The Virtual Knowledge Graph System Ontop


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Abstract. Ontop is a popular open-source virtual knowledge graph system that can expose heterogeneous data sources as a unified knowledge graph. Ontop has been widely used in a variety of research and industrial projects. In this paper, we describe the challenges, design choices, new features of the latest release of Ontop v4, summarizing the development efforts of the last 4 years.

1 Introduction

The Virtual Knowledge Graph (VKG) approach, also known in the literature as Ontology-Based Data Access (OBDA) [16,23], has become a popular paradigm for accessing and integrating data sources [24]. In such approach, the data sources, which are normally relational databases, are virtualized through a mapping and an ontology, and presented as a unified knowledge graph, which can be queried by end-users using a vocabulary they are familiar with. At query time, a VKG system translates user queries over the ontology to SQL queries over the database system. This approach frees end-users from the low-level details of data organization, so that they can concentrate on their high-level tasks. As it is gaining more and more importance, this paradigm has been implemented in several systems [3,4,18,21], and adopted in a large range of use cases. Here, we present the latest major release, Ontop v4, of a popular VKG system.

The development of Ontop has been a great adventure spanning the past decade. Developing such a system is highly non-trivial. It requires both a theoretical investigation of the semantics, and strong engineering efforts to implement all the required features. Ontop started in 2009, only one year after the first version of the SPARQL specification had been standardized, and OWL 2 QL [14] and R2RML [9] appeared 3 years later in 2012. At that time, the VKG research focused on union of conjunctive queries (UCQs) as a query language. With this target, the v1 series of Ontop was using Datalog as the core for data representation [20], since it was fitting well a setting based on UCQs. The development of Ontop was boosted during the EU FP7 project Optique
(2013–2016). During the project, the compliance with all the relevant W3C recommenda-
tions became a priority, and significant progress has been made. The last release of
Ontop v1 was v1.18 in 2016, which is the result of 4.6K git commits. A full description
of Ontop v1 is given in [3], which has served as the canonical citation for Ontop so far.

A natural requirement that emerged during the Optique project were aggregates
introduced in SPARQL 1.1 [12]. The Ontop development team spent a major effort,
internally called Ontop v2, in implementing this query language feature. However, it
became more and more clear that the Datalog-based data representation was not well
suited for this implementation. Some prototypes of Ontop v2 were used in the Optique
project for internal purposes, but never reached the level of a public release. We explain
this background and the corresponding challenges in Section 2.

To address the challenges posed by aggregation and others that had emerged in the
meantime, we started to investigate an alternative core data structure. The outcome has
been what we call intermediate query (IQ), an algebra-based data structure that unifies
both SPARQL and relational algebra. Using IQ, we have rewritten a large fragment of
the code base of Ontop. After two beta releases in 2017 and 2018, we have released
the stable version of Ontop v3 in 2019, which contains additional 4.5K commits with
respect to Ontop v1. After Ontop v3, the development focus was to improve compliance
and add several major features. In particular, aggregates are supported since Ontop v4-
beta-1, released late 2019. We have finalized Ontop v4 and released it in July 2020,
with additional 2.3K git commits. We discuss the design of Ontop v4 and highlight
some benefits of IQ that VKG practitioners should be aware of in Section 3.

Ontop v4 has greatly improved its compliance with relevant W3C recommenda-
tions and provides good performance in query answering. It supports almost all the
features of SPARQL 1.1, R2RML, OWL 2 QL and SPARQL entailment regime, and
the SPARQL 1.1 HTTP Protocol. Two recent independent evaluations [7,15] of VKG
systems have confirmed the robust performance of Ontop. When considering all the
perspectives, like usability, completeness, and soundness, Ontop clearly distinguishes
itself among the open source systems. We describe evaluations of Ontop in Section 4.

Ontop v4 is the result of an active developer community. The number of git commits
now sums up to 11.4K. It has been downloaded more than 30K times from Sourceforge.
In addition to the research groups, Ontop is also backed by a commercial company, On-
top s.r.l., born in April 2019. Ontop has been adopted in many academic and industrial
projects [24]. We discuss the community effort and the adoption of Ontop in Section 5.

2 Background and Challenges

A Virtual Knowledge Graph (VKG) system provides access to data (stored, for example,
in a relational database) through an ontology. The purpose of the ontology is to define
a vocabulary (classes and properties), which is convenient and familiar to the user, and
to extend the data with background knowledge (e.g., subclass and subproperty axioms,
property domain and range axioms, or disjointness between classes). The terms of the
ontology vocabulary are connected to data sources by means of a mapping, which can be
thought of as a collection of database queries that are used to construct class and prop-
erty assertions of the ontology (RDF dataset). Therefore, a VKG system has the follow-
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The Virtual Knowledge Graph System (VKG) consists of the following components: (a) queries that describe user information needs, (b) an ontology with classes and properties, (c) a mapping, and (d) a collection of data sources. W3C published recommendations for languages for components (a)–(c): SPARQL, OWL 2 QL, and R2RML, respectively; and SQL is the language for relational DBMSs.

A distinguishing feature of VKG systems is that they retrieve data from data sources only when it is required for a particular user query, rather than extracting all the data and materializing it internally; in other words, the Knowledge Graph (KG) remains virtual rather than materialized. An advantage of this approach is that VKG systems expose the actual up-to-date information. This is achieved by delegating query processing to data sources (notably, relational DBMSs): user queries are translated into queries to data sources (while taking account of the ontology background knowledge). And, as it has been evident from the early days [4,19,21,22], performance of VKG systems critically depends on the sophisticated query optimization techniques they implement.

**Ontop v1.** Early VKG systems, the focus was on answering conjunctive queries (CQs), that is, conjunctions of unary and binary atoms (for class and property assertions respectively). As for the ontology language, OWL 2 QL was identified [5,2] as an (almost) maximal fragment of OWL that can be handled by VKG systems (without materializing all assertions that can be derived from the ontology). In this setting, a query rewriting algorithm compiles a CQ and an OWL 2 QL ontology into a union of CQs, which, when evaluated over the data sources, has the same answers as the CQ mediated by the OWL 2 QL ontology. Such algorithms lend themselves naturally to an implementation based on non-recursive Datalog: a CQ can be viewed as a clause, and the query rewriting algorithm transforms each CQ (a clause) into a union of CQs (a set of clauses). Next, in the result of rewriting, query atoms can be replaced by their ‘definitions’ from the mapping. This step, called unfolding, can also be naturally represented in the Datalog framework: it corresponds to partial evaluation of non-recursive Datalog programs, provided that the database queries are SELECT–PROJECT–JOIN (SPJ) [16]. So, Datalog was the core data structure in Ontop v1 [20], which translated CQs mediated by OWL 2 QL ontologies into SQL queries. The success of Ontop v1 heavily relied on the semantic query optimization (SQO) techniques [6] for simplifying non-recursive Datalog programs. One of the most important lessons learnt in that implementation is that rewriting and unfolding, even though they are separate steps from a theoretical point of view, should be considered together in practice: a mapping can be combined with the subclass and subproperty relations of the ontology, and the resulting saturated mapping (or T-mapping) can be constructed and optimized before any query is processed, thus taking advantage of performing the expensive SQO only once [19].

**Ontop Evolution: from Datalog to Algebra** As Ontop moved towards supporting the W3C recommendations for SPARQL and R2RML, new challenges emerged.

- In SPARQL triple patterns, variables can occur in positions of class and property names, which means that there are effectively only two underlying ‘predicates’: triple for triples in the RDF dataset default graph, and quad for named graphs.
- More importantly, SPARQL is based on a rich algebra, which goes beyond expressivity of CQs. Non-monotonic features like OPTIONAL and MINUS, and cardinality-sensitive query modifiers (DISTINCT) and aggregation (GROUP BY with functions such as SUM, AVG, COUNT) are difficult to model even in extensions of Datalog.
Even without SPARQL aggregation, cardinalities have to be treated carefully: the
SQL queries in a mapping produce bags (multisets) of tuples, but their induced
RDF graphs contain no duplicates and thus are sets of triples; however, when a
SPARQL query is evaluated, it results in a bag of solutions mappings.

These challenges turned out to be difficult to tackle in the Datalog setting. For example,
one has to use three clauses and negation to model OPTIONAL, see e.g., [17,1]. Moreover,
using multiple clauses for nested OPTIONS can result in an exponentially large
SQL query, if the related clauses are treated independently. On the other hand, such
a group of clauses could and ideally should be re-assembled into a single LEFT JOIN
when translating into SQL, so that the DBMS can take advantage of the structure [25].
Curiously, the challenge also offers a solution because most SPARQL constructs have
natural counterparts in SQL: for instance, OPTIONAL corresponds to LEFT JOIN, GROUP
BY to GROUP BY, and so on. Also, both SPARQL and SQL have bag semantics and use
3-valued logic for boolean expressions.

As a consequence of the above observations, when redesigning Ontop, we replaced
Datalog by a relational-algebra-type representation, discussed in Section[5]

SPARQL vs SQL. Despite the apparent similarities between SPARQL and SQL, the
two languages have significant differences relevant to any VKG system implementation.

Typing Systems. SQL is statically typed in the sense that all values in a given relation
column (both in the database and in the result of a query) have the same datatype.
In contrast, SPARQL is dynamically typed: a variable can have values of different
datatypes in different solution mappings. Also, SQL queries with values of unexpected
datatypes in certain contexts (e.g., a string as an argument for ‘+’) are simply deemed
incorrect. In contrast, SPARQL treats such type errors as legitimate and handles them similarily to NULLs in SQL. For example, the basic graph pattern ?s ?p ?o FILTER (?o < 4)
retrieves all triples with a numerical object whose value is below 4 (but ignores all
triples with strings or IRIs, for example). Also, the output datatype of a SPARQL func-
tion depends on the types or language tags of its arguments (e.g., if both arguments
of ‘+’ are xsd:integer, then so is the output, and if both arguments are xsd:decimal,
then so is the output). In particular, to determine the output datatype of an aggregate
function in SPARQL, one has to look at the datatypes of values in the group, which can
vary from one group to another.

Order. SPARQL defines a fixed order on IRIs, blank nodes, unbound values, and
literals. For multi-typed expressions, this general order needs to be combined with the
orders defined for datatypes. In SQL, the situation is significantly simpler due to its
static typing: apart from choosing the required order modifier for the datatype, one only
needs to specify whether NULLs come first or last.

Implicit Joining Conditions. SPARQL uses the notion of solution mapping compatibility
to define the semantics of the JOIN and OPTIONAL operators: two solution mappings
are compatible if both map each shared variable to the same RDF term (sameTerm), that is,
the two terms have the same type (including the language tag for literals) and the
same lexical value. The sameTerm predicate is also used for AGGREGATEJOIN. In con-
trast, equalities in SQL are satisfied when their arguments are equivalent, but not nec-
essarily of the same datatype (e.g., 1 in columns of type INTEGER and DECIMAL), and may
even have different lexical values (e.g., timestamps with different timezones). SPARQL has a similar equality, denoted by ‘=’, which can occur in FILTER and BIND.

**SQL Dialects.** Unlike SPARQL with its standard syntax and semantics, SQL is more varied as DBMS vendors do not strictly follow the ANSI/ISO standard. Instead, many use specific datatypes and functions and follow different conventions, for example, for column and table identifiers and query modifiers; even a common function `CONCAT` can behave differently: `NULL`-rejecting in MySQL, but not in PostgreSQL and Oracle. Support for the particular SQL dialect is thus essential for transforming SPARQL into SQL.

### 3 Ontop v4: New Design

We now explain how we address the challenges in Ontop v4. In Section 3.1 we describe a variant of relational algebra for representing queries and mappings. In Section 3.2 we concentrate on translating SPARQL functions into SQL. We discuss query optimization in Section 3.3 and post-processing and dealing with SQL dialects in Section 3.4.

#### 3.1 Intermediate Query

Ontop v4 uses a variant of relational algebra tailored to encode SPARQL queries along the lines of the language described in [25]. The language, called Intermediate Query, or IQ, is a uniform representation both for user SPARQL queries and for SQL queries from the mapping. When the query transformation (rewriting and unfolding) is complete, the IQ expression is converted into SQL, and executed by the underlying relational DBMS.

In SPARQL, an RDF dataset consists of a default RDF graph (a set of triples of the form `s-p-o`) and a collection of named graphs (sets of quadruples `s-p-o-g`, where `g` is a graph name). In accordance with this, a ternary relation `triple` and a quaternary relation `quad` model RDF datasets in IQ. We use atomic expressions of the form

\[
\text{triple}(s, p, o) \quad \text{and} \quad \text{quad}(s, p, o, g),
\]

where `s`, `p`, `o`, and `g` are either constants or variables—in relational algebra such expressions would need to be built using combinations of `SELECT` (`σ`, to deal with constants and matching variables in different positions) and `PROJECT` (`π`, for variable names), see, e.g., [8]: for example, triple pattern `:ex :p ?x` would normally be encoded as \(π_{x/o}σ_{s=:ex,p=:p}\text{triple}\), where `s`, `p`, `o` are the attributes of `triple`. We chose a more concise representation, which is convenient for encoding SPARQL triple patterns.

We illustrate the other input of the SPARQL to SQL transformation (via IQ) using the following mapping in a simplified syntax:

\[
\begin{align*}
T_1(x, y) & \rightarrow :b(x) \ :p \ y, \\
T_2(x, y) & \rightarrow :b(x) \ :p \ y, \\
T_3(x, y) & \rightarrow :b(x) \ :p \ y, \\
T_4(x, y) & \rightarrow :b(x) \ :q \ y,
\end{align*}
\]

where the triples on the right-hand side of `\rightarrow` represent subject maps together with predicate/object maps for properties :p and :q. In database tables `T_1`, `T_2`, `T_3`, and `T_4`, the first attribute is the primary key of type `TEXT`, and the second attribute is non-nullable and of type `INTEGER`, `DECIMAL`, `TEXT`, and `INTEGER`, respectively. When we translate the mapping into IQ, the SQL queries are turned into atomic expressions `T_1(x, y), T_2(x, y),`
mapping assertions is then as follows: INTEGER to be cast into T INTEGER literals: the :b{} function lexical value and the term type as its arguments. In the example above, all triple subjects -jective because the separator of the three components, INTEGER database xsd:date contains more than one placeholder, then the template function may be non-injective. \[9\] to ensure injectivity of the function. For literals, however, if a template separators safe depends on the shape of the template. For IRI templates, one would normally use safe \[9\] plates function is injective \[9\] plates operation of relational algebra. The translation of the right-hand side is more elaborate. 6 Xiao et al. It involves an arithmetic sum over two variables, one of which, \(n\), is multi-typed: it can be an xsd:integer, xsd:decimal, or xsd:string. The translation of the SPARQL query into IQ requires the use of most of the algebra operations, which are defined next. A term is a variable, a constant (including NULL), or a functional term constructed from variables and constants using SPARQL function symbols such as numeric-add, SQL function symbols such as +, and our auxiliary function symbols such as IF, etc. (IF is ternary and such that \(\text{IF}(\text{true}, x, y) = x\) and \(\text{IF}(\text{false}, x, y) = y\). We treat predicates such as = and sameTerm as function symbols of boolean type; boolean connectives ¬, ∧, and ∨ are also boolean function symbols. Boolean terms are interpreted using the 3-valued logic, where NULL is used for the 'unknown value.' An aggregate term is an expression of the form \(\text{agg}(\tau)\), where \(\text{agg}\) is a SPARQL or SQL aggregate function symbol (e.g., \text{SPARQL}_\text{Sum} or \text{SUM}) and \(\tau\) a term. A substitution is an expression of the form \(x_1/\eta_1, \ldots, x_n/\eta_n\), where each \(x_i\) is a variable and each \(\eta_i\) either a term (for \text{PROJ}) or an aggregate term (for \text{AGG}). Then, IQs are defined by the following grammar:

\[
\phi : = \text{P}(t) \mid \text{PROJ}_\tau^x \phi \mid \text{AGG}_\tau^x \phi \mid \text{DISTINCT} \phi \mid \text{ORDERBY}_x \phi \mid \text{SLICE}_{i,j} \phi \mid ...
\]
FILTER_β ϕ | JOIN_β(ϕ₁, ..., ϕₖ) | LEFTJOIN_β(ϕ₁, ϕ₂) | UNION(ϕ₁, ..., ϕₖ),

where $P$ is a relation name (triple, quad, or a database table name), $t$ a tuple of terms, $x$ a tuple of variables, $r$ a substitution, $i, j \in \mathbb{N} \cup \{0, +\infty\}$ are values for the offset and limit, respectively, and $β$ is a boolean term. When presenting our examples, we often omit brackets and use indentation instead. The algebraic operators above operate on bags of tuples, which can be thought of as total functions from sets of variables to values, in contrast to partial functions in SPARQL (such definitions are natural from the SPARQL-to-SQL translation point of view; see [25] for a discussion). Also, JOIN and LEFTJOIN are similar to NATURAL (LEFT) JOIN in SQL, in the sense that the tuples are joined (compatible) if their shared variables have the same values. All the algebraic operators are interpreted using the bag semantics, in particular, UNION preserves duplicates (similarly to UNION ALL in SQL).

In our running example, the SPARQL query is translated into the following IQ:

\[
\text{PROJ}^{?s/\text{numeric-add}(?n, ?m)} \text{JOIN}^{\neg\text{isNull}(\text{numeric-add}(?n, ?m))} (\text{triple}(?x, ?p, ?n), \text{triple}(?x, ?q, ?m)),
\]

where the bound filter is replaced by $\neg\text{isNull}(\cdot)$ in the JOIN operation, and the $\text{BIND}$ clause is reflected in the top-level PROJ. When this IQ is unfolded using the mapping given above, occurrences of triple are replaced by unions of appropriate mapping assertions (with matching predicates, for example). Note that, in general, since the RDF dataset is a set of triples and quadruples, one needs to insert DISTINCT above the union of mapping assertion SQL queries; in this case, however, the DISTINCT can be omitted because the first attribute is a primary key in the tables and the values of $?n$ are disjoint in the three branches (in terms of sameTerm). So, we obtain the following:

\[
\text{PROJ}^{?s/\text{numeric-add}(?n, ?m)} \text{JOIN}^{\neg\text{isNull}(\text{numeric-add}(?n, ?m))} \text{UNION}
\]

\[
\text{PROJ}^{?x, ?n} \text{WHERE} (\text{d2t}(?x, \text{iri}(y_1), \text{iri}(\text{iri}(?y_1)) x, \text{iri}(\text{iri}(?y_1)) \text{iri}(\text{iri}(?y_1)) \text{iri}(\text{iri}(?y_1)), \text{xsd:integer})) T_1(y_1, z_1) \\
\text{PROJ}^{?x, ?n} \text{WHERE} (\text{d2t}(?x, \text{iri}(y_2), \text{iri}(\text{iri}(?y_2)) x, \text{iri}(\text{iri}(?y_2)) \text{iri}(\text{iri}(?y_2)) \text{iri}(\text{iri}(?y_2)), \text{xsd:decimal})) T_2(y_2, z_2) \\
\text{PROJ}^{?x, ?n} \text{WHERE} (\text{d2t}(?x, \text{iri}(y_3), \text{iri}(\text{iri}(?y_3)) x, \text{iri}(\text{iri}(?y_3)) \text{iri}(\text{iri}(?y_3)) \text{iri}(\text{iri}(?y_3)), \text{xsd:string})) T_3(y_3, z_3) \\
\text{PROJ}^{?x, ?m} \text{WHERE} (\text{d2t}(?x, \text{iri}(y_4), \text{iri}(\text{iri}(?y_4)) x, \text{iri}(\text{iri}(?y_4)) \text{iri}(\text{iri}(?y_4)) \text{iri}(\text{iri}(?y_4)), \text{xsd:integer})) T_4(y_4, z_4).
\]

This query, however, cannot be directly translated into SQL because, for example, it has occurrences of SPARQL functions (numeric-add).

### 3.2 Translating (Multi-Typed) SPARQL Functions into SQL Functions

Recall the two main difficulties in translating SPARQL functions into SQL. First, when a SPARQL function is not applicable to its argument (e.g., numeric-add to xsd:string), then the result is the type error, which, in our example, means that the variable remains unbound in the solution mapping; in SQL, such a query would be deemed invalid (and one would have no results). Second, the type of the result may depend on the types of the arguments: numeric-add yields an xsd:integer on xsd:integer and an xsd:decimal on xsd:decimal. Using the example above, we illustrate how an IQ with a multi-typed SPARQL operation can be transformed into an IQ with standard SQL operations.
First, the substitutions of PROJ operators are lifted as high in the expression tree as possible. In the process, functional terms may need to be decomposed so that some of their arguments can be lifted, even though other arguments are blocked. For example, the substitution entries for \( ?\) need to be decomposed: e.g., \( ?/\text{rdf}(i2t(z_1)), \text{xsd:integer} \) is decomposed into \( ?/\text{rdf}(v,t), v/\text{t2i}(z_1), \) and \( t/\text{xsd:integer} \). Variables \( v \) and \( t \) are re-used in the other branches, and, after the decomposition, all children of the UNION share the same entry \( ?/\text{rdf}(v,t) \) in their PROJ constructs, and so, this entry can be lifted up to the top. Note, however, that the entries for \( v \) and \( t \) remain blocked by the UNION. Observe that one child of the UNION can be pruned when propagating the JOIN conditions down: the condition is unsatisfiable as applying numeric-add to \( \text{xsd:string} \) results in the SPARQL type error, which is equivalent to false when used as a filter. Thus, we obtain

\[
\text{PROJ}_{v,t}^{2s} \text{numeric-add}(\text{rdf}(v,t), \text{rdf}(i2t(z_4)), \text{xsd:integer})
\]

\[
\text{JOIN} \quad \text{isNull}(\text{numeric-add}(\text{rdf}(v,t), \text{rdf}(i2t(z_4)), \text{xsd:integer}))
\]

\[
\text{UNION} \quad \text{PROJ}_{v,t}^{2s,p} \text{numeric-add}(\text{rdf}(v,t), \text{rdf}(i2t(z_4)), \text{xsd:integer})
\]

\[
T_4(y, z_4),
\]

However, the type of the first argument of numeric-add is still unknown at this point, which prevents transforming it into a SQL function. So, first, the substitution entries for \( t \) are replaced by \( t/f(1) \) and \( t/f(2) \), respectively, where \( f \) is a freshly generated dictionary function that maps 1 and 2 to \( \text{xsd:integer} \) and \( \text{xsd:decimal} \), respectively. Then, \( f \) can be lifted to the JOIN and PROJ by introducing a fresh variable \( p \):

\[
\text{PROJ}_{v,f(p)}^{2s} \text{numeric-add}(\text{rdf}(v,f(p)), \text{rdf}(i2t(z_4)), \text{xsd:integer})
\]

\[
\text{JOIN} \quad \text{isNull}(\text{numeric-add}(\text{rdf}(v,f(p)), \text{rdf}(i2t(z_4)), \text{xsd:integer}))
\]

\[
\text{UNION} \quad \text{PROJ}_{v,f(p)}^{2s,t} \text{numeric-add}(\text{rdf}(v,f(p)), \text{rdf}(i2t(z_4)), \text{xsd:integer})
\]

\[
T_4(y, z_4),
\]

where the changes are emphasized in boldface.

Now, the type of the first argument of numeric-add is either \( \text{xsd:integer} \) or \( \text{xsd:decimal} \), and so, it can be transformed into a complex functional term with SQL: the sum is on INTEGERS if \( p \) is 1, and on DOUBLES otherwise. Observe that these sums are cast back to TEXT to produce RDF term lexical values. Now, the JOIN condition is equivalent to true because the numeric-add does not produce \( \text{NULL} \) without invalid input types and nullable variables. A similar argument applies to PROJ, and we get

\[
\text{PROJ}_{v,f(p),d2t}(\text{IF}(p=1, i2t(i2d(v)+z_4), d2t(i2d(v)+i2d(z_4))), \text{IF}(p=1, \text{xsd:integer}, \text{xsd:decimal}))
\]

\[
\text{JOIN} \quad \text{UNION} \quad \text{PROJ}_{v,f(p),d2t}(\text{IF}(p=1, i2t(i2d(v)+z_4), d2t(i2d(v)+i2d(z_4))), \text{IF}(p=1, \text{xsd:integer}, \text{xsd:decimal}))
\]

\[
T_4(y, z_4),
\]

which can now be translated into SQL. We would like to emphasize that only the SPARQL variables can be multi-typed in IQs, while the variables for database attributes will always have a unique type, which is determined by the datatype of the attribute.

As a second example, we consider the following aggregation query:

\[
\text{SELECT } ?x \ (\text{SUM}(?n) \ AS \ ?s) \ \text{WHERE} \ \{ ?x :p ?n . \} \ \text{GROUP BY } ?x
\]
This query uses the same mapping as above, where the values of data property :p can belong to xsd:integer, xsd:decimal, and xsd:string from INTEGER, DECIMAL, and TEXT database attributes. The three possible ranges for :p require careful handling because of GROUP BY and SUM: in each group of tuples with the same x, we need to compute (separate) sums of all INTEGERS and DECIMALS, as well as indicators of whether there are any TEXTs and DECIMALs: the former is needed because any string in a group results in a type error and undefined sum; the latter determines the type of the sum if all values in the group are numerical. The following IQ is the final result of the transformations:

\[
\text{PROJ}_{x,y,z} \left( \text{union}\{ \text{PROJ}_{y,i,d}^{0,d,t} T_1(y,i), \quad \text{PROJ}_{y,d}^{i,d,t} T_2(y,d), \quad \text{PROJ}_{y,i}^{i,d,t} T_3(y,i) \} \right).
\]

Note that the branches of UNION have the same projected variables, padded by NULL.

### 3.3 Optimization Techniques

Being able to transform SPARQL queries into SQL ones is a must-have requirement, but making sure that they can be efficiently processed by the underlying DBMS is essential for the VKG approach. This topic has been extensively studied during the past decade, and an array of optimization techniques, such as redundant join elimination and pushing down JoTs to the data-level [13], are now well-known and implemented by many systems. In addition to these, Ontop v4 exploits several recent techniques, including the ones proposed in [25] for optimizing left joins due to OPTIONALs and MINUSES in the SPARQL queries.

**Self-join Elimination for Denormalized Data.** We have implemented a novel self-join elimination technique to cover a common case where data is partially denormalized. We illustrate it on the following example with a single database table loan with primary key id and all non-nullable attributes. For instance, loan can contain the following tuples:

<table>
<thead>
<tr>
<th>id</th>
<th>amount</th>
<th>organisation</th>
<th>branch</th>
</tr>
</thead>
<tbody>
<tr>
<td>10284124</td>
<td>5000</td>
<td>Global Bank</td>
<td>Denver</td>
</tr>
<tr>
<td>20242432</td>
<td>7000</td>
<td>Trade Bank</td>
<td>Chicago</td>
</tr>
<tr>
<td>30443843</td>
<td>100000</td>
<td>Global Bank</td>
<td>Miami</td>
</tr>
<tr>
<td>40587874</td>
<td>40000</td>
<td>Global Bank</td>
<td>Denver</td>
</tr>
</tbody>
</table>

The mapping for data property :hasAmount and object properties :hasAmount, :grantedBy and :branchOf constructs, for each tuple in loan, three triples to specify the loan amount, the bank branch that granted it, and the head organisation for the bank branch:

\[
\text{loan}(x,a,\ldots) \leadsto \text{triple}(\text{rdf}(:l1t)(x), \text{IRI}, :\text{hasAmount}, \text{rdf}(\text{i2t}(a), \text{xsd:integer})), \\
\text{loan}(x,\ldots, \text{o}, \text{b}) \leadsto \text{triple}(\text{rdf}(:l1t)(x), \text{IRI}, :\text{grantedBy}, \text{rdf}(:b1t(/t)(\text{o}, \text{b}), \text{IRI})), \\
\text{loan}(\ldots, \text{o}, \text{b}) \leadsto \text{triple}(\text{rdf}(:,b)(\text{o}, \text{b}), \text{IRI}, :\text{branchOf}, \text{rdf}(\text{:o}(\text{o}), \text{IRI}))
\]

(we use underscores instead of variables for attributes that are not projected). Observe that the last assertion is not ‘normalized’: the same triple can be extracted from many
different tuples (in fact, it yields a copy of the triple for each loan granted by the branch). To guarantee that the RDF graph is a set, these duplicates have to be eliminated.

We now consider the following SPARQL query extracting the number and amount of loans granted by each organisation:

```
SELECT ?o (COUNT(?l) AS ?c) (SUM(?a) AS ?s) WHERE {
```

After unfolding, we obtain the following IQ:

```
AGG{?c/SPARQL_Count(l), ?s/SPARQL_Sum(a)} JOIN
  PROJ{?a/\{rdf:st(a),xsd:integer\} loan(x1,o1,_,_)}
  PROJ{?b/\{rdf:st(b),/xsd:integer\} loan(x2,_,o2,b2)}
  DISTINCT PROJ{?o/\{rdf:st(o),\} loan(_,_,o3,b3)}.
```

Note that the DISTINCT in the third child of the JOIN is required to eliminate duplicates (none is needed for the other two since id is the primary key of table loan).

The first step is lifting the PROJ. For the substitution entries below the DISTINCT, some checks need to be done before (partially) lifting their functional terms. The rdf function used by ?o and ?b is injective by design and can always be lifted. Their first arguments are IRI template functional terms. Both IRI templates, :o(1) and :b(1), are injective (see Remark 1): the former is unary, the latter has a safe separator between its arguments. Consequently, both can be lifted. Note that these checks only concern functional terms, as constants can always be lifted above DISTINCTs. The substitution entry for ?l is lifted above the AGG because it is its group-by variable. Other entries are used for substituting the arguments of the aggregation functions. Here, none of the variables is multi-typed. After simplifying the functional terms, we obtain the IQ

```
AGG{?n/\{count(x1), m/\{sum(a)\}\} JOIN
  PROJ{?a/\{rdf:st(a),\} loan(x1,o1,_,_), loan(x1,_,o2,b2), loan(_,o2,b2), DISTINCT loan(_,_,o3,b3)}.}
```

Next, the well-known self-join elimination is applied to the first two children of the JOIN (which is over the primary key). Then, the DISTINCT commutes with the JOIN since the other child of JOIN is also a set (due to the primary key), obtaining the sub-IQ

```
DISTINCT JOIN(loan(x1,1,2), loan(_,o2,b2)),
```

on which our new self-join elimination technique can be used, as the two necessary conditions are satisfied. First, the JOIN does not need to preserve cardinality due to the DISTINCT above it. Second, all the variables projected by the second child (o2 and b2) of the JOIN are also projected by the first child. So, we can eliminate the second child, but have to insert a filter requiring the shared variables o2 and b2 to be non-NULL:

```
DISTINCT FILTER¬isNull(o2)∧¬isNull(b2)  loan(x1,1,2).
```

The result can be further optimized by observing that the attributes for o2 and b2 are non-nullable and that the DISTINCT has no effect because the remaining data atom
produces no duplicates. So, we arrive at

\[ \text{PROJ}_{o, c, s} \text{, AGG}_{x_1, \text{COUNT}(x_1), \text{SUM}(a_1) \text{, loan}(x_1, a_1, o_2, _2)} \]

where \( b_2 \) is replaced by \( _2 \) because it is not used elsewhere.

### 3.4 From IQ to SQL

In the VKG approach almost all query processing is delegated to the DBMS. Ontop v4 performs only the top-most projection, which typically transforms database values into RDF terms, as illustrated by the last query above. The subquery under this projection must not contain any RDF value nor any SPARQL function. As highlighted above, our IQ guarantees that such a subquery is not multi-typed.

In contrast to SPARQL, the ANSI/ISO SQL standards are very loosely followed by DBMS vendors. There is very little hope for generating reasonably rich SQL that would be interoperable across multiple vendors. Given the diversity of the SQL ecosystem, in Ontop v4 we model each supported SQL dialect in a fine-grained manner: in particular, we model (i) their datatypes, (ii) their conventions in terms of attribute and table identifiers and query modifiers, (iii) the semantics of their functions, (iv) their restrictions on clauses such as WHERE and ORDER BY, and (v) the structure of their data catalog. Ontop v4 directly uses the concrete datatypes and functions of the targeted dialect in IQ by means of Java factories whose dialect-specific implementations are provided through a dependency injection mechanism. Last but not least, Ontop v4 allows IQ to contain arbitrary, including user-defined, SQL functions from the queries of the mapping.

### 4 Evaluation

Compliance of Ontop v4 with relevant W3C recommendations is discussed in Section 4.1 and performance and comparison with other systems in Section 4.2.

#### 4.1 Compliance with W3C Recommendations

Since the relevant W3C standards have very rich sets of features, and they also interplay with each other, it is difficult to enumerate all the cases. The different behaviors of DBMSs make the situation even more complex and add another dimension to consider. Nevertheless, we describe our testing infrastructure and do our best to summarize the behavior of Ontop with all the different standards.

**Testing Infrastructure.** To ensure the correct behavior of the system, we developed a rich testing infrastructure. The code base includes a large number of unit test cases. To test against different database systems, we developed a Docker-based infrastructure for creating DB-specific instances for the tests. It uses docker-compose to generate a cluster of DBs including MySQL, PostgreSQL, Oracle, MS SQL Server, and DB2.

**SPARQL 1.1.** In Table 1 we present a summary of Ontop v4 compliance with SPARQL 1.1, where rows correspond to sections of the WC3 recommendation. Most of the features are supported, but some are unsupported or only partially supported.
### Table 1: SPARQL Compliance: unsupported features are crossed out.

<table>
<thead>
<tr>
<th>Section in SPARQL 1.1 [12]</th>
<th>Features</th>
<th>Coverage</th>
</tr>
</thead>
<tbody>
<tr>
<td>5–7. Graph Patterns, etc.</td>
<td>BGP, FILTER, OPTIONAL, UNION</td>
<td>4/4</td>
</tr>
<tr>
<td>8. Negation</td>
<td>MINUS, FILTER ([\text{NOT}]) EXISTS</td>
<td>1/2</td>
</tr>
<tr>
<td>9. Property Paths</td>
<td>PredicatePath, InversePath, ZeroOrMorePath, …</td>
<td>0</td>
</tr>
<tr>
<td>10. Assignment</td>
<td>BIND, VALUES</td>
<td>2/2</td>
</tr>
<tr>
<td>11. Aggregates</td>
<td>COUNT, SUM, MIN, MAX, GROUP_CONCAT, SAMPLE</td>
<td>6/6</td>
</tr>
<tr>
<td>12. Subqueries</td>
<td>Subqueries</td>
<td>1/1</td>
</tr>
<tr>
<td>13. RDF Dataset</td>
<td>GRAPH, FROM ([\text{NAMED}])</td>
<td>1/2</td>
</tr>
<tr>
<td>14. Basic Federated Query</td>
<td>SERVICE</td>
<td>0</td>
</tr>
<tr>
<td>15. Solution Seqs. &amp; Mods.</td>
<td>ORDER BY, SELECT, DISTINCT, REDUCED, OFFSET, LIMIT</td>
<td>6/6</td>
</tr>
<tr>
<td>16. Query Forms</td>
<td>SELECT, CONSTRUCT, ASK, DESCRIBE</td>
<td>4/4</td>
</tr>
<tr>
<td>17.4.1. Functional Forms</td>
<td>BOUND, IF, COALESCE, EXISTS, NOT EXISTS, ([\text{NOT}]=, \text{sameTerm}, \text{IN}, \text{NOT}\text{IN} ]</td>
<td>6/11</td>
</tr>
<tr>
<td>17.4.2. Fns. on RDF Terms</td>
<td>isIRI, isBlank, isLiteral, isNumeric, str, lang, datatype, iri, enqode, str, strlang, UUID, struuid</td>
<td>9/13</td>
</tr>
<tr>
<td>17.4.3. Fns. on Strings</td>
<td>STRLEN, SUBSTR, UCASE, LCASE, STRSTARTS, STRENDS, CONTAINS, STRBEFORE, STRAFTER, ENCODE_FOR_URI, CONCAT, LangMatches, REGEX, REPLACE</td>
<td>14/14</td>
</tr>
<tr>
<td>17.4.4. Fns. on Numerics</td>
<td>abs, round, ceil, floor, RAND</td>
<td>5/5</td>
</tr>
<tr>
<td>17.4.5. Fns. on Dates&amp;Times</td>
<td>now, year, month, day, hours, minutes, seconds, timezone, tz</td>
<td>8/9</td>
</tr>
<tr>
<td>17.4.6. Hash Functions</td>
<td>MD5, SHA1, SHA256, SHA384, SHA512</td>
<td>5/5</td>
</tr>
<tr>
<td>17.5. XPath Constructor Fns.</td>
<td>(\text{casting} )</td>
<td>0</td>
</tr>
<tr>
<td>17.6. Extensible Value Testing</td>
<td>user defined functions</td>
<td>0</td>
</tr>
</tbody>
</table>

- Property paths are not supported: the ZeroOrMorePath (*) and OneOrMorePath (+) operators require linear recursion, which is not part of IQ yet. An initial investigation of using SQL Common Table Expressions (CTEs) for linear recursion was done in the context of SWRL [26], but a proper implementation would require dedicated optimization techniques.
- \([\text{NOT}]\) EXISTS is difficult to handle due to its non-compositional semantics, which is not defined in a bottom-up fashion. Including it in IQ requires further investigation.
- Most of the missing SPARQL functions (Section 17.4) are not so challenging to implement but require a considerable engineering effort to carefully define their translations into SQL. We will continue the process of implementing them gradually and track the progress in a dedicated issue [2].
- The 5 hash functions and functions REPLACE and REGEX for regular expressions have limited support because they heavily depend on the DBMS: not all DBMSs provide

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all hash functions, and many DBMSs have their own regex dialects. Currently, the
SPARQL regular expressions of REPLACE and REGEX are simply sent to the DBMS.
– In the implementation of functions STRDT, STRLANG, and LANGMATCHES, the second
argument has to be a constant: allowing variables will have a negative impact on
the performance in our framework.

R2RML [9]. Ontop is fully compliant with R2RML. In particular, the support of
rr:GraphMap for RDF datasets and blank nodes has been introduced in Ontop v4. The
optimization hint rr:inverseExpression is ignored in the current version, but this is
compliant with the W3C recommendation. In the combination of R2RML with OWL,
however, ontology axioms (a TBox in the Description Logic parlance) could also be
constructed in a mapping; e.g., $T_1(x, y) \rightarrow \{x\} rdfs:subClassOf \{y\}$. Such mappings
are not supported in online query answering, but one can materialize the triples
offline and then include them in the ontology manually.

OWL 2 QL [14] and SPARQL 1.1 Entailment Regimes [11]. These two W3C
recommendations define how to use ontological reasoning in SPARQL. Ontop
supports them with the exception of querying the TBox, as in SELECT * WHERE
{ ?c rdfs:subClassOf :Person. ?x a ?c }. Although we have investigated this theo-
retically and implemented a prototype [13], a more serious implementation is needed
for IQ, with special attention to achieving good performance. This is on our agenda.

SPARQL 1.1 Protocol [10] and SPARQL Endpoint. We reimplemented the new
SPARQL endpoint from scratch and designed a new command-line interface for it. It
is stateless and suitable for containers. In particular, we have created a Docker image
for the Ontop SPARQL endpoint which has greatly simplified deployment. The end-
point is also packed with several new features, like customization of the front page with
predefined SPARQL queries, streaming query answers, and result caching.

4.2 Performance and Comparison with Other VKG Systems

Performance evaluation of Ontop has been conducted since Ontop v1 by ourselves and
others in a number of scientific papers. Here we only summarize two recent independent
evaluations of Ontop v3. Recall that the main focus of Ontop v4 compared to v3 has
been the extension with new features. Hence, we expect similar results for Ontop v4.

Chaloupka and Necasky [7] evaluated four VKG systems, namely, Morph, Ontop,
SparqlMap, and their own EVI, using the Berlin SPARQL Benchmark (BSBM). D2RQ
and Ultrawrap were not evaluated: D2RQ has not been updated for years, and Ultrawrap
is not available for research evaluation. Only Ontop and EVI were able to load the
authors’ version of the R2RML mapping for BSBM. EVI supports only SQL Server,
while Ontop supports multiple DBMSs. In the evaluation, EVI outperformed Ontop on
small datasets, but both demonstrated similar performance on larger datasets, which
can be explained by the fact that Ontop performs more sophisticated (and expensive)
optimizations during the query transformation step.

Namici and De Giacomo [15] evaluated Ontop and Mastro on the NPD and ACI
benchmarks, both of which have complex ontologies. Some SPARQL queries had to

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3 https://hub.docker.com/r/ontop/ontop-endpoint
be adapted for Mastro because it essentially supports only unions of CQs. In general, Ontop was faster on NPD, while Mastro was faster on ACI.

Both independent evaluations confirm that although Ontop is not always the fastest, its performance is very robust. In the future, we will carry out more evaluations, in particular for the new features of Ontop v4.

It is important to stress that when choosing a VKG system, among many different criteria, performance is only one dimension to consider. Indeed, in [7], also the aspects of usability, completeness, and soundness have been evaluated. When considering all of these, Ontop is a clear winner. In our recent survey [24], we have also listed the main features of popular VKG systems, including D2RQ, Mastro, Morph, Ontop, Oracle Spatial and Graph, and Stardog. Overall, it is fair to claim that Ontop is the most mature open source VKG system currently available.

5 Community Building and Adoption

Ontop is distributed under the Apache 2 license through several channels. Ready-to-use binary releases, including a command line tool and a Protégé bundle with an Ontop plugin, are published on Sourceforge since 2015. There have been 30K+ downloads in the past 5 years according to Sourceforge. The Ontop plugin for Protégé is available also in the plugin repository of Protégé, through which users receive auto-updates. A Docker image of the SPARQL endpoint is available at Docker Hub since the Ontop v3 release, and it has been pulled 1.1K times. The documentation, including tutorials, is available at the official website.

Ontop is the product of a hard-working developer community active for over a decade. Nowadays, the development of Ontop is backed by different research projects (at the local, national, and EU level) at the Free University of Bozen-Bolzano and by Ontopic s.r.l. It also receives regular important contributions from Birkbeck, University of London. As of 13 August 2020, the GitHub repository consists of 11,511 git commits from 25 code contributors, among which 10 have contributed more than 100 commits each. An e-mail list created in August 2013 for discussion currently includes 270 members and 429 topics. In Github, 312 issues have been created and 270 closed.

To make Ontop sustainable, it needed to be backed up by a commercial company, because a development project running at a public university cannot provide commercial support to its users, and because not all developments are suitable for a university research group. So, Ontopic s.r.l. was born in April 2019, as the first spin-off of the Free University of Bozen-Bolzano. It provides commercial support for the Ontop system and consulting services that rely on it, with the aim to push the VKG technology to industry. Ontopic has now become the major source code contributor of Ontop.

Ontop has been adopted in many academic and industrial use cases. Due to its liberal Apache 2 license, it is essentially impossible to obtain a complete picture of all use cases.
and adoptions. Indeed, apart from the projects in which the research and development team is involved directly, we normally learn about a use case only when the users have some questions or issues with Ontop, or when their results have been published in a scientific paper. Nevertheless, a few significant use cases have been summarized in a recent survey paper [24]. Below, we highlight two commercial deployments of Ontop, in which Ontopic has been involved.

**UNiCS** is an open data platform for research and innovation developed by SIRIS Academic in Spain. Using Ontop, the UNiCS platform integrates a large variety of data sources for decision and policy makers, including data produced by government bodies, data on the higher education & research sector, as well as companies’ proprietary data. For instance, the Toscana Open Research (TOR) portal[^1] is one such deployment of UNiCS. It is designed to communicate and enhance the Tuscan regional system of research, innovation, and higher education and to promote increasingly transparent and inclusive governance. Recently, Ontopic has also been offering dedicated training courses for TOR users, so that they can autonomously formulate SPARQL queries to perform analytics, and even create VKGs to integrate additional data sources.

**Open Data Hub-Virtual Knowledge Graph** is a joint project between NOI Techpark and Ontopic for publishing South Tyrolean tourism data as a Knowledge Graph. Before the project started, the data was accessible through a JSON-based Web API, backed by a PostgreSQL database. We created a VKG over the database and a SPARQL endpoint[^2] that is much more flexible and powerful than the old Web API. Also, we created a Web Component[^3] which can be embedded into any web page like a standard HTML tag, to visualize SPARQL query results in different ways.

6 Conclusion

Ontop is a popular open-source virtual knowledge graph system. It is the result of an active research and development community and has been adopted in many academic and industrial projects. In this paper, we have presented the challenges, design choices, and new features of the latest release v4 of Ontop.

Acknowledgements. This research has been partially supported by the Wallenberg AI, Autonomous Systems and Software Program (WASP) funded by the Knut and Alice Wallenberg Foundation, by the Italian Basic Research (PRIN) project HOPE, by the EU H2020 project INODE, grant agreement 863410, by the CHIST-ERA project PACMEL, by the Free Uni. of Bozen-Bolzano through the projects QUADRO, KGID, and GeoVKG, and by the project IDEE (FESR1133) through the European Regional Development Fund (ERDF) Investment for Growth and Jobs Programme 2014-2020.

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[^2]: [http://www.toscanaopenresearch.it/](http://www.toscanaopenresearch.it/)
[^3]: [https://sparql.opendatahub.bz.it/](https://sparql.opendatahub.bz.it/)
[^4]: [https://github.com/noi-techpark/webcomp-kq](https://github.com/noi-techpark/webcomp-kq)


