

Data Scaling in OBDA Benchmarks. The VIG Approach.

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Abstract. In this paper we describe VIG, a data scaler for benchmarks in the context of ontology-based data access (OBDA). Data scaling is a relatively recent approach, proposed in the database community, that allows for quickly scaling up an input data instance to s times its size, while preserving certain application-specific characteristics. The advantage of the approach is that the user is not required to manually input the characteristics of the data to be produced, making it particularly suitable for OBDA benchmarks, where the complexity of database schemas might pose a challenge for manual input (e.g., the NPD benchmark contains 70 tables with some containing more than 60 columns). As opposed to a traditional data scaler, VIG includes domain information provided by the OBDA mappings and the ontology in order to produce data. VIG is currently used in the NPD benchmark, but it is not NPD-specific and can be seeded with any data instance. The distinguishing features of VIG are (1) its simple and clear generation strategy; (2) its efficiency, as each value is generated in constant time, without accesses to the disk or to RAM to retrieve previously generated values; (3) and its generality, as the data is exported in CSV files that can be easily imported by any RDBMS system.

VIG is a java implementation licensed under Apache 2.0, and its source code is available on GitHub (<https://github.com/ontop/vig>) in the form of a Maven project. The code is being maintained since two years by the -ontop- team at the Free University of Bozen-Bolzano.

1 Introduction

An important research problem in Big Data is how to provide end-users with transparent access to the data, abstracting from storage details. The paradigm of Ontology-based Data Access (OBDA) [3] provides an answer to this problem that is very close to the spirit of the Semantic Web. In OBDA the data stored in a relational database is presented to the end-users as a *virtual RDF* graph over which SPARQL queries can be posed. This solution is realized through *mappings* that link classes and properties in the ontology to queries over the database.

Proper benchmarking of query answering systems, such as OBDA systems, requires scalability analyses taking into account data instances of increasing volume. Such instances are often provided by generators of synthetic data. However, such generators are either complex ad-hoc implementations working for a specific schema, or require considerable manual input by the end-user. The latter problem is exacerbated in the OBDA setting, where database schemas tend to be particularly big and complex (e.g., 70 tables, some with more of 80 columns in [9]). The result of having only few benchmarks

is that they become increasingly misused over time. For instance, evaluations on OBDA systems are usually performed on benchmarks originally designed to test triple stores, although the two systems are totally different and present different bottlenecks [9].

Data scaling [15] is a recent approach that tries to overcome this problem by automatically tuning the generation parameters through statistics collected over an initial data instance. Hence, the same generator can be reused in different contexts, as long as an initial data instance is available. A measure of quality for the produced data is defined in terms of results for the available queries, that should be *similar* to the one observed for real data of comparable volume. In the context of OBDA, taking as the only parameter for generation an initial data instance does not produce data of acceptable quality, since it has to comply with constraints deriving from the structure of the mappings and the ontology, that in turn derive from the application domain.

In this work we present VIG, a data scaler for OBDA benchmarks. In the VIG system, we lift the scaling approach from the instance level to the OBDA level, where the domain information of ontologies and mappings has to be taken into account as well. VIG is extremely efficient and suitable to generate huge amounts of data, as tuples are generated in constant time without disk accesses or need to retrieve previously generated values. Furthermore, different instances of VIG can be delegated to different machines, and parallelization can scale up to the number of columns in the schema, without communication overhead.

VIG is a Java implementation licensed under Apache 2.0, and its source code is available on GitHub in the form of a Maven project [10]. The code is maintained by the Ontop team at the Free University of Bozen-Bolzano, and it comes with extensive documentation in the form of Wiki pages.

The rest of the paper is structured as follows. In Section 2, we introduce the basic notions and notation to understand this paper. In Section 3, we define the scaling problem and discuss important measures on the produced data that define the quality of instances in a given OBDA setting. In Section 4, we discuss the VIG algorithm, and how it ensures that data conforming to the identified measures is produced. Sections 5 and 6 contain related work and conclusions, respectively.

2 Basic Notions and Notation

We assume that the reader has moderate knowledge of OBDA, and refer for it to the abundant literature on the subject, like [2]. Moreover, we assume familiarity with basic notions from probability calculus and statistics.

The W3C standard ontology language in OBDA is OWL 2 QL [11]. For the sake of conciseness, we consider here its mathematical underpinning $DL-Lite_{\mathcal{R}}$ [4]. Table 1 shows a portion of the ontology from the NPD benchmark, which is the foundation block of our running example.

The W3C standard query language in OBDA is SPARQL [7], with queries evaluated under the OWL 2 QL entailment regime [8]. Intuitively, under this semantics each basic graph pattern (BGP) can be seen as a single conjunctive query (CQ) *without existentially quantified variables*. As in our examples we will only refer to SPARQL queries containing exactly one BGP, we will use the more concise syntax for CQs rather than

Table 1: Portion of the ontology for the NPD benchmark. The first three axioms (left to right) state that the classes “DevelopmentWellbore”, “ExplorationWellbore”, and “SuspendedWellbore” are subclasses of the class “Wellbore”. The fourth axiom states that the classes “ExplorationWellbore” and “DevelopmentWellbore” are disjoint.

DevelopmentWellbore \sqsubseteq Wellbore	ExplorationWellbore \sqsubseteq Wellbore
SuspendedWellbore \sqsubseteq Wellbore	ExplorationWellbore \sqcap DevelopmentWellbore $\sqsubseteq \perp$

Table 2: Queries for our running example.

$q_1(y)$	\leftarrow Wellbore(y), developmentWellboreForField(x, y)
$q_2(x, n, y)$	\leftarrow Wellbore(x), name(x, n), completionYear(x, y)

the SPARQL syntax. Table 2 contains the queries that we will consider in our running example.

The mapping component links predicates in the ontology to queries over the underlying relational database. To present our techniques, we need to introduce this component in a formal way. The standard W3C syntax for mappings is R2RML [5], however here we use a more concise syntax that is common in the OBDA literature. Formally, a *mapping assertion* m is an expression of the form $X(\mathbf{f}, \mathbf{x}) \leftarrow \text{conj}(\mathbf{y})$, consisting of a *target* part $X(\mathbf{f}, \mathbf{x})$, which is an atom over function symbols \mathbf{f} (also called *templates*) and variables $\mathbf{x} \subseteq \mathbf{y}$, and a *source* part $\text{conj}(\mathbf{y})$, which is a CQ whose output variables are \mathbf{y} . We say that m *defines the predicate* X if X is in the target of m . A *basic mapping* is a mapping whose source part contains exactly one atom. Table 3 contains the mappings for our running example, as well as a short description of how these mappings are used in order to create a (virtual) set of *assertions*.

For the rest of this paper we fix an *OBDA instance* $(\mathcal{O}, \mathcal{M}, \Sigma, \mathcal{D})$, where \mathcal{O} is an OWL 2 QL ontology, Σ is a database schema with foreign and primary key dependencies, \mathcal{M} is a set of mappings linking predicates in \mathcal{O} to queries over Σ , and \mathcal{D} is a database instance that satisfies the dependencies in Σ and the disjointness axioms in \mathcal{O} . We denote by $\text{col}(\Sigma)$ the set of all columns in Σ . Given a column $C \in \text{col}(\Sigma)$, we denote by $C^{\mathcal{D}}$ the set of values for C in \mathcal{D} . Finally, given a term $f(\mathbf{x})$, where $\mathbf{x} = (x_1, \dots, x_p, \dots, x_n)$, we denote the argument x_p at position p by $f(\mathbf{x})|_p$.

3 Data Scaling for OBDA Benchmarks: VIG Approach

The *data scaling problem* introduced in [15] is formulated as follows:

Definition 1 (Data Scaling Problem). *Given a dataset \mathcal{D} , produce a dataset \mathcal{D}' which is similar to \mathcal{D} but s times its size.*

The notion of *similarity* is application-based. Being our goal benchmarking, we define similarity in terms of query results for the queries at hand. In [15], the authors do not consider such queries to be available to the generator, since their goal is broader than benchmarking over a pre-defined set of queries. In OBDA benchmarking, instead, the (SQL) workload for the database can be estimated from the mapping component.

Table 3: Mappings from the NPD benchmark. Results from the evaluation of the queries on the source part build predicates in the ontology. For example, each triple (a, b, c) in a relation for `development_wellbores` corresponds to a predicate `ShallowWellbore(w(a))` in the ontology. In the R2RML mappings for the original NPD benchmark the term $w(id)$ corresponds to the URI template `npd:wellbore/{id}`. Columns named `id` are primary keys, and the column `fid` in `development_wellbores` is a foreign key for the primary key `fid` of the table `fields`.

<code>DevelopmentWellbore(w(id))</code>	<code>← development_wellbores(id,name,year,fid)</code>
<code>ExplorationWellbore(w(id))</code>	<code>← exploration_wellbores(id,name,year,state)</code>
<code>SuspendedWellbore(w(id))</code>	<code>← exploration_wellbores(id,name,year,state), state='suspended'</code>
<code>Field(f(fid))</code>	<code>← fields(fid,name)</code>
<code>completionYear(w(id),year)</code>	<code>← development_wellbores(id,name,year,fid)</code>
<code>name(w(id),name)</code>	<code>← development_wellbores(id,name,year,fid)</code>
<code>completionYear(w(id),year)</code>	<code>← exploration_wellbores(id,name,year)</code>
<code>name(w(id),name)</code>	<code>← exploration_wellbores(id,name,year)</code>
<code>developmentWellboreForField(w(id),f(fid))</code>	<code>← development_wellbores(id,name,year,fid), fields(fid,fname)</code>

Therefore, VIG includes the mappings in the analysis, so as to obtain a more realistic and OBDA-tuned generation.

Concerning the size, similarly to other approaches, VIG scales each table in \mathcal{D} by a factor of s .

3.1 Similarity Measures for OBDA and Their Rationale

We overview the similarity measures used by VIG, and why they are important in the scenario of OBDA benchmarking.

Schema Dependencies. \mathcal{D}' should be a valid instance for Σ . VIG is, to the best of our knowledge, the only data scaler able to generate in constant time tuples that satisfy multi-attribute primary keys for *weakly-identified entities*¹. The current implementation of VIG does not support multi-attribute foreign keys.

Column-based Duplicates and NULL Ratios. They respectively measure the ratio of duplicates and of nulls in a given column, and are common parameters for the cost estimation performed by query planners in databases. By default, VIG maintains them in \mathcal{D}' to preserve the cost of joining columns in a key-foreign key relationship (e.g., the join from the last mapping in our running example). This default behavior, however, is not applied with *fixed-domain* columns, which are columns whose content does not depend on the size of the database instance. The column `state` in the table `exploration_wellbore` is fixed-domain, because it partitions the elements of `id` into a fixed number of classes². VIG analyzes the mappings to detect fixed-domain columns, and additional fixed-domain columns can be manually specified by the user.

¹ In a relational database, a weak entity is an entity that cannot be uniquely identified by its attributes alone.

² The number of classes in the ontology does not depend on the size of the data instance.

To generate values for a fixed-domain column, VIG reuses the values found in \mathcal{D} so as to prevent empty answers for the SQL queries in the mappings. For instance, a value ‘suspended’ must be generated for the column `state` in order to produce objects for the class `SuspendedWellbore`.

VIG generates values in columns according to a *uniform distribution*, that is, values in columns have all the same probability of being repeated. Replication of the distributions from \mathcal{D} will be included the next releases of VIG.

Size of Columns Clusters, and Disjointness. Query q_1 from our running example returns an empty set of answers, regardless of the considered data instance. This is because the function w used to build objects for the class `Wellbore` does not match with the function f used to build objects for `Fields`. Indeed, fields and wellbores are two different entities for which a join operation would be meaningless.

On the other hand, a standard OBDA translation of q_2 into SQL produces a union of CQs containing several joins between the two tables `development_wellbores` and `exploration_wellbores`. This is possible only because the mappings for `Wellbore`, `name`, and `completionYear` all use the *same* unary function symbol w to define wellbores. Intuitively, every pair of terms over the same function symbol and appearing on the target of two distinct basic mappings identifies sets of columns for which the join operation is semantically meaningful³. Generating data that guarantees the correct cost for these joins is crucial in order to deliver a realistic evaluation. In our example, the join between `development_wellbore` and `exploration_wellbore` over `id` is empty under \mathcal{D} (because `ExplorationWellbore` and `DevelopmentWellbore` are disjoint classes). VIG is able to replicate this fact in \mathcal{D}' . This implies that VIG can generate data satisfying disjointness constraints declared over classes whose individuals are constructed from a unary template in a basic mapping, if \mathcal{D} satisfies those constraints.

4 The VIG Algorithm

We now show how VIG realizes the measures described in the previous section. The building block of VIG is a *pseudo-random number generator*, that is a sequence of integers $(s_i)_{i \in \mathbb{N}}$ defined through a transition function $s_k := f(s_{k-1})$. The authors in [6] discuss a particular class of pseudo-random generators based on *multiplicative groups modulo a prime number*. Let n be the number of distinct values to generate. Let g be a generator for the multiplicative group modulo a prime number p , with $p > n$. Consider the sequence $S := \langle g^i \bmod p \mid i = 1, \dots, p \text{ and } (g^i \bmod p) \leq n \rangle$. Then S is a *permutation* of values in the interval $[1, \dots, n]$. Here we show how this generator is used in VIG to quickly produce data complying with foreign and primary key constraints.

From now on, let s be a scale factor, and let $\text{dist}(C, \mathcal{D})$ denote the number of distinct non-null values in a column C in the database instance \mathcal{D} . Let $\text{size}(T, \mathcal{D})$ denote the number of tuples occurring in the table T in the database instance \mathcal{D} . For each column c , VIG creates a set of intervals $\text{ints}(c)$ and generates values accordingly.

Initialization Phase. For each table T , VIG sets the number $\text{size}(T, \mathcal{D}')$ of tuples to generate to $\text{size}(T, \mathcal{D}) * s$. Then, VIG calculates the number of non-null distinct values

³ Therefore, for which a join could occur during the evaluation of a user query.

that need to be generated for each column, given s and \mathcal{D} . That is, for each column C , if C is not fixed-domain then VIG sets $\text{dist}(C, \mathcal{D}') := \text{dist}(C, \mathcal{D}) * s$. Otherwise, $\text{dist}(C, \mathcal{D}')$ is set to $\text{dist}(C, \mathcal{D})$.

Creation of Intervals. When C is a numerical column, VIG initializes $\text{ints}(C)$ by the interval $I_C := [\min(C, \mathcal{D}), \min(C, \mathcal{D}) + \text{dist}(C, \mathcal{D}') - 1]$ of distinct values to be generated, where $\min(C, \mathcal{D})$ denotes the minimum value occurring in $C^{\mathcal{D}}$. Otherwise, if C is non-numerical, $\text{ints}(C)$ is initialized to the interval $I_C := [1, \text{dist}(C, \mathcal{D}')$. The elements in $\text{ints}(C)$ will be transformed into values of the desired datatype by a suitable injective function in the final generation step.

Primary Keys Satisfaction. Let $K = \{C_1, \dots, C_n\}$ be the primary key of a table T . In order to ensure that values generated for each column through the pseudo-random generator will not lead to duplicate tuples in K , the least common multiple $\text{lcm}(\text{dist}(C_1, \mathcal{D}'), \dots, \text{dist}(C_n, \mathcal{D}'))$ must be greater than $\text{tuples}(T, \mathcal{D}')$. If this is not true, then VIG ensures the condition by slightly increasing $\text{dist}(C_i, \mathcal{D}')$ for some column C_i in K . Once the condition holds, data can be generated independently for each column without risk of generating duplicate tuples for K .

Columns Cluster Analysis. In this phase, VIG analyzes \mathcal{M} in order to identify columns that could be joined in a translation to SQL, and groups them together in *pre-clusters*. Formally, let $X_1(\mathbf{f}_1, \mathbf{x}_1), \dots, X_m(\mathbf{f}_m, \mathbf{x}_m)$ be the atoms defined by basic mappings in \mathcal{M} . Let $\mathcal{F} = \bigcup_{i=1 \dots m} \{f(\mathbf{x}) \mid f(\mathbf{x}) \text{ is a term in } X_i(\mathbf{f}_i, \mathbf{x}_i)\}$ be the set of all the terms occurring in such atoms. A set of columns pc is a *pre-cluster* if there exists a function f and a valid position p in f such that $\text{pc} = \{f(\mathbf{x})|_p \mid f(\mathbf{x}) \in \mathcal{F}\}$.

VIG evaluates on \mathcal{D} all combinations of such joins between columns in a pre-cluster pc , and produces values in \mathcal{D}' so that the selectivities for these joins are maintained. In order to do so, the intervals for the columns in pc are modified. This modification must be propagated to all the columns related via a foreign key relationship to some column in pc . In particular, the modification might propagate up to columns belonging to different pre-clusters, inducing a clash. VIG groups together such pre-clusters in order to avoid this issue. Formally, let \mathcal{PC} denote the set of pre-clusters for \mathcal{M} . Two pre-clusters $\text{pc}_1, \text{pc}_2 \in \mathcal{PC}$ are in *merge relation*, denoted as $\text{pc}_1 \rightsquigarrow \text{pc}_2$, iff $\mathcal{C}(\text{pc}_1) \cap \mathcal{C}(\text{pc}_2) \neq \emptyset$, where $\mathcal{C}(\text{pc}) = \{D \in \text{col}(\Sigma) \mid \text{there is a } C \in \text{pc} : D \overset{*}{\leftrightarrow} C\}$, where $\overset{*}{\leftrightarrow}$ is the reflexive, symmetric, and transitive closure of the single column foreign key relation between pairs of columns⁴. Given a pre-cluster pc , the set of columns $\{c \in \text{pc}' \mid \text{pc}' \overset{*}{\rightsquigarrow} \text{pc}\}$ is called a *columns cluster*, where $\overset{*}{\rightsquigarrow}$ is the transitive closure of \rightsquigarrow . Columns clusters group together those pre-clusters for which columns cannot be generated independently.

After identifying columns clusters, VIG analyzes the number of shared elements between the columns in the cluster, and creates new intervals accordingly. Formally, consider the columns cluster cc . Let $H \subseteq \text{cc}$ be a set of columns, and the set $\mathcal{K}_H := \{C \mid C \in K, H \subset K \subseteq \text{cc}\}$ of columns in the super-sets of H . For each such H , VIG creates an interval I_H such that $|I_H| := |\bigcap_{C \in H} C^{\mathcal{D}} \setminus \bigcap_{C \in \mathcal{K}_H} C^{\mathcal{D}}| * s$, and adds I_H to $\text{ints}(C)$ for all $C \in H$. Boundaries for all intervals I_H are set in a way that they do not overlap.

⁴ Remember that VIG does not allow for multi-attribute foreign keys.

Foreign Keys Satisfaction. At this point, foreign key columns D for which there is no columns cluster pc such that $D \in \mathcal{C}(pc)$, have a single interval whose boundaries have to be aligned to the (single) interval of the parent. Foreign keys relating pairs of columns in a cluster, instead, are already satisfied by construction of the intervals in the columns cluster. More work, instead, is necessary for columns belonging to $\mathcal{C}(cc) \setminus cc$, for some columns cluster cc . VIG encodes the problem of finding intervals for these columns that satisfy the number of distinct values and the foreign key constraints into a *constraint program* (see Table 4), which is solved by an off-the-shelf constraint solver, e.g., Choco [12].

Table 4: CSP Program for the Choco Solver. In the following, S is the set of intervals for the columns in the columns cluster cc , plus one extra disjoint interval. Each interval I in a column C is encoded as a pair of variables $X_{\langle C,I \rangle}, Y_{\langle C,I \rangle}$, keeping respectively the lower and upper limit for the interval.

```

Create Program Variables:
 $\forall I \in S. \forall C \in \mathcal{C}(cc). X_{\langle C,I \rangle}, Y_{\langle C,I \rangle} \in [I.min, I.max]$ 
Set Boundaries for Known Intervals:
 $\forall I \in S. \forall C \in \mathcal{C}(cc). I \in \text{ints}(C) \Rightarrow X_{\langle C,I \rangle} = I.min, Y_{\langle C,I \rangle} = I.max$ 
Set Boundaries for Known Empty Intervals:
 $\forall I \in S. \forall C \in cc. I \notin \text{ints}(C) \Rightarrow X_{\langle C,I \rangle} = Y_{\langle C,I \rangle}$ 
The Y's should be greater than the X's:
 $\forall I \in S. \forall C \in \mathcal{C}(cc). X_{\langle C,I \rangle} \leq Y_{\langle C,I \rangle}$ 
Foreign Keys (denoted by  $\subseteq$ ):
 $\forall I \in S. \forall C_1 \in (\mathcal{C}(cc) \setminus cc). \forall C_2 \subseteq C_1. X_{\langle C_1,I \rangle} \geq X_{\langle C_2,I \rangle}$ 
 $\forall I \in S. \forall C_1 \in (\mathcal{C}(cc) \setminus cc). \forall C_2 \subseteq C_1. Y_{\langle C_1,I \rangle} \geq Y_{\langle C_2,I \rangle}$ 
 $\forall I \in S. \forall C_1 \in (\mathcal{C}(cc) \setminus cc). \forall C_2 \subseteq C_1. X_{\langle C_1,I \rangle} \leq Y_{\langle C_2,I \rangle}$ 
 $\forall I \in S. \forall C_1 \in (\mathcal{C}(cc) \setminus cc). \forall C_2 \subseteq C_1. Y_{\langle C_1,I \rangle} \leq Y_{\langle C_2,I \rangle}$ 
Width of the Intervals:
 $\sum_{C,I} Y_{\langle C,I \rangle} - X_{\langle C,I \rangle} = |C|$ 

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Generation. At this point, each column in $\text{col}(\Sigma)$ is associated to a set of intervals. The elements in the intervals are associated to values in the column datatype, and to values from C^D in case C is fixed-domain. VIG uses the pseudo-random number generator to randomly pick elements from the intervals that are then transformed into database values. NULL values are generated according to the detected NULLS ratio. Observe that the generation of a value in a column takes constant time and can happen independently for each column, thanks to the previous phases in which intervals were calculated.

5 Related Work

UpSizeR [15] replicates two kinds of distributions observed on the values for the key columns, called *joint degree distribution* and *joint distribution over co-clusters*⁵. However, this requires several assumptions to be made on the Σ , for instance tables can have at most two foreign keys, primary keys cannot be multi-attribute, etc. Moreover, generating values for the foreign keys require reading of previously generated values,

⁵ The notion of co-cluster has nothing to do with the notion of columns-cluster introduced here.

which is not required in VIG. A strictly related approach is *Rex* [1], which provides, through the use of dictionaries, a better handling of the content for non-key columns.

In terms of similarity measures, the approach closest to VIG is *RSGen* [14], that also considers measures like NULL ratios or number of distinct values. Moreover, values are generated according to a uniform distribution, as in VIG. However, the approach only works on numerical data types, and it seems not to support multi-attribute primary keys.

In *RDF graph scaling* [13], an additional parameter, called *node degree scaling factor*, is provided as input to the scaler. The approach is able to replicate the phenomena of *densification* that have been observed for certain types of networks. We see this as a meaningful extension for VIG, and we are currently studying the problem of how this could be applied in an OBDA context.

Observe that all the approaches above do not consider ontologies nor mappings. Therefore, many measures important in a context with mappings and ontologies and discussed here, like selectivities for joins in a co-cluster, class disjointness, or reuse of values for fixed-domain columns, cannot be handled by any of them.

6 Conclusion and Development Plan

In this work we presented VIG, a data-scaler for OBDA benchmarks. VIG integrates some of the measures used by database query optimizers and existing data scalers with OBDA-specific measures, in order to deliver a better data generation in the context of OBDA benchmarks. VIG is available as a Java maven project on GitHub, and it comes with extensive documentation in form of wiki pages. VIG is a mature implementation that is being delivered since two years together with the NPD benchmark. VIG is licensed under Apache 2.0, and is maintained at the Free University of Bozen-Bolzano. It is extremely efficient and suitable to generate huge amounts of data. In our experience, VIG can generate hundreds of Gigabytes in just a few hours on a normal laptop. The current work plan is to enrich the quality of the data produced by adding support for multi-attribute foreign keys, joint degree and value distributions, and intra-row correlations (e.g., objects from *SuspendedWellbore* might not have a *completionYear*). Unfortunately, it can be proved that some of these measures conflict with the current feature of constant time for generation of tuples. Moreover, many of them require access to previously generated tuples in order to be calculated (e.g., joint-degree distribution [15]).

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