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OVI-3: A NoSQL visual query system supporting efficient anti-joins

Sami El-Mahgary[1] · Eljas Soisalon-Soininen[2] · Pekka Orponen[2] · Petri Rönnholm[1] · Hannu Hyyppä[1]

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Abstract
The aim of this work was to develop a technique to speed up complex joins in an incremental visual query system. When designing a visual, highly interactive interface for ad-hoc (read-only) queries, fast response times are of paramount importance. While a column-oriented DBMS reduces the inherent latency found in relational DBMS, there is still the question of how to index the data, especially so as to support complex joins. Equi-joins that involve a many-to-many relationship are an example of complex joins that arise frequently and whose efficient processing is essential for fast query processing. We present OVI-3, a NoSQL visual query system based on incremental querying that uses a simple directory-based indexing scheme for faster processing of such complex joins. The system has been piloted using real data from a student database at Aalto University. The results demonstrated that for certain complex joins the presented indexing scheme outperforms SQL queries from a data server, especially for queries involving anti-joins (negation), where OVI-3 provided an orders of magnitude speed improvement.

Keywords Visual querying · Joins · Incremental query · NoSQL

✉ Sami El-Mahgary
sami.mahgary@aalto.fi

Eljas Soisalon-Soininen
eljas.soisalon-soininen@aalto.fi

Pekka Orponen
pekka.orponen@aalto.fi

Petri Rönnholm
petri.ronnholm@aalto.fi

Hannu Hyyppä
hannu.hyyppa@aalto.fi

[1] Department of Built Environment, School of Engineering, Aalto University, P.O. Box 11000, FI-00076 Aalto, Finland

[2] Department of Computer Science, School of Science, Aalto University, P.O.Box 15400, FI-00076 Aalto, Finland

1 Introduction

Besides being intuitive and easy to use, a VQS must also provide fast response times. This is especially true when using *incremental query formulation*, a paradigm made popular back in the 1990's (Ahlberg & Shneiderman, 1994; Tanin et al., 1996). Incremental querying is based on *interactively browsing* the contents of a database (Larson, 1986) through filters. Interactive browsing is a user-friendly approach whereby the user simply modifies any of the existing query constraints by further restricting or relaxing them, thereby immediately producing a new answer set. In Tanin et al. (1996), the authors proposed that the term 'immediately' should refer to a delay of no more than one second, the time period that a user can afford to wait at each step for the new data (corresponding to the modified constraints) to appear. Later studies (Liu and Heer, 2014; Eichmann et al., 2020) have halved this threshold latency to 0.5s.

Incremental querying assumes a *continuous display* (Ahlberg & Shneiderman, 1994), whereby the user starts with a subset of the data considered to be relevant by the developer and then, incrementally, zooms in/out by placing further restrictions or relaxing some of the existing ones. Users thus explore, through visual elements, a subset of the database, the *active subset* (Derthick et al., 1999), and keep refining the query step-by-step until the active subset holds all the data the user is looking for and nothing else. When that is the case, the active subset becomes the final result set and the query can be considered to have successfully completed.

A key factor that can dramatically enhance response times for read-only queries is the data layout or the data arrangement architecture. This architecture can either be the traditional row-based arrangement found in relational databases or it can be column-based, as typically used in NoSQL approaches (Gessert et al., 2017). A column-based architecture stores each column separately on disk to speed up queries that only retrieve a few attributes from each relation. Even if the data layout is column-based, the result set must still be returned to the user in a row-based format, at which point the columns need to be assembled into a set of rows, known as *tuple reconstruction* (Abadi et al., 2008; Idreos et al., 2009).

Joins occur frequently in queries and remain a costly operation both in row-based (Mishra & Eich, 1992; Li & Ross, 1999) and column-based architectures (Idreos et al., 2009). Joins are a known bottleneck for query times, especially when the query involves a *many-to-many*, or *M:N relationship*. An M:N relationship arises when the relationship between two entities R and S is such that a tuple or row from one relation R can be joined to several tuples from another relation S and vice versa (Blasgen & Eswaran, 1977). Semantically, for instance, the relationship between students and courses at a university is M:N because a student can take several courses, and any given course in turn is taken by several students. For brevity, when there is an M:N relationship between two entities R and S, we refer to the join (assumed to be an equi-join) between the involved relations as an *M:N join*.

This article is about developing a VQS based on incremental querying that provides efficient support for complex joins that arise in M:N relationships. We use a technique of *directory-based indexing* or briefly *DBI*, presented in detail in Section 3.7. Based on this DBI approach, we have developed a prototype VQS that supports incremental querying, named OVI-3 (for "Offline Visual Incremental querying"). OVI-3 has been used in a pilot project to monitor students' academic progress at Aalto University.

OVI-3 is the culmination of some new ideas to improve on a previous VQS, OVI-2, short for Oodi's Visual Interface (El-Mahgary & Soisalon-Soininen, 2015) that was successfully used for several years by academic counsellors to perform ad-hoc queries on Aalto University's student database, known as Oodi. The '2' in the name OVI-2 is not a version number (there never was an OVI-1) but rather denotes the fact that OVI-2 used a two-stage querying. The first stage would return the user a superset of the required data, the result set of which was re-arranged into a more user-friendly temporary database created from scratch. The second stage then allowed the user to perform fast in-depth querying on the just created smaller dataset that was stored locally.

As to the '3' in the name OVI-3, it signifies the additional step required to regularly transfer data from the university database server to OVI-3 and build a new dataset using the DBI technique. The data transfer is handled through a separate batch application as described in Section 3.7.2. OVI-3 users thus never connect to the university database server. As we shall see in Section 4.6, the DBI approach can dramatically improve the performance of M:N joins, and is especially useful in queries that involve anti-joins, commonly known as *negations*. The present article is not a comprehensive treatment on the OVI-3 system, but rather focuses on techniques that support the implementation of fast joins and anti-joins in M:N relationships.

Regarding the arrangement of this article, Section 2 presents a minimal student database together with a review of Datalog and a look at the concept of negation. Datalog is a convenient tool for discussing joins and negations in queries, especially since the queries in our VQS are not handled through SQL. Section 3 briefly discusses some of the main concepts behind modern VQS together with their fundamental characteristics. Implementation issues are briefly dealt with in Section 3.7. Section 4 presents the visual querying aspects of OVI-3 through an example query and then contrasts the query results when using OVI-3 with an equivalent query that is run on the actual university's relational database server. Finally, conclusions are drawn in Section 5.

2 Concepts and terminology related to M:N joins

This section presents some important terminology and concepts related to M:N joins.

2.1 A simple toy database schema

Consider a basic toy database for managing courses taken by university students. For now we focus on just two tables, namely *Students* (Table 1), *Courses* (not shown) and *CoursesTaken* (Table 2). There is an M:N (many-to-many) relationship between tables *Students* and *Courses*, because a student can take several courses, and any given course can be taken by several students. In this case the table *CoursesTaken*, which contains column *StudentID* as a foreign key, is known as the *join table* or the *bridge table* (Ahmed et al., 2013).

Table 1 Three students in the toy table *Students* along with their four attributes. Note the lack of any capitals in the table entries, which are reserved for Datalog variables

StudID	FirstName	LastName	Major
22	taneli	huiskanen	mech_eng
34	ghislaine	millereux	mech_eng
35	delia	surhamsson	civ_eng

Table 2 Table *CoursesTaken* contains five course instances taken by the students

TakenID	CourseID	StudentID	DateTaken	InstructorID	Grade
t101	mech_1001	22	10_MAY_2022	i58	4
t102	mech_1001	22	24_MAY_2022	i77	4
t103	mech_1001	34	10_MAY_2022	i58	5
t104	mech_1002	34	24_MAY_2022	i77	4
t105	mech_1002	35	24_MAY_2022	i77	5

The OVI-3 approach essentially re-organizes the data into a column-based format where the keys that take part in an M:N join are stored separately using the DBI technique. As this article is about the efficient implementation of such joins (i.e., M:N joins and M:N anti-joins), we refer to the join between tables *Students* and *CoursesTaken* as a *primal join*.

A primal join thus always derives from an M:N relationship. Analogously, we refer to the anti-join between tables *Students* and *CoursesTaken* as a *primal anti-join*. Both of these join concepts are defined with the help of an example in Section 2.3.

2.2 The concept of viewpoints and the value store

We postulate that one of the tables in a primal join is crucial with respect to the query, as it identifies the semantic entity or (principal) concept (Soylu et al., 2016) in which the user is interested. This principal concept is similar to what Benzi et al. (1996) refer to as a *viewpoint*, to which we will return shortly. We call the table in the primal join that represents the principal concept the *primal table*T_{prim},[1] while the other table is called the *M:N foreign key table*, denoted T_{frgn}.

Now consider a query that finds students who took course 'MECH-1001' and that displays, for such students, the courses they took. In such a case the query's principal concept, or viewpoint, is students, T_{prim} refers to the table *Students* and T_{frgn} refers to the table *CoursesTaken*. Information on courses will be treated as *nested results* (Bakke and Karger, 2016), that is, the courses taken by a student are considered an extended property of each individual student in the result set.

Our notion of a viewpoint is similar to the 'anchor table' in Stonebraker et al. (2005), and in our case determines the choice of T_{prim}. The use of viewpoints is what brings intelligence to OVI-3, for given a viewpoint, T_{prim} is immediately known, and from this T_{frgn} is deduced. This lays the foundation for efficiently performing certain types of joins and anti-joins, as will be shown in Section 2.4. For a given VQS, the programmer only needs to create a limited number of viewpoints depending on the users' needs. A user normally selects a viewpoint just after starting the VQS, thereby determining the set of restrictions available and thus also changing the look of the VQS. With OVI-3, only two viewpoints are needed in our toy example: (i) a 'Students' viewpoint to retrieve students along with the courses they have taken and (ii) an 'Instructors' viewpoint for retrieving instructors along with the courses they have taught.

Because OVI-3 is geared towards a column-based data layout, a relation or table is actually implemented as a *value store* and hence we consider the three terms relation, table,

[1] For simplicity, we assume that the primal join is made up of a single pair of columns joined via an equi-join as in Hamdi et al. (2017).

and value store as synonyms. Since in our case a value store contains several attributes for each key, it is not a key-value store, nor is it exactly a wide-column store as there is only one level of indexing (keys) (Gessert et al., 2017). A value store can be considered a table, since it is equipped with a primary key and may contain foreign keys that are part of its compound primary key. However, unlike a table, a value store is normally accessed only via its primary key and not via joins. Moreover, normalization rules for normal forms 2NF and above are relaxed for a value store.

2.3 A review of Datalog and its relation to present work

This section provides a brief review of the Datalog query language, which is attractive for our purposes due to its lack of keywords and its close ties to relational databases. We also discuss the relationship of Datalog to some key concepts of this article.

Like SQL, Datalog is a declarative language. Unlike SQL, however, Datalog is based on logic programming and a program contains a set of one or more *predicates*. A predicate is made up of its name, followed by a fixed number of arguments (variables or constants) listed within parentheses, and evaluates to a Boolean value (Molina et al., 2009). The combination of a predicate followed by its arguments is known as an *atom* (Greco and Molinaro, 2016) and is the equivalent of a functional call in traditional programming languages (Molina et al., 2009).

Predicates are in Datalog the building blocks of *rules*. The common syntax for a rule is the head part, followed by the symbol ':-' (which can be read as 'if') and a body part that follows. A rule may consist of a single atom, with an empty body part (and no preceding ':-' symbol). In case its arguments are all constants, the rule is reduced to a *grounded fact*, known simply as a *fact* (Ceri et al., 1989; Greco & Molinaro, 2016). Using the notation from Sippu and Soisalon-Soininen (1996) and assuming arguments are represented as vectors ($\bar{X}$), an example of a rule R with predicate p at its head and a body made up of predicates $p_1 ... p_n$ would be

$$R : p(\bar{X}) \text{:-} p_1(\bar{X}_1), \dots , p_n(\bar{X}_n). \tag{1}$$

All predicates in the body of a rule R must evaluate to `true` for the rule's head predicate p itself to evaluate to `true`, which is why the body is known as a *conjunction* (Greco & Molinaro, 2016). A rule where the head predicate p evaluates to `true` in case just any single predicate among $p_1, \dots , p_n$ in the body evaluates to `true` would be a *disjunction*. Datalog however does not have direct support for disjunctions, so representing a disjunction of n body atoms requires n rules, where each rule R_i, $i = 1, \dots , n$, consists of the head atom $p(\bar{X})$ and a single atom $p_i(\bar{X}_i)$ in its body.

Each row or tuple i in a relational table T can be viewed as a fact F_{T_i} in Datalog. For instance, referring to the toy relation *Students* in Table 1, we could represent its first row as the fact *students*(22,*taneli*,*huiskanen*,*mech_eng*). Because facts actually exist in the database, a predicate associated directly with facts is considered an *extensional database predicate* (Ceri et al., 1989), and such a predicate together with its arguments is known as an *extensional atom* (Greco & Molinaro, 2016).

As we are not interested in recursive queries, we omit the possibility of recursion in Datalog, and consider a Datalog program as a collection of rules that are grounded in a dataset comprised of facts. A simple example of a Datalog program is presented in Listing 1 below, where the dataset (not shown) is assumed to be derived directly from Tables 1 and 2.

```
studentstookcourse(StudentID, CourseID^) :−
coursestaken(TakenID, CourseID^, StudentID, DateTaken, InstructorID, Grade),
students(StudentID, FirstName, LastName, Major).
```

Listing 1 A Datalog program consisting of a single rule or query to retrieve the student IDs of students who have taken a given course as specified by the user-assigned variable *CourseID*

We continue with the relation *Students* and the predicate *students*, but instead of constants, we now use variables for all the arguments in the predicate. We thus obtain the atom *students*(*StudentID, FirstName, LastName, Major*), which represents the whole *Students* relation, encompassing the full dataset comprising three rows and their four attributes. Because this formula physically corresponds to a relation in the database schema, it also is an example of an extensional atom.

Extensional predicates cannot by their nature appear in the head of rules, and predicates serving in that role are called *intensional predicates*, or if their arguments are included, *derived atoms* (Greco & Molinaro, 2016). A derived atom does not have a direct correlate in the relational database and it is precisely derived atoms such as $p(\bar{X})$ in rule R in (1) that allow inference, or query rules consisting of a head and a body to be constructed.

Before looking closer into the design of rules, a few notes on variables. In Datalog, variable names start with a capital first letter, while predicate names and constants are written fully in lowercase. In some cases the value for a variable is provided as a parameter by the user at the start of a program and remains unchanged throughout the program's execution. To distinguish between such user-assigned (parameter) variables and other (free) variables, we use the caret (^) suffix notation to indicate the former condition. A user-assigned variable with name *VarName* will thus be written as *VarName^*.

In the execution of a Datalog program, new facts are derived from known ones through the application of rules and the *instantiation* of variables. In instantiation, the variables in a predicate are substituted by the values of corresponding constants from a matching fact i.e., a fact whose name and arity match those of the predicate. (For details, see Greco and Molinaro (2016).)

Consider Listing 1 where the program consists of a single rule. At the head of the rule is the derived atom *studentstookcourse* with its two arguments, free variable *StudentID* and user-assigned variable *CourseID*. The value of variable *CourseID* remains constant for the duration of the session that the program is running whereas variable *StudentID* gets its value through evaluation of the two predicates in the body of the rule, *coursestaken* and *students*. These extensional predicates *coursestaken* and *students* correspond to Tables 1 and 2 respectively.

It is no coincidence that the free variable *StudentID* that appears in the head of the rule also appears in the body of the rule; this is due to a safety condition that stipulates that any variable in the head of a rule must also appear in the body of the rule (Ceri et al., 1989) so as to be instantiated with a proper value. The rule or query is evaluated by starting from predicate *coursestaken*, whose *CourseID* variable has been instantiated with a user-provided constant value. This in turn allows the instantiation of variable *StudentID* in the same predicate and also in predicate *students* to each student who took the course *CourseID*. These instantiated values for *StudentID* will then be passed on to the corresponding first argument of the derived atom in the head of the rule and returned to the user.

The latter instantiation with respect to relation *Students* is in fact an example of a primal join. A primal join arises when the following two conditions are met: (i) the two relations (here *CoursesTaken* and *Students*) are related via an M:N join and (ii) one of the tables in the join is the primal table associated with the principal concept or viewpoint. The query in

```
studentsdidnottakegivencourse(StudentID, FirstName, LastName, CourseID^) :-
students(StudentID, FirstName, LastName, Major),
not (studentstookcourse(StudentID, CourseID^)).
```

Listing 2 A Datalog query that finds students (their student IDs and names) who have not taken any course with the ID as specified in the user-assigned variable *CourseID^*

Listing 1 always returns information on students, which is its principal concept. Formally speaking, the query in Listing 1 has as its viewpoint the students, denoted $V_{STUDENTS}$, as its primal table T_{prim} the relation *Students*, and as its foreign key table T_{frgn} the relation *CoursesTaken*.

2.3.1 Datalog and negation

Although pure Datalog does not contain negation as such (Ceri et al., 1989), we can easily augment the formalism with a form of weak negation that derives from a *closed world assumption* (CWA). With a CWA, a given fact is `false` unless it is listed in the database as `true`. An example of weak negation is *safe negation*, which requires that each variable appearing in a negated predicate must also appear in some unnegated predicate (Gutiérrez-Basulto et al., 2015).

Let us now design a Datalog query that finds those students (student IDs, first and last names) in our toy database who have *not* taken a course with a given course ID. The query in Listing 2 satisfies the conditions of a safe negation, since the variable *StudentID* contained in the negated predicate **not** *studentstookcourse* also appears in another unnegated predicate, *students*. The safety conditions do not concern the parameter variable *CourseID*, because its value remains constant during the time the program is run.

When all the variables that appear in a negated predicate also all appear together in some unnegated *single* predicate, the negation is known as a *guarded negation* (Bárány et al., 2012; Gutiérrez-Basulto et al., 2015). This requirement is also clearly met in the query of Listing 2.

Finally, the negation induces a primal anti-join between the relations *CoursesTaken* and *Students*. A primal anti-join is admissible in Datalog when the following three conditions are met: (i) there is an M:N relationship between the entities, (ii) one of the tables involved is the primal table (here *Students*) and (iii) the negation is a guarded negation. Because guarded negation ensures that the query in Listing 2 returns only students who appear in relation *Students*, it can be efficiently implemented via the familiar *set difference* operation (Bárány et al., 2012).

Let us denote the foreign key in table T_{frgn} that is semantically equivalent to the primary key α_{prim} using $\hat{\phi}_{frgn}$. For the query in Listing 2, this implies that $\hat{\phi}_{frgn}$ refers to attribute *StudentID* in relation *CoursesTaken*, clearly distinct from ϕ_{frgn} (attribute *CourseID* in the same table). Assuming user-given ϕ_{frgn} (attribute *CourseID*) is 'mech_1001', then the values for $\hat{\phi}_{frgn}$ would consist of the set {22,34} (i.e., the student IDs of students who took course 'mech_1001'). Subtracting from the set of all values for primary key α_{prim} (table T_{prim} which is *Students*) the set of values for $\hat{\phi}_{frgn}$, we obtain: $\{22,34,35\}-\{22,34\} = \{35\}$. This singleton is the student ID of the one student ('delia') who did not take course 'mech_1001'.

2.4 Problem definition

In the simple query in Listing 1, the user provides one or more values for a foreign key (column *CourseID*) in table T_{frgn} (*CoursesTaken*) that is semantically distinct from the

```
('MECH−1001',{22,34});
('MECH−1002',{22,34,35}).
```

Listing 3 The contents of mapping relation *studentstookcourse* allows for finding the values of α_{prim} given ϕ_{frgn}. If ϕ_{frgn} = {'MECH-1001'} then α_{prim} = {22,34}

primary key (column *StudentID*) of table T_{prim} (*Students*). Let ϕ_{frgn} denote the set of these user-provided foreign key values and let α_{prim} denote the set of primal key values in T_{prim}. The problem can then be stated as follows:

Assuming the values for ϕ_{frgn} (foreign key in table T_{frgn} that is semantically distinct from the primary key α_{prim} in table T_{prim}) are given by the user, how do we efficiently retrieve the corresponding values for α_{prim} (the primary key for table T_{prim}) that are needed for the primal join?

Since finding the set α_{prim} is equivalent to evaluating the primal join, the corresponding anti-join[2] can then also be solved. Such queries are quite common in the real world, and assuming an appropriate database schema with an M:N join, examples would be *'What students have taken the following courses?'*, *'What instructors have not taught the following courses?'* and *'What authors have published in the following journals?'*. As pointed out in Goodman (1980), multi-table queries often contain an additional restriction besides the join. We take this observation further by assuming that this additional restriction specifies a set of user-provided values, ϕ_{frgn}, which refer to table T_{frgn}.

2.5 The mapping relation for fast joins and negation

A solution to the problem just described, that is, how to efficiently determine the set α_{prim} when given the foreign key set ϕ_{frgn}, can actually be found in Listing 1. In that listing on line no 1, predicate *studentstookcourse* is in the role of a *mapping relation* where each user-provided value of the attribute *CourseID^* (the foreign key) gets mapped to one or more corresponding value(s) of the attribute *StudentID* (the primary key α_{prim} of table T_{prim}). Variables other than *StudentID* (such as *TakenID*, *DateTaken*, *InstructorID*) do not appear in the head of the rule and do not thus affect the final outcome.

We note that the contents of the mapping relation are set and implemented when designing the VQS and its viewpoints. The implementation of the mapping relation is deferred until Section 3.7.1, but an example is in Listing 3, which shows that when given a set of values for ϕ_{frgn}, the whole set of corresponding values α_{prim} immediately becomes known.

In passing, we point out the analogy between the mapping relation and the vertically partitioned *fact table* found in data warehouses with the star schema (Bellatreche and Boukhalfa, 2005). A mapping relation's foreign key maps to the primary key of the T_{prim} in much the same way as the fact table gets joined to a dimension table. Moreover, both the mapping relation and the fact table are expected to grow at a rate faster than other tables (not involved in M:N relationships) in the schema.

2.5.1 Implementing negation

We implement anti-joins using guarded negation, which provides for the following guidelines, which are put to use in Section 3.7.1.

[2] Anti-joins are often evaluated using a join augmented with a NOT EXISTS predicate in SQL.

1. When querying for students who did not take a certain course, the VQS should check that the given course indeed exists. Using an SQL query for students who did not take course 'MECH-1001' would yield a very costly, useless query, should course 'MECH-001' not exist in the database.
2. Guarded negation in a primal anti-join is implemented via the set difference operation as shown in Section 2.3.1. In general, given a user-assigned value for ϕ_{frgn} in table T_{frgn}, we find, from the same table, the corresponding values for the other foreign key ϕ_{frgn} (that semantically matches the primary key α_{prim} in table T_{prim}) and subtract these values from the set of values for the primary key α_{prim}.
3. The actual (primal) join is implemented separately via a mapping relation (Listing 3) involving only the primary key α_{prim} from T_{prim} and the foreign key ϕ_{frgn} from T_{frgn}.
4. Assuming that the primary keys α_{prim} are kept in memory throughout the session, and that the corresponding foreign keys ϕ_{frgn} can be quickly retrieved from disk, the previously mentioned set difference can be implemented efficiently.

3 OVI-3 in the light of five fundamental aspects of modern VQSs

Despite its support for complex queries and its overall fast response, our previous VQS, OVI-2, was deemed a bit sluggish when it came to querying anti-joins (i.e., finding students who have not taken a given set courses) as it used a row-based data layout. In light of this, when developing OVI-3, we avoided a row-based architecture in favor of better query performance. We therefore developed a separate batch application to transfer the row-wise data from the relational database server into an offline column-based data store.

The underlying ideas used in OVI-3 will now be described in the light of five properties that characterize many modern VQSs, namely: (1) visual appearance, (2) the data layout, (3) the query paradigm used, (4) the expressive power of the VQS and (5) the way joins are handled.

3.1 The visual aspect

In their comprehensive work, Catarci et al. (1997) classify VQSs into four different categories based on their visual appearance. We use a slightly modified VQS classification with only three categories (El-Mahgary and Soisalon-Soininen, 2015), namely: (1) tabular or form-based, (2) diagrammatic/schema-based and (3) custom-based. When the VQS uses a traditional interface that takes the shape of a table or form, it is part of the first category (1). A VQS that arranges its visual appearance mainly according to its data schema belongs to category (2). Finally, approaches that implement a custom look that is beyond categories (1) and (2) are classified into a separate, third category, known as custom-based. The OVI-3 look, as presented in Section 4.3, is based on a visual form (complemented with checkboxes and radio-buttons) and therefore best classified into category (1).

3.2 The data layout

The data layout, as previously mentioned, is generally either column or row-based, with the latter usually implying that the VQS uses an SQL-server to query a relational database, with the SQL-statement typically generated behind the scenes. A well-known VQS using the column-based approach is Polaris (Stolte et al., 2002), better known under its commercial name Tableau.

Since it is column-based, OVI-3 does not use SQL at all. Instead, to evaluate a query, it uses the mapping relation to handle the primal join (by determining the primary key values α_{prim} from the M:N foreign key ϕ_{frgn} provided via the user) and uses value stores to retrieve the remaining required attributes. These implementation issues are postponed to Section 3.7.

3.3 The query paradigm and the use of viewpoints

The query paradigm is about how the VQS assists the user in defining the query and can be based either on the previously mentioned incremental query approach used by OVI-3 (similar to the *progressive query* model mentioned in Catarci et al. (1997)) or on the *single declarative query* (Nandi and Jagadish, 2011) model.

With the more common single declarative query model, the user generally sees the query results only after having fully built the query and requested that the VQS process the query (for instance by clicking on a button that runs the query). If the query results are not what the user had in mind, the user will need to determine what parts of the query require modification, then modify the query appropriately, and finally re-process the query.

OVI-3 uses viewpoints and the set of available viewpoints is decided before building the VQS, as it depends on the query needs of the users. For many VQSs, a few viewpoints will suffice. For OVI-3, only two viewpoints and thus two basic types of queries were deemed enough: (I) queries that retrieve students along with the courses they took and (II) queries to retrieve instructors along with the courses they taught.

3.4 The handling of joins

Although joins are an important part of a flexible query (Lo et al., 2010), the basic techniques for processing joins date from the late 1970s (Blasgen & Eswaran, 1977); these techniques also apply to the column-based model. As aptly put in Ilyas et al. (2004), a join between two tables is challenging since the tables' whole Cartesian product space is a source of potential matching rows. Moreover, a join is the only relational operation that may require several scans over the same relation (Goodman, 1980). We can assume from Section 2.4 that when solving a primal join (and hence an anti-join too), the user provides values for the foreign key in table T_{frgn}. Hence, the DBI approach uses those foreign key values to locate the file containing all the values for the primary key in table T_{prim}. We recall that the use of viewpoints contributes to determining T_{prim} (and hence T_{frgn}) and that incremental query implies that a primal anti-join can never be constructed without first defining the corresponding (non-negated) primal join. Since we implement an anti-join through a set difference,[3] the set of foreign key values is most likely to be found in the cache, as it is the immediately preceding operation before the anti-join. As for the set of primary key values related to T_{prim}, that set is always kept in memory in our VQS.

[3] As pointed out in Minock (2003), the set difference is a safe operation when applied to two relations (sets) with an identical domain and cardinality, which is the case here.

3.4.1 Very late materialization

When tuple reconstruction with a column-based dataset is performed in query processing as soon as the primary key is determined, the process is referred to as *early materialization*; at any later stage, the reconstruction is considered as *late materialization* (Abadi et al., 2008). For late materialization, we make a slight distinction in that whenever tuple reconstruction is delayed until the very last step where the results are presented to the user, it is known as *very late materialization* or VLM. With VLM, when the query is processed incrementally, the result set is made up of just the set of values in the primary key of T_{prim}. This is possible since selecting a viewpoint determines table T_{prim}. Tuple reconstruction occurs therefore within the results grid, at the answer set stage, whereby the missing attributes are retrieved in a separate call from the primary value store as the user scrolls through the results grid. This is further illustrated using the example query in Section 4.4.

3.5 The expressive power of a VQS

The expressive power of a VQS is intentionally less expressive than a formal language (Soylu et al., 2016) and may be considered adequate when it meets the needs of its users. Select-project-join queries, which possess the same expressive power as *conjunctive queries* (Schweikardt et al., 2010), play an important role in most queries. Extending a conjunctive query with union yields a select-project-join-union query or *SPJU query*, considered as the most widely used query type (Atserias et al., 2006). When SPJU queries are further augmented with guarded negation, the expressive power is significantly increased, and this is the expressive power of OVI-3.

3.6 The OVI-3 event-response model

Table 3 depicts how OVI-3 responds to two basic types of user-placed restrictions following the selection of the viewpoint $V_{STUDENTS}$, an event of type 0 generated by the user. Events of type (1) are used to restrict various students' properties (attendance status, year admitted, major, etc.) and are handled by using the values of α_{prim} of the active set (kept in memory) as keys to the primal table, i.e., the primary value store T_{prim}. Actions of type (2) involve restrictions on the courses taken and are implemented via the DBI. When displaying results on the grid, very late materialization means it is a set of values of α_{prim} that are written on the grid, and that the missing attributes are retrieved from the primary value store as needed (when scrolling for instance).

3.7 Some OVI-3 implementation issues

The OVI-3 data layout is divided into two parts, the first part contains the DBI data used for joins, while the second part contains the value stores that correspond to relations. The primal joins (with an M:N join) are implemented via the mapping relation as described in Section 3.7.1.

As for the value stores, we used an open source framework known as mORMot (Bouchez, 2018), which offers an efficient storage and retrieval mechanism through its 'Big Table' unit capable of interacting with various database servers, including Oracle. The mORMot

Table 3 An event-response table to illustrate how OVI-3 responds to user-generated events

Type of Event	User action		OVI-3 response	OVI-3 display
0	Viewpoint selected ($V_{STUDENTS}$)	$\rightarrow\rightarrow$	T_{prim} and T_{frgn} get set. Primary key values α_{prim} loaded from value store T_{prim} (*Students*) and kept in memory.	Default dataset shown.
1	Restriction placed on column from T_{prim}.	$\rightarrow\rightarrow$	Find new set of primary key values from T_{prim}.	Grid updated using VLM.
2	Restriction placed on foreign key ϕ_{frgn}.	$\rightarrow\rightarrow$	Use DBI to find key fragment file named ϕ_{frgn} and get new set of primary key values α_{prim}.	Grid updated using VLM.

framework is available for use with Delphi (Embarcadero Technologies, 2018), an enhanced Object-Pascal language which rivals C++ performance-wise, or through the open source version Free Pascal (Lazarus, 2018). We selected Delphi, as it was available to us.

The viewpoint $V_{STUDENTS}$ was implemented using just two different value stores, one for storing information on students (named 'Students.bin', about 23MB in size) and another, about 460MB in size, for storing all the courses taken by all students. The primary value store 'Students.bin' uses *StudentID* as its key to store various student properties; it contains all the required basic information about a student (e.g., a student's name, gender, date of admittance, major, degree status, GPA, total credits completed, registration status, degree being pursued (or completed), email) along with computed attributes such as *SemLastTookCourse* (the semester in which the student passed her/his last course). This primary value store thus helps in narrowing down the set of matching students after a user has placed a restriction relating to the student's aforementioned properties. The primary value store is also used when implementing very late materialization (Section 3.4.1). Value stores (presented in Section 2.2) are implemented as binary files (mORMot's key-multiple value object) that use a single artificial integer as their index, with support for up to 59 columns per primary key and built-in support for secondary indexes. The Big Table allows for a value store to hold up to 2GB of data in memory.[4]

3.7.1 Implementation of the mapping relation

The mapping relation that is used with a DBI depends on the selected viewpoint, and as pointed out earlier, is implemented at design time. The following steps describe how DBI is implemented in general; in parenthesis we give the specific case for OVI-3 which assumes a viewpoint of $V_{STUDENTS}$.

1. For each distinct value i of ϕ_{frgn} (*CourseID*) in table T_{frgn} (*CoursesTaken*), create a unique directory D_i.
2. Under each such D_i, generate a file F_i, known as the *key fragment file*, for table T_{prim} (*Students*).
3. For each T_{prim} key fragment F_i, store the set of those α_{prim} primary key values (column *StudentID*) from T_{prim} which are associated (joined) to the value i of the foreign key (*CourseID*) in table T_{frgn}.

3.7.2 The batch application creates the DBI layout

New data for OVI-3 is obtained by regularly running a separate batch application nightly that extracts the required information from the university's relational database and arranges it into a column format specifically tailored for rapid, read-only queries.

For brevity, throughout we only focus on the data structures needed when the user has selected $V_{STUDENTS}$ as the viewpoint, which implies that queries return answer sets based on students. For the steps in Section 3.7.1 we assume a main folder named 'Courses', under which the batch application implements the mapping relation by creating a folder D_i for each course C offered. Moreover, under each such folder D_i, the batch application generates a file

[4] In a Bouchez (2010) benchmark involving B^+-trees and Berkeley DB among others, Big Table had the fastest read and write times, faring twice as fast as a B^+-tree.

```
SELECT Distinct S.StudentID, StudentName, StudentEmail, Gender, CourseID,
    CourseName, InstructorName, GradeAchieved, DateTaken
FROM Students S, CoursesTaken CT, CoursesTaken CT2,
Courses C, Courses C2, Instructors I
WHERE AttendStatus = 'In attendance' AND CurSchool ='ENG'
AND CT.StudentID  = S.StudentID AND CT2.InstructorID = I2.InstructorID
AND CT.CourseID   = C.CourseID AND CT2.StudentID = CT.StudentID
AND CT2.CourseID  = C.CourseID AND CT.InstructorID = I.InstructorID
AND CT.CourseID IN ('MECH−1001','MECH−1002')
AND CT2.CourseID IN ('MECH−1004') AND NOT EXISTS
(SELECT S.StudentID FROM Students S, CoursesTaken CT, Instructors I
WHERE AttendStatus = 'In attendance' AND CurSchool = 'ENG'
AND CT.StudentID = S.StudentID AND CT.CourseID = C.CourseID
AND CT.InstructorID = I.InstructorID AND CT.CourseID IN ('MECH−1003')
```

Listing 4 The OVI-3 example query that is run in five steps $1 - 5$ (Table 4) is equivalent to the following SQL query:

F_i, the key fragment for T_{prim} that contains the set α_{prim}, that is, the *StudentID* values for the students who have completed course *C*.

4 Results on querying with OVI-3

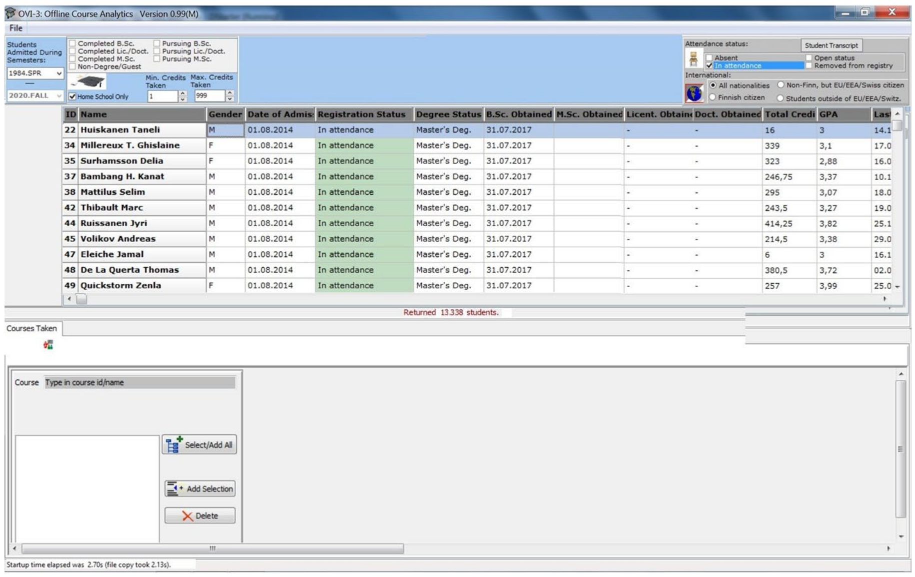
4.1 The hardware for the OVI-3 DBI queries and the SQL queries

All the equivalent SQL queries were tested on an Oracle server that houses the university database. Though our simplified SQL query (Listing 4) assumes that the data is contained in just four tables, it nevertheless contains the table *CoursesTaken*, which is at the heart of the real complex queries and M:N joins that were run on the Oracle server. Table *Courses-Taken* was the largest of all tables in the SQL database, containing some 1.25 million rows, while the table *Students* numbered at slightly less than 130000 rows. The Oracle database server was made up of the very same set of students and courses that were used in the DBI layout for running the OVI-3 queries. Both the OVI-3 queries and the equivalent SQL queries were run from the same hardware, which was a 64-bit Windows Server 2012 running as a virtual machine, consisting of two cores running at 2.5GHz each, with a rather modest 16GB of RAM memory and 250 GB of disk space. This virtual machine not only stored the OVI-3 data DBI layout and the values stores but also acted as a client when running the tested SQL queries by connecting to the Oracle server.

4.2 Querying with OVI-3

When OVI-3 is first launched, the viewpoint by default is $V_{STUDENTS}$, so at start-up, the user is presented with a grid that displays a subset of the students together with their various attributes from the primary value store *Students*. This subset of student IDs is by default set to include only students who belong to what is known as the *home school*. Aalto University is divided into six different schools and the home school can be set via the user to one of six schools. Currently, it is set to 'ENG', the School of Engineering. Figure 1a shows OVI-3 after

a


OVI-3: Offline Course Analytics Version 0.99(M)

File

Students Admitted During Semesters: 1984.SPR — 2020.FALL

☐ Completed B.Sc. ☐ Pursuing B.Sc.
☐ Completed Lic./Doct. ☐ Pursuing Lic./Doct.
☐ Completed M.Sc. ☐ Pursuing M.Sc.
☐ Non-Degree/Guest

✓ Home School Only — Min. Credits Taken: 1 — Max. Credits Taken: 999

Attendance status: ☐ Absent ✓ In attendance ☐ Open status ☐ Removed from registry

Student Transcript

International: ● All nationalities ○ Non-Finn, but EU/EEA/Swiss citizen ○ Finnish citizen ○ Students outside of EU/EEA/Switz.

ID	Name	Gender	Date of Admis	Registration Status	Degree Status	B.Sc. Obtained	M.Sc. Obtained	Licent. Obtain	Doct. Obtained	Total Credi	GPA	Las
22	Huiskanen Taneli	M	01.08.2014	In attendance	Master's Deg.	31.07.2017		-	-	16	3	14.1
34	Millereux T. Ghislaine	F	01.08.2014	In attendance	Master's Deg.	31.07.2017		-	-	339	3,1	17.0
35	Surhamsson Delia	F	01.08.2014	In attendance	Master's Deg.	31.07.2017		-	-	323	2,88	16.0
37	Bambang H. Kanat	M	01.08.2014	In attendance	Master's Deg.	31.07.2017		-	-	246,75	3,37	10.1
38	Mattilus Selim	M	01.08.2014	In attendance	Master's Deg.	31.07.2017		-	-	295	3,07	18.0
42	Thibault Marc	M	01.08.2014	In attendance	Master's Deg.	31.07.2017		-	-	243,5	3,27	19.0
44	Ruissanen Jyri	M	01.08.2014	In attendance	Master's Deg.	31.07.2017		-	-	414,25	3,82	25.1
45	Volikov Andreas	M	01.08.2014	In attendance	Master's Deg.	31.07.2017		-	-	214,5	3,38	29.0
47	Eleiche Jamal	M	01.08.2014	In attendance	Master's Deg.	31.07.2017		-	-	6	3	16.1
48	De La Querta Thomas	M	01.08.2014	In attendance	Master's Deg.	31.07.2017		-	-	380,5	3,72	02.0
49	Quickstorm Zenla	F	01.08.2014	In attendance	Master's Deg.	31.07.2017		-	-	257	3,99	25.0

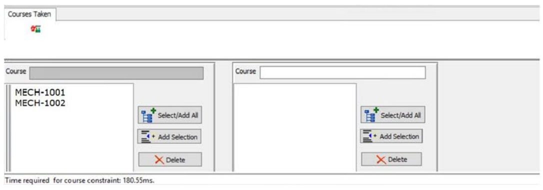
Returned 13.338 students.

Courses Taken

Course: Type in course id/name

Startup time elapsed was 2.70s (file copy took 2.13s).

b


Courses Taken

Course:
MECH-1001
MECH-1002

Course:

Time required for course constraint: 180.55ms.

Fig. 1 The query defined in Section 4.3 is being run incrementally in OVI-3. (All names and dates are fictitious). **a** The query interface showing the result set in the grid just after the user has specified the first restriction: only students who are currently in attendance. OVI-3 has automatically applied a default admission interval restriction and restricted the school to 'ENG'. **b** The user has specified part of the course requirements: either course 'MECH 1001' or 'MECH-1002' needs to have been taken. A second, empty course requirement box (bottom right) has appeared automatically, should the user wish to enter further course restrictions that will form a conjunction, i.e., be 'ANDed', with the leftmost course restriction box

startup, displaying those (13338) students who belong to the 'ENG' school, who were admitted during or after Fall semester 1984, who have completed at least one unit of credit and who are currently in attendance. These requirements are the result of default settings at startup.

The basic student information is made up of various student properties stored in the value store 'Students.bin' (Section 3.7). In short, it includes all the data of interest related to a student, except for the student transcript (the list of all courses taken by the student) which is displayed separately. Depending on the screen size and resolution, the display grid might show at a given time (without scrolling) from a few rows to over a hundred rows. As the user scrolls down the grid and a different *StudentID* value is encountered, the application automatically reads the missing basic student information from a separate primary value store. This is the very late materialization as discussed in Section 3.4.1.

Besides being able to scroll the set of students displayed in the grid, the user can now start incremental querying through four different types of query restrictions: (i) restricting/relaxing the time frame (the semesters during which a student was admitted), (ii) placing a restriction on the student's degree status, (iii) restricting the student's attendance status and (iv) placing a constraint on the courses that must be taken (events of type 2 in Table 3). Due to the choice of the viewpoint, any query generated by the user will always return data from the viewpoint of a student. The result set may of course also draw information from other relations, but the primary key of each row in the result set will remain *StudentId*.

4.3 An example OVI-3 query involving conjunctions, disjunctions and negation

We ran several queries with OVI-3 and tested them against the underlying SQL database. We examine these queries in more detail in Table 5 in Section 4.6. For now, we go through a full step-by-step example showing how OVI-3 is used to build a complex query that involves both a disjunction as well as negation. The query's implementation will be examined through the algorithm that is summarized in Algorithm 1.

```
1:  $S_0 \leftarrow \Pi_{(StudentID)}\sigma_{DegreeStatus='ENG'}, S_1 \leftarrow \emptyset, S_2 \leftarrow \emptyset$   comment: intialize
2:  $S_{Res} \leftarrow S_0$   comment: display initial result set
3:  $S_1 \leftarrow S_{Res} \cap \Pi_{(StudentID)}\sigma_{AttendanceStatus='Inattendance'}(Students.bin)$
4:  $S_{Res} \leftarrow S_1$   comment: display only students in attendance
5:  $S_2 \leftarrow \text{ReadFileinDir(MECH-1001)} \cup \text{ReadFileinDir(MECH-1002)}$
6:  $S_{Res} \leftarrow S_1 \cap S_2$   comment: students in attendance and who took
7:      comment: 'MECH-1001' or 'MECH-1002' (or both)
8:  $S_2 \leftarrow S_2 \cap \{\text{ReadFileinDir(MECH-1003)} \cup \text{ReadFileinDir(MECH-1004)}\}$
9:  $S_{Res} \leftarrow S_1 \cap S_2$
10: $S_2 \leftarrow S_2 \setminus \text{ReadFileinDir dir(MECH-1003)}$
11: $S_{Res} \leftarrow S_1 \cap S_2$   comment: display final answer set
```

Algorithm 1 Basic algorithm corresponding to the query in Listing 4 with symbol σ denoting a restriction and II denoting the projection of a column

The query is stated as follows:

Find out the set of students from the 'ENG' school who are currently in attendance, who have taken either course 'MECH-1001' or 'MECH-1002' (or both) and who have taken course 'MECH-1004' but who have not taken course 'MECH-1003'.

Listing 4 displays a heavily simplified equivalent SQL query of our example query. The simplification is due to the complexity of the university's database schema; the actual SQL queries that were ran referred to about ten tables. The SQL environment where the queries were ran is discussed in Section 4.1.

4.4 Steps 0-3 of the query

In the following steps, the query is set up from scratch to the point of containing a simple disjunction.

- *Step 0 of the query: start-up routines* When OVI-3 is first started and the user has determined the viewpoint, a startup routine is fired up. This routine fetches some files, the latest value stores, from a common directory and copies them to the user's private directory. As part of the startup-routine, the primary value store under the main folder 'Students' is also read into memory for speed. As this is an initialization step in the startup routine, it is denoted as step 0 in Table 4.

- *Step 1 of the query: initial result set* Once the *StudentID* values of all students in the 'ENG' school (setup as the home school) have been identified, they are stored in memory as set S_0 as shown in step 1 in Algorithm 1. All sets (S_0, S_1 and S_2) in the algorithm are implemented as indexed string collection classes. The set S_0 remains a superset of all the sets maintained during a session. Its value will change only in case the user removes the default checkmark next to the home school (top left in Fig. 1a). Following step 1, the user is presented with an initial dataset (step 2 in Algorithm 1).

  OVI-3 completed this step in 0.603s (step1 in Table 4). We note again that with very late materialization, when writing the result set to the display grid, only the primary key values get written, with the rest of the attributes retrieved from the primary value store as needed.
- *Step 2 of the query: students currently in attendance* This step restricts students to those currently in attendance, achieved by placing a checkmark in the section 'Attendance status' next to the text 'In attendance', as shown in the top right of Fig. 1a. Implementation-wise, a new set of student IDs gets created, set S_1, which is a subset of set S_0 and obtained by taking the contents of set S_0 and further restricting it to students who are in attendance (step 3 in Algorithm 1).

  The set S_1 gets modified anytime the user changes query restrictions that are not related to courses. The user is then presented with a restricted set of students (Step no 4 in Algorithm 1). OVI-3 required 0.354s (Table 4) in order to complete this step 2.
- Step 3 of the query: students who have taken course 'MECH-1001' or 'MECH-1002' The user now adds the requirement that at least course 'MECH-1001' or course 'MECH-1002' needs to have been taken by typing part of the course code in the empty input course box (lower left in Fig. 1a) and selecting the appropriate courses. The two courses then appear in the course restriction box as shown in Fig. 1b. Course restrictions placed in the same box therefore have an implicit disjunction among them.

  As this new restriction is course related, a third set, S_2, independent of the set S_1, gets generated. S_2 will contain the student IDs of all students who meet the current course restrictions as explained next.

  Whenever the user enters a restriction for *CourseID* denoted *C*, OVI-3 examines the folder *dir*(*C*) under it, from which it reads a single file, the key fragment of T_{prim} residing under that folder. OVI-3 will then have at its disposal a set of all the students (a key fragment file contains only the *StudentID* values) who have taken course *C*; this can be stored temporarily if necessary [5].

  Returning to our example query, two key fragment files for table T_{prim} are read, one for course 'MECH-1001' (read from under *dir('MECH-1001')*) and the other for course 'MECH-1002' (read under *dir('MECH-1001')*). These files together generate a set S_2 of students who took one (or both) of theses two courses as seen in Algorithm 1, Step 5. Finally, the result set is obtained by taking the intersection of set S_1 with set S_2 (Algorithm 1, Step 6) using the set intersection algorithm described in Section 4.5. It took OVI-3 84ms (Table 4) to complete this step 3.

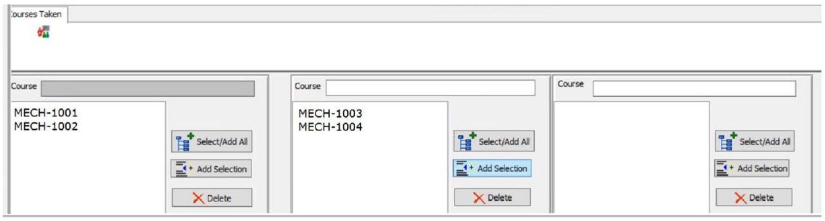
[5] The application at this stage is not concerned when a particular course was taken; in order to keep the user interface in OVI-3 simple, we assume that any student who has taken course *C* at some point in time gets included into set S_2.

Table 4 The initial step (step 0) and the five proper steps (1-5) needed to run the OVI-3 query in Section 4.3

Query Step	Description	Evaluation	Query time (secs)
0	Preliminary step done at startup: Copy latest data.	Copy latest key value stores for current user	2.287
1	Find students in home (‘ENG’) school who have achieved at least one unit of credit (done automatically at startup).	Read primary value store and generate new set S_0 containing only students in home school.	0.603
2	Restrict current set to students who are currently in attendance.	Use previous set S_0 to generate a more restrictive set S_1 excluding the student IDs of students not in attendance.	0.354
3	Generate separate set S_2 for students who have taken either course ‘MECH-1001’ or ‘MECH-1002’.	Generate a new set S_2 containing the student IDs of students who took ‘MECH-1001’ or ‘MECH-1002’ (or both). Display to user the result set of $S_1 \cap S_2$.	0.084
4	Restrict previous set to students who have also taken course ‘MECH-1003’ or course ‘MECH-1004’.	Update set S_2 to contain the student IDs of students who also took ‘MECH-1003’ or ‘MECH-1004’ (or both). Display to user the result set of $S_1 \cap S_2$.	0.0539
5	Restrict previous result set to students who have not completed course ‘MECH-1003’.	Update set S_2 to exclude the student IDs of students who took ‘MECH-1003’. Display the final result set as $S_1 \cap S_2$.	0.0804
		Total query time:	3.462
		Pure query time (excluding startup time):	1.175

The total time required to run the query (excluding the preliminary step) was slightly over one second, (1.175s in last row) while the equivalent SQL query in Listing 4 took 4.84s to complete. The last column shows the time required for each incremental OVI-3 step. Note that except for step 1, all steps are well within the suggested 0.5s threshold latency and that the fastest steps (3, 4 and 5) are those that make use of the DBI technique

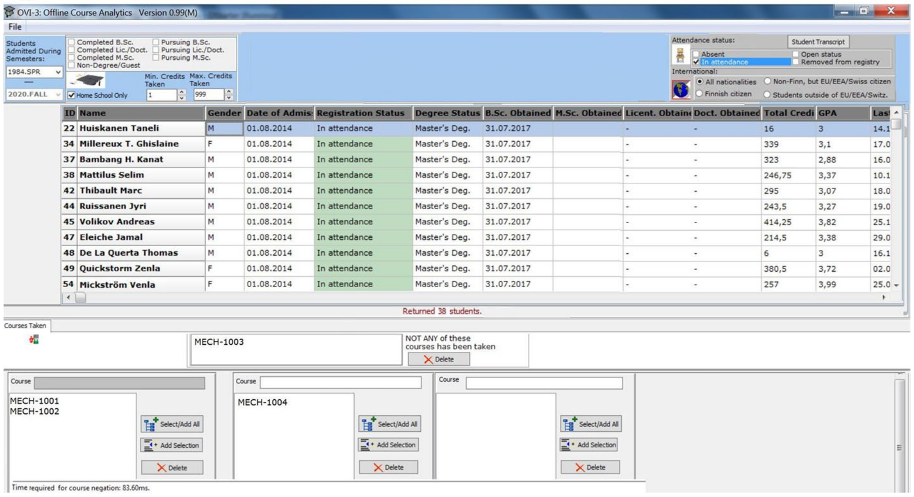
a



MECH-1001
MECH-1002

MECH-1003
MECH-1004

b



Students Admitted During Semesters: 1984.SPR — 2020.FALL

☐ Completed B.Sc. ☐ Pursuing B.Sc.
☐ Completed Lic./Doct. ☐ Pursuing Lic./Doct.
☐ Completed M.Sc. ☐ Pursuing M.Sc.
☐ Non-Degree/Guest

✓ Home School Only; Min. Credits Taken: 1; Max. Credits Taken: 999

Attendance status: ☐ Absent ✓ In attendance ☐ Open status ☐ Removed from registry

International: ● All nationalities ○ Finnish citizen ○ Non-Finn, but EU/EEA/Swiss citizen ○ Students outside of EU/EEA/Switz.

ID	Name	Gender	Date of Admis	Registration Status	Degree Status	B.Sc. Obtained	M.Sc. Obtained	Licent. Obtain	Doct. Obtained	Total Credi	GPA	Las
22	Huiskanen Taneli	M	01.08.2014	In attendance	Master's Deg.	31.07.2017		-	-	16	3	14.1
34	Millereux T. Ghislaine	F	01.08.2014	In attendance	Master's Deg.	31.07.2017		-	-	339	3,1	17.0
37	Bambang H. Kanat	M	01.08.2014	In attendance	Master's Deg.	31.07.2017		-	-	323	2,88	16.0
38	Mattilus Selim	M	01.08.2014	In attendance	Master's Deg.	31.07.2017		-	-	246,75	3,37	10.1
42	Thibault Marc	M	01.08.2014	In attendance	Master's Deg.	31.07.2017		-	-	295	3,07	18.0
44	Ruissanen Jyri	M	01.08.2014	In attendance	Master's Deg.	31.07.2017		-	-	243,5	3,27	19.0
45	Volikov Andreas	M	01.08.2014	In attendance	Master's Deg.	31.07.2017		-	-	414,25	3,82	25.1
47	Eleiche Jamal	M	01.08.2014	In attendance	Master's Deg.	31.07.2017		-	-	214,5	3,38	29.0
48	De La Querta Thomas	M	01.08.2014	In attendance	Master's Deg.	31.07.2017		-	-	6	3	16.1
49	Quickstorm Zenla	F	01.08.2014	In attendance	Master's Deg.	31.07.2017		-	-	380,5	3,72	02.0
54	Mickström Venla	F	01.08.2014	In attendance	Master's Deg.	31.07.2017		-	-	257	3,99	25.0

Returned 38 students.

MECH-1003 — NOT ANY of these courses has been taken

MECH-1001
MECH-1002

MECH-1004

Time required for course negation: 83.60ms.

Fig. 2 The final incremental steps for the OVI-3 query in Section 4.3. (All names and dates are fictitious). **a** A query that specifies that either course 'MECH-A1001' or 'MECH-1002' needs to have been taken in addition to course 'MECH-1003' or 'MECH-1004'. A third, empty course requirement box has appeared in case the user would like to enter further course restrictions to form a conjunction (be 'ANDed') with the two leftmost course restriction boxes. **b** The user has, through a right mouse button click, changed the status of course 'MECH-1003' to not-taken. The query therefore stipulates that in addition to course 'MECH-1004', students must have passed either course 'MECH-1001' or 'MECH-1002' and must not have taken course 'MECH-1003'

4.5 Steps 4 and 5 of the query

In the following final steps, the query is transformed into its final form with the negation.

- *Step 4 of the query: students who have also taken either course 'MECH-1003' or course 'MECH-1004'* OVI-3 deals with negation by first defining the negated restriction as a normal restriction, and then switching it to a negation in a separate step as shown next. We thus first add the requirement that besides the earlier course requirements, either course 'MECH-1003' or course 'MECH-1004' (or both) also needs to have been taken.

  As this new requirement builds on the previous course requirements, it gets placed in a separate, adjacent course box. Course restrictions that reside in adjacent course boxes thus have an implicit conjunction between them. The query in Fig. 2 still differs from our example query, which stipulated that course 'MECH-1003' must not have been taken.

Set S_2 is now updated to students (or rather their student IDs) who took either course 'MECH-1001' or 'MECH-1002' (or both) and who took either course 'MECH-1003' or 'MECH-1004' (or both), as shown in Steps 8 and 9 in Algorithm 1. This is achieved by first taking the set of students who took either 'MECH-1003' or 'MECH-1004' and then taking its intersection with the previous set S_2. We note that when there are three or more course boxes involved, we can compute the S_2 set in steps through binary set intersections or in a single operation that involves all sets (Culpepper and Moffat, 2007). OVI-3 uses the latter approach, and assuming a case with three adjacent course boxes defined, OVI-3 will determine the course box with the least number of elements (i.e., the smallest number of course IDs), say C_j, and then proceed to build the set S_2 by including only those students in course box C_j who also appear in the other key fragment files containing values for α_{prim} related to the other two course boxes. The restriction for step 4 was completed in just 53.9ms (Table 4).

- *Step 5 of the query: placing the negation* In the final step (which required 80.4ms as indicated in Table 4), the restriction for course 'MECH-1003' is changed from being taken to not being taken by selecting course restriction 'MECH-1003', and then pressing the right-mouse button, upon which restriction 'MECH-1003' moves into a separate negation area. The final query is shown in Fig. 2b.

  The set S_2 now gets updated to contain only students who have not taken course 'MECH-1003' by subtracting from set S_2 those students' IDs who took course 'MECH-1003'. These are Steps 10 and 11 in Algorithm 1.

  There is a clear benefit in requiring the user to define a negated restriction by first specifying it in a positive (non-negated) format. This way, when the restriction gets changed into a negation, it is highly likely that the key fragment file associated with the restriction (i.e., values for α_{prim}, or the student IDs in this case) is going to be found in the cache. Reading the data from cache rather than from slower main memory naturally reduces the query retrieval time (Morfonios & Ioannidis, 2008).

4.6 A comparison of running queries using OVI-3 and an SQL-database

We now compare the performance of the SQL query in Listing 4 to its equivalent OVI-3 query in Section 4.3, which is actually query Q_5 in Table 5. In addition, several other queries (denoted Q_1 to Q_4 and Q_6) tested using both OVI-3 and an equivalent SQL query are shown in Table 5. Note how query Q_3, which only contains a negation, is orders of magnitude faster when using DBI.

4.6.1 Cost comparison for an anti-join

We next compute the theoretical cost of an anti-join query using the OVI-3 approach and an equivalent SQL-based query. The hypothetical query finds those students who have not taken course 'MECH-1001', with the assumption that 256 students *have* taken that course. It involves two tables, of which R, the larger (1024000 rows), stands for *CoursesTaken*, while the smaller table S (124000 rows), stands for *Students*. We denote those 256 students who took course 'MECH-1001' through the set S', so that $R - S'$ is the query's answer set. We neglect the cost of writing the final answer set to disk and assume a blocking factor of 64 rows per data page.

For the database server side, we assume a text-book approach as in Molina et al. (2009) with a two pass set difference, requiring two block accesses for partitioning and one for the

Table 5 The total times required to run seven different queries operating on the same data via an SQL query and the equivalent OVI-3 approach

Query no	Description	SQL time (secs)	OVI-3 time (w/o file copy)
Q_0	Find students in home school ('ENG') who have taken course 'MECH-1003'.	1.3s	2.98s (0.23s)
Q_1	Find students in home school ('ENG'), currently in attendance who have not taken course 'MECH-1003'.	275.8s	3.67s (1.36s)
Q_2	Find students in home school ('ENG') who have not taken course 'MECH-1003'.	540s	3.52s (1.32s)
Q_3	Find students (include all schools) who have not taken course 'MECH-1003'.	3604s	4.91s (2.67s)
Q_4	Find students in home school ('ENG') who have not taken any of the four courses: 'MECH-1001', 'MECH-1002', 'MECH-1003', 'MECH-1004'.	209.3s	3.58s (1.37s)
Q_5	Find students in home school ('ENG') who are currently in attendance, have taken course 'MECH-1001' or 'MECH-1002' (or both) and have also taken course 'MECH-1004' but have not taken course 'MECH-1003'.	5.4s	3.46s (1.17s)
Q_6	Find students in home school ('ENG') and who are currently in attendance.	57.5s	3.43s (0.94s)

The times shown were obtained by running the same query three times for each of the two approaches and taking the median of the obtained times. For OVI-3, there was a startup time involved for each query that varied between 2.74s and 3.1s. The actual query times without the startup times are shown in parentheses actual set difference, amounting to a query cost $C[_{\text{SQL}}] = 3B(R) + 3B(S')$. Substituting, we get $B(R) = 1024000/64 = 16000$ and $B(S') = (124000 - 256)/64 = 1994$, so the query cost $C[_{\text{SQL}}] = 48000 + 5982 = 53982$ I/O blocks. Assuming an average access disk time of 8ms per block, 53982 *8ms≈432s. Little wonder then, that when a similar query (with a much larger number of tables and attributes as the one described here) was run in the Oracle SQL-server, it took about 1h to complete (Query Q_3 in Table 5).

$$C_{\text{OVI-3}} = h_R + F_{dir(\text{'MECH-1001'})} + antijoin_{(\text{InMemory})} \tag{2}$$

As for OVI-3, we assume that the DBI technique is implemented via a file management system that uses the B$^+$-tree (used with Windows ReFs or NTFS). We allow for 1 billion entries in the disk volume used in the DBI, so a B$^+$-tree with height $h_R = 5$ suffices. The cost for the OVI-3 approach, (2) is the sum of three parts, namely, (1) using DBI to locate the folder corresponding to course 'MECH-1001', (2) reading from that folder the contents of the key fragment file F containing values for α_{prim} (the set S'), and finally (3), obtaining the result set by subtracting from the primary value store the set S'. This last step is a memory operation that is assumed never to exceed 0.2s.

The size of file F is assumed to be 1kB (256 *4B) where 4B is the key size. Being clearly less than the block size 4kB, the key fragment file can thus be read with a single disk access. Again using an access time of 8ms and assuming 200ms for the memory operation, the cost $C_{\text{OVI-3}}$ is the sum of the previous parts (1) and (2): $(5 + 1) * 8ms + 200ms$ which translates to 248ms. The measured time for a similar query Q_3 in Table 5, is 2.67s and clearly much larger, due to the fact that negation in OVI-3 occurs in parts (preceded by a non-negated part).

When using OVI-3 to express a negation **not** A, it will always be immediately preceded by its non-negated restriction A. Thus when computing the negation, the non-negated part A can be assumed to be in memory while the set of all primary keys α_{prim} always resides in memory. The cost of a negated expression for OVI-3 with respect to its corresponding non-negated expression is thus merely an additional memory access rather than disk access. Computing the ratio for the SQL query costs (measured time over computed time) gives 3604s/ 432s ≈ 8.3 while the similar ratio for the OVI-3-query costs (measured over computed) yields 2.67s / 0.248s ≈ 10.8. This rather minor discrepancy between these two ratios (8.3 and 10.8) supports the notion that the computed costs for both the SQL and the OVI-3 approach are valid.

5 Conclusions

The four presented approaches used with OVI-3, namely (1) DBI, (2) viewpoints, (3) incremental querying and (4) very late materialization are certainly not revolutionary, but when used together, they do allow for efficient handling of primal joins and anti-joins. Incremental querying helps in avoiding unnecessary complex joins, since a new result set gets evaluated as soon as there is a change in the query definition.

Since most OLAP queries can be considered to be essentially ad-hoc, introducing incremental querying into the OVI-3 VQS proved very helpful. The incremental query technique does not fit well into a database server with SQL queries. For instance in VQS SIEUFERD (Bakke and Karger, 2016), the authors provided users with an impression of incremental querying rather than an actual implementation of it.

We did not use a data warehousing approach since the original data for OVI-3 already resided in a relational database. The option of configuring and setting up a big data platform such as SQL-on-Hadoop System (Alavi et al., 2014) was deemed too costly, and querying in the cloud was not an option due to university policy on sensitive data. Moreover, big data platforms are not without their challenges, often providing indexes only for the primary key (Agrawal et al., 2018).

Although OVI-3 is a novel query application that was in test use by three academic counsellors for under a year, it handled their analytical query needs at impressive speeds. The DBI scheme, together with the incremental query approach, truly encourages users to explore data, since each query will, in most cases, terminate well within one second.

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Declarations

Human and animal Ethics Not Applicable.

Ethics approval and consent to participate The included screenshots refer to imaginary students. There are no references to real life persons or to their opinions.

Consent for publication There are no references or identifiable details to any participants in this work.

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[6] The position listed for each person is the one that was active during the time that OVI-3 was being developed.

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