

Integrating Semi-structured Information using Semantic Technologies

An Evaluation of Tools and a Case Study on University Rankings Data

Alejandra Casas-Bayona and Hector G. Ceballos

Campus Monterrey, Tecnológico de Monterrey, Av. Eugenio Garza Sada 2501, 64849, Monterrey, Nuevo León, Mexico

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Abstract: Information integration is not a trivial activity. Information managers face problems like: heterogeneity (in data, schemas, syntax and platforms), distribution and duplicity. In this paper we: 1) analyze ontology-based methodologies that provide mediation frameworks for integrating and reconciling information from structured data sources, and 2) propose the use of available semantic technologies for replicating such functionality. Our aim is providing an agile method for integrating and reconciling information from semi-structured data (spreadsheets) and determining to which extent available semantic technologies minimize the need of ontological expertise for information integration. We present our findings and lessons learned from a case study on university rankings data.

1 INTRODUCTION

Information has become a fundamental asset for company's competitiveness. Integrating information distributed across systems and platforms in the organization for its later analysis has become the most important task for information managers. Integrating information residing in distributed and heterogeneous data sources is a well-known problem that faces two difficult challenges: heterogeneity and reconciliation.

Heterogeneity can be classified in four categories: 1) structural, i.e. different schemas in data sources; 2) syntactical, i.e. different ways of naming the same object (catalogues); 3) systemic, i.e. diverse platforms governed by different authorities; and 4) semantic, i.e. different meanings for same concept or different names for the same concept (Buccella, Cechich, & Brisaboa, 2005). For (Cui, Brien, & Park, 2000), resolving semantic heterogeneity consists in identifying equivalent concepts, no-related concepts and related concepts.

On the other hand, data reconciliation has been classified on two levels: schema and instance (Bakhtouchi, Jean, & Ait-ameur, 2012). Schema reconciliation consists on finding equivalences between tables and columns from different data sources, i.e. it addresses structural heterogeneity,

whereas instance reconciliation consists on identifying instances that represent the same entity in the real world despite their multiple representations (Zhao & Ram, 2008).

Ontologies are particularly suitable for integrating information as long as they deal with syntactic and semantic heterogeneity (Silvescu, Reinoso-castillo, & Honavar, 1997). The term ontology was introduced by Gruber in the context of knowledge sharing as "the conceptualization of a specification" (Gruber, 2009). This is, an ontology is the description of concepts and relationships that an agent or a community may use (Gruber, 2008).

Some ontology-based methodologies and techniques for information integration have been proposed (Buccella et al., 2005). For example, the project MOMIS (Mediator environment for Multiple Information Sources) allows integrating data from structured and semi-structured data sources (Beneventano et al., 2001). SIMS is another mediator platform that provides access to distributed data sources and online integration (ARENS et al., 1993). MIRSOF, unlike the other two approaches, does not map entirely the origin data sources but focuses on the minimum necessary data for answering the integration question (Bakhtouchi et al., 2012). These approaches support the task of data interpretation by requiring the participation of the domain expert at some extent and minimizing the

involvement of the database administrator.

In scenarios with periodic data extraction the cost of the required infrastructure and the time dedicated by the expert is justified. Nevertheless, in scenarios where an agile response is needed, information requirements are volatile, and data is provided by different departments in semi-structured formats, a more agile solution is needed. Our proposal is to use available semantic technologies for replicating the functionality that these approaches provide.

In section 2 we describe and analyse the facilities provided by each approach. In section 3 we described our approach for information integration and our criteria for selecting semantic technologies. In section 4 we exemplify our methodology by integrating faculty staff information from two data sources for a university ranking. Finally in section 5 we present a summary of lessons learned and conclude with closing remarks in section 6.

2 RELATED WORK

Ontology-based information integration approaches provide a solution for integrating heterogeneous databases and semi-structured data. Some of them additionally provide data reconciliation facilities.

Table 1 shows a comparison of the three analyzed methodologies found in literature related to ontology-based information integration. For the comparison we focused in five aspects: 1) the original information requirement, 2) the way on which information is mapped, 3) the way on which integration is performed, 4) reconciliation facilities, and 5) the schemas used for expressing queries. Numbers in each row represent the order followed in each methodology.

The MOMIS methodology starts in the extraction phase where it uses a wrapper that transform the structure of available data sources to a model ODLI3 based on Description Logics (Moreno Paredes, 2007). The integration process generates an integrated view of the data sources (global-as-view) through the generation of a thesaurus. Then it performs an analysis for determining affinity between terms and it makes clusters of similar classes (Beneventano et al., 2001). Queries are expressed in terms of thesaurus schemas.

SIMS, on the opposite way, was created assuming that data sources are dynamic; hence it starts by defining an initial question from which proceeds to the selection of suitable data sources, in order to minimize the cost of mapping schemas. The integration phase starts with an expert annotating data sources with ontology schemas and continues enriching initial mappings with other vocabularies automatically. SIMS elaborates query plans for answering queries expressed in terms of the used ontologies (Arens et al., 1996).

MIRSOFT departs from an initial user requirement and importing mediator ontology. Then it requires mapping data sources to mediator schemas, as well as expressing functional dependencies (FDs) of mapped classes, providing ontology-based database access, also known as OBDB or OntoDB. Before starting the mapping stage, a selection of relevant classes and properties is done, producing a pruned ontology. This methodology additionally uses functional dependencies for complementing queries and providing reconciliation in query results (Bakhtouchi, Bellatreche, Jean, & Ameur, 2012). Queries are expressed and answered in terms of the mediator ontology.

Table 1: Comparison of ontology-based methodologies for information integration.

Methodology	Requirement	Data source Mapping	Integration	Reconciliation	Query
MOMIS (2004)	-	1 Database to ODLI3 (Wrappers)	2 A mediator uses mappings and a thesaurus for codifying queries and decodifying results	-	3 Mediator schema generated from data sources
SIMS (1996)	1 User's requirement	2 Database to Ontology	3 Query plans using semantic annotations to data source schemas	-	4 Global ontology schemas
MIRSOFT (2013)	1 User's requirement	2 Database to pruned Ontology + FD	3 OBDB repository + queries enriched with FDs	4 Based on FDs	5 Global ontology schemas

3 INTEGRATION AND RECONCILIATION METHOD

We evaluated the use of semantic technologies in scenarios of periodic integration exercises where information used for answering queries is provided by different departments using spreadsheets with varying formats. Heterogeneity is present in all of its expressions: information resides in different systems (systemic), spreadsheets have different columns (structural), varying column names and use different catalogues (syntactical), and the same concept is defined distinctly in each data source (semantic). Additionally, equivalent individuals can be found across these data sources with contradictory information. In this scenario, we cannot rely on fixed structures, and mappings must be generated cost-effectively.

Based on the aspects analyzed in previous methodologies we propose a method suitable for this scenario that provides ontology-based information integration taking advantage of current Semantic Web standards and tools. Stages of our method are described Figure 1.

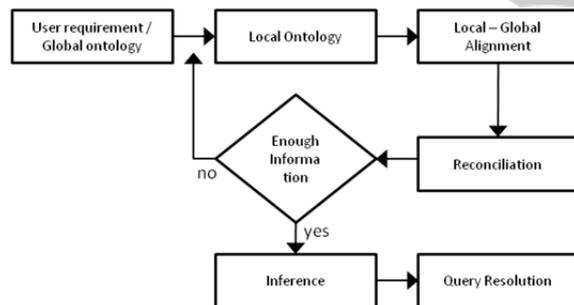


Figure 1: Information integration process.

3.1 User Requirement

We start with an initial user requirement expressed through a global schema represented by an extension O_G of an existing ontology O_B . A suitable OWL ontology for your domain can be chosen from ontologies repositories like Linked Open Vocabulariesⁱ. A data requirement is denoted by a class C_R that represents a set of individuals that must be identified and quantified across the available data sources. Each class C_R is declared in O_G as subclass of a class C_G originally contained in O_B in order to make query results compatible with the original ontology O_B .

ⁱ <http://lov.okfn.org/dataset/lov/>

In this step is important to declare consistency constraints like if two classes C_R are disjoint, this is, when an individual must be classified as member of only one of these classes.

3.2 Local Ontologies

Next, each datasheet is transformed to a RDF file where each row represents an individual of a new class C_L , columns represent properties of the class and cells are property values that describe each individual. The resulting class, properties and individuals constitute a local ontology O_L . Available tools for this purpose are referenced by W3Cⁱⁱ.

3.3 Local-Global Ontology Alignments

The ontology O_G is imported in each O_L for expressing the corresponding definition of each C_R . If the definition of C_R only requires information of a single data source then C_R is defined in O_L . If the definition of C_R requires information from multiple sources its definition must be done in the integrated ontology. The integrated ontology O_I is a new OWL file that imports O_D and each O_L .

This stage can be facilitated by ontology mapping tools that identify semantic correspondences between elements in two different schemas (Zohra et al., 2011). Available tools for this task are referred by the Open Semantic Framework initiativeⁱⁱⁱ.

3.4 Reconciliation

Product of local definitions we can have multiple individuals representing the same individual. Reconciliation of equivalent individuals is made declaring an OWL 2 constraint `HasKey` for classes C_R . Another alternative is declaring a SWRL rule or using a SPARQL `CONSTRUCT` query that assert statements `SameIndividual` for each pair of equivalent individuals, based on functional dependencies.

This procedure is especially important when datasheets contain multiple rows for the same individual that is being quantified in C_R .

ⁱⁱ <http://www.w3.org/wiki/ConverterToRdf>

ⁱⁱⁱ http://wiki.opensemanticframework.org/index.php/Ontology_Tools#Ontology_Mapping

3.5 Inference

Finally, a concept reasoner is used on O_I for classifying individuals in each C_R . Reasoners can be executed from the IDE of a comprehensive framework like Protégé or Top Braid, or be executed directly over O_I . Another alternative is using an RDF database with inference capabilities like Virtuoso^{iv} or Stardog^v.

In this stage, concept reasoners are used for detecting inconsistencies between definitions and data. In order to solve these inconsistencies, violated constraints can be lift or inconsistent individuals can be removed from the data set. For instance, an individual classified in two disjoint classes will be inconsistent and the solution will be up to the domain expert.

3.6 Query Resolution

Finally, the domain expert identify and quantifies individuals classified in each CR by formulating a query over a SPARQL end-point connected to the inferred model O_I' or by enquiring the RDF database using the reasoning level required by definitions. CR is quantified by a query like:

```
SELECT COUNT (DISTINCT (?ind))
WHERE { ?ind a CR }
```

Figure 2 shows the inputs (O_B , O_G , L_1 , L_2), the working models (O_{L1} , O_{L2} , O_I , O_I'), and tools. Stages of the method are numbered as well.

4 CASE STUDY

Our case study was carried out in a University that provides statistical data to an international Ranking organization. In this sense, the rankings department collects information in spreadsheets from several departments. In order to identify and classify the university academic staff, information is collected from both Human Resources and Academic departments.

The integration was initially performed by a computer science specialist with basic knowledge on ontologies, following the use cases from (Allemang & Hendler, 2008). After a series of integration exercises that allowed us to evaluate available tools we asked two other specialists in information

integration to replicate one of the integration exercises. For this purpose we prepared two user guides with a summary of use cases given in (Allemang & Hendler, 2008), where OWL constructors are classified according to integration or reconciliation purposes. Reconciliation guide is shown in the Appendix.

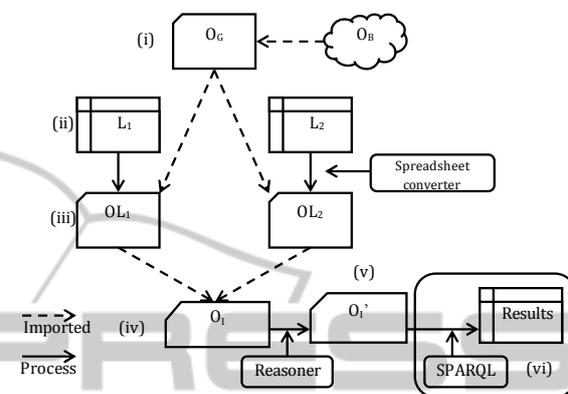


Figure 2: Datasets and Tools.

In this section we describe the results of the evaluation of tools and in section 5 we discuss our findings and perspectives on semantic technologies.

4.1 User Requirement

The initial requirement is given by definitions of the ranking evaluation criteria. In our integration exercise we identified six classes C_R that can be used for answering the faculty staff criteria: Faculty Staff, Full Time Professor, Part Time Professor, Local Professor, International Professor and Professor with PhD. Further calculations like the Full-time equivalent are out of the scope of the integration and reconciliation task.

We evaluated Neon Toolkit^{vi}, Protégé^{vii} and TopBraid Composer Standard Edition^{viii} based on the following criteria: 1) the usability of its interface, 2) visualization of definitions, 3) facilities for importing data from spreadsheets, 4) configurable reasoning levels, and 5) facilities for exporting query results. Additionally, our selection criteria considered the minimization of the number of tools used along the entire process, being TopBraid Composer chosen for the first four stages and Protégé for the last two.

On the other hand, we evaluated two ontologies:

^{iv} <http://virtuoso.openlinksw.com/rdf-quad-store/>
^v <http://stardog.com/>

^{vi} <http://neon-toolkit.org>
^{vii} <http://protege.stanford.edu/>
^{viii} <http://www.topquadrant.com/>

VIVO^{ix} and Semantic Web for Research Communities^x (SWRC) as base for our global ontology, and selected the last one because it provides enough expressivity for our purpose and has less and simpler schemas.

4.2 Local Ontologies

We used TopBraid Composer facilities for transforming spreadsheet data to local ontologies, generating a local ontology for each data source (one class and N properties). Two local ontologies were produced, denoted Local A (O_{L-A}) and Local B (O_{L-B}) in the following. Local classes (C_i) generated in each local ontology are denoted Person A (C_{L-A}) and Person B (C_{L-B}), respectively. Figure 2 illustrates with an example the heterogeneity between both data sources.

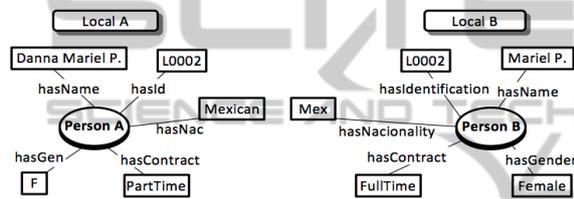


Figure 2: Example of data found in both data sources.

4.3 Local-Global Ontology Alignments

In the Global-Local ontology alignments stage we formulated one definition for each CR per local ontology, i.e. 12 definitions in total. Figure 3 illustrates some definitions made for OL-A and OL-B. Prefixes G: and A: represent the ontologies OG and OL-A respectively.

TopBraid Composer suggested mappings between equivalent properties in O_{L-A} and O_{L-B} after they were imported to the integrated ontology O_I . (see Figure 4). Mappings proposed by this tool were correct and facilitated using properties defined in local ontologies for recovering information from both data sources (see queries in section 4.6).

$G:PTProfessor \equiv A:Person \cap A:hasContrat = \{A,B,C\}$	(1)
$G:FTPProfessor \equiv A:Person \cap A:hasContrat = \{D, E, F\}$	(2)
$G:FacultyStaff \equiv G:PTProfessor \cup G:FTPProfessor$	(3)
$G:FTPProfessor \cap G:PTProfessor \subseteq \perp$	(4)
$G:LocalProfessor \equiv A:Person \cap A:hasNac = 'Mexican'$	(5)
$G:LocalProfessor \equiv B:Person \cap B:hasNacionality = 'Mex'$	(6)
$G:InternationalProfessor \equiv \neg A:MexicanProfessor$	(7)

Figure 3: Example of definitions in local ontologies.

ix <http://www.vivoweb.org>
x <http://ontoware.org/swrc/>

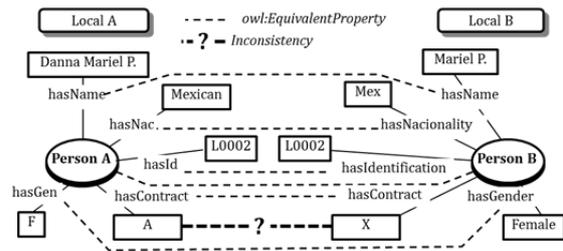


Figure 4: Equivalent classes and properties.

4.4 Reconciliation

Reconciliation was done through the assertion of statements SameIndividual between persons with the same employee identification number. In O_{L-A} this property is called hasId, whereas in O_{L-B} the equivalent property is named hasIdentification. This procedure was done with a SPARQL CONSTRUCT query.

4.5 Inference

For the reasoning stage we evaluated the reasoners integrated in Protégé and TopBraid Composer: FACT++, Hermit, OWLIM^{xi} and Pellet.

Not a single reasoner in TopBraid Composer could be configured for making the Closed World Assumption (CWA), hence it was not possible to classify individuals based on definitions like International Professor that uses a ComplementOf constraint. This was not the case of Hermit in Protégé which makes the CWA by default and correctly made this classification. The reasoner that had better performance in TopBraid Composer was OWLIM.

Thanks to the definition of Full-time Professor and Part-time Professor as disjoint classes it was possible to detect inconsistencies between data sources. Figure 4 illustrates an inconsistency of this type, where the same professor is classified as Part-time in O_A ($A:hasContract = A$) and as Full-time in O_B ($B:hasContract = X$), given local definitions. To solve this problem we removed the disjoint constraint and adjusted the query for retrieving Part-time professors as explained in next section.

4.6 Query Resolution

Information required for answering rankings

xi <http://owlim.ontotext.com/display/OWLIMv40/OWLIM-Lite+Reasoner>

questions were expressed in SPARQL through the combination of classes C_R . For instance, for determining the number of Full Time International Faculty Staff we used the intersection of Full Time Professor and International Professor.

Given that we found professors classified as Full-time and Part-time the query for retrieving Part-time Professors was adjusted as follows:

```
SELECT COUNT (DISTINCT (?ID))
WHERE {
  ?prof a G:PTProfessor .
  ?prof A:hasID ?ID .
  FILTER NOT EXISTS {?prof a G:FTPProfessor.}
```

We also needed to adjust the query for retrieving International professors using OWLIM. Given that it does not support CWA, the following query asks for faculty staff and discards local professors:

```
SELECT COUNT (DISTINCT (?ID))
WHERE {
  ?prof a G:FacultyStaff .
  ?prof A:hasID ?ID .
  FILTER NOT EXISTS {?prof a
G:MexicanProfessor.}
```

5 DISCUSSION

In this section we describe the lessons learned from tool's maturity and the experience of non-ontologist users with our methodology. We also identify the advantages of ontology-based versus relational-based integration, and delimit the reach of ontology mapping tools in the integration process.

5.1 Lessons Learned

From the proposed method and the evaluation of tools we get to the following conclusions.

- In our scenario, an ontologist expert could replicate most of the functionality provided by mediator architectures described in section 2, including reconciliation of individuals.
- It was possible to represent semantically the concepts in our case study with constructors supported by OWL 2 profiles.
- Deficiencies in inference support was remediated through the use of SPARQL.
- Inference in memory becomes unfeasible with a relative small amount of data (above a thousand records with more than 30 columns). We have to decide between preselect the columns to use in the integration, or use a RDF

database with inference support. In the first case, information that could be useful for further integrations is lost, and in the second we sacrifice the facilities provided by the IDE for making definitions and export results.

From the experience of users following our method and the selected tools we draw the following preliminary conclusions:

- The most difficult concept to understand for database specialists was the notion of Open World Assumption in the construction of definitions. Unfortunately most of the reasoners implement this assumption and forces the user to adopt the equally confusing notion of negation as failure (c.f. queries in section 4.6).
- The usability of the selected tools was the best given our evaluation and user guides prepared for applying OWL constructors in the integration and reconciliation stages (see Appendix), in despite the users found hard to understand the meaning of OWL constructors without a previous introduction that include notions of set theory.
- Interfaces for constructing OWL definitions are not suitable for non-experts on ontology languages.

5.2 Ontology-based versus Relational-based Integration

Volatile input formats in our scenario make affordable the use of semantic technology as long as avoids the necessity of creating fixed-data structures (tables) that cannot be reused in subsequent integrations.

On the other hand, the absence of common keys between datasources requires the use of entity resolution techniques, which have been developed for both technologies. Nonetheless, the semantic representation allows representing equivalences between individuals that produce an automatic horizontal integration once datasources are merged. Silk is an example of a tool devised for entity resolution in Linked Data (Volz, et al., 2009).

Despite reasoners allow inferring information like individual equivalences based on keys, it is necessary to merge the information from all datasources in a single repository or having distributed stream reasoning. This kind of technologies are still emerging. Stardog is an example of it.

5.3 Ontology Mapping Tools

Ontology mapping approaches may solve the problem of aligning local and global schemas, avoiding (or at least reducing) the need of a non-ontologist user to decide which OWL constructors to use for integrating and reconciling information.

Despite local schemas may contain few properties (datasheet columns), mapping them to large global ontologies may be largely benefited from the use of these tools, as illustrated by (Rodriguez, et al., 2011).

However, the automatic discovery of mappings could exacerbate the problem of reasoning in large amounts of data producing an excess of mappings between schemas that are not used to answer the question that motivates integration.

6 CONCLUSIONS

The need of an agile process for information integration has become more evident in large organizations, as much as for trivial questions as for building indicators that involve information managed by external organizations.

We presented a method supported by current semantic technologies that provide information integration of heterogeneous data sources. In scenarios where data is provided in semi-structured formats and varies over time, our method matches the results obtained by other robust mediator architectures in a cost-effective manner. Nevertheless, information integration requires a deep understanding of ontological representations in order to perform a proper integration and reconciliation, despite the facilities provided by current tools.

Despite semantic web languages and protocols as well as current semantic technologies are mature enough for enabling information integration there are still some issues that must be addressed. For instance, by providing scalable reasoning on large amounts of data, friendly interfaces for non-ontology experts and configuration options for reasoners that allows making the Closed World Assumption when the information is complete.

Solving these problems will allow taking advantage of ontology mapping tools for discovering all possible alignments between local and global schemas. Furthermore, it will be possible to select automatically the domain ontology that better suits (best scored matches) to a set of local schemas.

In this exercise we classified OWL constructors

according to their usage in the integration stage, but they can be further classified according to the heterogeneity type they address, in order to facilitate user's adoption.

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REFERENCES

- Allemang, D., & Hendler, J., 2008. *Semantic Web for the Working Ontologist: Effective Modeling in RDFS and OWL*. Morgan Kaufmann.
- Arens, Y., Chee, C., Hsu, C., In, H., Knoblock, C. A., & Rey, M., 1996. Query Processing in the SIMS Information Mediator. In *Proceedings of ARPI 1996*. 61-69.
- Arens, Y., Chee, C. Y., Hsu, C.-N., & Craig A., K., 1993. Retrieving and Integrating Data from Multiple Information Sources. *International Journal of Intelligent and Cooperative Information Systems*, 2. 127-158.
- Bakhtouchi, A., Bellatreche, L., Jean, S., & Ameer, Y. A., 2012. MIRSOFT: mediator for integrating and reconciling sources using ontological functional dependencies. *International Journal of Web and Grid Services*. doi:10.1504/IJWGS.2012.046731.
- Beneventano, D., Bergamaschi, F., Guerra, M., & Vincini, 2001. The MOMIS approach to Information Integration.
- Beneventano, Domenico, & Bergamaschi, S., 2004. The Momis Methodology For Integrating Heterogeneous Data Sources. Chapter in *Building the Information Society*, 19-24.
- Buccella, A., Cechich, A., & Brisaboa, N. R., 2005. Ontology-Based Data Integration Methods: A Framework for Comparison. *Revista Colombiana de Computación*, 6.
- Cui, Z., Brien, P. O., & Park, A., 2000. Domain Ontology Management Environment, In *Proceedings of the 33rd Hawaii International Conference on System Sciences*. 1-9.
- Gruber, T., 2009. What is Ontology? In *the Encyclopedia of Database Systems*, Ling Liu and M. Tamer Özsu (Eds.), Springer-Verlag.
- Lenzerini, M., Sapienza, L., Salaria, V., & Roma, I., 2002. Data Integration: A Theoretical Perspective. In *Proceedings of the twenty-first ACM SIGMOD-SIGACT-SIGART symposium on Principles of database systems*. 233 - 246.
- Moreno Paredes, A., 2007. *Técnicas de depuración e*

integración de ontologías en el ámbito empresarial. Universidad de Sevilla.

Rodríguez-Mancha, M., Ceballos, H., Cantú, F., & Díaz-Prado, A., 2011. Mapping relational databases through ontology matching: a case study on information migration. In *Proceedings of the 6th International Workshop on Ontology Matching (OM-2011)*. CEUR-WS Vol-814, 244–245.

Silvescu, A., Reinoso-castillo, J., & Honavar, V., 2001. Ontology-Driven Information Extraction and Knowledge Acquisition from Heterogeneous, Distributed, Autonomous Biological Data Sources. In *Proceedings of the IJCAI-2001 Workshop on Knowledge Discovery from Heterogeneous, Distributed, Autonomous, Dynamic Data and Knowledge Sources*.

Volz, J., Bizer, C., Gaedke, M., & Kobilarov, G., 2009. Discovering and Maintaining Links on the Web of Data. In *Proceedings of the 8th International Semantic Web Conference (ISWC 2009)*, 650–665.

Zhao, H., & Ram, S., 2008. Entity matching across heterogeneous data sources: An approach based on constrained cascade generalization. *Data & Knowledge Engineering*, 66(3), 368–381.

Zohra B., Angela B, Erhard R., 2011. Schema matching and mapping. Springer.

APPENDIX

Table 2 is an example of the guide with reconciliation operators provided to database specialist during the integration exercise. Cases and solutions were obtained from (Allemang & Hendler, 2008). A similar table was prepared for integration operators.

Table 2: User’s guide with OWL reconciliation operators.

How can I treat two concepts as the same?		
CASE	SOLUTION	Example
	Construct	
How can I affirm that an individual will be agreement as member in another class?	FTPProfessor rdfs:subClassOf FullProfessor	
How do I merge information from multiple source?	P rdfs:type owl:FunctionalProperty . P rdfs:type owl:InverseFunctionalProperty	
How can I say that two members are originally the same?		
CASE	SOLUTION	Example
	Construct	
How can I say that two individuals are the same?	J. Pérez owl:sameAs Juan Pérez	
How can I say that two members are not the same?		
CASE	SOLUTION	Example
	Construct	
How can I identify each individual?	hasnomina owl:hasKey	
How can I say that two individuals do not have common elements?	Juan Pérez G owl:disjointWith Juan Pérez L	