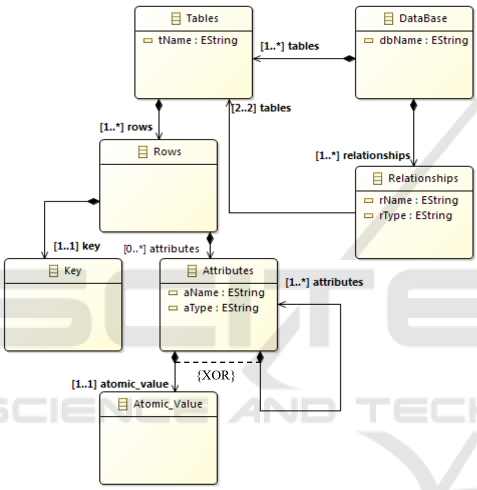


Figure 3: Target Metamodel.

4.3 Transformation Rules

R1: each CD is transformed into a database DB, where DB.N = CD.N.
R2: each class c ∈ C is transformed into a table t ∈ DB, where t.N = c.N, $IdentL^t$.N = $IdentO^c$.N.
R3: each attribute a^c ∈ c.A is transformed into an attribute a^t, where a^t.N = a^c.N, a^t.Type = a^c.C, and added to the attribute list of its transformed container t such as a^t ∈ t.A.
R4: each link l ∈ L between two classes c_1 and c_2 is transformed into a relationship r ∈ R between two tables t_1 and t_2, where r.N = l.N, r.Ty = l.Ty et r.Pr^r = l.Pr^l, where t_1 and t_2 are the tables representing c_1 and c_2.
R5: each link l ∈ L between n classes $\{c_1, \ldots, c_n\}$ (n>=3) is transformed into (1) a new table t^l, where t^l.N = l.N, and (2) n relationships $\{r_1, \ldots, r_n\}$, ∀ i ∈ {1,..,n} r_i links t^l to another table t_i representing a related class c_i, where r_i.N = (t^l.N)_(t_i.N), r_i.Type = Association and r_i. Pr^r = {(t^l, cr), (t_i, cr)}.
R6: each association class c_{asso} between n classes $\{c_1, \ldots, c_n\}$ (n>=2) is transformed like a link between multiple classes (R5) using (1) a new table t^{ac}, where t^{ac}.N = l.N, (2) n relationships $\{r_1, \ldots, r_n\}$, ∀ i ∈ {1,..,n} r_i links t^{ac} to another table t_i representing a related class c_i, where r_i.N = (t^{ac}.N)_(t_i.N), r_i.Type = Association et r_i. Pr^r = {(t^{ac}, cr), (t_i, cr)}. Like any other class, t^{ac} contain also a set of attributes A, where t^{ac}.A = c_{asso}.A.

These transformation rules have been formalized with QVT (figure 4.b), which is a standard defined by OMG for expressing models transformation.

5 GENERIC MODEL TO PHYSICAL MODEL TRANSFORMATION

In this section we present the second transformation in our approach UMLtoNoSQL (figure 2). It is in charge of creating NoSQL physical models from the proposed generic logical model.

5.1 Source: Generic Logical Model (Logical PIM)

The source of this transformation is the target of the previous UMLtoGenericModel transformation.

5.2 Target: NoSQL Physical Models (PSMs)

To illustrate our approach, we have chosen three NoSQL systems: Cassandra, MongoDB and Neo4j; three well known NoSQL systems.

5.2.1 Cassandra Physical Model

In Cassandra physical model, KeySpace (KS) is the top-level container that owns all the elements. It's defined as a tuple (N, F), where:

N is the keyspace name,

F is a set of columns-families. The schema of each columns-family f ∈ F is a tuple (N, Cl, PrimaryKey), where:

- f.N is the columns-family name,
- f.Cl = $\{cl_1, \ldots, cl_q\}$ is a set of q columns that will be used to define rows of f; each row can have a variable number of columns. The

schema of each column cl ∈ Cl is a pair (N,Ty) where “cl.N” is the column name and “cl.Ty” the column type.
- f.PrimaryKey is a special column of f; it has a name PrimaryKey^f. N and a type PrimaryKey^f.Ty (standard data type). PrimaryKey^f identifies each row of f.

5.2.2 MongoDB Physical Model

In MongoDB physical model, DataBase (DB^{MD}) is the top-level container that owns all the elements. It’s defined as a tuple (N, Cll), where:

N is the database name,

Cll is a set of collections. The schema of each collection cll ∈ Cll is a tuple (N, Fl, Id), where:
- cll.N is the collection name,
- cll.Fl = $\text{Fl}^{\text{A}} \cup \text{Fl}^{\text{CX}}$ is a set of atomic and complex fields that will be used to define rows, called documents, of Cll; each document can have a variable number of fields. The schema of each atomic field $\text{fl}^{\text{a}} \in \text{Fl}^{\text{A}}$ is a tuple (N,Ty) where “fl^{a}.N” is the field name and “fl^{a}.Ty” is the field type. The schema of each complex field $\text{fl}^{\text{cx}} \in \text{Fl}^{\text{CX}}$ is also a tuple (N, Fl’) where fl^{cx}.N is the field name and fl^{cx}.Fl’ is a set of fields where Fl’⊂ Fl.
- cll.Id is a special field of cll; it has a name Id^{cll}.N and a type Id^{cll}.Ty (standard data type). Id^{cll} identifies uniquely each document of cll.

5.2.3 Neo4j Physical Model

In Neo4j physical model, Graph (GR) is the top-level container that owns all the elements. It’s defined as a tuple (V, E), where:

V is a set of vertex. The schema of each vertex v ∈ V is a tuple (L, Pro, Id), where:
- v.L is the vertex label,
- v.Pro = $\{\text{pro}_1, \ldots, \text{pro}_q\}$ is a set of q properties. The schema of each property pro ∈ Pro is a pair (N,Ty), where “pro.N” is the property name and “pro.Ty” the property type.
- v.Id is a special property of v; it has a name Id^{v}.N, a type Id^{v}.Ty and the constraint “Is Unique ”. It identifies uniquely v in the graph.

E is a set of edges. The schema of each edge e ∈ E is a tuple (L, H_1, H_2), where:
- e.L is the edge label,
- e. H_1 and e. H_2 are the nodes related by e.

5.3 Transformation Rules

Several solutions can ensure the transformation of the generic logical model into a NoSQL physical model. We provide all transformation possibilities available; the developer chooses the one that meets better his needs. We note that the set of solutions proposed in this section is not inclusive. More marginal solutions may be considered.

5.3.1 To Cassandra Physical Model

R1: each database DB is transformed into a keyspace KS, where KS.N = DB.N.
R2: each table t ∈ DB is transformed into a columns-family f ∈ KS, where f.N = t.N, PrimaryKey^f.N = IdentL^t.N.
R3: each attribute a^t ∈ t.A is transformed into a column cl, where cl.N = a^t.N, cl.Ty = a^t.Ty, and added to the column list of its transformed container f such as cl ∈ f.Cl.
R4: each relationship r ∈ R between two tables t_1 and t_2 is transformed by using references. Cassandra does not support imbrication; the only solution we can use to express relations between columns-families consists in using references.

Depending on the relationship type, we distinguish the following solutions:
- if r = (N, Association, {(t_1,cr),(t_2,cr)}), we transform r according to its cardinalities :
  - if r = (N, Association, {(t_1,*),(t_2,1)}), there are two possible solutions:

<u>*Solution 1:*</u> r is transformed into a new column cl referencing f_2 (the columns-family representing t_2), where cl.N = (f_2.N)_Ref et cl.Ty = $\text{PrimaryKey}^{\text{f2}}$.Ty, and added to the columns list of f_1 (the columns-family representing t_1) such as cl ∈ f_1.Cl.
<u>*Solution 2:*</u> r is transformed into a new multivalued column cl referencing f_1 (the columns-family representing t_1), where cl.N = (f_1.N)_Ref et cl.Ty = set<$\text{PrimaryKey}^{\text{f1}}$>.Ty, and added to the columns list of f_2 (the columns-family representing t_2) such as cl ∈ f_2.Cl.
  - if r = (N, Association, {(t_1,1),(t_2,1)}) : r is transformed into a new column cl referencing the columns-family f representing one of the two related tables (t_1 or t_2), where cl.N = (f.N)_Ref et cl.Ty = $\text{PrimaryKey}^{\text{f}}$.Ty, and added to the columns list of the columns-family f’ representing the other related table such as cl ∈ f’.Cl.

- if r = (N, Association, {(t_1,*),(t_2,*)}), two solutions could be considered:

Solution 1: r is transformed into a new multivalued column cl referencing the columns-family f representing one of the two related tables (t_1 or t_2), where cl.N = (f.N)_Ref et cl.Ty = set<$PrimaryKey^f$>.Ty, and added to the columns list of the columns-family f' representing the other related table such as cl ∈ f'.Cl.

Solution 2: r is transformed into a new columns-family f, where f.N = r.N, f.Cl = {cl_1, cl_2}, cl_1.N = (f_1.N)_Ref, cl_1.Ty = $PrimaryKey^{f1}$.Ty, cl_2.N = (f_2.N)_Ref and cl_2.Ty = $PrimaryKey^{f2}$.Ty, where f_1 and f_2 are the columns-families represent t_1 and t_2.

- if r = (N, Composition, {(t_1,1),(t_2,*)}) : in composition relationship, cardinality of the composite is 1 which means that a component could be included in at most one composite at a time and the cardinality of the component is * which means that the composite could have multiple components. To transform it, there are two possible solutions:

Solution 1: r is transformed into a new multivalued column cl referencing the columns-family f_2 representing the component (t_2), where cl.N = (f_2.N)_Ref and cl.Ty = set <$PrimaryKey^{f2}$ >.Ty , and added to the columns list of the columns-family f_1 representing the composite (t_1) such as cl ∈ f_1.Cl.

Solution 2: r is transformed into a new column cl referencing the columns-family f_1 representing the composite (t_1), where cl.N = (f_1.N)_Ref et cl.Ty = $PrimaryKey^{f1}$.Ty , and added to the columns list of the columns-family f_2 representing the component (t_2) such as cl ∈ f_2.Cl.

- if r = (N, Generalization, {(t_1,1),(t_2, null)}) : in generalization relationship between a super-table t_1 and a sub-table t_2, cardinality of the super-table is 1 which means that each instance of the sub-table is also an indirect instance of the super-table. Because of this, generalization relationship is also informally called "Is A" relationship. We transform it into a new column cl referencing the columns-family f_1 representing the super-table (t_1), where cl.N = (f_1.N)_Ref et cl.Ty = $PrimaryKey^{f1}$.Ty , and added to the columns list of the columns-family f_2 representing the sub-table(t_2) such as cl ∈ f_2.Cl.

5.3.2 To MongoDB Physical Model

R1: each database DB is transformed into a MongoDB database DB^{MD}, where DB^{MD}.N = DB.N.

R2: each table t ∈ DB is transformed into a collection cll ∈ DB^{MD}, where cll.N = t.N et Id^{cll}.N = $IdentL^t$.N.

R3: each attribute a^t ∈ t.A is transformed into a field fl, where fl.N = a^t.N, fl.Ty = a^t.Ty, and added to the field list of its transformed container cll such as fl ∈ cll. Fl^A.

R4: a relationship r between two tables t_1 and t_2 could be transformed in MongoDB by using references or imbrication. Depending on the relationship type, we distinguish the following solutions:

- if r = (N, Association, {(t_1,cr),(t_2,cr)}), we transform r according to its cardinalities :
  - if r = (N, Association, {(t_1,*),(t_2,1)}), there are two possible solutions:

Solution 1: r is transformed into a new field fl referencing cll_2 (the collection representing t_2), where fl.N = (cll_2.N)_Ref and fl.Ty = Id^{cll_2}.Ty, and added to the fields list of cll_1 (the collection representing t_1) such as fl ∈ cll_1. Fl^A.

Solution 2: r is transformed into a new multivalued field fl referencing cll_1 (the collection representing t_1), where fl.N = (cll_1.N)_Ref and fl.Ty = set<Id^{cll_1}>.Ty, and added to the field list of cll_2 (the collection representing t_2) such as fl ∈ cll_2. Fl^A.

  - if r = (N, Association, {(t_1,1),(t_2,1)}) : r is transformed into a new field fl referencing the collection cll representing one of the two related tables (t_1 or t_2), where fl.N = (cll.N)_Ref and fl.Ty = Id^{cll}.Ty, and added to the field list of cll' representing the other related table such as fl ∈ cll'. Fl^A.
  - if r = (N, Association, {(t_1,*),(t_2,*)}), two solutions could be considered:

Solution 1: r is transformed into a new multivalued field fl referencing the collection cll representing one of the two related tables (t_1 or t_2), where fl.N = (cll.N)_Ref and fl.Ty = set<Id^{cll}>.Ty, and added to the field list of cll' representing the other related table such as fl ∈ cll'. Fl^A.

Solution 2: r is transformed into a new collection cll, where cll.N = r.N, cll.Fl = {fl_1, fl_2}, fl_1.N = (cll_1.N)_Ref, fl_1.Ty = Id^{cll_2}.Ty, fl_2.N = (cll_2.N)_Ref and fl_2.Ty = Id^{cll_2}.Ty, where cll_1 and cll_2 are the collections representing t_1 and t_2.

- if r = (N, Composition, {(t_1,1),(t_2,*)}) : there are three possible solutions:

Solution 1: r is transformed by embedding the collection cll_2 representing the component (t_2) in the collection cll_1 representing the composite (t_1), where cll_2 ∈ cll_1. Fl^{CX}.

Solution 2: r is transformed into a new field fl referencing the collection cll_1 representing the composite (t_1), where fl.N = (cll_1.N)_Ref et fl.Ty = Id^{cll1}.Ty , and added to the field list of the collection cll_2 representing the component (t_2) such as fl ∈ cll_2. Fl^A.

Solution 3: r is transformed into a new multivalued field referencing the collection cll_2 representing the component (t_2), where fl.N = (cll_2.N)_Ref and fl.Ty = set <Id^{cll2} >.Ty , and added to the field list of the collection cll_1 representing the composite (t_1) such as fl ∈ cll_1. Fl^A.

- if r = (N, Generalization, {(t_1,1),(t_2, null)}) : it's transformed into a new field fl referencing the collection cll_1 representing the super-table (t_1), where fl.N = (cll_1.N)_Ref and fl.Ty = Id^{cll1}.Ty , and added to the field list of the collection cll_2 representing the sub-table (t_2) such as fl ∈ cll_2. Fl^A.

5.3.3 To Neo4j Physical Model

R1: each table t ∈ DB is transformed into a vertex v ∈ V, where v.L = t.N, Id^v.N = $IdentL^t$.N.
R2: each attribute a^t ∈ t.A is transformed into a property pro, where pro.N = a^t.N, pro.Ty = a^t.Ty, and added to the property list of its transformed container v such as pro ∈ v.Pro.
R3: Each relationship r between two tables t_1 and t_2 is transformed into an edge e, where e.L = r.N, e. H_1 = v_1 and e. H_2 = v_2, where v_1 and v_2 are the vertex representing t_1 and t_2.

6 EXPERIMENTS

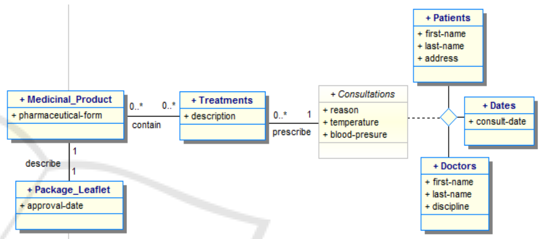
In this section, we first provide the implementation of UMLtoGenericModel transformation as presented in sections 4, and then we show how to generate NoSQL physical models starting from the proposed generic logical model.

6.1 Experimental Environment

We carry out the experimental assessment using: (1) *Eclipse Modeling Framework (EMF):* a modeling framework and code generation to support the development of tools and model driven applications; *(2) Ecore:* a metamodeling language that we used to create our metamodels; (3) *XML Metadata Interchange (XMI):* XML based standard for metadata interchange. We use XMI to create models as instance of metamodels; and (4) *Query / View / Transformation (QVT):* the OMG standard for models transformation.

6.2 UMLtoGenericModel Transformation

Before proceeding to the implementation of the transformation rules, first, we created Ecore metamodels corresponding to the source (Figure 2) and the target (Figure 3). The next step is to create an instance of the source metamodel (Figure 4.a). In parallel, we used QVT plugin to implement the transformation rules (Figure 4.b); the comments in the script indicate the rules used. Finally, we tested the transformation by running the QVT script. The execution of this script provides the generic logical model (figure 4.c).



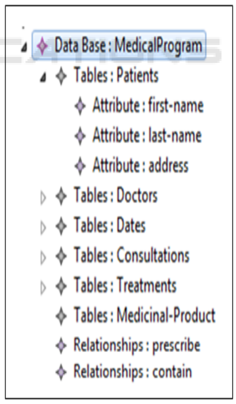
(a) : Source Model (excerpts).

```
modeltype ConceptualPIM uses
"http://UMLmm.com";

modeltype LogicalPIM uses
"http://GenericModelmm.com";

transformation
TransformationUmlToNoSQL(in Source:
ConceptualPIM, out Target:
LogicalPIM);

main() {
Source.rootObjects()[CD] -> map
toDataBase();
}
-- Transforming Class Diagram to
DataBase
mapping
ClassDiagram::toDataBase():DataBase{
name := self.name;
tables:=self.classes -> map
toTable();
}
-- Transforming Class to Table
 mapping UML
::Class::toTable():COLM::Table{
name:=self.name;
attributes:=self.attributes -> map
toAttribute();
}
-- Transforming Class Attribute to
Table Column
mapping UML
::Attribute::toAttribute():COLM::Colu
mn{
tname:=self.cname;
type:=self.type -> map toType();
}
-- Transforming binary link to
```



(b) QVT Rules. (c) Target Model..

Figure 4: UMLtoGenericModel transformation.

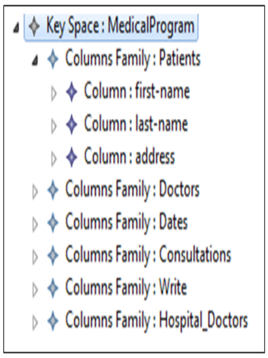
6.3 GenericModeltoPhysicalModel Transformation

The generic model proposed in this paper does not imply a specific system. Consequently, several NoSQL physical models could be generated starting from it. Lack of place, we show only Cassandra physical model (figure 5.b) generated from the generic logical model (figure 4.a). An excerpt from the QVT transformation script is shown in Figure 5.a.

```
main() {
Source.rootObjects()[DataBase] ->
map toKeySpace();
}

mapping
DataBase::toKeySpace():KeySpace{
name := self.name;
columnsfamily:=self.tables -> map
toColumnsFamily();
}
-- Transforming Ctable to
ColumnsFamily
 mapping COLM
::Table::toColumnsFamily():Cassandr
a::ColumnsFamily{
name:=self.name;
column:=self.columns -> map
toColumn();
}
-- Transforming Attribute to Column
mapping COLM
::Column::toColumn():Cassandra::Col
umn{
if (self.cType="Rid"){
```

(a) QVT Rules.



(b) Cassandra Model.

Figure 5: GenericModeltoCassandraModel transformation.

7 RELATED WORK

To the best of our knowledge, there are only few solutions that have dealt with NoSQL databases conceptual modeling. Chevalier et al. (Chevalier, 2015) defined a set of rules to map a multidimensional model into column-oriented and document-oriented models. The links between facts and dimensions have been converted using imbrications. Although the transformation process proposed by authors start from a conceptual level (multidimensional model), this specific model is different from the UML standard; it contains facts, dimensions and one type of links only. Other studies investigate the process of transforming relational databases into HBase (Li, 2010) and MongoDB (Vajk, 2013). However, the relational model does not present the semantic richness of UML (especially through the several types of relationships between classes: association, composition, generalization, etc.). Few works have presented approaches to implement UML conceptual models in NoSQL databases. Li et al. (Li, 2014) propose a MDA-based approach to transform UML class diagram into HBase. After building the source and the target metamodels, the authors have proposed mapping rules to realize the transformation from the conceptual level to the physical level. These rules are applicable to HBase, only. Daniel et al. (Daniel, 2016) describe the mapping between UML conceptual models and graph databases via an intermediate graph metamodel. These rules are specific to graph databases used as a framework for managing complex data with many connections. Generally, this kind of NoSQL databases is used in social networks where data are highly connected.

8 CONCLUSION AND PERSPECTIVES

In this paper we have presented a MDA-based approach to implement UML conceptual model describing Big Data in NoSQL systems. Our approach consists of a chain of transformations that generate a generic logical model compatible with the three types of NoSQL systems (column, document and graph) and independent of a specific NoSQL platform, which makes it easier to transform it into several NoSQL physical models. As future work, we plan to complete our transformation process and propose a mapping for OCL expressions defined in the conceptual model; queries languages provided by NoSQL databases could be used for this.

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