Ingestion of a Data Lake into a NoSQL Data Warehouse: The Case of Relational Databases

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Abstract: The exponential growth of collected data, following the digital transformation of companies, has led to the evolution of databases towards Big Data. Our work is part of this context and concerns more particularly the mechanisms allowing to extract datasets from a Data Lake and to store them in a unique Data Warehouse. This one will allow to realize, in a second time, decisional analyses facilitated by the functionalities offered by the NoSQL systems (richness of the data structures, query language, access performances). This article proposes an extraction mechanism applied only to relational databases of the Data Lake. This mechanism relies on an automatic approach based on the Model Driven Architecture (MDA) which provides a set of schema transformation rules, formalized with the Query/View/Transform (QVT) language. From the physical schemas describing relational databases, we propose transformation rules that allow to generate a physical model of a Data Warehouse stored on a document-oriented NoSQL system (OrientDB). This paper presents the successive steps of the transformation process from the meta-modeling of the datasets to the application of the rules and algorithms. We provide an experimentation using a case study related to the health care field.

1 INTRODUCTION

Due to the considerable increase of data generated by human activities, Data Lakes have been created within organizations, often spontaneously, by the physical grouping of datasets related to the same activity. A Data Lake (Nargesian, Zhu, Miller, Pu, & Arocena, 2019) is a massive grouping of data consisting of structured or unstructured datasets. These datasets generally have the following characteristics: (1) they can be stored on heterogeneous systems, (2) each of them is exploited independently of the others, (3) some of them can contain raw data, i.e., data stored in their original form and without being organized according to the use that will be made of them, (4) the types and formats of the data can vary. In practice, a Data Lake can group together different datasets (Khine & Wang, 2018) such as relational databases, object databases, Comma Separated Values (CSV) files, texts, spreadsheet folders. The massive data contained in a Data Lake represents an essential reservoir of knowledge for business decision makers. This data can be organized according to a multidimensional data model in order to support certain types of decision processing (El Malki, Kopliku, Sabir, & Teste, 2018). For example, in the French health sector, a Data Lake has been created by the French public health insurance company under the name of "Espace Numérique de Santé" (ENS)[1]; it includes the electronic health records of insured persons, access authorization directories, health questionnaires, and care planners. The case study presented in Section 2 is in the context of insurance companies' exploitation of the ENS. It is this application that motivated our work. Indeed, the heterogeneity of storage systems combined with the diversity of content in the Data Lake is a major obstacle to the use of data for decision-making. To manipulate a Data Lake, a solution consists in ingesting the data into a Data Warehouse and then transforming it (grouping, calculations, etc.). Ingestion is a process that consists

[1] https://opusline.fr/health-data-hub-an-ambitious-french-initiative-for-tomorrows-health/

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in extracting data from various sources and then transferring them to a repository where they can be transformed and analyzed. For example, in (Meehan, Tatbul, Aslantas, & Zdonik, s. d.) massive data from various sources are ingested into a Data Warehouse and exploited in the context of information retrieval on the Web. Other works have introduced the concept of polystore which preserves the initial data sources (no ingestion) and allows querying them by creating "data islands", each of which contains several systems sharing a common query language. For example, all relational databases are connected to the "relational island", which is queried using standard SQL. This solution, developed in particular in the BiGDAWG (Duggan, Kepner, Elmore, & Madden, 2015) and ESTOCADA (Alotaibi et al., 2020) projects, keeps the data in their native formats.

Our work aims at performing decisional processing on a Data Lake. This problem is part of a medical application in which massive data are stored in a Data Lake that will be used by medical decision makers. We have chosen to ingest the data from the Data Lake into a Data Warehouse that will later be reorganized for Big Data Analytics. This article deals with the ingestion of relational databases and voluntarily excludes other forms of datasets present in the Data Lake. This choice is justified (1) by the majority presence of relational databases in the ENS used by our case study (cf. Section 2.1) and (2) by the major difficulty of translating relational key type links (attribute values) into pointer type links (references in object-oriented models).

Our paper is organized as follows: in the following Section 2, we present the medical application that justifies our work's purpose. Section 3 describes the context of our study as well as our research problem which aims at facilitating the querying of data contained in a Data Lake by decision makers. Section 4 describes the metamodels of the databases used in our application. Section 5 presents our contribution which consists in formalizing with the Model Driven Architecture (MDA), the process of transforming the databases of a Data Lake into a NoSQL Data Warehouse. Section 6 describes an experimentation of the proposed process based on our medical application. Section 7 contrasts our proposal with related works. Finally, Section 8 concludes this paper and highlights possible directions for exploring the continuity of the work.

2 CONTEXT OF WORK

In this section, we present the case study that motivated our work as well as the problem addressed in this article.

2.1 Motivating Scenario

Our work is motivated by a project developed in the health field for a group of private health insurance companies. These insurance companies, stemming from the social and solidarity economy, propose to their customers a coverage of the medical expenses which comes in complement of those refunded by a public institution: the public health insurance fund.

To ensure the management of their clients, these private health insurance companies are faced with a significant increase in the volume of data processed. This is all the truer since some of these companies act as social security centers, i.e., clients transmit the entire rebate file to a private insurance company, which performs all the data processing related to the file. In order to monitor these files, numerous exchanges are necessary between the health insurance fund, the private insurance companies and the health professionals. Under the impetus of the State, the health insurance fund has developed a digital health platform (ENS). This allows the storage of the medical data of each insured person. This data is confidential, but the holder can authorize a health professional or institution to consult or feed his ENS. All accesses and actions carried out on the ENS by non-holders are traced. Private health insurance companies therefore have limited access to the ENS, from which they can extract data in order to process the files of their policyholders and, more broadly, to carry out analyses of any kind (in compliance with confidentiality rules).

For each insured person, the ENS contains administrative data, the medical file (vitals, medical imaging archives, reports, therapeutic follow-ups, etc.), the history of rebates and questionnaires. When the ENS is fully deployed at the national level, its volume will be considerable since it concerns 67 million insured persons.

This project is being developed by Trimane[2] on behalf of insurance companies.

In the context of this project, the ENS constitutes a real Data Lake because of (1) the diversity of data types, media, and formats (2) the volumes stored which can reach several terabytes and (3) the raw nature of the data. The objective of the project is to

[2] https://www.trimane.fr

study the mechanisms for extracting data from the ENS and organizing it to facilitate analysis (Big Data Analytics). For our application, the extracted data comes mainly from relational databases present in the ENS.

2.2 Problematic

Our work aims to develop a system allowing private companies to create a Data Warehouse from a Data Lake. This article deals more specifically with the mechanisms of extraction and unification from commonly used databases, we limit the framework of our study as follows:

- The ENS Data Lake is the source of the data; in this article, we voluntarily reduce its content to relational databases. Indeed, this category of datasets represents an important part of the ENS data;
- The generated Data Warehouse is managed by a document-oriented NoSQL database system. This type of system offers (1) great flexibility in reorganizing objects for analysis and (2) good performance in accessing large volumes of data (using MapReduce).

To achieve our goal, each database in the Data Lake is extracted and converted into another model to allow its storage in the Data Warehouse as shown in Figure 1. We do not address here the problems related to the selective extraction of data and their aggregative transformation.

To test our proposals, we have developed a Data Lake with multiple relational databases managed by MySQL[3] and PostgreSQL[4] systems. These databases contain respectively data describing the follow-up of the insured and the processing of the files in a medical center. The available metadata are limited to those accessible on the storage systems (absence of ontologies for example). The Data Warehouse, which is supported by an OrientDB platform, must allow the analysis of the care pathways of insured persons with chronic pathologies. We chose the OrientDB[5] system to store the Data Warehouse. Indeed, this document-oriented NoSQL system allows to consider several types of semantic links such as association, composition and inheritance links; it is thus well adapted to our case of study where the richness of the links between objects constitutes an essential element for decisional processes.

3 RELATED WORKS

In this section, we present research work on extracting data from a Data Lake and more specifically data from several relational databases and creating a NoSQL Data Warehouse. The advent of Big Data has created several challenges for the management of massive data; among these we find the creation of architectures to ingest massive data sources as well as the integration and transformation of these massive data (Big Data) allowing their subsequent query. In this sense, some works have focused on the proposal of architectures (physical and logical) allowing the use and the management of Data Lakes. The article (Diamantini et al., 2018) proposes an approach to structure the data of a Data Lake by linking the data sources in the form of a graph composed of keywords. Other works propose to extract the data of a Data Lake from the metamodels of the sources. The authors in (Candel, Ruiz, & García-Molina, 2021) have proposed a metamodel unifying NoSQL and relational databases. There are several formalisms (Bruel et al., 2019) to express model transformations such as the QVT standard, the ATL language (Erraissi & Banane, 2020) which is a non-standardized model transformation language more or less inspired by the QVT standard of the Object Management Group, etc.

Other works have studied only the transformation of a relational database into a NoSQL database. Thus in (Hanine, Bendarag, & Boutkhoum, 2015; Stanescu, Brezovan, & Burdescu, 2016) the authors developed a method to transfer data from relational databases to MongoDB. This approach translates the links between tables only by nesting documents. In (Liyanaarachchi, Kasun, Nimesha, Lahiru, & Karunasena, 2016), the authors present MigDB, an application that converts a relational database (MySQL) to a NoSQL one (MongoDB). This conversion is done over several steps: transforming tables into JSON files, then transmitting each JSON file to a neural network. This network allows to process the links at the JSON file level, either by nesting or by referencing. This work considers all association links (of different cardinalities) only. The same is true in (Chickerur, Goudar, & Kinnerkar, 2015), where the authors propose a method for transferring relational databases to MongoDB by converting the tables into CSV files that are then imported into MongoDB. However, the proposed method simply converts tables into MongoDB

[3] https://www.mysql.com
[4] https://www.postgresql.org
[5] https://orientdb.com/docs/3.0.x/

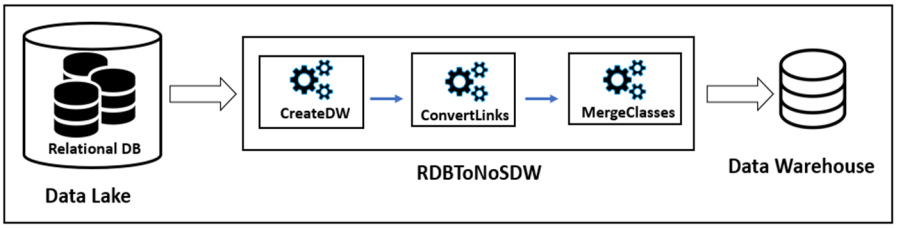


Figure 1: Architecture of the data extraction process from a Data Lake: RDBToNoSDW.

collections without supporting the various links between tables.

4 OVERVIEW OF OUR SOLUTION

Although a Data Lake can contain files of any format, we focus in this article on the extraction of relational databases and the feeding of a NoSQL Data Warehouse. Several works have dealt with the transfer of a relational database to a NoSQL database. Thus, some works have proposed algorithms for converting relational data to document-oriented systems such as MongoDB (Mahmood, 2018); however, these works transform relational links into document nesting or DBRef links. However, these NoSQL linkage solutions are not satisfactory with respect to object systems [6]. Moreover, to our knowledge, no study has been conducted to convert several relational databases contained in a Data Lake into a NoSQL Data Warehouse.

In our ingestion process, we have defined three modules as shown in Figure 1. Our proposal is based on Model Driven Architecture (MDA) which allows to describe separately the functional specifications and the implementation of an application on a platform. Among the three models present in MDA (CIM, PIM and PSM), we are located at the PSM level where the logical schemas are described. We also use the declarative language Query/View/transform (QVT) [7] specified by the Object Management Group OMG[8] which allows us to describe the ingestion of data by model transformations.

To use the MDA transformation mechanism, we proposed two metamodels describing respectively the source and target databases. From these metamodels, we specified the transformation rules in QVT language to ensure data ingestion.

5 DATABASES METAMODELING

We present successively the metamodels of a source Relational database and a target NoSQL database.

5.1 Relational Metamodel

The Data Lake, source of our process, can contain several relational databases. A relational database contains a set of tables made of a schema and an extension. The schema of a table contains a sequence of attribute names associated with atomic types (such as the predefined types Integer, String, Date). The extension is composed of a set of rows grouping attribute values. Among the attributes of a table, we distinguish the primary key whose values identify the rows and the foreign keys which materialize the links. Figure 2 represents the Ecore [9] metamodel of a relational database.

5.2 Document-oriented NoSQL Metamodel

The target of our process corresponds to the Data Warehouse represented by a NoSQL database. A document-oriented NoSQL database contains a set of classes. Each class gathers objects that are identified (by a reference) and composed of couples (attribute, value); a value is defined by a basetype, multivalued or structured. We distinguish a particular basic type, the reference, whose values make it possible to link the objects. These concepts are represented in Figure 3 according to the Ecore formalism.

[6] http://www.odbms.org/odmg-standard/reading-room/odmg-2-0-a-standard-for-object-storage/
[7] https://www.omg.org/spec/QVT/1.2/PDF
[8] The Object Management Group (OMG) https://www.omg.org
[9] https://download.eclipse.org/modeling/emf/emf/javadoc/2.9.0/org/eclipse/emf/ecore/package-summary.html

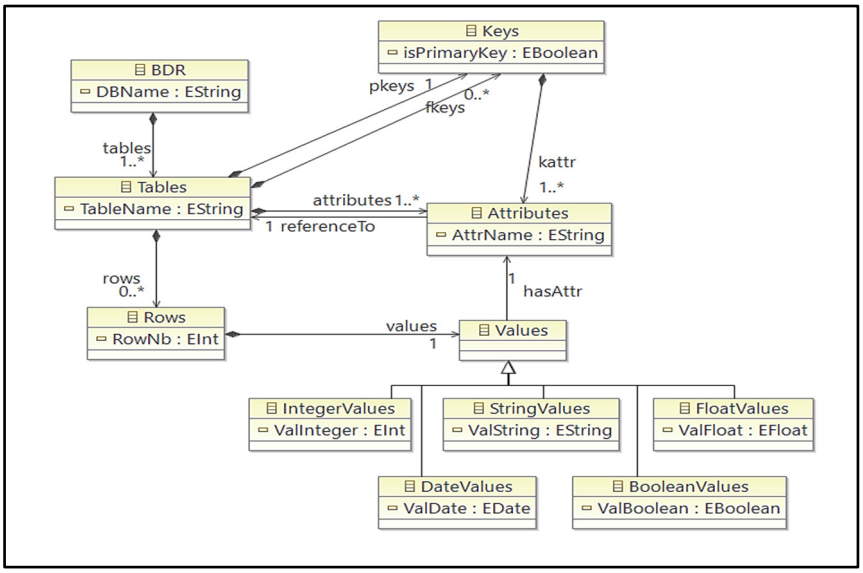


Figure 2: Metamodel of a relational database stored in the Data Lake.

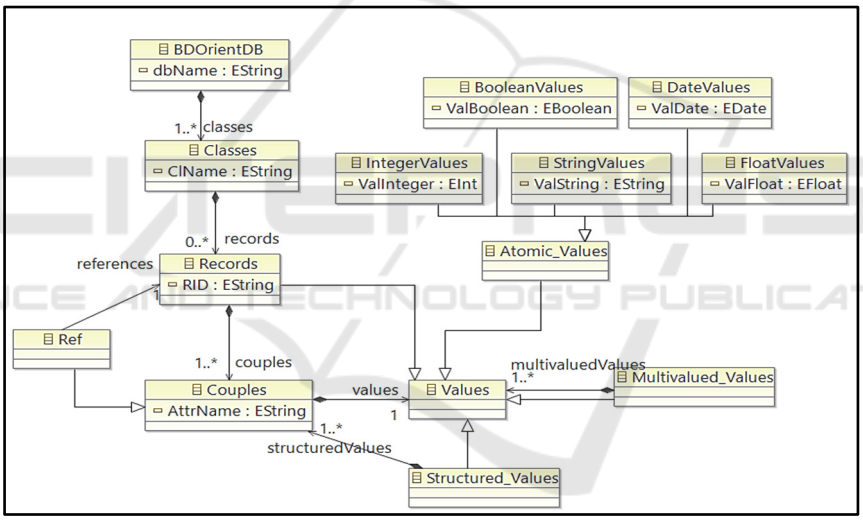


Figure 3: The Data Warehouse metamodel: a document-oriented NoSQL database.

6 OUR DATA PROCESSING SOLUTION

This involves transferring relational databases from the Data Lake to a NoSQL database corresponding to the Data Warehouse. To carry out this ingestion process, we have defined three modules that will successively ensure (1) the transformation of relational data into NoSQL data (CreateDW module), (2) the conversion of relational links (foreign keys) into references (ConvertLinks module) and (3) the merging of tables containing objects of the same semantics (MergeClasses module).

6.1 CreateDW Module

This module transforms each relational database of the Data Lake into a unique NoSQL database according to the MDA approach. The NoSQL warehouse being unique, it will contain the data coming from the different relational databases of the Data Lake. The application of a set of transformation rules defined on the metamodels of Section 4, generates a set of classes in a NoSQL database. We informally present the rules that have been expressed in the QVT language.

Rule 1: Each table in a relational database is transformed into a class in the NoSQL database. To avoid synonymy, the name of the class is prefixed by the name of the original database.

Rule 2: Each row of a table, associated with its schema, is transformed into a record in the corresponding target class; the record then contains a set of couples (attribute, value). The primary key is stored as any attribute. At this stage, the foreign keys are also stored with their relational values; they will be converted into references by the ConvertLinks module.

These two rules, which we formalized in QVT language, are applied for each relational database of the Data Lake and feed the NoSQL database; we will present their syntax in Figure 4 of the experimentation section. In parallel with the application of these transformation rules, an algorithmic processing allows to record metadata; these metadata match each relational primary key with the Record ID (RID) of the corresponding record in the NoSQL database.

6.2 ConvertLinks Module

In the standard object-oriented systems[10], links are materialized by references. Since this principle is used in NoSQL systems, it is necessary to convert relational foreign keys that have been transferred to the Data Warehouse into references.

The mechanism we have developed in ConvertLinks is not based on the expression of MDA rules but corresponds to an algorithmic process. In the NoSQL database, all records of a class are systematically marked with identifiers (RID for Record ID). During the transfer of data into the records, the relational primary and foreign keys were transferred in the form of pairs (attribute, value). Thus, thanks to the metadata recorded by the previous CreateDW module, the values of the foreign keys are converted into RID.

6.3 MergeClasses Module

Data ingestion from the Data Lake was performed by transferring data from different relational databases to the NoSQL database (in the previous processes). However, it is frequent that tables with the same semantics from different relational databases are transferred; these tables are called "equivalent". For example, the DB1-Insured and DB2-Patients tables from the DB1 and DB2 databases contain data on the insured; some properties in these tables are redundant and others are complementary. Two tables are considered "equivalent" if they contain data related to the same entity (same primary key). The CreateDW module has allowed us to create a class in the NoSQL database for each table. It is therefore useful to group the data contained in "equivalent" tables into a single class in the NoSQL database. To achieve this grouping, we relied on an ontology establishing the correspondences between the terms of the relational databases contained in the Data Lake. This ontology is provided by data administrators bringing their business expertise. These administrators, after consultation, provided the business rules that apply to the tables considered as semantically equivalent.

By exploiting this ontology[11], the MergeClasses module creates new classes in the NoSQL database. In the presence of several equivalent tables, the module groups the data in a single class. This treatment is not limited to a union operation between records; in fact, distinct records concerning the same entity can have complementary attributes that will be combined in a single record.

7 IMPLEMENTATION AND TECHNICAL ENVIRONMENT

In this section, we describe the techniques used to implement the RDBToNoSDW process of Figure 1. The first module (CreateDW) implements transformation rules, we used a technical environment adapted to modeling, metamodeling and model transformation. We used the Eclipse Modeling Framework (EMF) [12] model transformation environment with the Ecore metamodeling language to create and manipulate metamodels. Ecore is based on XMI to instantiate the models. Algorithmic processing has been coded in Java. In fact, EMF is compatible with Java. Figure 4 shows the complete architecture of our RDBToNoSDW process.

[10] http://www.odbms.org/wp-content/uploads/2013/11/001.04-Ullman-CS145-ODL-OQL-Fall-2004.pdf

[11] The principles of exploitation of the ontology are not detailed in this article.

[12] https://www.eclipse.org/modeling/emf

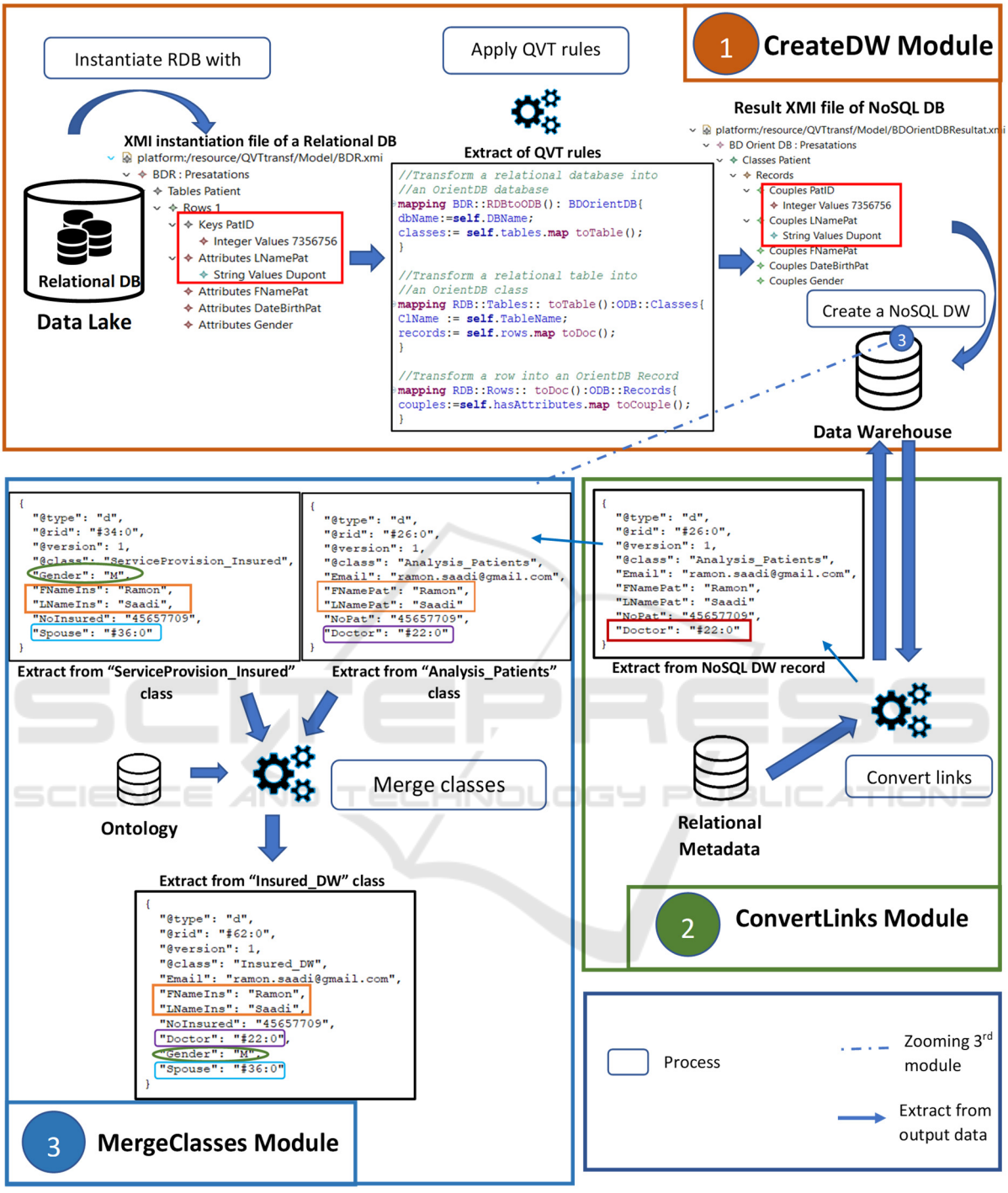
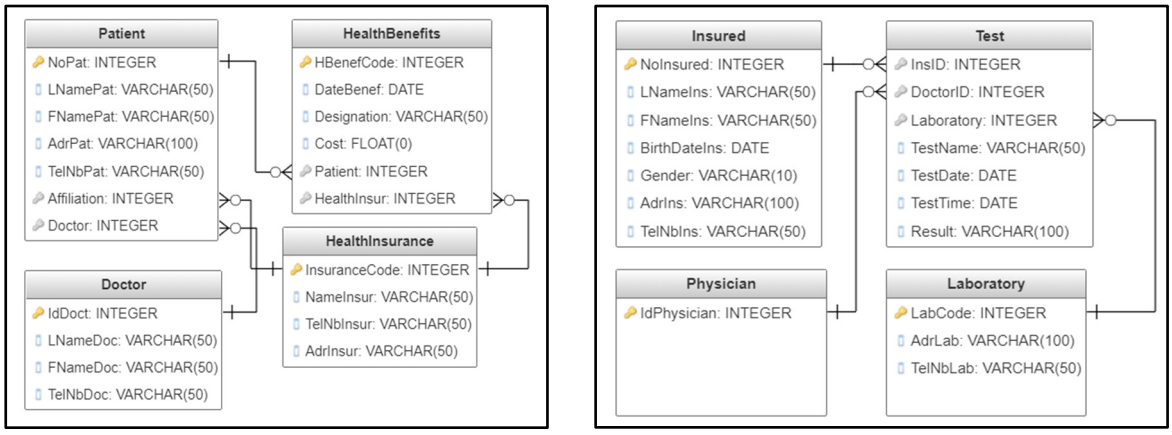


Figure 4: Data flow and processing in the RDBToNoSDW process.

To experiment our process, we stored several relational databases in the Data Lake; these are test databases directly inspired by the medical case study (Section 2.1). Figure 5 shows two extracts of the schemas of two databases: the "Service Provision" database and the "Analysis" database. They have been implemented with the PostgreSQL RDBMS and the MySQL RDBMS respectively.



a) The « Service Provision » database

b) The « Analysis » database

Figure 5: Extracts from the relational schemas of a two Data Lake databases.

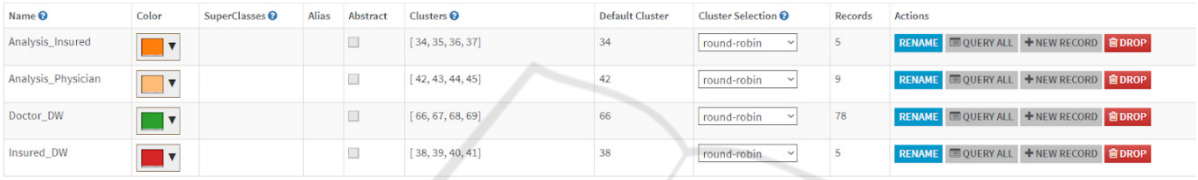


Figure 6: Extract from the list of Data Warehouse classes stored in OrientDB.

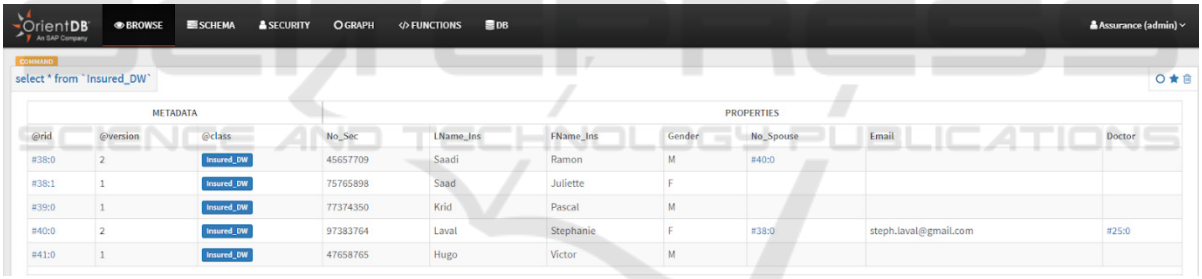


Figure 7: Extract from the "Insured_DW" class.

The CreateDW module (1) of our process (Figure 4) generates a unique NoSQL database from the two Data Lake's databases. To do so, it uses a relational metamodel and a NoSQL metamodel as represented with Ecore (Figures 2 and 3) as well as the instantiation with the XMI language of the two relational databases. The transformation rules have been translated with the QVT language and apply to all relational databases independently of the RDBMS. The ConvertLinks module (2) allows converting foreign keys into RID links. For example, in Figure 5, the fields "Affiliation" and "Doctor" in the table "Patient" will be converted. Finally, the MergeClasses module (3) groups the records of the classes considered as "equivalent" based on the ontology provided by the experts.

The result of the treatments carried out by the 3 modules described above is represented by Figure 6. Figure 6 represents the list of classes (corresponding to the relational database tables).

Figure 7 shows an extract of the new class "Insured_DW" containing the merged records of the two classes "ServiceProvision_Patient" and "Analysis_Insured".

8 DISCUSSION

Various articles have studied the extraction and management of data from a Data Lake. Thus, some works have focused on proposing solutions to structure heterogeneous data coming from different

databases in a Data Lake. The paper (Diamantini et al., 2018) proposes an approach to structure the data of a Data Lake by linking the data sources in the form of a graph composed of keywords. Other works propose a metamodel unifying several data source metamodels thus allowing the unification of data from multiple sources. The authors in (Candel, Ruiz, & García-Molina, 2021) proposed a metamodel unifying the logical schemas of the four most common types of NoSQL systems and relational systems. Our solution is based on extracting data from a data lake and loading it into a data warehouse. To do so, we first proposed two metamodels representing the physical models of each database: the first metamodel concerns relational databases as source, the second metamodel concerns document-oriented NoSQL databases as target database of our solution. We used EMF as our metamodeling tools. EMF allowed us to formalize the transformation rules from a source metamodel to the target metamodel. We relied on the QVT standard to express our transformation rules. The solution we propose allows the interrogation of data contained in a Data Lake thanks to the creation of a Data Warehouse.

9 CONCLUSION AND PERSPECTIVES

This paper proposed a process to ingest data from a Data Lake to a Data Warehouse; this one is made of a unique NoSQL database and the Data Lake contains several databases. We have limited the content of the Data Lake to relational databases. Three modules ensure the ingestion of the data. The CreateDW module transforms each relational database into a unique NoSQL database by applying MDA rules.

This mechanism will be used and extended to transform other types of databases in the Data Lake. The ConvertLinks module translates relational links (keys) into references in accordance with the principles of object databases supported by the OrientDB system. Finally, the MergeClasses module merges semantically equivalent classes from different Data Lake databases; this merge is based on an ontology provided by business experts.

Currently, we are continuing our work on the ingestion of other types of data sources from a Data Lake. Indeed, the Data Lake of our medical case study contains various database types.

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