Enhancing OBDA Query Translation over Tabular Data with Morph-CSV

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Abstract. Ontology-Based Data Access (OBDA) has traditionally focused on providing a unified view of heterogeneous datasets (e.g., relational database, CSV, JSON), either by materializing integrated data into RDF or by performing on-the-fly integration via SPARQL-to-SQL query translation. In the specific case of tabular datasets comprised of several CSV or Excel files, query translation approaches have been applied taking as input a lightweight schema with table and column names, and considering each source as a single table that can be loaded into a relational database system (RDB). This naïve approach does not consider implicit constraints in this type of data, e.g., referential integrity among data sources, datatypes, or data integrity; thus, completeness and performance of query processing can be affected. Our work is focused on explicitly enforcing implicit constraints during OBDA query translation over tabular data. We propose Morph-CSV, a framework that enforces constraints and can be used together with any SPARQL-to-SQL OBDA engine. Morph-CSV resorts to both a Constraints component and a set of operators that apply each type of constraint to the input with the aim of enhancing query completeness and performance. We evaluate Morph-CSV against a set of real-world open tabular datasets in the domain of the public transport; Morph-CSV is compared with existing approaches in terms of query result completeness and performance.

Keywords: OBDA · Tabular Data · Mapping Languages

1 Introduction

Following Open Data principles, governments and private organizations are regularly publishing wide amounts of public data in open data portals. For example, almost a million of datasets are available in the European Open Data Portal (EODP³). Most of these datasets are available in tabular formats (e.g., CSV, Excel). This is common in most open data portals, see Table [1]. The main reason why this format is so popular is its simplicity: many common office tools

³ https://www.europeandataportal.eu
Table 1. Most commonly used formats and percentage over the total number of datasets to expose data in mature EU open data portals in October 2019. Each dataset may be shared in different formats.

| Data Portal | 1st Format | 2nd Format | 3rd Format |
|-------------|------------|------------|------------|
| Spain       | CSV (50%)  | XLS (35%)  | JSON (33%) |
| Norway      | CSV (77%)  | GEOJSON (17%) | JSON (14%) |
| Italy       | CSV (76%)  | JSON (35%) | XML (25%)  |
| Croatia     | XLS (63%)  | CSV (40%)  | HTML (33%) |

(e.g., Excel, Calc) are available to facilitate their generation and consumption. However, advanced users (e.g., developers, data scientists) face significant challenges when consuming tabular data. The lack of a unified way to query tabular data presented in other formats (e.g., RDB, JSON, XML) hinders the integration of sources that have datatype inconsistencies. Moreover, data may not be normalized, and metadata about relationships or column names are not always descriptive or homogeneous. Hence, data consumers are usually forced to apply ad-hoc or manual data wrangling processes to make use of the data accessible via open data portals.

Following Linked Data [4] and FAIR initiatives [5], data providers are encouraged to make data available using an RDF-based representation following the 5-star linked data principles [6]. The Ontology-Based Data Access (OBDA) [7] paradigm facilitates the transformation of tabular data into RDF. OBDA uses ontologies as a unified view over a set of data sources, and mappings that describe the relationships between the ontology model and the data sources. The two main OBDA techniques are: materialization, where data are transformed to RDF [8], and virtualization, where SPARQL queries are translated into the underlying data source query language [9].

Materialization approaches have been enhanced with features such as functions in mappings [10] and source metadata, i.e., annotations [11], so as to deal with the aforementioned challenges of tabular data. In the virtualization approach, the main problem in the context of tabular data is that traditional OBDA query translation engines usually load the tabular data directly into an SQL-based system (e.g., MySQL, Apache Drill, Spark SQL, Presto) in order to reuse the proposed query translation techniques but do not consider semantics implicit in this type of data such as relationships among sources, datatypes or valid data constraints, thus completeness and performance of query execution is affected. Completeness is affected because of heterogeneity issues of data sources (e.g., date columns are treated as simple strings), and performance is affected because the usual relational constraints are not defined over the data sources (i.e., primary and foreign key constraints are not defined in the lightweight schema), so the optimization techniques proposed in the query translation process [3] do not take effect.

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4. https://www.go-fair.org/fair-principles/
5. https://5stardata.info/en/
6. https://github.com/oeg-upm/morph-rdb/wiki/Usage#csv-files
7. https://github.com/ontop/ontop/wiki/MappingDesignTips#database-tips
Implicit constraints over data sources are usually explicitly defined in mappings and tabular metadata, e.g., the W3C recommendation to annotate tabular data, CSVW [28]. This information has not been included in the majority of OBDA query translation engines [24], and those engines that have included it [22], are not fully documented for their use. Examples of these constraints are the standardization of the column format (e.g., dates), integrity constraints or datatypes. Exploiting these constraints on the fly improves the query translation process in terms of query execution and number of results.

**Problem and Proposed Solution.** We address the problems of current OBDA query translation techniques over tabular data. Our main goal is to extend the definition of OBDA with the inclusion of Constraints, and define a set of operators that apply each type of constraint to the input in order to improve query completeness and performance. Additionally, we describe a set of new steps over the workflow of SPARQL-to-SQL query translation, implement them, and compare the obtained results with previous proposals.

**Contributions:** The main contributions of the paper are:

1. Extension of the current OBDA definition [23] with a Constraints component that is comprised of all of the data restrictions that are represented in mappings and tabular metadata.

2. Workflow for the application of constraints. The proposed framework, Morph-CVS, takes as input a dataset, a set of mappings, tabular metadata, and a SPARQL query. With this input, it automatically: (i) selects the sources and attributes needed to answer the query, (ii) transforms and normalizes the selected sources, and (iii) defines an SQL schema to ensure that the optimizations included in the OBDA techniques will be effective.

3. Development as a proof of concept of Morph-CVS, an engine that implements source selection and the application of constraints through the exploitation of well-known declarative proposals (RML+FnO [13,9] and CSVW [28]) annotations in combination with mapping translation [7]. The engine can be used by any SPARQL-to-SQL OBDA tool.

4. Evaluation of the impact of the extended OBDA with Constraints approach over two well-known open source engines: Morph-RDB [24] and Ontop [3] in the domain of public transport.

The rest of the paper is structured as follows: Section 2 gives a motivating example in the transport domain, on the problem of OBDA query translation over tabular data. Section 3 describes the identified challenges for querying and integrating tabular data. Section 4 presents Morph-CVS, an approach for enhancing OBDA query translation over tabular data by applying a set of constraints on the fly. Section 5 reports on the results of our empirical study. We present the related work in Section 6, and our conclusions and future work in Section 7.
Fig. 1. Motivating Example. SPARQL query evaluation over two tabular data files in the transport domain through a common OBDA approach. It loads the files as single tables in an SQL-based system and uses the mapping rules for query translation. The number of results differs with respect to the expected results due to the heterogeneity of the raw data. Additionally, query performance may be affected by the join condition between the two tables, the absence of indexes and the loading of columns that are not needed to answer the input query (wheelchair).

2 Motivating Example

Consider the de-facto standard for publishing open data in the transport domain, GTFS. This model provides information such as schedules, stops and routes using 15 different inter-related CSV files called a GTFS feed. Each feed usually specifies the information of one type of transportation mode (e.g., metro, train or tram). Linking these feeds based on their stops enables route planners to offer multi-modal routes, a route that can be travelled using various types of transportation. The GTFS feeds from the metro and the buses of the city of Madrid have several stop and stations in common; they are created by different transport authorities, and the names of their stops are defined in different manners. Figure 1 depicts a SPARQL query asking for bus and metro stops with the same name, and information related to their closing dates during holidays. Since GTFS uses temporal identifiers for its resources, links have to be established joining stop names. However, as it is usual in open datasets, stop names do not follow a

\[\text{SELECT} \ ?\text{stop_name} \ ?\text{date1} \ ?\text{date2} \\
\text{WHERE} \ { \\
?\text{stop1} \ \text{gtfs:sameStop} \ ?\text{stop2} \\
?\text{stop1} \ \text{gtfs:name} \ ?\text{stop_name} \\
?\text{stop1} \ \text{gtfs:close\_date} \ ?\text{date1} \\
?\text{stop2} \ \text{gtfs:close\_date} \ ?\text{date2} \\
\text{FILTER} \ (?\text{date1} \neq \ ?\text{date2}) \} \]
standard structure (e.g., “Colonia Jardin” in bus_stops.csv and “Colonia_jardin” in metro_stops.csv). A similar issue is presented in closing dates, where there are multi-valued cells and their format is not the standard one (e.g., yyyy-MM-dd).

Following the approach commonly employed by typical OBDA engines, the two files would be loaded into an SQL-system and treated as separate tables. The obtained result set only contains one answer where the stop names in the two data sources are identical (“Noviciado”). However, the expected result set should include more answers by performing an improved join among the names stops of the bus and metro, through the normalization of multi-valued date columns.

3 Tabular Data Querying Challenges under OBDA

In this section, we describe challenges that are relevant for querying tabular data using an OBDA approach, and that have not yet been addressed by current proposals. We motivate the reader on the need to deal with these challenges and explain how they can have a negative effect in terms of completeness and performance of query evaluation:

- **Selection:** Existing approaches load all of the files specified as sources in the mapping rules into an SQL database before executing the query-translation process. This step has to be repeated every time a SPARQL query is evaluated to ensure up-to-date results, resulting in unnecessary longer loading time and thus affecting the performance.

- **Normalization:** Tabular data formats do not provide restrictions on how to structure data. As a result, cells may contain multiple values, and files may represent multiple entities. Having non-normalized tables may affect the completeness of the query. When a CSV file with multiple-valued cells is loaded to an RDB table, the cell’s value is interpreted by the RDBMS as an atomic value, thus reducing completeness for queries that filter or “join” on the corresponding column. Representing several entities in a single file may lead to duplicate answers, and in turn decrease query performance.

- **Heterogeneity:** Tabular data normally contains values that need to be transformed before query evaluation (e.g., insertion of column default values or normalization of date formats). This issue directly impacts query completeness: there may be different formats for the same datatype or default values may have not been included in the data.

- **Lightweight Schema:** Most of the tabular data only provide minimal information about their underlying schema in the form of column names in the header, if at all present. Also, although there is implicit information on keys and relationships among sources, there is no way to specify primary key or foreign key constraints. The same can be said on indexes and datatypes. This type of information is used by OBDA engines for performing semantic optimization in their query evaluation techniques, thus, the lack of this information affects the performance of OBDA engines.

In the next section, we explain how our approach extracts a set of functions from the input (query, mappings and annotations), and applies them to improve query completeness and performance in an OBDA query translation approach.
4 The Morph-Csv Framework

The formal framework presented in \[31\] defines an OBDA specification as a tuple \( \mathcal{P} = \langle \mathcal{O}, \mathcal{S}, \mathcal{M} \rangle \) where \( \mathcal{O} \) is an ontology, \( \mathcal{S} \) is a relational database schema, and \( \mathcal{M} \) a set of mappings. Following, we define our extended specification:

**Definition 1.** An OBDAT specification is a tuple \( \mathcal{P}^T = \langle \mathcal{O}, \mathcal{S}_{lw}, \mathcal{M}_{tabular}, \mathcal{C} \rangle \) where \( \mathcal{O} \) is an ontology, \( \mathcal{S}_{lw} \) is a lightweight tabular schema described in terms of metadata, e.g., file and column names, \( \mathcal{M}_{tabular} \) is a set of mapping rules for tabular data, and \( \mathcal{C} \) is a set of constraints.

Constraints are conjunctive rules specified for tabular data that restrict the valid data in one or more tables. \( \mathcal{C} \) is a set of constraints, where each constraint \( c \) is a logical statement that expresses the condition that needs to be satisfied by the data in order to be valid.

Each constraint is applied through a function. For example, tabular metadata allow expressing a primary key constraint for a table. \( \text{primaryKey}(t, a) \) is a function that applies this constraint to a source \( t \) and a set of columns \( a \) in the metadata, and generates a primary key constraint in the output schema. An example of the function with bounded variables is \( \text{primaryKey}(\text{metro.stops}, \{\text{stop.id}\}) \).

According to \[31\], an OBDA instance is defined as \( I = \langle \mathcal{P}, \mathcal{D} \rangle \) where \( \mathcal{P} \) is an OBDA specification and \( \mathcal{D} \) are the instances of the RDB. Similarly, an OBDAT instance is defined as follows:

**Definition 2.** An OBDAT instance is a tuple \( \mathcal{I}^T = \langle \mathcal{P}^T, \mathcal{D}_{tabular} \rangle \) where \( \mathcal{P}^T \) is an OBDAT specification and \( \mathcal{D}_{tabular} \) is a tabular dataset that is composed of a set of data sources, defined as \( \mathcal{D}_{tabular} = \{S_1, \ldots, S_n\} \) where each \( S_i \) has a set of columns \( \{A_{i1}, \ldots, A_{im}\} \).

Given an OBDA instance \( I = \langle \mathcal{P}, \mathcal{D} \rangle \), the function \( \text{eval}(Q, I) \) retrieves a SPARQL certain answer set \[23\] that is the result of the translation of \( Q \) from SPARQL to SQL using the mapping rules \( \mathcal{M} \) defined in \( \mathcal{P} \), and then evaluating the query directly over \( \mathcal{D} \). The time required to evaluate this function is the sum of the execution times of the different phases of a typical OBDA system, as defined in \[19\], i.e. starting, query rewriting, query translation, and execution phases. In previous proposals \[22,24\], when \( \mathcal{D} = \mathcal{D}_{tabular} \), the starting phase time is negatively impacted since the system has to load the data sources to a RDBMS before executing the rest of the phases. Additionally, the performance is also affected during the execution phase due the absence of integrity constraints over the schema. In the case of an OBDAT instance, the function \( \text{eval}(Q, \mathcal{I}) \) extends the evaluation function of OBDA, through the application of constraints to improve query execution time and answer completeness.

**Problem statement:** Given a function \( \text{eval}(Q, \mathcal{I}) \), the problem of OBDA query translation over tabular data is defined as the problem of exploiting the knowledge encoded in the constraints defined in \( \mathcal{I} \) such that:

- The number of results obtained in the evaluation of \( Q \) over \( \mathcal{I} \) is equal or greater than the number of results in the evaluation of the same query \( Q \) over \( I \), i.e., \( \#\text{answ}(\text{eval}(Q, \mathcal{I})) \geq \#\text{answ}(\text{eval}(Q, I)) \) where \( I \) is an OBDA instance with \( \mathcal{D} = \mathcal{D}_{tabular} \).
The total execution time of evaluating a SPARQL query $Q$ over $IT$ is minimized compared to the evaluation of the same query $Q$ over $I$, i.e., $time(\text{eval}(Q, IT)) \leq time(\text{eval}(Q, I))$ where $I$ is an OBDA instance with $D = D_{\text{tabular}}$.

**Proposed solution:** We propose Morph-CSV, an alternative to the traditional OBDA workflow for query translation when the input is a tabular dataset. Morph-CSV interprets the function $\text{eval}(Q, IT)$ as $\text{eval}(t(Q, IT))$ where $t$ is a function that pushes down the application of the constraints directly over $IT$. More in detail, $t(Q, IT) = I'$ where $I'$ is an enriched OBDA instance obtained after the application of the constraints, hence, this proposal can also reuse optimizations proposed on query translation over the common OBDA specification [324].

We show the workflow of the framework in Figure 2. Morph-CSV receives an OBDAT instance $IT = \langle PT, D_{\text{tabular}} \rangle$ and a query $Q$ and extends the starting phase of a typical OBDA workflow by including the following steps: source selection, normalization, data preparation and schema generation. Morph-CSV extracts the constraints used during these steps from the mapping rules $M_{\text{tabular}}$ represented in a mapping language for tabular data that includes declarative transformation functions, e.g., RML+FnO [10], and metadata represented as annotations for tabular data, e.g., CSVW [28]. Additionally, Morph-CSV performs a mapping translation step [7] to transform the mapping rules $M_{\text{tabular}}$ to...
standard OBDA mappings \( M \) (e.g., RML+FnO to R2RML) to allow any OBDA system to incorporate this workflow.

4.1 Steps performed in the Morph-Csv framework

We describe the steps performed in Morph-Csv. The input to all of these steps is an OBDA instance \( IT = \langle PT, D_{tabular} \rangle \) and a query SPARQL \( Q \). We describe each step more in detail together with their corresponding constraints. These constraints, implemented as a set of functions over \( IT \), address the challenges defined in Section 3 and are independent from the input sources.

**Step 1: Source Selection.** Before starting the application of constraints, Morph-Csv takes as input the SPARQL query, the set of mapping rules and the tabular dataset, and uses the information encoded in the query and the rules of the mapping to only select the files and columns from \( S_{lw} \) that are required to answer the query. After that, Morph-Csv also removes the irrelevant rules from the mapping document. The output of this step is a new OBDA instance \( IT' \) where the number of results of \( evalt(Q, IT) \) is the same as \( evalt(Q, IT') \). This function tackles the **Selection** challenge identified in Section 3. Note that the following steps are executed over the selected data sources and columns.

**Step 2: Data Normalization** There are two functions for performing data normalization. The first one is the treatment of multi-values in a column. In this case, Morph-Csv performs the function \( split(A_i, S_j, sep) \) where \( A_i \) is the multi-valued column of source \( S_j \) and \( sep \) is the character defined in the metadata that divides the values (e.g., \( split(date, stops, -) \)). The application of this function is known as the normalization step for 2NF [6].

The second function is the treatment of multiple entities in the same source. Morph-Csv takes the mapping rules and the lightweight schema and executes the function \( cut(M_{tabular}, S_{lw}) \). This function analyzes the mapping rules \( M_{tabular} \) and performs a 3NF [6] normalization step over \( S_{lw} \), when there are two sets of mapping rules that have the same source and the intersection of their references is empty. Additionally, both functions rewrite the mapping rules according to the changes performed over the lightweight tabular schema. These functions tackle the **Normalization** challenge and their output is a new OBDA instance \( IT' \).

**Step 3: Data preparation** In this step, Morph-Csv addresses the challenge of **Heterogeneity** and performs two different functions: \( sub \) and \( create \). The first one is defined as \( sub(exp(A_i), S_j, val) \) where \( exp(A_i) \) is a boolean function over column \( A_i \) of source \( S_j \) that when true, the value of \( A_i \) is substituted by \( val \). For example, the GTFS spec in the exception_type column in the calendar_dates.csv file, the value 2 means false. To prepare the data to be queried, Morph-Csv extracts that information from the tabular metadata and performs the function \( sub(exception_type = 2, calendar_dates.csv, false) \). There are multiple substitution functions that Morph-Csv executes such as default values, null values and date formats. The second function creates a new column in a specific source \( S_j \). It is defined as \( create(c(A_n, \ldots, A_m), S_j) \), where \( c(A_n, \ldots, A_m) \) means the application of a set of transformation functions over a set of selected columns \( A_n, \ldots, A_m \) from source \( S_j \). This function is used when ad-hoc transformations
Table 2. Summary of constraints and corresponding functions applied by Morph-CVS.  
The proposed steps and their relation with the input, the output performed by each function, and the addressed challenge.

| Step                          | Constraint | Function | Input                      | Output                      | Challenge         |
|-------------------------------|------------|----------|----------------------------|-----------------------------|-------------------|
| Data Normalization            | 2NF        | split    | Column, Source, Separator  | Schema, Data, Mappings      | Normalization     |
|                               | 3NF        | cut      | Mappings, Schema           | Schema                      |                   |
| Data Preparation              | Standardization | sub     | Expression, Column, Source, Value | Data                        | Heterogeneity     |
|                               |            | create   | Expression, Columns, Source | Schema, Data, Query         |                   |
| Schema Creation and Load      | Primary Key | primaryKey | Column, Source, Query     | Schema                      | Lightweight Schema|
|                               | Foreign Key | foreignKey | Column, Source, Query      | Schema                      |                   |
|                               | DataType   | datatype | Column, Source, Query      | Schema                      |                   |
|                               | Index      | index    | Column, Source, Query      | Schema                      |                   |

For example, to give the same structure to stop names in GTFS, the function is defined as $create(lower(replace(name,\s*,\s*)), stops.csv)$. The output of both functions is a new OBDA instance $I'$.  

**Step 4: Schema Creation and Load.** The final step before translating and executing the query is to create an SQL schema applying a set of constraints and a function to load the tabular data sources. The constraints that Morph-CVS incorporates in this step are $primaryKey(A_i, S_j)$, $foreignKey(A_i, S_j)$, $index(A_i, S_j)$ and $dataType(A_i, S_j, type)$, that are typical constraints applied in SQL-based systems. However, Morph-CVS exploits the information encoded in the query to apply a set of heuristics in this process with the aim of improving query execution. First, the integrity constraints ($primaryKey$, $foreignKey$) are only applied in the case that the query performs a join among the references of these constraints. Additionally, the application of the $index$ constraints is based on the selectivity of a column $A$ and the query filters, i.e., the engine decides on-the-fly to create an index based on these inputs. Finally, the data is loaded in a RDB following the newly created schema. This step tackles the problem of Lightweight Schema and its output is an OBDA instance $I'$ that can be the input to any SPARQL-to-SQL OBDA engine.

The summary of the steps and the constrains applied are shown in Table 2. In terms of implementation, Morph-CVS accepts, as inputs, the mapping rules specified in RML [13] together with the extension of the Function Ontology [9] and the tabular annotations follow the W3C recommendation CSV on the Web [28]. The output of the engine is a RDB instance together with R2RML mapping rules, the typical inputs of SPARQL-to-SQL OBDA engines.
Table 3. Query evaluation performance (time in seconds) over multiple sizes of a GTFS dataset (the number indicates the scale factor: 1, 10, 100 and 1000). The absence of a value means that the OBDA engine does not support the features of the SPARQL query. Execution time is a lower-is-better metric; best results are highlighted in bold.

| Engines/Queries | Q1 | Q2 | Q4 | Q6 | Q7 | Q9 | Q12 | Q13 | Q17 | Geometric Mean |
|-----------------|----|----|----|----|----|----|-----|-----|-----|---------------|
| **GTFS-1**      |    |    |    |    |    |    |     |     |     |               |
| Morph-RDB       | 6.94 | 3.04 | 2.78 | 2.78 | timeout | timeout | 6.23 | 3.97 | 3.14 | 20.56         |
| Morph-CSV & Morph-RDB | 8.18 | 4.22 | 4.01 | 3.91 | 4.31 | 24.15 | 4.22 | 4.39 | 4.42 | 5.50          |
| Ontop           | 9.93 | 6.06 | -   | -   | -   | -   | 6.62 | 6.56 | 7.30 |               |
| Morph-CSV & Ontop | 11.54 | 8.36 | -   | -   | -   | -   | 8.25 | 8.32 | 9.02 |               |
| **GTFS-10**     |    |    |    |    |    |    |     |     |     |               |
| Morph-RDB       | 25.90 | 6.08 | 5.20 | 4.20 | timeout | timeout | 38.15 | 38.90 | 109.21 |               |
| Morph-CSV & Morph-RDB | 23.99 | 5.01 | 4.20 | 3.84 | 4.87 | 93.72 | 9.58 | 4.92 | 5.50 | 8.49          |
| Ontop           | 37.97 | 19.48 | -   | -   | -   | -   | 19.21 | 19.54 | 22.95 |               |
| Morph-CSV & Ontop | 77.73 | 8.80 | -   | -   | -   | -   | 8.50 | 8.62 | 14.96 |               |
| **GTFS-100**    |    |    |    |    |    |    |     |     |     |               |
| Morph-RDB       | timeout | 43.59 | 38.72 | 38.43 | timeout | timeout | timeout | timeout | timeout | 1276.35       |
| Morph-CSV & Morph-RDB | 205.99 | 9.88 | 4.90 | 3.99 | 9.07 | 11.53 | 8.54 | 11.88 | 11.97 |               |
| Ontop           | 1513.72 | 15.21 | -   | -   | -   | -   | 43.14 | 45.54 | 107.68 |               |
| Morph-CSV & Ontop | 127.06 | 14.26 | -   | -   | -   | -   | 10.67 | 12.75 | 22.28 |               |
| **GTFS-1000**   |    |    |    |    |    |    |     |     |     |               |
| Morph-RDB       | timeout | timeout | timeout | timeout | timeout | timeout | timeout | timeout | timeout |               |
| Morph-CSV & Morph-RDB | timeout | 93.86 | 7.01 | 4.24 | 66.35 | timeout | 71.43 | 44.29 | 68.64 | 32.74         |
| Ontop           | timeout | timeout | -   | -   | -   | -   | timeout | timeout | timeout |               |
| Morph-CSV & Ontop | timeout | timeout | -   | -   | -   | -   | timeout | timeout | timeout |               |

5 Evaluation

In this section, we show the empirical evaluation conducted to test the effect of respecting constraints, on the fly, during OBDA query translation over tabular data. Our aim is to answer the following research questions: 

**RQ1)** What is the effect of combining different types of constraints over a tabular dataset? 

**RQ2)** What is the impact of the constraints when the tabular dataset size increases?

To answer these questions, we setup the following experimental studies:

**Datasets and queries.** The GTFS-Madrid Benchmark [9] consists of an ontology, an initial dataset of the metro system of Madrid following the GTFS model, a set of mappings in several specifications, a set of queries according to the ontology that cover relevant features of the SPARQL query language, and a data generator based on a state of the art proposal [20]. We select the tabular sources of this benchmark (i.e., the CSV files) and we scale up the original data in several instances, we use the scale factors 10, 100 and 1000. The resources provided by the benchmark address all the issues in the challenges we identified for querying tabular data in OBDA. We select the queries from the benchmark that include SPARQL features supported by at least, one the OBDA engines used during

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9 Paper under review. Resources available at: [https://github.com/oeg-upm/gtfs-bench](https://github.com/oeg-upm/gtfs-bench)
Table 4. Query completeness over multiple sizes of a GTFS dataset (the number indicates the scale factor: 1, 10, 100 and 1000). The absence of a value means that the OBDA engine does not support the features of the SPARQL query.

| Engines/Queries | Q1 | Q2 | Q4 | Q6 | Q7 | Q9 | Q12 | Q13 | Q17 |
|-----------------|----|----|----|----|----|----|-----|-----|-----|
| **GTFS-1**      |    |    |    |    |    |    |     |     |     |
| Virtuoso        | 58540 | 765 | 13 | 1 | 2 | 151439 | 6 | 734 | 855 |
| Morph-RDB       | 58540 | 765 | 13 | 1 | 2 | 151439 | 6 | 734 | 855 |
| Morph-Csv & Morph-RDB | 58540 | 765 | 13 | 1 | 2 | 151439 | 6 | 734 | 855 |
| Ontop           | 58540 | 765 | - | - | - | - | 734 | 855 |
| Morph-Csv & Ontop | 58540 | 765 | - | - | - | - | 734 | 855 |
| **GTFS-10**     |    |    |    |    |    |    |     |     |     |
| Virtuoso        | 353660 | 6312 | 130 | 1 | 67 | 718317 | 130 | 2650 | 8550 |
| Morph-RDB       | 353660 | 6312 | 130 | 1 | 67 | 718317 | 130 | 2650 | 8550 |
| Morph-Csv & Morph-RDB | 353660 | 6312 | 130 | 1 | 67 | 718317 | 130 | 2650 | 8550 |
| Ontop           | 353660 | 6312 | - | - | - | - | 2650 | 8550 |
| Morph-Csv & Ontop | 353660 | 6312 | - | - | - | - | 2650 | 8550 |
| **GTFS-100**    |    |    |    |    |    |    |     |     |     |
| Virtuoso        | 3536600 | 63100 | 1300 | 1 | 67 | 7183174 | 1300 | 26500 | 85500 |
| Morph-RDB       | timeOut | 63100 | 1300 | 1 | timeOut | timeOut | timeOut | timeOut | timeOut |
| Morph-Csv & Morph-RDB | 3536600 | 63100 | 1300 | 1 | 67 | timeOut | 1300 | 26500 | 85500 |
| Ontop           | 3536600 | 63100 | - | - | - | - | 26500 | 85500 |
| Morph-Csv & Ontop | 3536600 | 63100 | - | - | - | - | 26500 | 85500 |
| **GTFS-1000**   |    |    |    |    |    |    |     |     |     |
| Virtuoso        | 35366000 | 1261368 | 13000 | 1 | 69 | 19077083 | 13000 | 420666 | 855000 |
| Morph-RDB       | timeOut | timeOut | timeOut | timeOut | timeOut | timeOut | timeOut | timeOut | timeOut |
| Morph-Csv & Morph-RDB | timeOut | 1261368 | 13000 | 1 | 69 | - | 13000 | 420666 | 855000 |
| Ontop           | timeOut | timeOut | - | - | - | - | timeOut | timeOut | timeOut |
| Morph-Csv & Ontop | timeOut | timeOut | - | - | - | - | timeOut | timeOut | timeOut |

the evaluation (Q1, Q2, Q4, Q6, Q7, Q9, Q12, Q13, Q17). The description and features of each query is also available online.\footnote{https://github.com/oeg-upm/gtfs-bench/tree/master/queries}

**Engines.** We use as our baselines two open source OBDA engines: Ontop\footnote{https://github.com/ontop/ontop} v3.0.0 and Morph-RDB v3.9.1\footnote{https://github.com/oeg-upm/morph-rdb}. To evaluate the na"ıve approach we manually generate a relational database schema without constraints and measure the load and query execution times. In order to measure the impact of the additional steps proposed by Morph-Csv\footnote{https://zenodo.org/badge/latestdoi/219717229} we integrate our solution on top of the two OBDA engines. To ensure the reproducibility of the experiments, we also provide all of the resources in a docker image. In order to test the number of answers,
the benchmark also provides a gold standard dataset in RDF that we loaded in a Virtuoso triple store and where we run the selected queries[13]..

**Metrics.** We measure the total query execution time including all the steps proposed by Morph-CSV in the starting phase, and the number of answers obtained. Each query was executed 5 times with a timeout of 2 hours in cold mode. The experiments were run in an Intel(R) Xeon(R) equipped with a CPU E5-2603 v3 @ 1.60GHz 20 cores, 100G memory with Ubuntu 16.04LTS.

The experimental evaluation of the query execution time is shown in Table 3. When analyzing the results, we generally observe that the incorporation of Morph-CSV in the workflow of the OBDA engines enhances the performance of the queries. With respect to the results over each query, we can observe on one hand that the behaviour of the engines over simple queries (Q1, Q2, Q3, Q4, Q6) is similar. This is understandable as the selected data sources needed to answer the query do not include the application of several constraints (e.g., there are no joins in the query); on the other hand, complex queries such as Q7, Q9, Q12, Q13 and Q17, where the needed tabular sources to answer the query have several implicit constraints, have a negative impact over the naïve approach. For example, in the case of query Q7, the naïve approach is not able to answer the question in time (less than 2 hours), while in the case of Morph-CSV, applying a large number of constraints over the tabular data sources and then running the query with the same engine, the query is answered in reasonable time for all of the datasets.

If we analyze the results obtained in each dataset, we can observe that for small datasets (GTFS-1) the cost of applying the proposed steps of Morph-CSV impacts the total execution time. However, when the size of the dataset increases, the naïve approach is impacted due to the fact that it has to load all of the input data sources in the RDB before executing the query, low performance is reported for GTFS-100 and timeout is reported for all of the queries against GTFS-1000. Thanks to the application of the constraints and to the source selection step, for Morph-CSV together with Morph-RDB or Ontop, the return of the results of the queries has a high performance most of the time. In the cases where Morph-CSV reports a timeout (e.g., Q1 in GTFS-1000) it is because the number of results that should be obtained is so high that the OBDA engine used cannot process them.

In terms of query completeness, the results are shown in Table 4. We observe that the number of answers are similar. However, one of the main benefits of including Morph-CSV in the OBDA query translation process is that the user can decide which engine will be used based on the support of features in the input SPARQL queries. For example, in this case, queries Q4, Q5, Q7, Q9 and Q12, contain features that are only supported by Morph-RDB, hence, the user will obtain a larger number of results for the benchmark if this engine is used. Another important characteristic of Morph-CSV that is shown in these results is that, although it performs several steps selecting, modifying and normalizing the

[13] http://gtfs-bench.linkeddata.es/sparql
data sources, there is not a negative impact on the number of answers, obtaining the same results as the gold standard.

6 Related Work

In this section we refer to previous works in integration systems that precede the OBDA approach, then we refer to the general techniques used in systems that handle raw data, following we describe current Ontology Based Data Integration (OBDA) systems that handle tabular data, and finally we describe existing tabular annotation languages and the use of transformation functions in mappings.

The most relevant concept that predates the OBDA data integration approach is that of mediator \[29\], defined in the early 90’s by Wiederhold. In the proposed architecture for information systems, mediators form a middle layer that makes user applications independent of the data resources. The idea is to transform heterogeneous data sources into a common data model, which can then be processed and integrated. Classical examples of systems that implemented the original mediator architecture were TSIMMIS \[5\], Information Manifold \[25\], and GARLIC \[26\]. Through the years these ideas were formalized evolving from the use of description logics \[4\], to the use of ontologies as a common model for data access \[3\]. Morph-CSV follows a data integration approach that not only uses ontologies but exploits additional information from mappings, tabular annotations and the query.

Related to our work are those approaches that allow querying directly information stored in flat files \[16\], Drill \[15\], NoDB \[1\]. These systems provide a layer where “raw” data is queried, adaptively load and store the data, and then execute the query using an assortment of strategies. \[16\] extends a column-store, whereas \[1\] extends a relational DBMS and Drill loads the data into NoSQL databases. Current Ontology Based Data Integration (OBDA) open source systems that take tabular data as input are Ontario \[15\] and Squerall \[22\]. Ontario is a federated query processing approach for heterogeneous data sources. For source selection, Ontario uses source descriptions named RDF Molecule Templates \[14\] which keep information on the sources. The system handles tabular data among other formats, and implements a virtualization approach to query answering focusing on techniques for efficient execution. Similarly, Squerall is a system that implements OBDA for heterogeneous data sources. It takes input data and mappings and offers a middleware that is able to aggregate the intermediate results in a distributed manner. Although the aforementioned systems evaluate queries against raw tabular data and exploit some information encoded in the query, they do not exploit the constraints declare in annotations or mapping rules to enhance this process.

CSV on the Web (CSVW) \[16\] is a W3C proposal for the definition of metadata on CSV files such as datatypes, valid values, data transformations, and

\[15\] https://drill.apache.org/
\[16\] https://www.w3.org/TR/tabular-data-primer/
primary and foreign key constraints. A related W3C proposal defines procedures and rules for the generation of RDF\footnote{https://www.w3.org/TR/csv2rdf/} from tabular data and there are a few implementations that refer to this proposal. The CSV2RDF tool is presented in \cite{21}, authors define algorithms to transform CSV data into RDF using CSVW metadata annotations, and their experimental study uses datasets from the CSVW Implementation Report\footnote{https://w3c.github.io/csvw/tests/reports/index.html}. Another tool, COW: Converter for CSV on the Web\footnote{https://csvw-converter.readthedocs.io/en/latest/} allows the conversion of datasets expressed in CSV and uses a JSON schema expressed in an extended version of the CSVW standard. Both tools focus on RDF materialization. To the best of our knowledge, no existing system exploit information in CSVW annotations for querying tabular data in an OBDA approach.

Another area related to our work is the definition and application of data transformation functions. An approach independent of a specific implementation context is described in \cite{11}. It enables the description, publication and exploration of functions and instantiation of associated implementations. The proposed model is the Function Ontology and the publication method follows the Linked Data principles Previous works related to this topic are focused on developing ad-hoc and programmed functions. For example, R2RML-F \cite{12} allows using functions in the value of the \texttt{rr:objectMap} property, so as to modify the value of the table columns from a relational database. KR2RML \cite{27}, used in Karma, also extends R2RML by adding transformation functions in order to deal with nested values. OpenRefine allows such transformations with the usage of GREL functions, which can be also used in its RDF extension. Morph-CSV uses the extension of RML together with the Function Ontology \cite{10} that allows to incorporate ad-hoc transformation functions over the data sources in a declaratively.

7 Conclusions and Future Work

In this paper, we have presented an extension of the common OBDA specification to address the problem of query translation over tabular data, OBDA\textsc{t}. We describe and evaluate Morph-CSV, a framework that exploits the information of constraints defined in the OBDA\textsc{t} specification. It pushes down the application of these elements in order to improve query evaluation and query completeness. One of the main contributions of this proposal is that it can be used together with any OBDA framework.

The definition, application and optimization of new functions and constraints to address other challenges for querying tabular data is one of the main lines for future work \cite{17}. We also want to study the performance of the proposed workflow over OBDA distributed query systems such as the ones proposed in \cite{16,22}. In addition, we will study the challenges for querying other data formats (e.g., XML, JSON) in an OBDA context and extend our approach to incorporate them.
Finally, we will adapt this proposal for a materialization process, and study its effects comparing it with previous proposals.

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