Language-Integrated Queries: a BOLDR Approach
Véronique Benzaken, Giuseppe Castagna, Laurent Daynes, Julien Lopez, Kim Nguyen, Romain Vernoux

To cite this version:
Véronique Benzaken, Giuseppe Castagna, Laurent Daynes, Julien Lopez, Kim Nguyen, et al..

HAL Id: hal-01717995
https://hal.science/hal-01717995v2
Submitted on 27 Feb 2018

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L’archive ouverte pluridisciplinaire HAL, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d’enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.
Language-Integrated Queries: a BOLDR Approach

Véronique Benzaken  
Université Paris-Sud, France

Giuseppe Castagna  
CNRS, Univ Paris Diderot, France

Laurent Daynes  
Oracle France, France

Julien Lopez  
Université Paris-Sud, France

Kim Nguyễn  
Université Paris-Sud, France

Romain Vernoux  
ENS Paris-Saclay, France

ABSTRACT

We present BOLDR, a modular framework that enables the evaluation in databases of queries containing application logic and, in particular, user-defined functions. BOLDR also allows the nesting of queries for different databases of possibly different data models. The framework detects the boundaries of queries present in an application, translates them into an intermediate representation together with the relevant language environment, rewrites them in order to avoid query avalanches and to make the most out of database optimizations, and converts the results back to the application. Our experiments show that the techniques we implemented are applicable to real-world database applications, successfully handling a variety of language-integrated queries with good performances.

KEYWORDS

Language-integrated queries, databases, data-centric languages, R

ACM Reference Format:

1 INTRODUCTION

The increasing need for sophisticated data analysis encourages the use of programming languages that either better fit a specific task (e.g., R or Python for statistical analysis and data mining) or manipulate specific data formats (e.g., JavaScript for JSON). Support for data analysis in data processing platforms cannot follow the pace of innovation sustained by these languages. Therefore, databases are working on supporting these languages: Oracle R Enterprise [Oracle 2017a], and PL/R for R; PL/Python [PostgreSQL 2017], Amazon Redshift [Amazon 2017], Hive [Apache 2017a], and SPARK [Apache 2017b] for Python; or MongoDB [MongoDB 2017] and Cassandra’s CQL [Apache 2017c] for JavaScript. APIs for these embedded languages are low-level, and data is accessed by custom operations, yielding non-portable code. In opposite to this ad hoc approach, language-integrated querying, popularized with Microsoft’s LINQ framework [Microsoft 2017], proposes to extend programming languages with a querying syntax and to represent external data in the model of the language, thus shielding programmers from having to learn the syntax or data model of databases. To that end, LINQ exposes the language to a set of standard query operators that external data providers must implement. However, LINQ suffers from a key limitation: queries can only execute if they can be translated into this set of operators. For instance, the LINQ query

\[ db.Employee.Where(x => x.sal >= 2000 * getRate("USD", x.cur)) \]

which is intended to return the set of all employees which salary converted in USD is greater than 2000, will throw an error at runtime since LINQ fails to translate the function getRate to an equivalent database expression. One solution is to define getRate in the database, but this hinders portability and may not be possible at all if the function references runtime values of the language. A more common workaround is to rewrite the code as follows:

\[ db.Employee.AsEnumerable() .Where(x => x.sal >= 2000 * getRate("USD", x.cur)) \]

But this hides huge performance issues: all the data is imported in the runtime of the language, potentially causing important network delays and out-of-memory errors, and the filter is evaluated in main memory thus neglecting all possible database optimizations.

In this work, we introduce BOLDR (Breaking boundaries Of Language and Data Representations), a language-integrated query framework that allows arbitrary expressions from the host language (language from which the query comes from) to occur in queries and be evaluated in a database, thus lifting a key limitation of the existing solutions. Additionally, BOLDR is tied neither to a particular combination of database and programming language, nor to querying only one database at a time: for instance, BOLDR allows a NoSQL query targeting a HBase server to be nested in a SQL query targeting a relational database. BOLDR first translates queries into a Query Intermediate Representation (or QIR for short), an untyped λ-calculus with data-manipulation built-in operators, then applies a normalization process that may perform a partial evaluation of the QIR expression. This partial evaluation composes distinct queries that may occur separated in the code of the host language into larger queries, thus reducing the communication overhead between the client runtime and the database and allowing databases to perform whole query optimizations. Finally, BOLDR translates and sends the queries to the targeted databases.

Consider again our LINQ query containing the call to getRate. In BOLDR, its translation produces a QIR expression according to three different scenarios: (i) if getRate can be translated into the query language of the targeted database, then the whole expression is translated into a single query expressed in the query language of the targeted database; (ii) if getRate cannot be entirely translated but contains one or several queries that can be translated, then BOLDR produces the corresponding translated subqueries and sends them to their respective databases, and combines the results at QIR level; (iii) if getRate cannot be translated at all, then BOLDR creates a
query containing the serialized host language abstract syntax tree of getRate to be potentially executed on the database side.

Our implementation of BOLDR uses Truffle [Würthinger et al. 2013], a framework developed by Oracle Labs to implement programming languages. Several features make Truffle appealing to BOLDR: first, Truffle implementations of languages must compile to an executable abstract syntax tree that BOLDR can directly manipulate; second, languages implemented with Truffle can be executed on any JVM, making their addition as an external language effortless in databases written in Java (e.g., Cassandra, HBase, …), and relatively simple in others such as PostgreSQL. Third, work on one Truffle language can easily be transposed to other Truffle languages.

Our implementation currently supports the PostgreSQL, HBase and Hive databases, as well as FastR [Oracle 2017a] (Truffle implementation of the R language) and Oracle’s SimpleLanguage (a dynamic language with syntax and features inspired by JavaScript). The following R program illustrates the key aspects of BOLDR:

```r
getRate = function(rfrom, rto) {
  t = tableRef("change", "PostgreSQL")
  if (rfrom == rto) 1
  else subset(t, cfrom == rfrom & cto == rto, c(rate))
}
# Employees earning at least minSalary in the current currency
atLeast = function(minSalary, cur) {
  # table employee has two columns: name, sal
  t = tableRef("employee", "PostgreSQL")
  subset(t, sal >= minSalary * getRate("USD", cur), c(name))
}
richUSPeople = atLeast(2000, "USD")
richEURPeople = atLeast(2000, "EUR")
richUSPeople = atLeast(2000, "USD")
richEURPeople = atLeast(2000, "EUR")
print(executeQuery(richUSPeople))
print(executeQuery(richEURPeople))
```

This example is a standard R program with two exceptions: the function `tableRef` (Line 4 and 11) referencing an external source in lieu of creating a data frame (R implementation of tables) from a text file; and the function `executeQuery` (Line 16 and 17) that evaluates a query. We recall that in R, the `c` function creates a vector, the `subset` function filters a table using a predicate, and optionally keeps only the specified columns. The first function `getRate` takes the code of two currencies and queries a table using `subset` to get their exchange rate. The second function `atLeast` takes a minimum salary and a currency code and retrieves the names of the employees earning at least the minimal salary. Since the salary is stored in dollars in the database, the `getRate` function is used to perform the conversion.

In BOLDR, `subset` is overloaded to build an intermediate query representation if applied on an external source reference. The first call to `atLeast(2000, "USD")` builds a query and captures the variables in the local scope. When `executeQuery` is called, then (i) the intermediate query is normalized, inlining all bound variables with their values; (ii) the normalized query is translated into the target database language (here SQL); and (iii) the resulting query is evaluated in the database and the results are sent back. After normalization and translation, the query generated for the first call on Line 14 is:

```sql
SELECT name FROM employee WHERE sal >= 2000 * 
(SELECT rate FROM change WHERE rfrom = "USD" AND rto = "EUR")
```
Therefore, BOLDR not only supports user-defined functions (UDFs) in queries, it also merges subqueries together to create fewer and larger queries, thus benefiting from database optimizations and avoiding the “query avalanche” phenomenon [Grust et al. 2010].

While similar approaches exist (see Section 8 on related work), BOLDR outperforms them on UDFs that cannot be completely translated. For instance, consider:

```r
getRate = function(rfrom, rto) {
  rate = c("USD", "JPY", "EUR", "JPY", "EUR", "USD")
  if (rfrom == rto) 1
  else subset(t, cfrom == rfrom & cto == rto, c(rate))
}
```

This function builds an in-memory data frame using the built-in function `data.frame`. BOLDR cannot translate it to SQL since it calls the underlying runtime, so instead it generates the following query:

```sql
SELECT name FROM employee WHERE sal >= 2000 * 
(SELECT rate FROM change WHERE rfrom = "USD" AND rto = "EUR")
```
where the string “@…” is a reference to a closure for `getRate`.

Mixing different data sources is supported, although less efficiently. For instance, we could refer to an HBase table in the function `getRate`. BOLDR would still be able to evaluate the query by sending a subquery to both the HBase and PostgreSQL databases, and by executing in main memory what could not be translated.

The general flow of query evaluation in BOLDR is described in Figure 1. During the evaluation (1) of a host program, QIR terms are lazily accumulated. Their evaluation, when triggered, is delegated to the QIR runtime (2) that normalizes (3) the QIR terms to defragment them, then translates (4) them to new QIR terms that contain database language queries (e.g., in SQL). Next, the pieces of these terms are evaluated where they belong, either in main-memory (5) or in a database (6). “Frozen” host language expressions occurring in these terms are evaluated either by the runtime of the host language that called the QIR evaluation (6), or in the runtime embedded in a target database (8). Results are then translated from the database to QIR (9), then from QIR to the host language (10).

**Overview and Contributions.** In this work, we introduce BOLDR, a multi-language framework for integrated queries with a unique combination of features such as the possibility of executing user-defined functions in databases, of partially evaluating and merging distinct query fragments, and of defining single queries that operate on data from different data sources. Our technical developments are organized as follows. We first give a formal definition of QIR (Section 3). We then present the translation from QIR to query languages and focus on a translation from QIR to SQL, as well as a type system ensuring that well-typed queries translate into SQL and are avalanche-free (Section 4). We continue by presenting a normalization procedure on the QIR to optimize the translation of a query (Section 5). We next describe the translation from the host language R to QIR (Section 6). Finally, we discuss experimental results (Section 7) of our implementation that supports the languages R and SimpleLanguage and the databases PostgreSQL, HBase and Hive. We show that queries generated by BOLDR perform on a par
with hand-written ones, and that UDFs can be efficiently executed in a corresponding runtime embedded in a target database.

2 DEFINITIONS

We give some basic definitions used throughout the presentation.

Definition 2.1 (Host language). A host language \( \mathcal{H} \) is a 4-tuple \((\mathcal{E}_H, \mathcal{V}_H, \mathcal{O}_H, \delta_H)\) where:

- \( \mathcal{E}_H \) is a set of syntactic expressions
- \( \mathcal{I}_H \) is a set of variables, \( \mathcal{I}_H \subseteq \mathcal{E}_H \)
- \( \mathcal{V}_H \) is a set of values
- \( \delta_H : 2^{\mathcal{I}_H \times \mathcal{V}_H} \times \mathcal{E}_H \rightarrow 2^{\mathcal{I}_H \times \mathcal{V}_H} \times \mathcal{V}_H \) is the evaluation function

We abstract a host language \( \mathcal{H} \) by reducing it to its bare components: a syntax given by a set of expressions \( \mathcal{E}_H \), a set of values \( \mathcal{V}_H \), and a set of variables \( \mathcal{I}_H \). Lastly, we assume that the semantics of \( \mathcal{H} \) is given by a partial evaluation function \( \delta_H \). This function takes an evaluation environment (a set of pairs of variables and values, ranged over by \( \sigma \)) and an expression and returns a new environment and a value resulting from the evaluation of the input expression. To integrate a host language we need to be able to manipulate syntactic expressions of the language, inspect and build environments, and have access to an interpreter for the language.

Definition 2.2 (Database language). A database language \( \mathcal{D} \) with support for a host language \( \mathcal{H} \) is a 4-tuple \((\mathcal{E}_D, \mathcal{V}_D, \mathcal{O}_D, \delta_D)\) where:

- \( \mathcal{E}_D \) is a set of syntactic expressions
- \( \mathcal{V}_D \) is a set of values
- \( \mathcal{O}_D \) is a set of supported data operators
- \( \delta_D : 2^{\mathcal{I}_H \times \mathcal{V}_H} \times \mathcal{E}_D \rightarrow 2^{\mathcal{I}_H \times \mathcal{V}_H} \times \mathcal{V}_D \) is the evaluation function

Similarly to host languages, we abstract a database language \( \mathcal{D} \) as a syntax \( \mathcal{E}_D \), a set of values \( \mathcal{V}_D \), and an evaluation function \( \delta_D \) which takes an \( \mathcal{H} \) environment and a database expression and returns a new \( \mathcal{H} \) environment and a database value. Such an evaluation function allows us to abstract the behavior of modern databases that support queries containing foreign function calls. Last, but not least, a database language exposes the set \( \mathcal{O}_D \) of data operators it supports, which will play a crucial role in building queries that can be efficiently executed by a database back-end.

3 QUERY INTERMEDIATE REPRESENTATION

3.1 Core calculus

In this section, we define our Query Intermediate Representation, a \( \lambda \)-calculus with recursive functions, constants, basic operators, data structures, data operators, and foreign language expressions.

Definition 3.1. Given a countable set of variables \( \mathcal{I}_{QIR} \), we define the set of QIR expressions, denoted by \( \mathcal{QIR} \) and ranged over by \( q \), as the set of finite productions of the following grammar:

\[
q ::= x \mid \text{fun}(x) \rightarrow q \mid q \circ q \mid op(q, \ldots, q) \mid \text{if } q \text{ then } q \text{ else } q \\
\}
\]

where \( \mathcal{H} \) is a host language.

Besides lambda-terms, QIR expressions include constants (integers, strings, ...), and some built-in operations (arithmetic operations, ...). The data model consists of records and sequences. Records are deconstructed through field projections. Sequences are deconstructed by the list matching destructor whose four arguments are: the list to destruct, a pattern that binds the head and the tail of the list to variables, the term to evaluate (with the bound variables in scope) when the list is not empty, and the term to return when the list is empty. The new additions to these mundane constructs are database operators and host language expressions. A database operator \( o(q_1, \ldots, q_n | q'_1, \ldots, q'_m) \) is similar to the notion of operator in the relational algebra. Its arguments are divided in two groups: the \( q_i \) expressions are called configurations and influence the behavior of the operator; the \( q'_j \) expressions are the sub-collections that are operated on. Finally, a host expression \( \mathcal{H}(\sigma, e) \) is an opaque construct that contains an evaluation environment \( \sigma \) and an expression \( e \) of the host language \( \mathcal{H} \). We use the following syntactic shortcuts:

- \( [q_1, \ldots, q_n] \) stands for \( q_1, \ldots, q_n \)
- \( \text{fun}(x_1, \ldots, x_n) \rightarrow q \) stands for \( \text{fun}(x_1) \rightarrow (\ldots (\text{fun}(x_n) \rightarrow q)) \)
- \( q \circ (q_1, \ldots, q_n) \) stands for \( (\ldots (q \circ q_1) \ldots) \circ q_n \)

Functions can be defined recursively by using the recursion variable that indexes the \( \text{fun} \) keyword, that we omit when useless.

Definition 3.2 (Reduction rules). Let \( \rightarrow^r \subseteq \mathcal{QIR} \times \mathcal{QIR} \) be a reduction relation for basic operators and \( \rightarrow^c \subseteq \mathcal{E}_\mathcal{QIR} \times \mathcal{E}_\mathcal{QIR} \) be the reduction relation defined by:

\[
\begin{align*}
\text{fun}(x) & \rightarrow q_1, \text{if } \text{fun}(x) \rightarrow q_1, x \rightarrow q_2 \\
\text{if true then } q_1 \text{ else } q_2 & \rightarrow q_1 \\
\text{if false then } q_1 \text{ else } q_2 & \rightarrow q_2 \\
\vdots \end{align*}
\]

Crucially, embedded host expressions as well as database operator applications whose arguments are all reduced are irreducible.
We next define how to interface host languages and databases with QIR. We introduce the notion of a database driver, a set of functions that translate values from one world to another.

**Definition 3.3 (Language driver).** Let \( \mathcal{H} \) be a host language. A language driver for \( \mathcal{H} \) is a 3-tuple \((\mathcal{H}, \mathcal{D}, \mathcal{Q})\) of total functions such that:

- \( \mathcal{H}^{\text{Exp}} : \mathcal{E}_{\mathcal{H}} \rightarrow \mathcal{Q}_{\mathcal{H}} \) takes an \( \mathcal{H} \) environment and an \( \mathcal{H} \) expression and translates the expression into QIR
- \( \mathcal{H}^{\text{Val}} : \mathcal{V}_{\mathcal{Q}} \rightarrow \mathcal{V}_{\mathcal{H}} \) translates QIR values to \( \mathcal{H} \) values
- \( \mathcal{H}^{\cdot} : \mathcal{V}_{\mathcal{Q}} \rightarrow \mathcal{V}_{\mathcal{H}} \cup \{\Omega\} \) translates \( \mathcal{H} \) values to QIR values where the special value \( \Omega \) denotes a failure to translate.

**Definition 3.4. (Database driver)** Let \( \mathcal{D} \) be a database language. A database driver for \( \mathcal{D} \) is a 3-tuple \((\mathcal{D}, \mathcal{Q}, \mathcal{V})\) of total functions such that:

- \( \mathcal{D}^{\text{Exp}} : \mathcal{E}_{\mathcal{D}} \rightarrow \mathcal{Q}_{\mathcal{D}} \) translates a QIR expression into \( \mathcal{D} \) expressions
- \( \mathcal{D}^{\text{Val}} : \mathcal{V}_{\mathcal{D}} \rightarrow \mathcal{V}_{\mathcal{D}} \cup \{\Omega\} \) translates QIR values to \( \mathcal{D} \) values
- \( \mathcal{D}^{\cdot} : \mathcal{V}_{\mathcal{D}} \rightarrow \mathcal{V}_{\mathcal{D}} \cup \{\Omega\} \) translates \( \mathcal{D} \) values to QIR values where the special value \( \Omega \) denotes a failure to translate.

We are now equipped to define the semantics of QIR terms, extended to host expressions and database operators.

**Definition 3.5 (Extended QIR semantics).** Let \( \mathcal{H} \) be a host language, \((\mathcal{H}^{\text{Exp}}, \mathcal{H}^{\text{Val}}, \mathcal{H}^{\cdot})\) a driver for \( \mathcal{H}, \mathcal{D} \) a database language, and \((\mathcal{D}^{\text{Exp}}, \mathcal{D}^{\text{Val}}, \mathcal{D}^{\cdot})\) a driver for \( \mathcal{D} \). We define the extended semantics \( \sigma, q \Rightarrow \sigma', q' \) of QIR by the following set of rules:

\[
\sigma, q \Rightarrow \sigma', q' \quad \text{where} \quad \text{as many subterms as possible have been translated into native query languages}
\]

Since QIR is an intermediate language from a host language to a database language, the evaluation of QIR terms will always be initiated from the host language runtime. It is therefore natural for the extended semantics to evaluate a QIR term in a given host language environment. If this QIR term is neither a database operator nor a host language expression, then the simple semantics of Definition 3.2 is used to evaluate the term, otherwise the extended semantics of Definition 3.5 is used. Host expressions are evaluated using the evaluation relation of the host language in the environment formed by the union of the current running environment and the captured environment. This allows us to simulate the behavior of most dynamic languages (in particular R, Python, and JavaScript) that allow a function to reference an undefined global variable as long as it is defined when the function is called. Last, but not least, the evaluation of a database operator consists in (i) finding a database language that supports this operator, (ii) use the database driver for that language to translate the QIR term into a native query, (iii) use the evaluation function of the database to evaluate the query, and (iv) translate the results back into QIR.
What we obtain is a simply typed λ-calculus extended with records and sequences without recursive functions, which entails strong correctness requirements on the configuration arguments since we limit ourselves to pure expressions, and by restricting the data operators to take as arguments and return expressions that have basic types.

Theorem 4.1 (Subject reduction). Let \( q \in \text{QIR} \) and \( \Gamma \) an environment from QIR variables to QIR types. If \( \Gamma \vdash q : T \), and \( q \rightarrow q' \), then \( \Gamma \vdash q' : T \).

Theorem 4.2 (Soundness of translation). Let \( q \in \text{QIR} \) such that \( \emptyset \vdash q : T \), and \( q \rightarrow^* v \), and \( v \) is in normal form. If \( T \equiv B \) or \( T \equiv R \) or \( T \equiv \text{list} \) then \( v \rightarrow s, \text{SQL} \).

Proofs of these theorems are detailed in Appendix B in which we show that typable QIR terms have particular normal forms imposed by their type that can be translated into SQL expressions.

5 QIR HEURISTIC NORMALIZATION

Our guarantees only hold for a QIR query targeting one database supporting SQL. However, a QIR term may mix several databases or use features that escape the hypotheses of Theorem 4.2. In particular, outside these hypotheses, we cannot guarantee the termination of the normalization. We are therefore stuck between two unsatisfactory options: either (i) trying to normalize the term (to fully reduce all applications) and yield the best possible term w.r.t. query translation but risk diverging, or (ii) translate the term as-is at the risk of introducing query avalanches. We tackle this problem with a heuristic normalization procedure that tries to reduce QIR terms enough to produce a good translation by combining subqueries.

To that end, we define a measure of "good" QIR terms, and ask that each reduction step taken yields a term with a smaller measure. To formally define this measure, we first introduce a few concepts.

Definition 5.1 (Compatible data operator application). Let \( D \) be the set of database languages. A QIR data operator \( o(q_1, \ldots, q_n \mid q_1', \ldots, q_m') \) is a compatible operator application if and only if:

\[
\exists D \in \mathcal{D}, e_1, \ldots, e_m \in D \text{ s.t. } \exists q \in \text{QIR} \text{ s.t. } q \rightarrow^* (\text{eval}^D(e_1) \ldots (\text{eval}^D(e_m))) \}
\]

Intuitively, a compatible data operator application is one where the configuration arguments are in a form that is accepted by the specific translation of the database language \( D \). We now define the related notion of fragment.

Definition 5.2 (Fragment). A fragment \( F \) is a subterm of a QIR term \( q \) such that \( q = C[T(q_1, \ldots, q_{i-1}; F[e_1, \ldots, e_n]; q_{i+1}, \ldots, q_j)] \) where \( C \) is a one-hole context made of arbitrary expressions; \( T \) is a non-compatible \( j \)-ary expression; \( q_1, \ldots, q_{i-1}, q_{i+1}, \ldots, q_j \) and \( F \) are the children of \( T \); \( F \) is an \( n \)-hole context made only of compatible operators applications of the same database language \( D \); and all \( e_1, \ldots, e_n \) have head expressions that are not compatible.
Op the execution time of the whole process compared to tasks such as measure that the normalization represents a negligible fraction of step (e.g., choosing those with more arguments), or which maximalization such as choosing which reduction rule to apply at each as a guide through the reduction of a QIR term: it applies all possible of compatible \( q \). We now define a measure of “good” QIR terms.

This measure works as follows. During a step of reduction of a Definition 5.3 (measure). We recall that, in \( \Gamma \), \( e \) binds the values of each column of the row to a variable of \( \Sigma, \ldots, \sigma_n \) being the assignment operator as well as \( \sigma \) or a newline; structured data types such as vectors and tables.

We now highlight how data frames are manipulated in standard \( \Sigma \). As mentioned in Section 1, the function filters a data frame:

6 FROM A HOST LANGUAGE TO QIR

In this section, we outline how to interface a general-purpose programming language with BOLDR. As explained in Section 1, our aim is to allow programmers to write queries using the constructs of the language they already master. Therefore, instead of extending the syntax of the language, we extend its runtime by reusing existing functionalities, in particular by overloading existing functions.

We use the language R as example of a host language to show how to implement a language driver. The full details of our treatment to R can be found in Appendix C. R programs include class-first functions; side effects ("=" being the assignment operator as well as the variable definition operator); sequences of expressions separated by "|" or a newline; structured data types such as vectors and tables with named columns (called \textit{data frames} in R’s lingo); and static scoping as it is usually implemented in dynamic languages (e.g., as in Python or JavaScript) where identifiers that are not in the current static scope are assumed to be \textit{global} identifiers even if they are undefined when the scope is created. For instance, the R program:

\[ \texttt{f = function(x) \{ x + y \}; y = 3; z = f(2);} \]

is well-defined and stores \( z \) in \( x \) (but calling \( r \) before defining \( y \) yields an error). We next define the core syntax of R.

\[ \text{Definition 6.1. The set Eq of expressions (e) and values (v) of R are generated by the following grammars:} \]

\[ e ::= c \mid x \mid \text{function}(x, \ldots, x)[e] \mid (e, \ldots, e) \mid \text{op } e \ldots e \mid x = e \mid e; e \mid \text{if } (e) \text{ e else } e \]

\[ v ::= c \mid \text{function}_0(x, \ldots, x)[e] \mid c(v, \ldots, v) \]

where \( c \) represents constants, \( x \in \text{IR} \), and \( \sigma \in \{ \text{bool} \}^n \) is the environment of the closure.

We recall that, in R, \( c(e_1, \ldots, e_n) \) builds a vector. Definition 6.1 only defines expressions that can be translated to QIR. Expressions not listed in the definition are translated into host expression nodes.

We now highlight how data frames are manipulated in standard R. As mentioned in Section 1, the \texttt{subset} function filters a data frame:

\[ \text{subset}(t, \text{sal} > \text{getRate("USD", cur), c(name))} \]

This function returns the data frame given as first argument, filtered by the predicate given as second argument, and restricted to the columns listed in the third argument. Note that before resolving its second and third arguments, and for every row of the first argument, \texttt{subset} binds the values of each column of the row to a variable of
the corresponding name. This is why in our example the variables `sal` and `name` occur free: they represent columns of the data frame `t`.

The join between two data frames is implemented with the function `merge`. We recall that the join operation returns the set of all combinations of rows in two tables that satisfy a given predicate.

To integrate R with BOLDR, we define two builtin functions:

- `tableRef` takes the name of a table and the name of the database the table belongs to, and returns a reference to the table.
- `executeQuery` takes a QIR expression, closes it by binding its free variables to the translation to QIR of their value from the current R environment, sends it to the QIR runtime for evaluation, and translates the results into R values.

We also extend the set of values `V_R`:

\[ V_R \supseteq \ldots | \text{tableRef}(t, \ldots, v) | q_\sigma \]

where `q_\sigma` are QIR closure values representing queries associated with the R environment `\sigma` used at their definition.

The functions `subset` and `merge` are overloaded to call the translation \( R \rightarrow \text{EXP} \) on themselves if their first argument is a reference to a database table created by `tableRef`, yielding a QIR term `q` to which the current scope is affixed, creating a QIR closure `q_\sigma`. Free variables in `q_\sigma` that are not in `\sigma` are global identifiers whose bindings are to be resolved when `q_\sigma` is executed using `executeQuery`.

We now illustrate the whole process on the introductory example of Section 1.

### Evaluation of the query expression: When an expression recognized as a query is evaluated, it is translated to QIR (using Definition C.2). In the introductory example, the function call

\[ \text{richUSPeople} = \text{atLeast}(2000, \text{"USD"}) \]

triggers the evaluation of the function `atLeast`:

\[ \text{atLeast} = \text{function}(\text{minSalary}, \text{cur}) \{ \text{\# table employee has two columns: name, sal} \]
\[ \text{t} = \text{tableRef}(\text{"employee"}, \text{\"PostgreSQL\")} \]
\[ \text{subset}(t, \text{sal} \geq \text{minSalary} \ast \text{getRate}(\text{\"USD"}, \text{cur}), \text{c}(\text{name})) \]

in which the function `subset` (Line 12) is evaluated with a table reference as first argument, and is therefore translated into a QIR expression. `richUSPeople` is then bound to the QIR closure value:

\[ \text{Project}(\text{fun}(t)\rightarrow \{ \text{name}:t \cdot \text{name} \}) \]
\[ \text{Filter}(\text{fun}(e)\rightarrow e \cdot \text{sal} \geq \text{minSalary} \ast \text{getRate}(\text{\"USD"}, \text{cur}) \mid \text{From(employee)}) \]
\[ (\text{minSalary}=2000, \text{getRate}=-\text{function}_e(\text{rfrom}, \text{to})(\ldots), \text{cur}==\text{\"USD"}) \]

### Query execution: A QIR closure is executed using the function `executeQuery`. In our example, this happens at Line 16 and 17:

\[ \text{print(executeQuery(richUSPeople))} \]
\[ \text{print(executeQuery(richEURPeople))} \]

`executeQuery` then resolves each free variable by applying them to the translation to QIR of their value in the R environment:

\[ \text{(fun(getRate)\rightarrow)} \]
\[ \text{(fun(minSalary, cur)\rightarrow} \]
\[ \text{Project(fun(t)\rightarrow \{ name:t \cdot name \})} \]
\[ \text{Filter(fun(e)\rightarrow e \cdot sal \geq (e \cdot \text{sal}, \ast (\text{minSalary}, \text{getRate}(\text{\"USD"}, \text{cur})) \mid \text{From(employee)}) \]
\[ (2000, \text{\"USD\")} \]
\[ \text{(func(rfrom, to)\rightarrow \ldots)} \]

Next, the QIR runtime is called, and the query is normalized to:

\[ \text{Project(fun(t)\rightarrow \{ name:t \cdot name \})} \]
\[ \text{Filter(fun(e)\rightarrow \geq (e \cdot \text{sal}, 2000) \mid \text{From(employee)})} \]

then translated to SQL as:

\[ \text{SELECT T.name AS name FROM (} \]
\[ \text{SELECT * FROM (SELECT * FROM employee) AS E WHERE E.sal >= 2000 ) AS T} \]

This query is sent to PostgreSQL, and the results are translated back to QIR using PostgreSQL-VAL, then to R using VAL-R.

### 7 IMPLEMENTATION AND RESULTS

#### Implementation

BOLDR consists of QIR, host languages, and databases. To evaluate our approach, we implemented the full stack, with R and SimpleLanguage as host languages and PostgreSQL, HBase and Hive as databases. Table 1 gives the numbers of lines of Java code for each component to gauge the relative development effort needed to interface a host language or a database to BOLDR. All developments are done in Java using the Truffle framework.

<table>
<thead>
<tr>
<th>Component</th>
<th>L.o.c.</th>
<th>Remark</th>
</tr>
</thead>
<tbody>
<tr>
<td>FastR/SimpleLanguage</td>
<td>17300/</td>
<td>not part of the framework</td>
</tr>
<tr>
<td>Detection of queries</td>
<td>600</td>
<td>modification of builtins/operators</td>
</tr>
<tr>
<td>R to QIR /SL to QIR</td>
<td>750</td>
<td>the translation of Section 6</td>
</tr>
<tr>
<td>QIR</td>
<td>4000</td>
<td>norm/generic translation/evaluator</td>
</tr>
<tr>
<td>QIR to SQL /HBase language</td>
<td>500</td>
<td>the translation SQL / HBase</td>
</tr>
<tr>
<td>PostgreSQL /HBase / Hive binding</td>
<td>150 / 100</td>
<td>low-level interface</td>
</tr>
</tbody>
</table>

### Table 1: BOLDR components and their sizes in lines of code.

As expected, the bulk of our development lies in the QIR (its definition and normalization) which is completely shared between all languages and database backends. Compared to its 4000 L.o.c., the development cost of languages or database drivers, including translations to and from QIR is modest (between 700 and 1000 L.o.c.).

Even though our main focus is on Truffle-based languages, on which we have full control over their interpreters, all our requirements are also met by the introspection capabilities of modern dynamic languages. For instance, in R, the `environment` function returns the environment affixed to a closure as a modifiable R value, the body function returns the body of a closure as a manipulable abstract syntax tree, and the `formals` function returns the modifiable names of the arguments of a function. These introspection capabilities could be used to achieve an even more seamless integration.

**Experiments.** The results of our evaluation\(^1\) are reported in Table 2. Queries named `TPC-H-n` are SQL queries taken from the TPC-H performance benchmark [TPC 2017]. These queries feature joins, nested queries, grouping, ordering, and various arithmetic subexpressions. Table 2A and 2B illustrate how our approach fare against hand-written SQL queries. Each row reports the expected cost (in disk page fetches as reported by the `EXPLAIN ANALYZE` commands) as well as the actual execution time on a 1GB dataset. Row SQL represents the hand-written SQL queries, Row SQL+UDFs represents the same SQL queries where some subexpressions are expressed as function calls of stored functions written in PL/SQL. Row R represents the SQL queries generated by BOLDR from equivalent R.

\(^1\)The test machine was a PC with Ubuntu 16.04.2 LTS, kernel 4.4.0-83, with the latest master from the Truffle/Graal framework and PostgreSQL 9.5, Hive 2.1.1, and HBase 1.2.6 all with default parameters.
expressions, and Row R+UDFs represents the same SQL queries as in Row SQL+UDFs generated by BOLDR from equivalent R expressions with R UDFs. Lastly, for R+++, we added untranslatable subexpressions kept as host language nodes to impose a call to the database embedded R runtime. The results show that we can successfully match the performances of SQL with Row R, and that BOLDR outperforms PostgreSQL in Row R+UDFs against Row SQL+UDFs. This last result comes from the fact that PostgreSQL is not always able to inline function calls, even for simple functions written in PL/SQL. In stark contrast, no overhead is introduced for a SQL query generated from an R program, since the normalization is able to inline function calls properly, yielding a query as efficient as a hand-written one. As an example, the TPCH-15 query was written in R+UDFs as:

```sql
SELECT * FROM movie WHERE year > 1974 ORDER BY title
```

BOLDR was able to inline this query, whereas the equivalent in SQL+UDFs could not be inlined by the optimizer of PostgreSQL.

Table 2 illustrates the overhead of calling the host language evaluator from PostgreSQL by comparing the cost of a non-inlined pure PL/SQL function with the cost of the same function implemented in a host expression within the query. While incur a high overhead, it remains reasonable even for expensive queries (such as TPCH-1) compared to the cost of network delays that would happen otherwise since host expressions represent expressions that are impossible to inline or to translate in the database language.

Table 2.C illustrates the overhead of calling the host language evaluator from Hive against a pure inlined Hive query. For instance

```sql
SELECT * FROM movie WHERE year > 1974 ORDER BY title
```

against

```sql
SELECT * FROM movie WHERE R.APPLY('@...', array(year))ORDER BY title
```

where '@...' is the serialization of an R closure, and R.APPLY is a function we defined that applies an R closure to an array of values from Hive (including the necessary translations between Hive, QIR, and R). The results are that with one (Query 1/2) or two (Query 3) calls to the external language runtime, the overhead is negligible compared to the execution of the query in Map/Reduce.

Table 2.D gives the performances of queries mixing two data sources between a PostgreSQL, a HBase, and a Hive database. We executed the example in the Introduction and varied the data sources for the functions getRate and atLeast. In the current implementation, a join between tables from different databases is performed on the client side (see our future work in the Conclusion), therefore the queries in which the two functions target the same database perform better, since they are evaluated in a unique database implying less network delays and less work on the client side.

## 8 RELATED WORK

The work in the literature closest to BOLDR is T-LINQ and P-LINQ by Cheney et al. [2013] which subsumes previous work on LINQ and Links and gives a comprehensive “practical theory of language integrated queries”. In particular, it gives the strongest results to date for a language-integrated queries framework. Among their contributions stand out: (i) a quotation language (a λ-calculus with list comprehensions) used to express queries in a host language, (ii) a normalization procedure ensuring that the translation of a query cannot cause a query avalanche, (iii) a type system which guarantees that well-typed queries can be normalized, (iv) a general recipe to implement language-integrated queries and (v) a practical implementation that outperforms Microsoft’s LINQ. Some parts of our work are strikingly similar: our intermediate representation is a λ-calculus using reduction as a normalization procedure. However, our work diverges radically from their approach because we target a different kind of host languages. T-LINQ requires a pure host language, with quotation and anti-quotation support and a type-system. Also, T-LINQ only supports one (type of) database per query and a limited set of operators (essentially, selection, projection, and join, expressed as comprehensions). While definitely possible, extending T-LINQ with other operators (e.g., “group by”) or other data models (e.g., graph databases) seems challenging since their normalization procedure hard-codes in several places the semantics of SQL. The host languages we target do not lend themselves as easily to formal treatment, as they are highly dynamic, untyped, and impure programming languages. We designed BOLDR to be target databases agnostic, and to be easily extendable to support new languages and databases. We also endeavored to lessen the work of driver implementers (adding support for a new language or database) through the use of embedded host language expressions, which take advantage of the capability of modern databases to execute foreign code. This contrasts with LINQ where adding new back-ends is known to be a difficult task [Eini 2011]. Lastly, we obtained formal results corresponding to those of T/P-LINQ by grafting a specific SQL type system on our framework.

QIR is not the first intermediate language of its kind. While LINQ proposes the most used intermediate query representation, recent work by Ong et al. [2014] introduced SQL+*, an intermediary query representation whose goal is to subsume SQL and NoSQL. In this work, a carefully chosen set of operators is shown to be sufficient...
to express relational queries as well as NoSQL queries (e.g., queries over JSON databases). Each operator supports configuration options to account for the subtle differences in semantics for distinct query languages and data models (treatment of the special value NULL, semantics of basic operators such as equality, . . . ). In opposite, we chose to let the database expose the operators it supports in a driver.

Grust et al. [2010] present an alternative compilation scheme for LINQ, where SQL and XML queries are compiled into an intermediate table algebra expression that can be efficiently executed in any modern relational database. While this algebra supports diverse querying primitives, it is designed to specifically target SQL databases, making it unfit for other back-ends.

Our current implementation of BOLDR is at an early stage and, as such, it suffers several shortcomings. Some are already addressed in existing literature. First, since we target dynamic programming languages, some forms of error cannot be detected until query evaluation. This problem has been widely studied and, besides T-LINQ, works such as SML# [Ohori and Ueno 2011] or ScalaDB [Garcia et al. 2010] use the static type system of the language to ensure the absence of a large class of runtime errors in generated queries. Second, our treatment of effects is rather crude. Local side effects, such as updating mutable references scoped inside a query, work as expected while observable effects, such as reading from a file on host machine memory, is unspecified behavior. The work of Cook and Wiedermann [2011] shows how client-side effects can be re-ordered and split apart from queries. Third, at the moment, when two sub-queries target different databases, their aggregation is done in the QIR runtime. Costa Seco et al. [2015] present a language which allows manipulation of data coming from different sources, abstracting their nature and localization. A drawback of their work is the limitation in the set of expressions that can be handled. Our use of arbitrary host expressions would allow us to circumvent this problem.

9 CONCLUSION AND FUTURE WORK

We presented BOLDR, a framework that allows programming languages to express complex queries containing application logic such as user-defined functions. These queries can target any source of data as long as it is interfaced with the framework, more precisely, with our intermediate language QIR. We provided methods for programming languages and databases to interface with QIR, as well as an implementation of the framework and interfaces for R, SimpleLanguage, PostgreSQL, HBase, and Hive. We described how QIR reduces and partially evaluates queries in order to take the most of database optimizations, and showed that BOLDR generates queries performing on a par with hand-written SQL queries.

Future work includes the creation of a domain-specific language to define translations from QIR to database languages, leaving the implementation details to the language itself, with the associated gains of speed, clarity, and concision. Currently, queries targeting more than one data sources are partially executed in the host language runtime. We plan to determine when such queries could be executed efficiently in one of the targeted data sources instead. For instance, in a join between two distinct data sources, it could be more efficient to send data from one data source to the other that will complete the join. ORMs and LINQ can type queries since they know the type of the data source. BOLDR cannot do it yet since QIR queries may contain dynamic code, and we do not want to type-check the whole host language. While we cannot foresee any general solution, we believe that to exploit any type information available we could use gradual typing [Siek and Taha 2006], a recent technique blending static and dynamic typing in the same language. In particular, we would be able to use type information from database schemas (when available) to infer types for the queries.

REFERENCES


Appendices

A QIR AS A DATABASE LANGUAGE

An important design decision of any intermediate query representation is the set of supported database operators. The choice might prove to be difficult due to the following conflicting aspects:

• an operator may be specific to a particular data model (e.g., computing the transitive closure in a graph database);
• an operator may be generic enough but not natively supported
  by some back-ends (NoSQL databases usually do not support
  join operations).

The set of operators exposed by the intermediate representation
should be broad enough so that the end users do not have to re-
implement operators in host languages, and generic enough so
that translating queries from the intermediate representation to a
database representation stays manageable.

To experiment with this vast design space, we equip the QIR
with a particular database language, dubbed MEM. MEM shares its
values and expressions with QIR, and its data operators constitute
a first attempt at defining a core set of operators that should be
implemented by BOLDR even though some back-ends may not
support them natively.

**Definition A.1 (MEM database language).** The MEM language
MEM = (E_{MEM}, V_{MEM}, O_{MEM}, \text{MEM}) is defined by:

- E_{MEM} = E_{QIR}
- O_{MEM} = \{Filter, Project, Join\}
- V_{MEM} is the set of finite terms generated by the grammar
  \[ V : \left\{ \text{fun}\langle (x) \rightarrow q \mid c \mid \{1 : v, \ldots, l : v\} \mid \{\}_2 \mid v : v \mid \mathbb{N}\sigma(v, e) \right\} \]
- MEM is the operational semantics of the QIR (relation \( \rightarrow \) in Definition 3.2).

Of course the semantics of the MEM target language
would be incomplete without the definition of a driver for MEM:

**Definition A.2 (MEM driver).** The driver for the MEM database
language is the 3-tuple \(( \text{EXP}^{MEM}(), \text{VAL}^{MEM}(), \text{MEM}^{\rightarrow}() )\) of total functions such that:

- \( \text{VAL}^{MEM}(\_): V_{QIR} \rightarrow V_{MEM} \cup \{\Omega\} \) is the identity function.
- \( \text{MEM}^{\rightarrow}(\_): V_{QIR} \rightarrow V_{MEM} \cup \{\Omega\} \) is the identity function.
- \( \text{EXP}^{MEM}(\_): E_{QIR} \rightarrow E_{MEM} \) is defined by case as

\[
\text{EXP}^{MEM}(\text{Filter}(f \mid l)) = \left(\text{fun}_{\text{filter}}(l) \mapsto h \mid z \mapsto ? \text{ if } f \text{ then } h \text{ else } (\text{filter } t \mapsto [\_] \mid l)\right)
\]

\[
\text{EXP}^{MEM}(\text{Project}(f \mid l)) = \left(\text{fun}_{\text{project}}(l) \mapsto h \mid z \mapsto ? \text{ if } f \text{ then } h \text{ else } (\text{project } t \mapsto [\_] \mid l)\right)
\]

\[
\text{EXP}^{MEM}(\text{Join}(f_1, f_2 \mid l_1, l_2)) = \left(\text{fun}_{\text{join}}(l) \mapsto h \mid z \mapsto ? \text{ if } f \text{ then } h \text{ else } (\text{join } t_1 \mapsto [\_] \mid l_1)\right)
\]

The definition of the operators supported by MEM is straightforward
and well-known to functional programmers. Filter \( f \mid l \) is
implemented as a recursive function that iterates through an input
list \( l \) and keeps elements for which the input predicate \( f \) returns
true. Project \( f \mid l \) (also known as map) applies the function \( f \)
every element of \( l \) and returns the list of the outputs of \( f \).
Lastly the Join \( f_1, f_2 \mid l_1, l_2 \) operator is defined as a double iteration which
tests for each record element \( h_1 \) of \( l_1 \) and each record element \( h_2 \)
of \( l_2 \) if the pair \( h_1, h_2 \) satisfies the join condition given by the function
\( f_2 \), then the two records are concatenated and added to the result.
Finally, the function \( f_1 \) is applied to every element to obtain the
final result. For simplicity, we express Join in terms of Project
and Filter, but we could have given a direct definition.

**B QIR TO SQL**

In this section, we give technical details of our translation
from QIR to SQL. The set of supported operators of the translation is:

\[ \text{OSQL} = \{\text{Project}, \text{From}, \text{Filter}, \text{GroupBy}, \text{Sort}, \text{Join}, \text{Limit}\} \]

The semantics of Filter, Project, and Join was described in
Section A. From \( n \) loads the contents of a table from its name,
GroupBy \( f, agg \mid l \) partitions elements of \( l \) for which \( f \) returns
the same value into groups, and returns the list of the results of applying
agg to each group. Sort \( f \mid l \) sorts a collection \( l \) using a sorting
key returned by applying \( f \) to each element of the list. The specific
translation \( \text{EXP}^{QIR} \rightarrow \text{osql} \) is defined by the judgment \( q \Rightarrow e \) stating that
a QIR expression \( q \) can be translated into a SQL expression \( e \). The
derivation of this judgment is given by the rules in Figure 5.

Data operators are translated into their SQL equivalent. Constants
are translated using the translation function \( \text{VAL}^{QIR} \rightarrow \text{sql} \) provided
by the driver, identifiers are translated as they are. Field access is
handled by (SQL-field-simp) if the first argument is syntactically
an identifier, and by (SQL-field-cplx) otherwise. Basic operators
are translated into their SQL counterpart by rule (SQL-basic-op).
Conditional expressions are translated into the corresponding
CASE construct. Host language expressions are evaluated using a
BOLDR-provided function that calls the evaluator of the host language
in the database. Lastly, the (SQL-error) rule propagates errors
and ensures that the whole translation fails if one of the sub-cases fails.

Next we show that the type-system defined in Section 4.2 statically
detects QIR terms that can be soundly translated into SQL, that is,
QIR terms in which all subterms can be handled by our specific
translation. This property is formally stated by Theorem 4.2:

Let \( q \in E_{QIR} \) such that \( \Gamma \vdash q : T, q \rightarrow^* v, \) and \( v \) is in normal form. If \( T \equiv B \) or \( T \equiv R \) or \( T \equiv R \text{ list} \) then \( \nu \Rightarrow s, \text{SQL} \).

To prove this theorem, we proceed in three steps. First, we show
through the usual property of subject reduction that the normal
form \( v \) has the same type as \( q \). Second, we show that normal
forms of a given type have a particular shape. Lastly, we show by
case analysis on the translation rules that the translation can never
fail.

**SUBJECT-REDUCTION.** Let \( q \in E_{QIR} \) and \( \Gamma \) an environment from
QIR variables to QIR types. If \( \Gamma \vdash q : T, q \rightarrow q', \) then \( \Gamma \vdash q' : T \).
We prove the property by induction on the typing derivation.

- \( \text{fun}(x) \rightarrow q_1 \rightarrow q_2 : q_1 (f / \text{fun}(x) \rightarrow q_1, x / q_2) : T' \) to \( T \)

\[
\Gamma \vdash (\text{fun}(x) \rightarrow q_1) \rightarrow q_2 : T \quad \Gamma \vdash q_1 : T' \quad \Gamma \vdash q_2 : T
\]

- \( \text{if true then } q_1 \text{ else } q_2 : T \) to \( T \)

\[
\Gamma \vdash \text{true} : \text{bool} \quad \Gamma \vdash q_1 : T \quad \Gamma \vdash q_2 : T
\]

\[
\Gamma \vdash \text{if true then } q_1 \text{ else } q_2 : T
\]
Figure 5: Translation from QIR to SQL
The next step is to show that a normal form of QIR has a particular shape depending on its type.

Definition B.1. A normal form \( v \) of QIR is a finite production of the following grammar:

\[
\begin{align*}
v & ::= x \\
v & ::= \text{fun}^x(x) \rightarrow v \\
v & ::= \text{true} \quad \text{false} \\
v & ::= \emptyset \\
v & ::= \exists (v, \ldots, v) \\
v & ::= \lambda (v, \ldots, v) \\
\end{align*}
\]

We now isolate a subset of normal forms that are translatable into SQL, that is a set of normal forms for which the translation succeeds.

Definition B.2 (Translatable normal forms). We define translatable normal forms as the finite terms produced by the following grammar:

\[
\begin{align*}
s & ::= r:: | \text{r::s} | s@s | \text{Project} (\text{fun}^x(x) \rightarrow r | s) \\
s & ::= \text{From} (b) | \text{Filter} (\text{fun}^x(x) \rightarrow b | s) \\
s & ::= \text{Join} (\text{fun}^x(x) \rightarrow r, \text{fun}^y(y) \rightarrow b | s, s) \\
s & ::= \text{GroupBy} (\text{fun}^z(z) \rightarrow s, \text{fun}^y(y) \rightarrow r | s) \\
s & ::= \text{Sort} (\text{fun}^y(y) \rightarrow r | s) \\
r & ::= \text{true} \quad \text{false} \\
r & ::= 0 | 1 \\
r & ::= x \cdot 1 \\
r & ::= b \quad \text{if then else} \quad b \quad \ldots
\end{align*}
\]

Lemma B.3. Let \( v \) be a normal form of QIR and \( \Gamma \) an environment from QIR variables to QIR types such that \( \forall x \in \text{dom}(\Gamma), \Gamma(x) \equiv R \), and \( \Gamma \vdash v : T \), then:

- If \( T \equiv R \rightarrow R \rightarrow R \) then \( v \equiv \text{fun}^x(x) \rightarrow \text{fun}^y(y) \rightarrow r \)
- If \( T \equiv R \rightarrow \text{fun}^x(x) \rightarrow v \)
- If \( T \equiv \{l : T, \ldots, l : T\} \) then \( v \equiv x \) or \( \exists \{l : v, \ldots, l : v\} \)

Proof.

Hypothesis 1 (H1). \( v \) is in normal form

Hypothesis 2 (H2). \( \forall x \in \text{dom}(\Gamma), \Gamma(x) \equiv R \)

We prove the property by structural induction on the typing derivation of \( \Gamma \vdash v : T \). We proceed by case analysis on \( T \):

- If \( T \equiv B \) then if the last typing rule used in the proof of \( \Gamma \vdash v : B \) is the coercion rule, then \( \Gamma \vdash v : \{l : B\} \text{ list} \), so by induction hypothesis \( v \equiv s \) else
  - If \( v = x \) then impossible since \( \Gamma \vdash x : \Gamma(x) \equiv R \) by Hypothesis H2
  - If \( v = \text{fun}^x(x) \rightarrow \text{fun}^y(y) \rightarrow v \) then impossible since \( \Gamma \vdash \text{fun}^x(x) \rightarrow \text{fun}^y(y) \rightarrow v \)
  - If \( \Gamma \vdash v_1 \vdash v_2 \) then by the typing rule of the application: \( \Gamma \vdash v_1 \vdash T_1 \rightarrow T_2 \), so by induction hypothesis \( v_1 \equiv \text{fun}^x(x) \rightarrow v \), which is impossible by Hypothesis H1
- If \( v = c \) then \( v \equiv b \)
- If \( v = \text{op}(v_1, \ldots, v_n) \) then by the typing rule of operators: \( \forall i \in 1..n, \Gamma \vdash v_i : B_i \), so by induction hypothesis \( \forall i \in 1..n, v_i \equiv b \), so \( v = \text{op}(v_1, \ldots, v_n) \equiv \text{op}(b, \ldots, b) \) else
  - If \( v = \text{if v1 then v2 else v3} \) then by the typing rule of the conditional expression: \( \forall i \in 1..3, \Gamma \vdash v_i : B_i \), so by induction hypothesis \( \forall i \in 1..3, v_i \equiv b \), so \( v = \text{if v1 then v2 else v3} \equiv \text{if b then b else b} \equiv b \)
  - If \( v = \text{Project}(v_1 | v_2) \) then impossible since \( \Gamma \vdash \{l_1 : v_1, \ldots, l_n : v_n\} \), so by induction hypothesis either \( v' \equiv \{l_1 : v_1, \ldots, l_n : v_n\} \), which is impossible by Hypothesis H1, or \( v' \equiv x \), then \( v = v' \cdot l \equiv \exists x \cdot l \equiv b \)
  - If \( v = \text{From}(v') \) then impossible since \( \Gamma \vdash \text{From}(v') : R \text{ list} \)
  - If \( v = \text{Filter}(v_1 | v_2) \) then impossible since \( \Gamma \vdash \text{Filter}(v_1 | v_2) : R \text{ list} \)
  - If \( v = \text{Join}(v_1, v_2 | v_3, v_4) \) then impossible since \( \Gamma \vdash \text{Join}(v_1, v_2 | v_3, v_4) : R \text{ list} \)
  - If \( v = \text{GroupBy}(v_1, v_2 | v_3) \) then impossible since \( \Gamma \vdash \text{GroupBy}(v_1, v_2 | v_3) : R \text{ list} \)
  - If \( v = \text{Sort}(v_1 | v_2) \) then impossible since \( \Gamma \vdash \text{Sort}(v_1 | v_2) : R \text{ list} \)
- If \( T \equiv R \) then
  - If \( v = x \) then \( v \equiv r \)
  - If \( v = \text{fun}^x(x) \rightarrow \text{fun}^y(y) \rightarrow v \) then impossible since \( \Gamma \vdash \text{fun}^x(x) \rightarrow \text{fun}^y(y) \rightarrow v \)
  - If \( \Gamma \vdash v_1 \vdash v_2 \) then impossible for the same argument as for \( T \equiv B \)
  - If \( v = c \) then impossible since \( \Gamma \vdash c : \text{typeof}(c) \equiv B \)
if $v = op(v_1, \ldots , v_n)$ then impossible since
$\Gamma \vdash op(v_1, \ldots , v_n) : B$

if $v = \text{if } v_1 \text{ then } v_2 \text{ else } v_3$ then impossible since
$\Gamma \vdash \text{if } v_1 \text{ then } v_2 \text{ else } v_3 : B$

if $v = \{l_1 : v_1, \ldots , l_n : v_n\}$ then by the typing rule of the record constructor $\forall i \in \{1, \ldots , n\}, \Gamma \vdash v_i : B_i$, so by induction hypothesis $\forall i \in \{1, \ldots , n\}, v_i \equiv b$, so $v = \{l_1 : v_1, \ldots , l_n : v_n\} \equiv \{l_1 : b, \ldots , l_n : b\} \equiv r$

if $v = []$ then impossible since \texttt{[]} cannot be typed

if $v = v_1 :: v_2$ then impossible since $\Gamma \vdash v_1 :: v_2 : R \texttt{list}$

if $v = v' :: l$ then by the typing rule of the record destructor $\Gamma \vdash v' : \{l_1 : T_1, \ldots , l_n : T_n\}$, so by induction hypothesis either $v' \equiv \{l : v, \ldots , l : v\}$, which is impossible by Hypothesis H1, or $v' \equiv x$, but then by Hypothesis H2 $\Gamma \vdash v' \equiv x : \Gamma(x) \equiv R'$, so impossible since by the typing rule of the record destructor $\Gamma \vdash v' = l : B$

if $v = \text{Project}(v_1 \mid v_2)$ then impossible since
$\Gamma \vdash \text{Project}(v_1 \mid v_2) : R \texttt{list}$

if $v = \text{From}(v')$ then impossible since
$\Gamma \vdash \text{From}(v') : R \texttt{list}$

if $v = \text{Filter}(v_1 \mid v_2)$ then impossible since
$\Gamma \vdash \text{Filter}(v_1 \mid v_2) : R \texttt{list}$

if $v = \text{Join}(v_1, v_2 \mid v_3, v_4)$ then impossible since
$\Gamma \vdash \text{Join}(v_1, v_2 \mid v_3, v_4) : R \texttt{list}$

if $v = \text{GroupBy}(v_1, v_2 \mid v_3)$ then impossible since
$\Gamma \vdash \text{GroupBy}(v_1, v_2 \mid v_3) : R \texttt{list}$

if $v = \text{Sort}(v_1 \mid v_2)$ then impossible since
$\Gamma \vdash \text{Sort}(v_1 \mid v_2) : R \texttt{list}$

if $T \equiv R$ then
- if $v = x$ then impossible since $\Gamma \vdash x : \Gamma(x) \equiv R$ by Hypothesis H2
- if $v = \text{fun}^f(x) \rightarrow v'$ then impossible since
$\Gamma \vdash \text{fun}^f(x) \rightarrow v' : T_1 \rightarrow T_2$
- if $v = v_1 v_2$ then impossible for the same argument as for $T \equiv B$
- if $v = c$ then impossible since $\Gamma \vdash c : \text{typeof}(c) \equiv B$
- if $v = op(v_1, \ldots , v_n)$ then impossible since
$\Gamma \vdash op(v_1, \ldots , v_n) : B$
- if $v = v_1 \text{ if } v_2 \text{ else } v_3$ then impossible since
$\Gamma \vdash v_1 \text{ if } v_2 \text{ else } v_3 : B$
- if $v = [l_1 : v_1, \ldots , l_n : v_n]$ then impossible since
$\Gamma \vdash [l_1 : v_1, \ldots , l_n : v_n] : \{l_1 : T_1, \ldots , l_n : T_n\}$
- if $v = []$ then impossible since \texttt{[]} cannot be typed
- if $v = v_1 :: v_2$ then impossible for the same argument as for $T \equiv B$

- if $v = \text{Project}(v_1 \mid v_2)$ then impossible since
$\Gamma \vdash \text{Project}(v_1 \mid v_2) : R \texttt{list}$
- if $v = \text{From}(v')$ then impossible since
$\Gamma \vdash \text{From}(v') : R \texttt{list}$
- if $v = \text{Filter}(v_1 \mid v_2)$ then impossible since
$\Gamma \vdash \text{Filter}(v_1 \mid v_2) : R \texttt{list}$
- if $v = \text{Join}(v_1, v_2 \mid v_3, v_4)$ then impossible since
$\Gamma \vdash \text{Join}(v_1, v_2 \mid v_3, v_4) : R \texttt{list}$
- if $v = \text{GroupBy}(v_1, v_2 \mid v_3)$ then impossible since
$\Gamma \vdash \text{GroupBy}(v_1, v_2 \mid v_3) : R \texttt{list}$
- if $v = \text{Sort}(v_1 \mid v_2)$ then impossible for the same argument as for $T \equiv B$
If $v = \text{fun}^f(x) \rightarrow v'$ then by typing rule of the function:
\[ \Gamma, x : R \vdash v' : R, \text{so by induction hypothesis } v' \equiv s, \text{so } v = \text{fun}^f(x) \rightarrow v' \equiv \text{fun}^f(x) \rightarrow s \]
- all other cases are impossible for the same arguments as for $T \equiv R \rightarrow B$
- If $T \equiv R \rightarrow R \text{list}$ then
- $v = \text{fun}^f(x) \rightarrow v'$ then by typing rule of the function:
\[ \Gamma, x : R \vdash v' : R \text{list}, \text{so by induction hypothesis } v' \equiv s, \text{so } v = \text{fun}^f(x) \rightarrow v' \equiv \text{fun}^f(x) \rightarrow s \]
- all other cases are impossible for the same arguments as for $T \equiv R \rightarrow B$
- If $T \equiv R \rightarrow R \text{ then}
- $v = \text{fun}^f(x) \rightarrow v'$ then by typing rule of the function:
\[ \Gamma, x : R \vdash v' : R, \text{so by induction hypothesis } v' \equiv s, \text{so } v = \text{fun}^f(x) \rightarrow v' \equiv \text{fun}^f(x) \rightarrow s \]
- all other cases are impossible for the same arguments as for $T \equiv R \rightarrow B$
- If $T \equiv T_1 \rightarrow T_2$ then
- $v = \text{fun}^f(x) \rightarrow v'$ then the property is true
- all other cases are impossible for the same arguments as for $T \equiv R \rightarrow B$
- If $T \equiv \{ l_1 : T_1, \ldots, l_n : T_n \}$
- $v = x$ then the property is true
- $v = \text{fun}^f(x) \rightarrow v'$ then impossible since
\[ \Gamma \vdash \text{fun}^f(x) \rightarrow v' : T_1 \rightarrow T_2 \]
- $v = v_1 \cdot v_2$ then impossible for the same argument as for $T \equiv R \rightarrow B$
- $v = c$ then impossible since $\Gamma \vdash c : \text{typeof}(c) \equiv B$
- $v = \text{op}(v_1, \ldots, v_n)$ then impossible since
\[ \Gamma \vdash \text{op}(v_1, \ldots, v_n) : B \]
- $v = \text{if } v_1 \text{ then } v_2 \text{ else } v_3$ then impossible since
\[ \Gamma \vdash \text{if } v_1 \text{ then } v_2 \text{ else } v_3 : B \]
- $v = \{ l_1 : v_1, \ldots, l_n : v_n \}$ then the property is true
- $v = [ ]$ then impossible since $\{ \}$ cannot be typed
- $v = v_1 \cdot v_2$ then impossible since $\Gamma \vdash v_1 \cdot v_2 : R \text{list}$
- $v = v_1 \otimes v_2$ then impossible since $\Gamma \vdash v_1 \otimes v_2 : R \text{list}$
- $v = v' \cdot l$ then impossible for the same argument as for $T \equiv R$
- $v = \text{Project}(v_1 | v_2)$ then impossible since
\[ \Gamma \vdash \text{Project}(v_1 | v_2) : R \text{list} \]
- $v = \text{From}(v')$ then impossible since
\[ \Gamma \vdash \text{From}(v') : R \text{list} \]
- $v = \text{Filter}(v_1 | v_2)$ then impossible since
\[ \Gamma \vdash \text{Filter}(v_1 | v_2) : R \text{list} \]
- $v = \text{Join}(v_1, v_2 | v_3, v_4)$ then impossible since
\[ \Gamma \vdash \text{Join}(v_1, v_2 | v_3, v_4) : R \text{list} \]
- $v = \text{GroupBy}(v_1, v_2 | v_3)$ then impossible since
\[ \Gamma \vdash \text{GroupBy}(v_1, v_2 | v_3) : R \text{list} \]
- $v = \text{Sort}(v_1 | v_2)$ then impossible since
\[ \Gamma \vdash \text{Sort}(v_1 | v_2) : R \text{list} \]

\[ \square \]

We have shown that well-typedness of a QIR term restricts its syntactic form. We can finally show that terms that have a relational type can be translated into SQL by our specific translation.

**Lemma B.4.** Let $v$ be a normal form of QIR such that $v \equiv b$, or $v \equiv r$, or $v \equiv s$, then $\exists e \in \text{ESQL}$ such that $v \sim e$.

**Proof.** The rules of Figure 5 used to derive the judgment $v \sim e$ are syntax-directed (at most one rule applies), and terminate since the premises are always applied on a strict syntactic subterm of the conclusion. Thus, since $v$ is finite by definition of a QIR term, the translation derivation is finite and unique. We can therefore prove our lemma by induction on the translation derivation. We will use II (Hypothesis Induction) to denote the induction hypothesis and proceed by case analysis.

- If $v \equiv b$ then
  - If $v = c$ then:
    \[ \begin{array}{c}
    \text{(SQL-ct)} \\
    c \sim e \\
    \text{VAL} \Rightarrow \text{SQL}(c) \\
    \hline
    \text{(SQL-i)}
    \end{array} \]
    - If $v = \text{if } b_1 \text{ then } b_2 \text{ else } b_3$ then:
      \[ \begin{array}{c}
      \hline
      \text{SELECT CASE WHEN (} e_1 \text{) THEN } (e_2) \text{ ELSE } (e_3) \text{ END} \\
      \end{array} \]
    - If $v = x \cdot l$ then:
      \[ \begin{array}{c}
      \text{(SQL-tdestr-simpl)} \\
      \hline
      \text{SELECT X.L} \\
      \end{array} \]
      - If $v = \text{op}(b_1, \ldots, b_n)$ then:
        \[ \begin{array}{c}
        \text{(SQL-basic-op)} \\
        \hline
        \text{SELECT } X \text{.L} \\
        \end{array} \]
      - If $v = \text{has}(\langle e_1, \ldots, e_n \rangle)$ then:
        \[ \begin{array}{c}
        \text{(SQL-ct)} \\
        e_1 \neq \Omega \\
        i \in 1..n \\
        \hline
        \text{SELECT } X \text{.L} \\
        \end{array} \]
    - If $v \equiv r$ then
      - If $v = x$ then:
        \[ \begin{array}{c}
        \text{(SQL-var)} \\
        x \sim X \\
        \hline
        \end{array} \]
If $v = \{ l_1 : b_1, \ldots, l_n : b_n \}$ then:

\[
\begin{array}{c}
\text{(SQL-record)}
\hline
\mid v \\
\mid \quad (\text{HI})
\end{array}
\]

- If $v = \{ l_1 : b_1, \ldots, l_n : b_n \}$ then:

\[
\begin{array}{c}
\text{SELECT (} e_i \text{) AS } X_i, \ldots, (e_n) \text{ AS } X_n
\end{array}
\]

- If $v = \emptyset$ then:

\[
\begin{array}{c}
\text{SELECT * FROM (} e_i \text{) AS } X
\end{array}
\]

- If $v = r :: \{ \}$ then:

\[
\begin{array}{c}
\text{SELECT * FROM (} e_i \text{) AS } X
\end{array}
\]

- If $v = r :: s$ then:

\[
\begin{array}{c}
\text{SELECT * FROM (} e_i \text{) AS } X
\end{array}
\]

\[
\begin{array}{c}
\text{PROJECT(} \text{fun}^f(x) \rightarrow r \mid s \text{)} \quad \text{SQL}
\end{array}
\]

\[
\begin{array}{c}
\text{SELECT e}_1 \text{ FROM (} e_2 \text{) AS X}
\end{array}
\]

\[
\begin{array}{c}
\text{FILTER(} \text{fun}^f(x) \rightarrow r \mid s \text{)} \quad \text{SQL}
\end{array}
\]

\[
\begin{array}{c}
\text{JOIN(} \text{fun}^f(x, y) \rightarrow r, \text{fun}^f(x, y) \rightarrow b \mid s_1, s_2 \text{)} \quad \text{SQL}
\end{array}
\]

\[
\begin{array}{c}
\text{GROUPBY(} \text{fun}^f(x) \rightarrow s_1, \text{fun}^f(x) \rightarrow r \mid s_2 \text{)} \quad \text{SQL}
\end{array}
\]

\[
\begin{array}{c}
\text{SORT(} \text{fun}^f(x) \rightarrow r \mid s \text{)} \quad \text{SQL}
\end{array}
\]

Last, but not least, we can prove our sound translation theorem as a direct corollary of Theorem 4.1, and Lemmas B.3 and B.4.

**TRANSLATION.** Let $q \in E_{\text{eqR}}$ such that $\emptyset \vdash q : T, q \rightarrow^* v$, and $v$ is in normal form. If $T \equiv B$ or $T \equiv R$ or $T \equiv R \text{ list}$ then $v \rightarrow s, \text{SQL}$.

By Theorem 4.1, we have: $\emptyset \vdash v : T$. Thus, we can apply Lemma B.3 and deduce: $v \equiv b$ or $v \equiv r$ or $v \equiv s$. Consequently, by Lemma B.4, we obtain: $v \rightarrow s, \text{SQL}$. Finally, we apply the rule (db-op) of our generic translation, and since the specific translation was able to translate $v$ to SQL, it is able to translate the sources of the query (which are syntactically strict subterms of $v$) to SQL. Therefore, the rule (db-op) succeeds at translating $v$ to a term of SQL.

**C FROM R TO QIR**

We give some technical details of our translation from R to QIR. Even though we do not modify the parsing of R programs, we still need to translate R closures into QIR λ-expressions. For instance, given the R program:

```
less2000 = function(x) { x <= 2000 }
t = tableRef("employee", "PostgreSQL")
subset(t, less2000(sal))
```

we want to end up with the QIR term (before normalization):

```
(fun(less2000, t)→
  Filter(fun(r)→less2000 • sal ∣ t)
)(fun(x)→ ≤ (x, 2000), From(employee))
```

which becomes, after normalization:

```
Filter(fun(r)→ ≤ (r • sal, 2000) ∣ From(employee))
```

While it seems obvious from this example that the function less2000 should be translated into `fun(x)→ ≤ (x, 2000)`, it is not always sound to do so. Indeed, a variable $x$ can be soundly translated into a QIR variable $x$ if it is not the subject of side effects, otherwise accesses to $x$ must be nested inside host language expressions $\sigma_R(x)$ so that the correct value for $x$ can be retrieved.

The set of modified variables can be approximated by the $\text{Mod}$ function defined as such:
Figure 6: Translation from R to QIR terms

Definition C.1 (Approximation of modified variables). Let \( e \in E_R \) be an expression and \( \sigma \) an evaluation environment for \( R \). The set \( \text{Mod}(\sigma, e) \) of modified variables in \( e \) is inductively defined as:

\[
\begin{align*}
\text{Mod}(\sigma, x) & = \{ x \} \text{ if } x \notin \text{dom}(\sigma) \\
\text{Mod}(\sigma, x = e) & = \{ x \} \cup \text{Mod}(\sigma, e) \\
\text{Mod}(\sigma, x) & = \{ x \} \cup \text{Mod}(\sigma, e) \\
\text{Mod}(\sigma, \text{function}(\ldots)e) & = \text{Mod}(\sigma, e) \\
\text{Mod}(\sigma, e_1 \ldots e_n) & = \{ \} \\
\text{Mod}(\sigma, e_1, e_2) & = \text{Mod}(\sigma, e_1) \cup \text{Mod}(\sigma, e_2) \\
\text{Mod}(\sigma, e_1, \ldots, e_n) & = \text{Mod}(\sigma, e_1) \cup \cup_{i=2}^n \text{Mod}(\sigma, e_i) \\
\end{align*}
\]

The first five cases of the \( \text{Mod} \) function are the most interesting ones (the others being only bureaucratic subterm calls). First, if a variable is used, but is not in the current scope, it is not marked as modified. If the variable is being assigned to, then it is added to the set of modified variables. If the variable is bound in the current scope, to a value that is not closure, then it is also marked as unmodified. However, if a variable is bound to a closure, then the body of the latter is traversed, in an environment augmented with the closure environment. Lastly, the body of anonymous functions are recursively explored to collect modified variables. We can now tackle the translation from R expressions to QIR terms.

Definition C.2. We define the judgment \( \gamma, \sigma \vdash e \sim q \), which means that given a set of modified variables \( \gamma \) and an R environment \( \sigma \), the R expression \( e \) can be translated into a QIR expression \( q \). The derivation of this judgment is given by the rules in Figure 6. We define the translation \( \text{RExp}(\sigma, e) = q \) as \( \text{Mod}(\sigma, e), \gamma \vdash e \sim q \).

Constants and identifiers are translated into QIR equivalents. Anonymous functions are translated into QIR lambdas. More interesting is the translation of the builtin function \( \text{subset} \). Its first two arguments are recursively translated, but the second one requires some post-processing. Recall that in the case of \( \text{subset} \), the second argument \( e_2 \) contains free variables bound to column names. We simulate this behavior by introducing a lambda abstraction whose argument is a fresh name \( t \) and replace all occurrences of a free variable \( x \) in the translation by \( t \cdot x \). The last argument is expected to be a list of column names we use to build a lambda abstraction to project over these names. The \( \text{merge} \) function is similarly translated into a \( \text{Join} \) operator. The last interesting case is when a local variable is defined in a sequence of expressions. If the variable is not modified in the subsequent expression, then we translate this definition into a lambda application. Expressions that are not handled are kept in host expression nodes that will be evaluated either locally, in a QIR term that is not shipped to a database, or remotely, using the R runtime embedded in a database.

Now that we have defined the translation of expressions in a given scope, we can easily define the translation of values from R to QIR. The translation of constants, sequences and data frames is straightforward. The translation of a closure \( \text{function}(x_1, \ldots, x_n)_{\sigma}[e] \) is simply the translation of the body wrapped in a lambda: \( \text{fun}(x_1, \ldots, x_n) \rightarrow \text{RExp}(\sigma, e) \).