Mapping Patterns for Virtual Knowledge Graphs

Marco Montali Alessandro Mosca Roee Shraga

Diego Calvanese Avigdor Gal Davide Lanti

Free-University of Bozen-Bolzano, Bolzano, Italy {calvanese, lanti, montali, mosca}@unibz.it Umeå University, Sweden Technion – Israel Institute of Technology, Haifa, Israel {avigal@, shraga89@campus.}technion.ac.il

Abstract

Virtual Knowledge Graphs (VKG) constitute one of the most promising paradigms for integrating and accessing legacy data sources. A critical bottleneck in the integration process involves the definition, validation, and maintenance of mappings that link data sources to a domain ontology. To support the management of mappings throughout their entire lifecycle, we propose a comprehensive catalog of sophisticated mapping patterns that emerge when linking databases to ontologies. To do so, we build on well-established methodologies and patterns studied in data management, data analysis, and conceptual modeling. These are extended and refined through the analysis of concrete VKG benchmarks and real-world use cases, and considering the inherent impedance mismatch between data sources and ontologies. We validate our catalog on the considered VKG scenarios, showing that it covers the vast majority of patterns present therein.

1 Introduction

Data integration and access to legacy data sources using end user-oriented languages are increasingly challenging contemporary organizations. In the whole spectrum of data integration and access solutions, the approach based on *Virtual Knowledge Graphs (VKG)* is gaining momentum, especially when the underlying data sources to be integrated come in the form of relational databases (DBs) [\[40\]](#page-17-0). VKGs replace the rigid structure of tables with the flexibility of a graph that incorporates domain knowledge and is kept virtual, eliminating duplications and redundancies. A VKG specification consists of three main components: *(i) data sources* (in the context of this paper, constituted by relational DBs) where the actual data are stored; *(ii)* a domain *ontology*, capturing the relevant concepts, relations, and constraints of the domain of interest; *(iii)* a set of *mappings* linking the data sources to the ontology. One of the most critical bottlenecks towards the adoption of the VKG approach, especially in complex, enterprise scenarios, is the definition and management of mappings. These mappings play a central role in a variety of data management tasks, within both the semantic web and the DB communities. For example, in schema matching, mappings (typically referred to as *matches*) aim at expressing correspondences between atomic, constitutive elements of two different relational schemas, such as attributes and relation names [\[34\]](#page-17-1). This simple type of mappings led to a plethora of very sophisticated (semi-)automated techniques to bootstrap mappings without prior knowledge on the two schemata [\[14,](#page-16-0) [12,](#page-16-1) [38\]](#page-17-2).

A similar setting arises in the context of ontology matching (also referred to as ontology alignment), where the atomic elements to be put in correspondence are classes and properties [\[15\]](#page-16-2). Just like with schema matching, a huge body of applied research has led to effective (semi-)automatic techniques for establishing mappings [\[22,](#page-16-3) [25\]](#page-16-4).

In data exchange, instead, more complex mapping specifications (like the wellknown formalism of TGDs) are needed so as to express how data extracted from a source DB schema should be used to populate a target DB schema [\[28\]](#page-17-3). Due to the complex nature of these mappings, research in this field has been mainly foundational, with some notable exceptions [\[16,](#page-16-5) [11\]](#page-15-0).

The VKG approach appears to be the one that poses the most advanced challenges when it comes to mapping specification, debugging, and maintenance. Indeed, on the one hand, VKG mappings are inherently more sophisticated than those used in schema and ontology matching. On the other hand, while they appear to resemble those typically used in data exchange, they need to overcome the abstraction mismatch between the relational schema of the underlying data storage, and the target ontology; consequently, they are required to explicitly handle how (tuples of) data values extracted from the DB lead to the creation of corresponding objects in the ontology.

As a consequence, management of VKG mappings throughout their entire lifecycle is currently a labor-intensive, essentially manual effort, which requires highly-skilled professionals [\[39\]](#page-17-4) that, at once: *(i)* have in-depth knowledge of the domain of discourse and how it can be represented using structural conceptual models (such as UML class diagrams) and ontologies; *(ii)* possess the ability to understand and query the logical and physical structure of the DB; and *(iii)* master languages, methodologies, and technologies for representing the ontology and the mapping using standard frameworks from semantic web (such as OWL and R2RML). Even in the presence of all these skills, writing mappings is demanding and poses a number of challenges related to semantics, correctness, and performance. More concretely, no comprehensive approach currently exists to support ontology engineers in the creation of VKG mappings, exploiting all the involved information artifacts to their full potential: the relational schema with its constraints and the extensional data stored in the DB, the ontology axioms, and a conceptual schema that lies, explicitly or implicitly, at the basis of the relational schema.

Bootstrapping techniques [\[23,](#page-16-6) [24\]](#page-16-7) have been developed to relieve the ontology engineer from the "blank paper syndrome." However, they are typically adopted in scenarios where neither the ontology nor the mappings are initially available, and where various assumptions are posed over the schema of the DB (e.g., in terms of normalization). Hence, they essentially bootstrap at once the ontology, as a lossless mirror of the DB, and corresponding one-to-one mappings. This explains why bootstrapping techniques cannot properly handle the relevant, practical cases where the relational schema is poorly structured (e.g., a denormalized, legacy DB), and/or where the ontology is already given and presents a true abstraction mismatch with the DB.

These recurring scenarios typically emerge in the common situation where both

the ontology and the DB schema are derived from a conceptual analysis of the domain of interest. The resulting knowledge may stay implicit, or may lead to an explicit representation in the form of a structural conceptual model, which can be represented using well-established notations such as UML, ORM, or E-R. On the one hand, this conceptual model provides the basis for creating a corresponding domain ontology through a series of semantic-preserving transformation steps. On the other hand, it can trigger the design process that finally leads to the deployment of an actual DB. This is done via a series of restructuring and adaptation steps, considering a number of aspects that go beyond pure conceptualization, such as query load, performance, volume, and taking into account the abstraction gap that exists between the conceptual and logical/physical layers. It is precisely the reconciliation of these two transformation chains (resp., from the conceptual model to the ontology, and from the conceptual model to the DB) that is reflected in the VKG mappings.

In this work, we build on this key observation and propose a catalog of mapping patterns that emerge when linking DBs to ontologies. To do so, we build on wellestablished methodologies and patterns studied in data management (such as W3C direct mappings – W3C-DM [\[1\]](#page-15-1) – and their extensions), data analysis (such as algorithms for discovering dependencies), and conceptual modeling (such as relational mapping techniques). These are suitably extended and refined, by considering the inherent impedance mismatch between data sources and ontologies, which requires to handle how objects are built starting from DB values, and by analyzing the concrete mapping strategies arising from six VKG benchmarks and real-world use cases, covering a variety of different application domains.

The resulting patterns do not simplistically consider single elements from the different information artefacts, but rather tackle more complex structures arising from their combination, and potentially from the cascaded application with other patterns.

Exploiting this holistic approach, we then discuss how the proposed patterns can be employed in a variety of VKD design scenarios, depending on which information artifacts are available, and which ones have to be produced.

Finally, we go back to the concrete VKG scenarios and benchmarks, and report on the coverage of mappings appearing therein in terms of our patterns, as well as on how many times the same pattern recurs. This also gives an interesting indication on which patterns are more pervasively used in practice.

2 Preliminaries

In this work, we use the **bold** font to denote tuples, e.g., **x**, **y** are tuples. When convenient, we treat tuples as sets and allow the use of set operators on them.

We rely on the VKG framework of [\[33\]](#page-17-5), which we formalize here through the notion of *VKG specification*, which is a triple $S = \langle T, M, \Sigma \rangle$ where T is an *ontology TBox*, M is a set of *mappings*, and Σ is the schema of a DB. The ontology $\mathcal T$ is formulated in OWL 2 QL [\[30\]](#page-17-6), whose formal counterpart is the description logic $DL\text{-}Lie_{\mathcal{R}}$ [\[9\]](#page-15-2), and for conciseness we actually adopt the DL notation. Consider four mutually disjoint sets **NI** of *individuals*, **NC** of *class names*, **NP** of *object property names*, and **ND** of *data property names*. Then an OWL 2 QL *TBox* T is a finite set of axioms of the form

 $B \sqsubseteq C$ or $r_1 \sqsubseteq r_2$, where B, C are *classes* and r_1 , r_2 are *object properties*, according to the following grammar, where $A \in NC$, $d \in ND$, and $p \in NP$:

 $B \rightarrow A \mid \exists r \mid \exists d \qquad C \rightarrow B \mid \neg B$ $r \rightarrow p \mid p^{-}$

Observe that for simplicity of presentation we do not consider here datatypes, which are also part of the OWL 2 QL standard.

Mappings specify how to populate classes and properties of the ontology with individuals and values constructed starting from the data in the underlying DB. In VKGs, the adopted standard language for mappings is R2RML [\[13\]](#page-16-8), but for conciseness we use here a more convenient abstract notation: A *mapping m* is an expression of the form

$$
s: Q(\mathbf{x})
$$

$$
t: L(\mathbf{t}(\mathbf{x}))
$$

where $Q(x)$ is a SQL query over the DB schema Σ , called *source query*, and $L(t(x))$ is a *target atom* of the form $C(t_1(x_1)), p(t_1(x_1), t_2(x_2)),$ or $d(t_1(x_1), t_2(x_2)),$ where $t_1(x_1)$ and $t_2(x_2)$ are terms that we call *templates*. In this work we express source queries using the notation of *relational algebra* and actually omit answer variables, assuming that they coincide with the variables used in the target atom. Intuitively, a template (**x**) in the target atom of a mapping corresponds to an *R2RML template*, and is used to generate object *IRIs* (i.e., Internationalized Resource Identifiers) or (RDF) *literals*, starting from DB values retrieved by the source query in that mapping.

As for the *semantics* of VKG mappings, we illustrate it by means of an example, and refer, e.g., to [\[33\]](#page-17-5) for more details. For examples, we use the concrete syntax adopted in the Ontop VKG system [\[8\]](#page-15-3), in which the answer variables of the source query are indicated in the target atom by enclosing them in $\{\cdots\}$, and in which each mapping is identified by an Id. The following is an example mapping expressed in such syntax:

mappingId mPerson source SELECT " ssn" FROM " person_info" target : person/{ssn} a : Person.

The effect of such mapping, when applied to a DB instance $\mathcal D$ for Σ , is to populate the class :Person with IRIs constructed by replacing the answer variable ssn occurring in the template in the target atom with the corresponding assigments for that variable in the answers to the source query evaluated over D.

3 Mapping Patterns

We now enter into the first contribution of this paper, namely a catalog of *mapping patterns*. In specifying each pattern, we consider not only the three main components of a VKG specification – namely the relevant portions of the DB schema, the ontology, and the mapping between the two – but also the conceptual schema of the domain of interest and the underlying data, when available. As pointed out in Section [1,](#page-0-0) we do not fix which of these information artifacts are given, and which are produced as output, but we simply describe how they relate to each other, on a per-pattern basis.

To present each pattern, we describe the complete set of attributes of each table. However, these have to be understood as only those attributes that are relevant for the considered portion of the application domain. We show the fragment of the conceptual schema that is affected by the pattern in E-R notation (adopting the original notation by Chen) – but any structural conceptual modeling language, such as UML or ORM, would work as well. To compactly represent sets of attributes, we use a small diamond in place of the small circle used for single attributes in Chen notation. In the DB schema, we use $T(K, A)$ to denote a *table* with name T, *primary key* consisting of the attributes K , and additional attributes A . Given a set U of attributes in T , we denote by unique_T (U) the fact that U form a *key* for T. Referential integrity constraints (like, e.g., foreign keys) are denoted with edges, pointing from the referencing attribute(s) to the referenced one(s). For readability, we denote sets of the form $\{o \mid condition\}$ as ${o}_{condition}$.

Formally, a mapping pattern is a quadruple (C, S, M, O) where C is a conceptul schema, S is a database schema with a distinguished table (called *pattern main table*), M is a set of mappings, and O is an (OWL 2 QL) ontology. In such mapping, the pair (C, S) is the *input*, putting into correspondence a conceptual representation to one of its (many) admissible (i.e., formally sound) database schemata. Such variants are due to differences in the applied methodology, as well as to considerations about efficiency, performance optimization, and space consumption of the final database. The pair (M, O), instead, is the output, where the *database schema ontology* O is the OWL 2 QL encoding of the conceptual schema C, and the set M of *database schema mappings* provides the link between the S and O.

We organize patterns in two major groups: *schema-driven patterns*, shaped by the structure of the DB schema and its explicit constraints, and *data-driven patterns*, which in addition consider constraints emerging from specific configurations of the data in the DB. Observe that, for each schema-driven pattern, we actually identify a data-driven version in which the constraints over the schema are now not explicitly specified, but hold in the data. We denote such pattern as its schema-driven counterpart, but with a leading "D" in place of "S" (e.g., in Table [1,](#page-5-0) DE is the data-driven version of SE). The two types of patterns can be used in combination with additional semantic information from the ontology, for instance on how the data values from the DB translate into RDF literals. These considerations lead us to introduce, where necessary, *pattern modifiers*.

It is important to note that some of the patterns come with accessory views defined over the DB-schema. The purpose of these views is to make explicit the presence of specific structures over the DB schema that are revealed through the application of the pattern itself. Such views can be used themselves, together with the original DB schema, to identify the applicability of further patterns.

3.1 Schema-driven Patterns

Next we briefly comment on schema-driven patterns, shown in Table [1.](#page-5-0)

Schema Entity (SE). This fundamental pattern considers a single table T_E with primary key **K** and other attributes **A**. The pattern captures how T_E is mapped into a corresponding class C_E . The primary key of T_E is employed to construct the objects that are instances of C_E , using a template t_E specific for that class. Each relevant attribute of T_E is mapped to a data property of C_E .

Table 1: Schema-driven Patterns. For patterns yielding views, we show the views together with the DB schema, separating them from the original tables using a thick horizontal bar.

 K_E is not inherited by the child table, because it is a constant value c. The dependency between T_F and T_E is an inclusion dependency, rather than a foreign key dependency.

Example: A client registry table containing SSNs of clients, together with their name as an additional attribute, is mapped to a Client class using the SSN to construct its objects. In addition, the SSN and name are mapped to two corresponding data properties.

References: This pattern is widespread, and it is already mentioned in the W3C-DM.

Schema Relationship (SR). This pattern considers three tables T_R , T_E , and T_F , in which the primary key of T_R is partitioned into two parts K_{RE} and K_{RF} that are foreign keys to T_E and T_F , respectively. T_R has no additional attributes. The pattern captures how T_R is mapped to an object property p_R , using the two parts \mathbf{K}_{RE} and \mathbf{K}_{RF} of the primary key to construct respectively the subject and the object of the triples in p_R .

Example: An additional table in the client registry stores the addresses of each client, and has a foreign key to a table with locations. The former table is mapped to an address object property, for which the ontology asserts that the domain is the class Person and the range an additional class Location, which corresponds to the latter table.

References: This pattern is widespread. For instance, it is described both in BootOX [\[23\]](#page-16-6) and in Mirror [\[29\]](#page-17-7).

Schema Relationship with Identifier Alignment (SRa). Such pattern is pattern **SR** plus a *modifier a*, indicating that the pattern can be applied after the identifiers involved in the relationship have been *aligned*. The alignment is necessary because now the foreign key in T_R does not point to the primary key \mathbf{K}_F of T_F , but to an additional key U_F . Since the instances of the class C_F corresponding to T_F are constructed using the primary key \mathbf{K}_F of T_F (cf. pattern **SE**), also the pairs that populate p_R should refer in their object position to that primary key, which can only be retrieved by a join between T_R and T_F on the additional key.

Note that alignment variants can be defined in a straightforward way for other patterns involving relationships. For conciseness, we prune these variants from our catalog.

Example: The primary key of the table with locations is not given by the city and street, which are used in the table that relates clients to their addresses, but is given by the latitude and longitude of locations.

References: This pattern is widespread. In particular, the alignment of identifiers is mentioned in the W3C-DM.

Schema Relationship with Merging (SRm). Such pattern considers a table T_E in which the foreign key \mathbf{K}_{EF} to a table T_F is disjoint from its primary key \mathbf{K}_E . The table T_E is mapped to an object property, whose subject and object are derived respectively from \mathbf{K}_E and \mathbf{K}_{EF} .

Example: The relationship between a client and its *unique* billing address has been merged into the client table. In the ontology, a billingAddress object property relates the Client class to the Location class, and is populated via a mapping from the client table. References: This pattern is widespread, and is one of the basic patterns described in the W3C-DM.

Schema Reified Relationship (SRR). Such pattern considers a table T_R whose primary key is partitioned in at least three parts K_{RE} , K_{RF} , and K_{RG} , that are foreign keys to three additional tables; or when the primary key is partitioned in at least two such parts, but there are additional attributes in T_R . Such a table naturally corresponds to an *n*-ary relationship R with $n > 2$ (or with attributes), and to represent it at the ontology level we require a class C_R , which reifies R, whose instances are built from the primary key of T_R . The mapping accounts for the fact that the components of the *n*-ary relationship have to be represented by suitable object properties, one for each such component, and that the tuples that instantiate these object properties can all be derived from T_R alone. Example: A table containing information about university exams, which involve a student, a course, and a professor teaching that course. This information is represented by a relationship that is inherently ternary. The ontology should contain a class corresponding to the reified relationship, e.g., a class Exam.

References: This pattern, which corresponds to *reification* in ontological and conceptual modeling [\[10,](#page-15-4) [3\]](#page-15-5), is one of the basic patterns described in the W3C-DM. A variant of it is also present in Mirror where, however, reification is required in the data.

Schema Hierarchy (SH). Such pattern considers a table T_F whose primary key is a foreign key to a table T_E . Then, T_F is mapped to a class C_F in the ontology that is a sub-class of the class C_E to which T_E is mapped. Hence, C_F "inherits" the template t_E of C_E , so that the instances of the two classes are "compatible".

Example: An entity Student in an ISA relation with an entity Person.

References: This pattern goes beyond W3C-DM, and is first discussed in Mirror (but not in the form presented here) and BootOX.

Schema Hierarchy with Identifier Alignment (SHa). Such pattern is like **SH**, but the foreign key in T_F is over a key U_F that is not primary. The objects for C_F have to be built out of \mathbf{U}_F , rather than out of its primary key. For this purpose, the pattern creates a view V_F in which U_F is the primary key, and the foreign key relations are preserved. Example: An ISA relation between entities Student and Person. Students are identified by their matriculation number, whereas persons are identified by their SSN.

References: We are not aware of works formalizing, or identifying, this pattern.

3.2 Data Driven Mapping Patterns

Data-driven patterns are mapping patterns that depends both on the schema and on the actual data in the DB. They are not limited to the variants corresponding to the schema-driven patterns, but they also comprehend specific patterns that do not have a corresponding schema version, e.g., due to *denormalized tables*. Such patterns, for which we provide a detailed description below, are shown in Table [2.](#page-9-0)

Data Entity with Merged 1-N Relationship and Entity with Attributes (DR1Nm). Such pattern considers a table T_E that has, besides its primary key \mathbf{K}_E , also attributes \mathbf{K}_F which functionally determine attributes \mathbf{A}_F . Observe that the latter condition is not possible if the DB schema is in normal form. When this pattern is applied, the key \mathbf{K}_F and the attributes \mathbf{A}_F that go along with it, can be projected out from T_F , resulting in a view V_F to which further patterns can be applied, including **DR1Nm** itself on additional attributes. Two additional views V_F and V_R are created, representing the tables corresponding to the entities E and R , respectively.

Example: A single students table containing information about students and attended courses, e.g., the course identifier and the course name. The course identifier, which is not a key for students, uniquely determines course names. The ontology defines both a Student and a Course class. The course identifier is used to build instances of Course,

and course name is mapped to a data property that has as domain the Course class. References: We are not aware of works formalizing, or identifying, this pattern.

Data 1-1 Relationship with Merging (DR11m). Such pattern could be applied when a table T_E has, besides its primary key \mathbf{K}_E , also an additional key \mathbf{K}_F , and domain knowledge or the ontology indicate that objects whose IRI is constructed from **K** are relevant in the domain, and that they have data properties that correspond to the attributes A_F of T_E . When this pattern is applied, the key K_F and the attributes A_F that go along with it, can be projected out from T_E , resulting in a view V_E to which further patterns can be applied, including **DR11m** itself on additional attributes.

Example: A single table containing the information about universities, and the information about their rector. The ontology contains both a University and a Rector class. The attribute SSN, identifying rectors, is used to build instances of Rector, and additional attributes that intuitively belong to the rector (such as his name) are mapped to data properties that have as domain the Rector class (as opposed to the University class). Notice that domain knowledge is required to apply this pattern. E.g., if the table contains an attribute for the salary of the rector, this could either be considered a property of the university (e.g., if the rector salary is determined by some regulation), or of the rector (e.g., if the rector salary is negotiated individually).

References: We are not aware of works formalizing, or identifying, this pattern.

Data Entity with Optional Participation in a Relationship (DH01). Such pattern is characterized by a table T_F that represents the merge of child entity E_R into a father entity E , and E_R has a mandatory participation in a relationship R . The join between the table T_R and T_E identifies the objects in E instances of E_R , and is used in a mapping to create instances of the class C_{R_E} , as well as the object property R connecting E_R to F. This pattern produces a view V_{E_R} to which further patterns can be applied.

Example: A students table and a table connecting students to undergraduate courses. Each student participating such relationship is an undergraduate student.

References: To the best of our knowledge, this pattern was first described in BootOX, which also provides techniques to automatically discover and use it to generate mappings.

Clustering Entity to Class/Data Property/Object Property (CE2C/CE2D/CE2O).

Such patterns are characterized by an entity E and a *derivation rule* defining sub-entities of E according to the values for attributes \bf{B} in E . Instances in these sub-entities can be mapped to objects in the subclasses $C_E^{\mathbf{v}}$ of the ontology (**CE2C**), to objects connected through a data property to some literal constructed through a *value invention* function ξ applied on **v** (**CE2D**), or to objects connected through an object property to some IRI built from **v** (**CE2O**). The definition of ξ depends on the actual ontology. As other patterns, this pattern produces views according to the possible values **v** of **B**.

Example: A table contains people with an attribute defining their gender and ranging over 'F' or 'M'. The ontology defines a data property hasGender, ranging over the two RDF literals "Male" and "Female". Then, pattern **CE2D** clusters the table according to the gender attribute, so as to obtain objects to be linked to either of the two RDF literals. References: For what concerns the **CE2C** variant, the clustering pattern is widespread, and it is mentioned in several works on bootstrapping like BootOX. We are not aware of mentions regarding the **CE2D** and **CE2O** variants.

Table 2: Data-driven Patterns

E-R DIAGRAM	DB SCHEMA	MAPPING PATTERN	ONTOLOGY									
Data Entity with Merged 1-N Relationship and Entity (DR1Nm) $T_E(K_E, A_E, K_F, A_F)$												
$K_F A_F$ $K_E A_E$	$\operatorname{fd}(T_E: \mathbf{K}_F \to \mathbf{A}_F)$ $V_E(\mathbf{K}_E, \mathbf{A}_E) = \pi_{\mathbf{K}_E, \mathbf{A}_E}(T_E)$ $V_R(\mathbf{K}_E^{\mathsf{T}}, \mathbf{K}_F) = \pi_{\mathbf{K}_E, \mathbf{K}_F}(T_E)$ $V_F(\mathbf{K}_F, \mathbf{A}_F) = \pi_{\mathbf{K}_F, \mathbf{A}_F}(T_E)$	$s: T_F$ t: $C_F(\mathbf{t}_F(\mathbf{K}_F)),$ ${d_A(t_F(K_F),A)}_{A\in K_F\cup A_F}$ $p_R(\mathsf{t}_E(\mathsf{K}_E), \mathsf{t}_F(\mathsf{K}_F))$	$\{\exists d_A \sqsubseteq C_F\}_{A\in\mathbf{K}_F\cup\mathbf{A}_F}$ $\exists p_R \sqsubseteq C_E$ $\exists p_R^- \sqsubseteq C_F$									
Data 1-1 Relationship with Merging (DR11m)												
$K_E A_E$	$T_E(\mathbf{K}_E, \mathbf{A}_E, \mathbf{K}_F, \mathbf{A}_F)$ unique $_{T_F}$ (K _F) $V_E(\mathbf{K}_E, \mathbf{A}_E) = \pi_{\mathbf{K}_E, \mathbf{A}_E}(T_E)$ $V_R(\underbrace{\mathbf{K}_E^{\mathsf{T}}, \mathbf{K}_F}_{\mathsf{F}}) = \pi_{\mathbf{K}_E, \mathbf{K}_F} (T_E)$ $V_F(\overline{\textbf{K}_F, \textbf{A}_F}) = \pi_{\textbf{K}_F, \textbf{A}_F}(T_E)$	$s: T_E$ t: $C_F(t_F(K_F)),$ $\{d_A(\mathsf{t}_F(\mathsf{K}_F),A)\}_{A\in\mathsf{K}_F\cup\mathsf{A}_F},$ $p_R(t_E(K_E), t_F(K_F))$	$\{\exists d_A \sqsubseteq C_F\}_{A \in \mathbf{K}_F \cup \mathbf{A}_F}$ $\exists p_R \sqsubseteq C_E$ $\exists p^-_p \sqsubseteq C_F$									
Data Entity with Optional Participation in a Relationship (DH01)												
$K_F A_F$	$T_E\left(\underline{\mathbf{K}_E}, \mathbf{A}_E\right)$. $T_F\left(\underline{\mathbf{K}_F}, \mathbf{A}_F\right)$ $T_R(K_{RE}^{\uparrow}, K_{RF})$ $V_{E_{\rm P}}(\mathbf{K}_E, \mathbf{A}_E) =$ $\pi_{\mathbf{K}_E,\mathbf{A}_E}(T_R \bowtie_{\mathbf{K}_{RE}=\mathbf{K}_E} T_E)$	s_1 : T_R t_1 : $p_R(t_E(K_{RE}), t_F(K_{RF}))$ s_2 : $T_R \Join_{K_{RF}=K_F} T_E$ t_2 : C_{E_R} (t_E (K _{RE})), $\{d_A(t_E(\mathbf{K}_{RE}),A)\}_{A\in\mathbf{K}_E\cup\mathbf{A}_E}$	$C_{E_R} \sqsubseteq C_E$ $\exists p_R \sqsubseteq C_{E_R}$ $\exists p_{\mathbf{p}}^- \sqsubseteq C_F$									
Clustering Entity to Class (CE2C)												
$B \subseteq K \cup A$, partition $\mathcal{P}_0(\mathbf{B}, E)$	T_F (K, A) unique $_{T_F}$ (K) $B \subseteq K \cup A$ partition $\mathcal{P}(\mathsf{B}, E)$ ${V_{F_n}(\mathbf{K}, \mathbf{A}) =$ $\sigma_{\mathbf{B}=\mathbf{v}}(T_E) \}_{\mathbf{v} \in \pi_{\mathbf{B}}(T_E)}$	$\{s : \sigma_{\mathbf{B}=\mathbf{V}}(T_E)\}$ $t: C_F^{\mathbf{v}}(\mathfrak{t}_E(\mathbf{K}))\}_{\mathbf{v}\in\pi_{\mathbf{B}}(T_E)}$	$\{C_E^{\mathbf{v}}\sqsubseteq C_E\}_{\mathbf{v}\in\pi_{\mathbf{B}}(T_E)}$									
		Clustering Entity to Data/Object Property (CE2D/CE2O)										
E $B \subseteq K \cup A$ partition η (B , <i>E</i>)	T_E (K, A) unique $_{T_F}$ (K) $B \subseteq K \cup A$	$\{s : \sigma_{\mathbf{B}=\mathbf{v}}(T_E)\}$ $t: d_{\mathbf{B}}(\mathbf{t}_E(\mathbf{K}), \xi(\mathbf{v}))\}_{\mathbf{v}\in \pi_{\mathbf{A}}(T_E)}$	$\exists d_{\mathbf{B}} \sqsubseteq C_E$									
	$partition_{\mathcal{D}}(\mathbf{B},E)$ ${V_{F_u}(\mathbf{K}, \mathbf{A}) =$ $\sigma_{\mathbf{B}=\mathbf{v}}(T_E)\}_{\mathbf{v}\in\pi_{\mathbf{B}}(T_E)}$	$\{s : \sigma_{\mathbf{B}=\mathbf{v}}(T_E)\}$ $t: p_{\mathbf{B}}(\mathfrak{t}_E(\mathbf{K}), \mathfrak{t}_{\mathbf{v}}(\mathbf{v}))\}_{\mathbf{v}\in\pi_{\mathbf{B}}(T_E)}$	$\exists p_{\mathbf{B}} \sqsubseteq C_E$									
Clustering Relationship to Object Property (CR2O)												
$K_E A_E$ $K_F A_F$ $\mathbf{B} \subseteq \mathbf{K}_{RE} \cup \mathbf{K}_{RF}$, partition η (B , <i>R</i>)	$T_R(K_{RE}, K_{RF}),$ $B \subseteq K_{RE} \cup K_{RF}$ partition $\mathcal{P}(\mathsf{B}, R)$ ${V_{R_n}(\mathbf{K}_{RE}, \mathbf{K}_{RF})}$ = $\sigma_{\mathbf{B}=\mathbf{v}}(T_R)\}_{\mathbf{v}\in\pi_{\mathbf{B}}(T_R)}$	$\{s : \sigma_{\mathbf{B}=\mathbf{v}}(T_R)\}$ $t: p_R^{\mathbf{v}}(\mathbf{t}_E(\mathbf{K}_{RE}),$ $t_F(K_{RF}))\}_{\mathbf{v}\in\pi_{\mathbf{B}}(T_R)}$	$\{p_R^{\mathbf{v}} \sqsubseteq p_R\}_{\mathbf{v} \in \pi_\mathbf{B}(T_R)}$									

Clustering Relationship to Object Property CR2O. Such pattern is a similar to the previous clustering patterns, but the table being clustered corresponds to a relationship R and the result of the clustering are sub-properties of the object property relative to R . Example: A table relating professors to courses. Lecturers are identified by a multiattribute key in which one attribute discriminates between full or associate professors. Courses are identified by a multi-attribute key in which one attribute discriminates between undergraduate or graduate courses. Such table is mapped to four object properties in the ontology, one for each combination of type of lecturer and type of course (e.g., an undergraduate course taught by a full professor).

References: We are not aware of works formalizing, or identifying, this pattern.

3.3 Variations and Combinations

More complex patterns arise from the combination of the patterns described so far. For instance, recall the example we discussed for pattern **DH01**. Graduate students, which are a by-product of the application of such pattern, might be in relationship with an entity Graduation. The object property capturing the relationship might be created by applying pattern **DR**. In our analysis, we have observed that combinations are quite common in VKG specifications where the DB has been created independently from the ontology.

Another important variation is the one introduced by modifiers, such as *value invention or combination*, in which DB values are used and combined to get RDF literals, typically by relying on R2RML *templates*. We have already encountered an instance of value invention, specifically when we introduced the **CE2D** pattern.

4 Usage Scenarios for VKG Patterns

We now comment on how having a catalog of patterns for VKG specifications like the one introduced in Section [3](#page-3-0) is instrumental in a number of usage scenarios.

Debugging of a VKG Specification. This scenario arises when a full VKG specification is already in place and must be debugged. Here, each component of the specification can be checked for compliance against the patterns.

Conceptual Schema Reverse Engineering. Another relevant scenario arising when a full VKG specification is given, is that of inferring a conceptual schema of the DB that represents the domain of interest by reflecting the content of the VKG specification. Here the ontology provides the main source to reconstruct entities, attributes, and relationships, while the DB and the mappings provide the basis to ground the conceptual model in the actual DB, and to infer additional constraints that are not captured by the ontology (e.g., for limited expressivity of OWL 2 QL).

Mapping Bootstrapping. In this scenario, the DB and the ontology are given, but mappings relating them are not. Patterns can be used to (semi-)automatically bootstrap an initial set of mappings, which can then be further refined and extended manually, possibly exploiting again the patterns. Schema patterns are the most suitable ones to automatically guide the bootstrapping process. When patterns contain tables that merge multiple entities/relationships, the presence of a conceptual schema becomes crucial to configure the left-hand side of bootstrapped mappings. This is, e.g., the case for **DR1Nm** and **DR11m**, and patterns based on clustering. If the conceptual schema is not available in this tricky case, boostrapping can still be attempted by relying on schema matching techniques [\[34\]](#page-17-1), as done in BootOX. Specifically, schema matching comes handy when a pattern involves two (or more) under-specified schemas. For instance, in the case of pattern **DR**, *pair candidates* between primary keys can be *matched* in order to make implicit relationships explicit. This can be done through matchers (such as string similarity matchers [\[17\]](#page-16-9)) that employ attribute names, instance data, schema structure, etc. To separate genuine relationships from false positives generated by poor matchers, ranking techniques have to be employed [\[19\]](#page-16-10).

Ontology+Mapping Bootstrapping. Here, neither the ontology nor the mappings are given as input, and have to be synthesized. This scenario can be reduced to the one of mapping bootstrapping by first inducing a baseline ontology mirroring the structure of the DB schema. This ontology is typically at a much lower level of abstraction than the one expected by domain experts. In fact, this problem can be tackled in a much more effective way in the case where an explicit conceptual schema is provided. In this case, standard techniques to encode conceptual schemas into corresponding ontology axioms (e.g., [\[6\]](#page-15-6)) can be readily applied.

VKG Bootstrapping. In this scenario, we just have a conceptual schema of the domain, and the goal is to set up a VKG specification. The conceptual schema can be then transformed into a normalized DB schema using well-established *relational mapping* techniques (e.g., [\[21\]](#page-16-11)). At the same time, as pointed above, a direct encoding into ontology axioms can be applied to bootstrap the ontology. The generation of mappings becomes then a quite trivial task, considering that the induced DB and ontology are very close in terms of abstraction. This setting resembles, in spirit, that of *object-relational mapping*, used in software engineering to instrument a DB and corresponding access mechanisms starting from classes written in object-oriented code.

5 Analysis of Scenarios

In this section we look at a number of VKG scenarios in order to understand how patterns occur in practice, and with which frequency. To this purpose, we have gathered 6 different scenarios, coming either from the literature on VKGs, or from actual real-world applications. Table [3](#page-13-0) shows the results of our analysis, and for each cell pattern/scenario, it reports the number of applications of that pattern over that scenario (leftmost number in the cell) and the number of mappings involved (rightmost number in the cell). The last column in the table reports total numbers. We have manually classified a total of 1559 mapping assertions, falling in 407 applications of the described patterns. Of these applications, about 52.8% are of schema-driven patterns, 44.7% of data-driven patterns, and 2.5% are of patterns falling outside of our categorization. In the remainder of this section we describe the detailed results for each scenario.

Berlin Sparql Benchmark (BSBM) [\[4\]](#page-15-7). This scenario is built around an e-commerce use case in which products are offered by vendors and consumers review them. Such benchmark does not natively come with mappings, but these have been created in different works belonging to the VKG literature. We analyzed those in [\[27\]](#page-17-8). The ontology in BSBM reflects quite precisely the actual organization of data in the DB. Due to this, each mapping falls into one of the patterns we identified. Notably, in the DB foreign key constraints are not specified. Therefore, we notice a number of applications of data-driven patterns, which cannot be captured by simple approaches based on W3C-DM.

NPD Benchmark (NPD) [\[26\]](#page-16-12). This scenario is built around the domain of oil and gas extraction. It presents the highest number of mappings $(>\!1k)$. The majority of these were automatically generated, and fall under W3C-DM or schema-driven patterns. There are, however, numerous exceptions. Mainly, there are a few denormalized tables which require the use of the **DR1Nm** pattern, such as for the following mapping:

```
mappingId Mapping :00877: Table : Extra : ex5 : npdv : Quadrant
target npd : quadrant /{ wlbNamePart1 } a npdv : Quadrant .
source SELECT " wlbNamePart1 " FROM " wellbore_development_all "
```
A quadrant is not an entity in the DB schema (because wlbNamePart1 is not a key of wellbore development all), but it is represented as a class in the ontology. Moreover, quadrants have themselves their own data (resp., object) properties, triggering the application of other patterns in composition with **DR1Nm**.

University Ontology Benchmark (UOBM) [\[41\]](#page-17-9). This scenario is built around the academic domain. Such benchmark provides a tool to automatically generate OWL ontologies, but does not include mappings nor a DB instance. These two have been manually crafted in [\[7\]](#page-15-8), by reverse-engineering the ontology. The mappings in this setting are quite interesting, and are mostly data-driven as witnessed by the many applications of the clustering patterns. One critical aspect about these mappings is the use of a sophisticated version of the identifier alignment pattern modifier. Specifically, the table People has the following primary key:

PRIMARY KEY (ID , deptID , uniID , role)

Table GraduateStudent, which at the conceptual level corresponds to a subclass of the class People, has the following key which is incompatible with the one of the superclass:

PRIMARY KEY (studentID , deptID , uniID)

The subclass relation between People and GraduateStudents requires the two keys to be aligned. This is done "artificially", in the sense that the missing field role is created on-the–fly by the mapping:

mappingId Graduate Student target <http://www.Dept{deptID}.Univ{univID}.edu/{role}{studID}> a :GraduateStudent source SELECT deptID , univID , studID , ' GraduateStudent ' as role FROM GraduateStudents

Suedtirol OpenData (ST-OD)[1](#page-12-0). This is an application scenario coming from the turism domain. The ontology has been created independently from the DB. Moreover, the DB is itself highly de-normalized, since it is essentially a relational rendering of a JSON file. These aspects have a direct impact on the patterns we observed. In particular, we identified several applications of the **DR11m** pattern, which, as we discussed, poses a huge challenge to automatic generation of mappings. Further complications arise from a number of applications of the value invention pattern modifier, which appears quite often in the form, for instance, of language tags:

```
mappingId municipality
target : mun/mun={istat_code} a : Municipality ; rdfs:label {name_i}@it, {name_d}@de .
source SELECT istat_code , name_i , name_d FROM municipalities
```
Open Data Hub VKG (ODH)[2](#page-12-1). This setting is the one behind the SPARQL endpoint located at the Open Data Hub portal from the Province of Bozen-Bolzano (Italy). This

¹<https://github.com/dinglinfang/suedTirolOpenDataOBDA>

²<https://sparql.opendatahub.bz.it/>

Table 3: Occurrences of Mapping Patterns over the Considered Scenarios.

	BSBM		NPD		UOBM		ODH		ST-OD		Cordis		Total	
SE	8	52	61	454	8	16	10	43	8	37	13	60	108	662
SR					\overline{c}	\overline{c}					3	3	5	5
SRm	8	8	74	74	5	5	-	-	7	7	10	10	97	97
SRR				12							1	16	$\overline{2}$	28
SH			3	132									3	132
DE							-	-	3	7	4	9	7	16
DRm	5	5	17	17	36	36	2	\overline{c}	1	1	\overline{c}	\mathfrak{D}	63	63
DH	-	-			5	9	-						5	9
DRR	\overline{c}	2											2	\overline{c}
DR1Nm	4	$\overline{4}$	19	54					9	15	1	1	33	74
D11Rm							6	78	5	14			11	92
DH0N												\overline{c}	1	$\overline{2}$
CE ₂ C		-	11	82	6	19	5	23				12	23	136
CE ₂ D	-		23	49									23	49
CE ₂₀			13	148									13	148
CR2O					1	12	-					1	1	12
UNKNOWN			3	6	1	1	1	4	1	12	4	9	10	32

setting is also a denormalized one, and the same considerations we made for ST-OD apply to this setting as well.

Cordis[3](#page-13-1). This setting is provided by SIRIS Academic S.L., a consultancy company specialized in higher education and research, and is designed around the domain of competitive research projects. As opposed to the previous two scenarios, this one comes with a well-structured relational schema, which reflects in a number of applications of schema patterns. Although in this scenario we have DB views, such views have explicit constraints defined on them (such as, UNIQUE constraints in SQL) that allow for the application of schema patterns.

6 Related Work

In the last two decades a plethora of tools and approaches have been developed to bootstrap an ontology and mappings from a DB. The approaches in the literature differ in terms of the overall *purposes* of the bootstrapping (e.g., OBDA, data integration, ontology learning, check of DB schema constraints using ontology reasoning), the *ontology and mapping languages* in place (e.g., OWL 2 profiles or RDFS, as ontology languages, and R2RML or custom languages, for the specification of mappings), the different focus on *direct and/or complex mappings*, and the assumed *level of automation*. The majority of the most recent approaches closely follow W3C-DM, deriving ontologies that mirror the structure of the input DB.

Our work makes no exception, in the sense that many of the patterns discussed here mostly subsume the W3C-DM recommendation. The exceptions are on those bits where the recommendation itself differentiates from R2RML (e.g., on the treatment of blank nodes as object identifiers).

Work in [\[35\]](#page-17-10) is very closely related ours, as it also introduces a catalog of mapping patterns. However, there are major differences between such work and the present,

³<https://www.sirisacademic.com/wb/>

namely in that work:

- patterns are not formalized, and presented in a "by-example" fashion following the R2RML syntax;
- patterns are derived from "commonly-occurring mapping problems" based on the experience of the authors, whereas in this work patterns are derived from conceptual modeling and database design principles;
- patterns are not evaluated against a number of different real-world, and complex scenarios over heterogeneous domains and design practices as it was done here.

To the best of our knowledge, there are no other works whose main focus is a systematic categorization of mappings in VKGs. [\[29\]](#page-17-7) and [\[23\]](#page-16-6) provide indeed such a categorization, but it is aimed at supporting bootstrapping of mappings. In addition, the vast majority of the scientific contributions, restrict their attention to the algorithms behind the generation of mappings, notably [\[31,](#page-17-11) [8,](#page-15-3) [36\]](#page-17-12) for the R2RML language. Another notable difference between our work and mapping bootstrappers is that we provide foundations towards other tasks than bootstrapping, as discussed in Section [4.](#page-10-0)

For the sake of completeness w.r.t. the existing bootstrapping approaches, we mention here some of the most prominent tools that have been recently implemented. Unfortunately, we have not been able to find, in their related literature, an explicit description of the mappings generated by the tools, and this prevented us from a deeper comparison between the mapping patterns introduced here and these approaches. In **Karma** [\[20\]](#page-16-13), (ontology) learning techniques are used to mine the source data. In the schema matching literature, simple rule-based mappings are used to create a uniform representation of the data sources to be matched, may they be schemata or ontologies [\[2,](#page-15-9) [18,](#page-16-14) [31\]](#page-17-11). For example, in **COMA++** [\[2\]](#page-15-9), class hierarchies, attributes, and relationship types are mapped into a generic model based on directed acyclic graphs. Using such mappings, schema matchers are applied to the uniform model to create a matching result. Similarly, **IncMap** [\[2\]](#page-15-9) relies on a graph structure called IncGraph to represent schema elements from both ontologies and relational schemata in a unified way. The tools that today are by far most popular are those that are based on W3C-DM, and leave the user to manually refine the extracted outputs, e.g., the **D2RQ** system [\[5\]](#page-15-10). In such category we find also commercial tools, notably **Ultrawrap** [\[36\]](#page-17-12) in the context of data integration. We point also to a selection of surveys [\[37,](#page-17-13) [39,](#page-17-4) [32\]](#page-17-14) with further information about the tools and techniques mentioned here, and their performance evaluations.

We finally notice that, in our review, we did not find any study introducing an in depth analysis of existing real scenarios of DB-to-ontology mapping, as we do in the present paper, aimed at showing that the identified categories actually reflect the real design choices and methodologies in use by the mapping designers.

7 Conclusion and Future Work

In this work we propose to use a number of mapping patterns to facilitate the task of linking DBs to ontologies in a typical VKG setting. We argue that such patterns can enable a number of relevant tasks, apart from the classic one of bootstrapping mappings in an incomplete VKG scenario. Through a systematic analysis of various VKG scenarios, ranging from benchmarks to real world and denormalized ones, we observed that the patterns we formalized occur in practice, and capture most cases.

This work is only a first step, with respect to both categorization of patterns, and their actual use. Regarding the former, we plan to better explore the interaction between patterns and pattern modifiers, such as value invention or identifier alignment. Regarding the latter, in this paper we have used patterns to investigate, and highlight, the specific problems to address when setting-up a VKG scenario. We plan to investigate solutions to these problems, by exploiting approaches from other fields, e.g., schema matching.

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