Conversational Databases: Explaining Structured Queries to Users

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***Abstract*— Many applications offer a form-based environment for naïve users for accessing databases without being familiar with the database schema or a structured query language. Do-It-Yourself, database-driven web application platforms empower non-programmers to rapidly create applications. Users interactions are translated to structured queries and executed. However, as a user is unlikely to know the underlying semantic connections among the fields presented in a form, it is often useful to provide her with some feedback about the queries built without exposing her to the underlying query language, in order to assist her in forming queries correctly. Explaining queries may be also useful for users who explicitly use a structured query language for verification or debugging purposes. In this paper, we take a graph-based approach to the query translation problem. We represent various forms of structured queries as directed graphs and we annotate the graph edges with template labels using an extensible template mechanism. We present different graph traversal strategies for efficiently exploring these graphs and composing textual query descriptions. Finally, we present experimental results for the efficiency and effectiveness of the proposed methods.**

I. Introduction

Structured query languages are powerful tools at the hands of advanced searchers and experienced developers but the vast majority of users are not familiar with them. For this reason, many applications (e.g., museum portals, digital libraries, e-commerce sites, and so forth) offer a form-based environment for formulating queries to search (web-based) databases. In addition, emerging Do-It-Yourself (DIY), database-driven web application platforms empower non-programmers to rapidly and cheaply create and evolve applications customized to their needs by manipulating visual elements [1], [2]. In all these scenarios (i.e., involving searching and programming over a database), user interactions with the interface are translated to structured queries. Explaining these implicitly built queries without exposing the details of the underlying query language becomes vital especially when executing a query may have a different outcome or effect from what the user has anticipated. Translation of a user's choices on a certain form in a narrative would assist her in forming queries correctly, even without being familiar with a specific interface or a query language. Especially in large forms, a user is likely to not know the underlying semantic connections among the fields presented in the form, and a textual explanation may come in handy.

Explaining queries in text may be useful in some cases for users that use a structured query language for writing queries. Before the query is sent for execution, it may be useful to see the query expressed in a more familiar way in order to check that it captures correctly the intended meaning. A user trying to understand an error message concerning her mistaken query would prefer to have an explanation of that query in a familiar language, instead of getting back an error code and a generic error description. As another example, when a query returns an empty answer, an explanation of the query may help identify parts of the query that are responsible for the failure. Similarly, when a query returns a very large number of answers, a query explanation may highlight the reasons, in case a rewrite would reduce the number significantly and serve the user better.

In general, in any situation where explanation of queries is warranted, such textual interpretation may be very useful and effective. Insertions, deletions, and updates, especially those with complicated qualifications or nested constructs, will benefit from a translation into natural language. Likewise for view definitions and integrity constraints, which borrow most of their syntax from queries. Although here we focus on SQL, similar arguments can be made about RDF queries in SPARQL or RQL, even Datalog programs, and others.

The requirement for translating structured queries to text is further dictated by current trends. Automating computer-to-human speech translation is recognized as one of the seven most important IT challenge for the next 25 years by Gartner analysts who examine technologies that will have a broad impact on all aspects of people's lives [3].

Translating queries into narratives has been largely ignored so far. Traditionally, the application of natural-language techniques to the front-end of an information system environment has been one-directional: from NL requests for information to queries production (e.g., [4]). Unfortunately, the fact that NLP tools are trying to match SQL query patterns with NL queries significantly bounds the idea of reversing their functionality for getting the NL translation of an SQL query.

Outline of Work. The problem we are studying can be informally stated as follows: Given a query q over a database D, we would like to generate a narrative that captures the intended meaning or objective of q. Translating a structured query to text is challenging due to a number of reasons, including insufficient SQL semantics and the complexity of the queries, which may have nested queries, complex query

Departments(DepID, DepCode, Name) Courses(CourseID, DepID, Title)
Instructors(InstrID, Name) Students(SuID, Name, Class, GPA)
CourseSched(CourseID, Year, Term, InstrID, TimeSlot)
StudentHistory(SuID, CourseID, Year, Term, Grade)
Comments(SuID, CourseID, Year, Term, Text, Rating, Date)

Fig. 1. An example course database

conditions and different query constructs (group-by, order-by, etc). In addition, there are several alternative expressions of a query in a formal language that are equivalent, based on associativity, commutativity, and other algebraic properties of the query constructs. Capturing the query elements in the right order so that the corresponding textual expression is natural and meaningful independent of the way the user has expressed the query is not straightforward.

We take a graph-based approach for representing various forms of structured queries as directed graphs. We annotate the graph elements with labels using an extensible template mechanism. We present three translation strategies. In the first one (BST algorithm), the translation consists of a composition of clauses each one focusing on specific query semantics. In the second strategy (MRP algorithm), the translation is realized in a holistic manner, where information from all parts of the query graph is blended in the translation as we traverse the graph. The last strategy (TMT algorithm) enables the use of predefined, richer, templates for query parts in an effort to produce more concise translation. Our approach mainly targets queries like those found in [2]. However, a query language has different semantics than a spoken language. In our previous work, we have presented a taxonomy of queries based on their complexity and expressivity [5]. There are queries that are very difficult or even impossible to be translated in a meaningful way. We can still handle some of these using pre-defined patterns.

Contributions. In summary, our contributions are:

- We introduce a novel query graph model for capturing the possible semantics of a query.
- We give semantics to the various parts of a query by annotating the query graph edges with template labels using an extensible template mechanism.
- We present different, domain-independent graph traversal strategies for efficiently exploring query graphs and composing query descriptions as phrases in natural language.
- We present an algorithm for selecting the best templates for a query given (possibly overlapping) templates for different query parts.
- We compare the translation algorithms and show their applicability and effectiveness through experimental results.

II. Query Representation

We focus on relational databases and SQL queries. In this section, we introduce our query graph representation that captures query elements and their semantic associations.

A. Database Graph

A database D comprises a set of relations. A relation R_i has a set of attributes. We use A_j^i to refer to an attribute of R_i. We represent the database D by its *database graph* $\mathbf{G}(\mathbf{V}, \mathbf{E})$, a directed graph corresponding to the schema of D extended to capture the basic roles of attributes in queries over the relations of the database. Nodes in $\mathbf{V}$ are: (a) *relation nodes*, $\mathbf{R}$ - one for each relation in the schema; (b) *attribute nodes*, $\mathbf{A}$ - one for each attribute in the schema. Edges in $\mathbf{E}$ are:

- *membership edges*, $\mathbf{E}^{\mu}$ - connecting an attribute node to its container relation node. A membership edge μ between an attribute A_j^i and a relation R_i formally is: $e_\mu : R_i \xleftarrow{\mu} A_j^i$.
- *selection edges*, $\mathbf{E}^{\sigma}$ - connecting each relation to each of its attributes. A selection edge σ between a relation R_i and its attribute A_j^i represents a possible selection of tuples from R_i based on a condition that involves A_j^i. Formally: $e_\sigma : R_i \xrightarrow{\sigma} A_j^i$ or $e_\sigma : R_i \xleftarrow{\sigma} A_j^i$.
- *predicate edges*, $\mathbf{E}^{\theta}$ - emanating from an attribute node and ending at another attribute node. A predicate edge θ between two attributes A_j^i and A_k^m represents a potential join between two relations R_i and R_m using the attributes. Formally: $e_\theta : A_j^i \xrightarrow{\theta} A_k^m$.

Therefore, the database schema graph is a directed graph $\mathbf{G}(\mathbf{V}, \mathbf{E})$, where $\mathbf{V} = \mathbf{R} \cup \mathbf{A}$ and $\mathbf{E} = \mathbf{E}^{\mu} \cup \mathbf{E}^{\sigma} \cup \mathbf{E}^{\theta}$.

For our examples, we consider the course database depicted in Figure 1 [6]. Figure 2 shows how a join between two relations, Students and StudentHistory, is captured on the database graph: we can start from Students and join to StudentHistory using the path Students $\xrightarrow{\sigma}$ SuID $\xrightarrow{\theta}$ SuID $\xrightarrow{\sigma}$ StudentHistory or vice versa using the path StudentHistory $\xrightarrow{\sigma}$ SuID $\xrightarrow{\theta}$ SuID $\xrightarrow{\sigma}$ Students. This example shows how our query graph representation captures the query semantics (in contrast to other query representations [7], [8]): operationally the two paths may be equivalent, e.g., in the case of equi-joins. Semantically they may have different translations. As we will in Section IV, for the same join between two relations, we may choose one path over the other (e.g. choose between "courses taken by the students" or "students have passed courses") depending on the query and the translation.

B. Query Graphs

We first consider SPJ queries and then we extend our graphs to handle queries that contain query elements, such as functions, groupings, as well as subqueries.

A SPJ query q is represented by its *query graph* $G_q(V_q, E_q)$, a directed graph that is an extension of the database graph. Nodes in V_q are: (a) *relation* nodes - one for each relation and tuple variable in the query; (b) *attribute* nodes - one for each attribute in the query possibly duplicated if the attribute is found in different parts of the query; and (c) *value* nodes - one for each value or a set of values specified in the query qualification. Edges in E_q are defined as follows:

- *membership edges*: for each attribute A_j^i projected from a relation R_i, there is a membership edge: $e_\mu : R_i \xleftarrow{\mu} A_j^i$.
- *predicate edges*: for each predicate of the form $A_j^i\ \theta\ \Omega$, where Ω can be a single value or a set of values or an attribute, and θ denotes a comparison operator (e.g., $=$, $<$, $>$, $<>$ and $LIKE$), there is a predicate edge. We

Fig. 2. A join on database graph

distinguish two cases: If Ω is a single value or a set of values, then it is a selection predicate edge: $e_\theta : A_j^i \xrightarrow{\theta} \Omega$. If Ω is an attribute A_k^m, then it is a join predicate edge: $e_\theta : A_j^i \xrightarrow{\theta} A_k^m$. In this case, we also capture the inverse direction: $e_{\theta'} : A_j^i \xleftarrow{\theta} A_k^m$, where θ' is the inverse of θ (e.g, if θ is $>$ then θ' is $\leq$).

- *selection edges*: for each predicate of the form $A_j^i\ \theta\ \Omega$, where Ω is a value (or set of values), there is a selection edge from its container relation R_i to A_j^i: $e_\sigma : R_i \xrightarrow{\sigma} A_j^i$. If Ω is an attribute, then there is also $e_\sigma : R_i \xleftarrow{\sigma} A_j^i$.

Example 1 Let us consider the following query.

```
select  s.name, s.GPA, c.title, i.name, co.text
from    students s, comments co
        studenthistory h, courses c, departments d,
        coursesched cs, instructors i,
where   s.suid = co.suid and
        s.suid = h.suid and h.courseid = c.courseid and
        c.depid = d.depid and
        c.courseid = cs.courseid and cs.instrid = i.instrid and
        s.class = 2011 and co.rating > 3 and
        cs.term = 'spring' and d.name =' CS'
```

Its graph representation is shown in Fig. 3. We observe that each join in the query is mapped to two paths with inverse directions between the relations joined. We also observe how a condition involving an attribute and a value, e.g., s.class $=$ 2011 is captured as a path composed of selection and predicate edges, like Students$\xrightarrow{\sigma}$ class $\xrightarrow{=}$ 2011.

To capture functions, expressions, and renaming operations as well as order $-$ by, group $-$ by and having clauses, we extend the query graph with the following edge and node types:

- *function nodes*: A function node f is used for representing a function, an expression or a renaming operation that is applied on an attribute A_j^i or a set of attributes.
- *transformation edges*: A transformation edge r is used for connecting an attribute A_j^i with a function f that is applied to A_j^i. If A_j^i is in the select clause of the query, then the edge is defined: $e_r : A_j^i \xleftarrow{r} f$. If A_j^i is in the where clause of the query, then the edge is defined: $e_r : A_j^i \xrightarrow{r} f$.
- *order edges*: An order edge o is used for representing an ordering. If the query results are ordered based on the attributes A_j^i, A_l^k, ... (in that order), then we consider a set of order edges, the first one starting from the container relation R_i to A_j^i ($e_o : R_i \xrightarrow{o} A_j^i$), and each of the remaining ones starting from each attribute and ending at the subsequent in the order attribute ($A_j^i \xrightarrow{o} A_l^k$, ...). o shows if it is an ascending or descending order.
- *grouping edges*: A grouping edge γ is used to represent a grouping. If the grouping attributes are A_j^i, A_l^k, ... (in that order), then we consider a set of grouping edges, the first one starting from the container relation R_i to A_j^i ($e_\gamma : R_i \xrightarrow{\gamma} A_j^i$), and each of the remaining ones starting from each attribute and ending at the subsequent in the grouping attribute ($e_\gamma : A_j^i \xrightarrow{\gamma} A_l^k$, ...).
- *having edges*: a having edge h is used to show attributes in having clauses. For each participating attribute A_j^i of a relation R_i, there is an edge: $e_h : R_i \xrightarrow{h} A_j^i$.

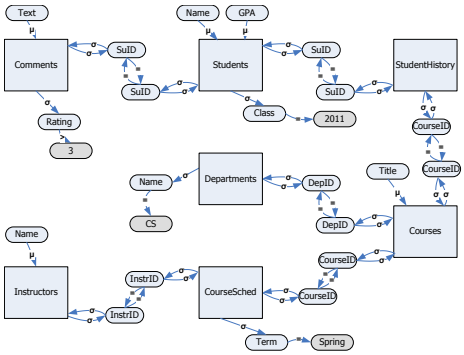


Fig. 3. A SPJ query

Example 2 Let us consider the following query.

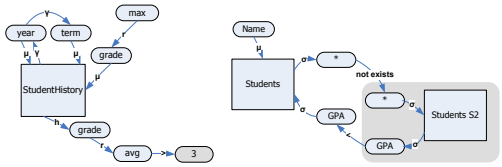
```
select   year, term, max(grade)
from     studenthistory
group by year, term   having   avg(grade) > 3
```

Its graph representation is shown in Fig. 4(a). The grouping attributes are year and term, hence there are two grouping edges γ, one from the relation where year belongs and the other from year to the next attribute in the grouping order, i.e., term. The projecting attributes are year, term and grade; but the latter is an aggregated attribute, which is connected with a transformation edge to an aggregate function node max. Moreover, the attribute grade aggregated (with a different function here) is in the having clause. This is captured as a path involving a having edge, connecting the attribute with its relation, a transformation edge, connecting the attribute with the function node avg, and a predicate edge connecting the function node with the value. If a function involved more than one attribute, then more than one attribute node will be connected to the same function node in the query graph through transformation edges. Finally, we use two copies of the attribute grade depending on its role for making the example clear. We could have one instance of this attribute.

We now consider queries with nesting. A parenthesized select-from-where statement (subquery) can be used in a number of places: in a from clause, where it is treated as a table that is joined to other tables in the query, in a select, where it is treated as a set of attributes to be projected or in a where or having clause, where it can be treated as a list of values or a single value that participates in a predicate in this clause. We consider that in a predicate of the form $A_j^i\ \theta\ \Omega$, θ denotes a comparison operator (e.g., $=$, $<$, ...), or *a set comparison operator*, such as $(NOT)EXISTS$, $(NOT)IN$, $\theta' ANY$ and $\theta' ALL$, where θ' is a comparison operator.

Given a query q (the "parent" query), *each subquery block* q_m in q is represented as a separate query subgraph. This subgraph is treated as a "virtual" relation and it is connected to the parent graph as follows depending on its position:

- Each predicate in q of the form $A_j^i\ \theta\ q_m$, where q_m *returns*



(a) A group-by query (b) A nested query

Fig. 4. Example queries

an attribute A_k^m, is represented as a path connecting the attribute A_j^i with its relation R_i through a selection edge and with the respective A_k^m through a predicate edge that starts from A_j^i and ends at A_k^m, i.e.: $R_i \xrightarrow{\sigma} A_j^i \xrightarrow{\theta} A_k^m$.

- Each predicate of the form $A_j^i\ \theta\ A_k^m$ in q where A_k^m is an attribute *returned* by the subquery q_m and A_j^i belongs to a relation in the parent query is represented as usual.
- Each predicate of the form $A_j^i\ \theta\ A_k^m$ *defined in the subquery* q_m, where A_k^m is an attribute defined in the scope of q_m and A_j^i is an attribute defined outside q_m (i.e., in the query q) is represented as a path connecting the attribute A_k^m with its relation R_m through a selection edge and with the respective A_j^i through a predicate edge that starts from A_k^m and ends at A_j^i and A_j^i with its relation R_i in q with a selection edge, i.e.: $R_m \xrightarrow{\sigma} A_k^m \xrightarrow{\theta} A_j^i \xrightarrow{\sigma} R_i$.

A query in the where-clause is an example of the first case above, unless queries are correlated; then it is the last case. A query in the from-clause is an instance of the second case.

Example 3 Let us consider the following query.

```
select  s.name   from   students s
where   NOT EXISTS  (select * from students s2
                     where s2.GPA > s.GPA)
```

Figure 4(b) shows the query graph for this query. This example covers the first and third cases: the subquery is in the where-clause and it references an attribute of the parent query (i.e., correlated queries). That is why we observe the two paths between the two relation nodes: one going towards the subquery (for the first case) and one coming out of it (for the third case). Here we see that if θ is $(NOT)EXISTS$, the subquery q_m does not return any attributes. In that case, we use dummy attribute nodes, one connected to the query subgraph and one connected to the parent query graph. This example also shows how multiple instances of a relation each one corresponding to a different tuple variable over the relation are mapped in the query graph.

III. Capturing Query Semantics

To capture query semantics over a database D, we capture the semantics of its nodes and edges. Then, when a query graph for a new query is given, we apply different strategies (see Section IV) to find which parts of our knowledge can be mapped onto the graph and how we can compose this knowledge for understanding the semantics of the whole graph. In this section, we describe a template mechanism that allows us to represent semantics of query graph elements.

Labels. Each node v that can be part of a query graph over a database D has a *conceptual* meaning. For example, the conceptual meaning of a relation node represents its entity type; e.g., for Students the conceptual meaning is 'students'. The conceptual meaning of a function captures its outcome (e.g., the function max represents "the greatest" of its input.) For expressions or unknown functions, we consider default labels, such as "an expression on" or "a function".

We define as the *label* l of a node v the conceptual meaning of the node, and we denote it as $l(v)$. For example, the label l(Name) of the attribute node Name may be "name". Values are treated as literals, so for a value node val: $l(val) = val$.

Each edge (or path) connecting two nodes can be annotated by a label that signifies the meaning, in natural language, of the relationship between the source and destination nodes. For example, each membership edge from an attribute A_j^i to its container relation R_i is annotated by a label that signifies the meaning of the relationship of A_j^i with R_i's conceptual meaning. Referring to Fig. 3, the membership edge connecting Students to its attribute Name may have the label "of", and the predicate edge participating in the join of Students and Courses (in this direction) may have the label "have taken". Fig. 5 shows example labels for the graph of Fig. 3.

Labels are stored on the database graph for both nodes and edges. A query graph inherits these edges from the database graph. Node labels can be automatically extracted from the names of database constructs using schema matching and entity resolution techniques. As a second step (or even first when such names are not meaningful), the system designer should correct or complement these findings. Our implementation does support default labels (e.g., "of" for membership edges), but as the designer provides the system with more fine-tuned labels, the translation results are even more descriptive.

Templates. Our translation methods (Section IV) traverse the query graph and create phrases by composing labels found on the way. For producing more natural results, we define template labels at different granularity levels and we provide an extensible template mechanism to fuse these labels.

A *template label*, $l((v,u))$, is assigned to an edge (v,u) or more generic, to a path connecting v to u. This template is used for the interpretation of the relationship between v and u in a narrative. A generic template label may have the form:

$$l((v,u)) = expr_1 + l(v) + expr_2 + l(u) + expr_3 \quad (1)$$

where $expr1$, $expr2$, $expr3$ are alphanumeric expressions and the operator "+" acts as a concatenation operator. For using or registering template labels, we use a template language (based on [9]) that supports variables, loops, functions, and macros. Example macros implemented in our system, are:

(a) $l_M(v)$, which creates a phrase containing information of all template labels involving the membership edges of v (if any); i.e., $l((x,v)), \forall edge\ (x,v) \in E^{\mu}$.

(b) $l_V(v)$, which creates a phrase containing information of all template labels involving the paths starting from v and ending to its values (if any); i.e., $l((v,y))$, $\forall (v,y) \in E^{\sigma}$, $(y,z) \in E^{\theta}$, z is a value node.

(c) $l_{MV}(v)$ = $l_M(v)$ + $expr1$ + l(v) + $expr2$ + $l_V(v)$; this macro provides a *full translation* of v, in the sense that it translates anything related to v.

Operators	Translation	Translation variables	Translation	Template labels	Description
$l(=)$	'is'	VAL_SEL	"whose"	$l(e_\sigma)$	$l(R_i)$+VAL_SEL+$l(A_j^i)$
$l(\leq)$	"does not exceed"	$COORD\_CONJ$	"and"	$l(e_\theta)$	$l(A_j^i) + l(\theta) + l(\Omega)$
$l(>)$	"greater than"	$CONJ\_NOUN$	"that"	$l(e_\mu)$	" the " + $l(A_j^i)$ + " of " + $l(R_i)$
$l(LIKE)$	"looks like'	$CONJ\_PROJ$, $CONJ\_SEL$	"and"	$l(R_i \xrightarrow{\sigma} A_j^i \xrightarrow{\theta} A_j^i \xrightarrow{\sigma} R_i)$	$l(R_i)$ + " with the same " + $l(A_j^i)$

TABLE I

EXAMPLE LABELS FOR TEMPLATE CONSTRUCTS

We consider templates of two types: *generic* and *specific*. The former are defined on edges and are constructed automatically following the form (1). Example generic templates are depicted in Table I. A generic template is essentially database-agnostic. Applying $l(e_\sigma)$ template to Students $\xrightarrow{\sigma}$ Name gives the label "students whose name". Templates for predicates, $l(e_\theta)$, contain labels for operators, $l(\theta)$ (Table I). Also, for ensuring the extensibility of templates, we encourage the use of template variables. For example, for combining a sentence with a noun phrase, we use the variable $CONJ\_NOUN$ that coordinates this conjunction. Table I shows the default values used in our implementation. The designer can change these values globally or change a value corresponding to a subset of constructs (e.g., only the label of a specific e_μ).

Specific templates can be defined not only on edges, but on paths as well. These are created manually and stored in an external structure (see Section IV-C). Since the specific templates are created by a human, they can produce high quality and concise text. Hence, when they exist, they should be preferred for query translation. As a short example, a specific template for the selection edge $e_\sigma(\mathsf{Students}, \mathsf{Name})$ may be the following: $l(e_\sigma(\mathsf{Students}, \mathsf{Name})) = l(\mathsf{Students}) +$ " named ".

Note, template labels follow the direction of edges; thus, if between two nodes there exist two edges with inverse directions, then template labels may be assigned to both.

IV. QUERY TRANSLATION

In this section, we present algorithms for the query translation problem. The translation of a generic SPJ query involves three parts: (a) *subject*, i.e., the primary entity of our interest, (b) *information*, i.e., the attributes of the subject whose values we wish to know, (c) *subject qualification* for focusing on entities with certain properties. (This classification is extended to cover grouping and ordering semantics in Section IV-D.)

First, we discuss the issue of query subject, and then we present three translation strategies. The first two, termed BST and MRP, use *generic* template labels on the edges of the query graph and they compose them as they traverse the graph. The third strategy (TMT algorithm) extends to *specific* templates for reducing the text size and producing more concise translation.

The query described in the *Example 1* and its query graph (Fig. 3) will serve as a reference example. Fig. 5 depicts a simplified version of this query graph (join paths have been replaced by a single "virtual" edge) annotated with labels.

A. Query Subject

The query subject represents what the query refers to. Identifying the query subject is important because it determines

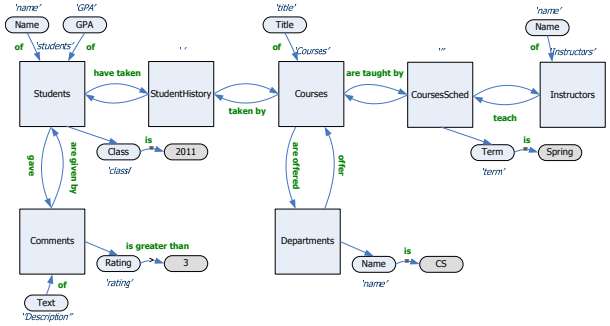


Fig. 5. Our running example with labels

how we traverse the query graph, i.e., the query translation direction, and what kind of clauses we generate. Naturally, it is a relation with attributes projected in the select-clause. Unfortunately, when more than one relation projects attributes, the query subject cannot be determined solely based on the select-clause, due to the limited semantics of SQL. For example, a request for the names of students and the titles of the courses they took and a request for the titles of the courses and the names of the students that took these courses are both expressed with the same SQL query.

To illustrate this challenge, let us consider a rather simple query:

```
select  s.name, c.title
from    students s, studenthistory h, courses c
where   s.suid = h.suid and h.courseid = c.courseid and
        h.term = "spring" and h.year = 2009 and
        s.class = 2010
```

There are two possible, both valid, interpretations of the query: "show the names of students and the titles of the courses they have taken" (the students play the central role and everything else refers explicitly or implicitly to them), or "show the titles of the courses and the names of the students that have taken these courses" (the courses play the central role). A different scenario is shown with the following query:

```
select  h.grade
from    studenthistory h
where   h.term = "spring"
```

It may be easy for a human to understand that this is a request for the grades of students (or possibly of courses) in the spring quarter but none of the relations, i.e., Students or Courses, for each potential query subject are in the query. Consequently, we cannot determine the query subject solely based on the select and/or from-clause.

In what follows, we first give some basic definitions and then we describe our approach for determining the query subject.

Definition 1: Primary relation R_P. A relation storing information for a set of entities of the same type is called *primary*.

Definition 2: Secondary relation R_S. A relation that stores information for a relationship of entities that are stored in different relations is called *secondary*.

For example, referring to Fig. 5, Students is a primary relation, whereas StudentHistory shows how courses and students connect and is secondary. Primary relations can be identified either by the designer or inferred during the construction of the database schema from an E/R diagram (entities in a E/R diagram make primary relations). The rest are secondary. Primary relations whose attributes are projected in the query result, are candidates for query subject. Intuitively, since the query subject is a reference point around which the query explanation is built, it is reasonable to select one that is "central" in the query graph, so that all references to it can be as short and concise as possible. A formal definition follows.

Consider a query q and its query graph $G_q(V_q, E_q)$. $\mathbf{R}$ is the set of nodes corresponding to the query relations. The distance $\delta(R_i, R_x)$ between two relations R_i and R_x on the graph G_q is the length of the shortest path between the two relations. Since in our context query graphs are typically connected it holds that $\delta(R_i, R_x) > 0$, $\forall R_i, R_x \in \mathbf{R}, R_i \neq R_x$.

Definition 3: Query subject, R_q. The query subject is a primary relation $R_q \in \mathbf{R}$ with attributes projected in q s.t.: $\max_{R_x \in \mathbf{R}}(\delta(R_q, R_x)) \leq \{\max_{R_x \in \mathbf{R}}(\delta(R_i, R_x)) : \forall R_i \in \mathbf{R}\}$.

In words, the query subject is a primary relation with attributes projected in the query and its distance to the furthest relation on the graph is shorter than (or at the worst equal to) the distance of any other relation from its furthest relation on the graph.

In Fig. 5, primary relations with projected attributes in the query are Students, Courses, Comments, and Instructors. The longest path of each one of them has length: 12, 9, 15, 15, respectively (each "virtual" edge connecting two relations contains 3 edges). Hence, Courses has the minimum longest path and it becomes the query subject.

1) QSUB *Algorithm:* The algorithm for selecting the query subject (Fig. 6) computes for each primary relation with attributes projected in the query, the shortest paths on the query graph to all reachable relation nodes and the resulting distances performing a breadth-first traversal of the graph. The length of the shortest path between each pair of nodes R_i and R_x in the graph is stored in a distance matrix D in $D[R_i][R_x]$. Then, for each primary relation with projected attributes, the longest path distance is found and the query subject is the relation with the shortest longest path. We resolve ties by preferring a relation with more attributes projected. If more than one candidate query subject meets the criteria, we pick one or show alternative translations using different query subjects. If there is no primary relation in the query (i.e., the query involves only one secondary relation), then we use as query subject a primary relation of the database graph, which is the closest to the query relation. (The latter is not shown to Fig. 6.)

Algorithm QSUB

Input: query graph $G_q(V_q, E_q)$, relation nodes $\mathbf{R}$
Output: query subject R_q

Begin
0. Initialize D;
1. **Foreach** R_i in $\mathbf{R}$
1.1. **If** R_i is primary and has projected attributes
1.1.1 D = BFS(R_i, $G_q(V_q, E_q)$, D);
2. Initialize $maxD$;
3. **Foreach** primary R_i in $\mathbf{R}$ with projected attributes
3.1. $maxD[R_i]$ = max($\{D[R_i][R_x] : R_x \in \mathbf{R}\}$);
4. d = min($maxD[]$);
5. return R_q having $maxD[R_q]$=d and more projected attributes

End

Fig. 6. Query subject selection.

B. Query graph traversal

Here we discuss strategies for query translation. For presentation reasons, we do not discuss grouping and ordering. At the end, we return to these two.

1) INAF *Algorithm:* The translation of a generic SPJ query involves three parts: the query subject, information on the attributes of the subject that are of interest, and the subject qualification.

Our first strategy comprises three steps and composes separate clauses for the parts of the query:

- (*Read information*). This is essentially performed by translating all membership edges on the query graph.
- (*Associate entities*). This step connects all query relations to the subject through the joins in the query.
- (*Focus*). This step reads all paths from relations to values to focus on the entities of interest.

Our first strategy composes separate clauses for each part of the query. It translates all projections, then it connects all query relations to the subject through the joins in the query, and finally it reads the selection conditions to focus on the entities of interest.

In order to avoid multiple passes of the query graph, the algorithm (Fig. 7) performs a depth-first search of the graph $G_q(V_q, E_q)$ starting from the query subject R_q to all relations through the joins that exist among them. Along the way, it concurrently builds the three parts of the query explanation, which are combined at the end to form the query explanation. The core of INAF is the recursive BST, that returns three clauses $pStr$, $fStr$, and $wStr$, corresponding, respectively, to the three steps mentioned above. After having these clauses, we enrich them with a few descriptive expressions (e.g., 'Find', 'for', etc.) and then, we combine them to produce the final text.

BST is a recursive algorithm that performs a dfs-like traversal of the query graph. It gets as inputs a graph $g(V_g, E_g)$ and a root node v. It also takes three strings that constitute its output too. In a single pass of the graph, it creates three clauses corresponding to the translation of membership edges (clause $pStr$), of the associate entities (clause $fStr$), and of the paths that connect relations to value nodes that are specified for attributes on these relations (clause $wStr$).

For creating the latter two, we need to translate paths that start from the v node (ln:3). Hence, we examine the outgoing

Algorithm INAF

Input: query graph $G_q(V_q, E_q)$, query subject R_q
Output: query text t

Begin
0. $open = close = \oslash$; $pStr$=$fStr$=$wStr$='';
1. BST(R_q,G_q,$open$,$close$,$pStr$,$fStr$,$wStr$);
2. t = 'Find ' + $pStr$ + ' for ' + $fStr$ + '.';
3. **If** (wStr!='') t += ' Return results only for ' +$wStr$ +'.';
4. output t

End

Fig. 7. INAF for query translation.

$$v \xrightarrow[\sigma]{e} t \xrightarrow{eo} to \qquad\qquad v \xleftarrow[ei]{\mu} ti$$

Fig. 8. Cases examined in BST

edges $e = (v, t)$ of v (see Fig. 8(left)). For looking for paths that end at value nodes, we examine the outgoing edges $eo = (t, to)$ of the v's neighbor t. If to is a value, then the translation of this path $v \dashrightarrow to$ contributes to $wStr$ (ln:3.1). Referring to Fig. 5, if v=Students and t=CLASS, then (ln:3.1.1) str = 'students'+VAL_SEL+'class'+' '+'is'+' '+'2011' = 'students whose class is 2011'. VAL_SEL is used for automating the conjunction of a noun ('student') to a noun clause. Since there may exist more than one such path from v, we create a single clause for each one and then, we combine the clauses with a coordinating conjunction $CONJ\_SEL$ (e.g., 'and').

If to is not a value, then we are interested only in the edge e. If we haven't visited t so far and if e is a selection edge, i.e., $e \in E_g^\sigma$, the path $v \dashrightarrow t$ represents part of a join and thus, it contributes to $fStr$ (ln:3.1.2). The translation of this part is stored in $fStr$ and then, (ln:4) we enrich the labels of v's children with appropriate expressions, so when these children are about to be translated their produced phrases will be combined appropriately with the existing one. In particular, for translating meaningfully entities associations (essentially the contents of query's from-clause), we enrich the produced clauses with suitable words for smoothing the conjunction of a main phrase to a noun clause (i.e., $CONJ\_NOUN$ – for example 'that') or for combining equivalent phrases (i.e., $COORD\_CONJ$ – for example 'and') (ln:4). Referring again to Fig. 5, if v=Courses, then t can be Courses's ids used for joining eventually Courses with Instructors and Departments (and Students too). Thus, the $fStr$ is created as follows:

v=Courses, $fStr$ = 'courses'

v=Instructors, $fStr$ += 'that are taught by instructors'

v=Departments, $fStr$ += 'and are offered by departments'

and finally: 'courses that are taught by instructors and are offered by departments'

Before leaving v, we examine its incoming edges $ei = (ti, v)$ (ln:7) (see Fig. 8(right)). If ei is a membership edge, i.e., $e \in E_g^\mu$, then it contributes to $pStr$. All incoming edges ei are stored in $children$, in order to find their actual number. Then, $pStr$ is created using conjunctive expressions (e.g., 'and') in appropriate places (ln:7-8). Regarding Fig. 5, if v=Students, then ti can be both NAME and GPA. Then, $pStr$ can be

Algorithm BST

Input: node v, graph $g(V_g, E_g)$, list $open$, list $close$, and clauses $pStr$, $fStr$, and $wStr$
Output: clauses $pStr$, $fStr$, and $wStr$

Begin
0. $sel\_edges = 0$; $children = \oslash$;
1. $close \leftarrow v$;
2. **If** ($v \notin R_S$) $fStr$ += $l(v)$;
3. **Foreach** edge e $(v, t) \in E_g$, $t \in V_g$ {
3.1 **Foreach** edge eo $(t, to) \in E_g$, $to \in V_g$ {
3.1.1 **If** (to *is a value*) {
str=$l(v)$+VAL_SEL+$l(t)$+' '+$l(eo)$+' '+$l(to)$+' ';
$wStr$ += $make\_lbl(wStr, str, CONJ\_SEL)$;
}
3.1.2 **If** (($t \notin close$) && (to *is not a value*)) {
If ($e \in E_g^\sigma$) sel_edges++;
$children \leftarrow t$;
$fStr = fStr + l(e)$+" ";
3.2. } } }
4. **While** ($children \neq \oslash$) {
4.1 $tv \leftarrow children.pop()$;
4.2 **If** (--$sel\_edges > 0$) $l(tv)$ += $COORD\_CONJ$;
4.3 **Else If** ($sel\_edges = 0$) $l(tv)$ += $CONJ\_NOUN$;
4.4 $open \leftarrow tv$;
4.5 }
5. **Foreach** edge ei $(si, v) \in E_g, si \in V_g$
5.1 **If** ($ei \in E_g^\mu$) $children \leftarrow (l(si), l(ei))$;
6. str = '';
7. **While** ($children \neq \oslash$) {
7.1 $(x, y) \leftarrow children.pop()$;
7.2 str += ' the ' + x + ' ' + y + ' ' + $l(v)$;
7.3 **If** ($sizeof(children) \neq 1$) str += ', ';
7.4 }
8. **If** ($str \neq$'') $make\_lbl(pStr, str, CONJ\_PROJ)$;
9. **If** ($open \neq \oslash$) {
9.1 $v \leftarrow open.pop()$;
9.2 BST(v,g,$open$,$close$,$fStr$,$pStr$,$wStr$);
9.3 }

End

$make\_lbl(clause, label, def)$ {
If ($clause$ ='') return $clause = label$;
Else return $clause$ += def + $label$;
}

Fig. 9. BST: dfs-like query translation in three steps.

'the gpa of students, the name of students'. For smoothing results, we use a simple find-and-replace mechanism, termed $resolve\_common\_expressions$ (RCE) [9], that removes repeating information (not shown in Fig. 9 due to space limits). The final result will be: 'the gpa and name of students'.

This process is repeated until we have visited all nodes of the query graph. Regarding the example of Fig. 5, the final result (having used RCE too) will be:

> *"Find the title of courses, the name of instructors, the gpa and name of students, and the description of comments for courses that are taught by instructors, are taken by students that gave comments, and are offered by departments. Return results only for courses whose term is spring, students whose class is 2011, comments whose rating is greater than 3, and departments whose name is CS."*

2) MRP *Algorithm:* Our second strategy blends all three types of information that INAF considers individually. The challenge is to avoid creating extremely complex and lengthy phrases. Observe the part of Fig. 5 that relates to the primary relations Students, Courses, and Instructors. For this example, assume Students as a starting point. Then, an attempt to translate at once this part produces the following phrase:

> *"Find the names of students and the titles of the courses taken by these students and the names of the instructors that taught courses taken by these students"*

This example shows the use of demonstrative pronouns to refer to the same query object, i.e., the query subject. In other words, the query subject was used as a reference point for the translation. The example also illustrates the problem of using a single reference point. As we move away from the query subject (as in the case of instructor names), we need to build longer phrases to connect projected attributes to the query subject.

As in natural language we break our sentences by using multiple entities as reference points for avoiding long, possibly unnatural, sentences, we semantically split the translation at multiple points, called *reference points*, RP, as in the example below:

> *"Find the names of students and the titles of the courses taken by these students and the names of the instructors that taught these courses"*

Introducing multiple reference points allows us to translate shorter paths on the graph that connect a projected attribute with some, closer to the attribute, relation instead of the query subject relation.

Considering the query graph as a DAG, i.e., having decided only one direction for join relationships based on the query subject, we consider the following definitions.

Definition 4: Branching point, BP. It is a relation on the query graph that connects to more than one relation through paths (essentially representing joins) directed from this relation to the other relations.

Definition 5: Leaf relation, RL. It is a relation on the query graph that has no outgoing paths to other relation on the query graph.

Starting the traversal of the query graph from the query subject, we can identify a subset of graph relations as reference points, according to the following definition.

Definition 6: Reference point, RP. A reference point is a relation RP belonging to the query graph and having each one of the following properties:

- RP is a primary relation with μ edges,
- RP is a branching point,
- RP is a leaf relation,
- the minimum distance of RP from the closest reference point is greater than a pre-defined threshold ψ.

The last property allows us to tune the semantic length of the resulting phrases by regulating the distance among the reference points, or equivalently, by regulating the number of reference points used in the translation.

Algorithm MRP

Input: nodes v, rp, u, graph $G_q(E_q, V_q)$, lists $open$, $close$, $path$, and clause $cStr$
Output: clause $cStr$

```
Begin
0.   close ← v;
1.   If ((u,v) ∈ E_q) path.push_back() ← (u,v);
2.   If (v is RP) {
3.     pr = rp; rp = v;
4.     If (∃(a,v)∈E_q^μ, a∈V_q) {
4.1.     cStr += l_MV(rp);
4.2.     While (path ≠ ∅) {
4.2.1      (x,y) ← path.pop_back();
4.2.2      If (x ≠ pr) cStr += l(y,x) + l_V(x);
4.2.3      If (x = pr) cStr += l(y,x) + l(x);
4.2.4    }}
5.     If (∄(a,v)∈E_q^μ, a∈V_q) {
5.1.     cStr += l(pr);
5.2.     While (path ≠ ∅) {
5.2.1      (x,y) ← path.pop_front();
5.2.2      cStr += l(x,y) + l_V(y);
5.2.3    }}
6.     path = ∅;
7.   }
8.   Foreach (v,t) ∈ E_q
8.1    If (t ∉ visited) open.push_back() ← {v,rp,u};
9.   If (open ≠ ∅) {
9.1    {v,rp,u} ← open.pop_back();
9.2    MRP(v,rp,u,G_q,open,close,path,cStr);
9.3  }
End
```

Fig. 10. MRP: dfs-like query translation using reference points.

The Multi Reference Points algorithm (MRP) translates a query graph $G_q(V_q, E_q)$ based on the notion of reference points (RP). MRP's inputs are the query subject R_q and the query graph G_q. However, due to its recursive nature, it uses the following parameters as well: v is the node being processed in each turn; rp the reference point for v; u the parent node of v; the lists $open$ and $close$ for storing the nodes to be visited and the already visited ones, respectively; the list $path$ for storing the edges between rp and v; and finally, the clause $cStr$ that stores the translation of G_q. $cStr$ is MRP's output.

MRP "collects" and combines projections, selection and join predicates as it traverses G_q. The following text shows MRP's effect on the query of Fig. 5.

> *"Find the title of courses for courses that are offered by departments whose name is CS, and also, the gpa and name of students for students whose class is 2011 and that have taken these courses, and also, the description of comments for comments whose rating is greater than 3 and that are given by these students, and also, the name of instructors that teach courses whose term is spring."*

MRP traverses the query graph in a dfs-like manner. Interestingly, although it traverses the graph following a certain direction, the actual translation is happening by flipping directions depending on where it stands. MRP just traverses the graph until it reaches a reference point. Then, it creates a phrase containing the translation of the subgraph connecting the previously met RP, pr, and the current one, rp. This

subgraph may contain joining relations and paths that end at value nodes. We distinguish two cases: (a) If rp does not have μ edges, then it can be either a branching point, a leaf relation or its distance from pr is greater than the allowed threshold ψ. Then, the translation always follows a direction from pr to rp. (b) If rp has μ edges, the translation follows the direction from rp to pr. The algorithm's behavior is explained by the need to connect reference points correctly. In case (a), the new reference point rp is a "weak" point in the sense that it provides no information of interest to the query and hence it cannot "stand" by itself. Hence, we make the previous reference point pr to textually connect to rp. In case (b), rp has information of interest (i.e., projected attributes) and we can ask for this information and then link back to pr.

Going back to Fig. 5, for the sake of the example assume that Students is the starting point. Then, Students, Courses, and Instructors are RPs. If only Students and Instructors contained μ edges, then the translation directions would be: Students $\rightarrow$ Courses and Courses $\leftarrow$ Instructors.

In more details, the MRP algorithm is shown in Fig. 10. If the current node v under examination is RP (ln:2) and has μ edges (ln:4), then (v becomes rp) since this is the first time we meet rp, we *fully translate* it: $l_{MV}(rp)$ (ln:4.1) (see Section III). Next, we translate the path from rp to pr, which is the reverse direction of the one we followed to meet rp. Therefore, we pop out (x, y) edges from the $path$ list (ln:4.2.1) and we compose a clause by translating the reverse edges, (y, x), and taking extra care for potential selection edges connected to $path$ (ln:4.2.2). For doing this, we exploit that joins are bidirectional and are annotated with appropriate template labels in each direction. When we reach pr there is no need for a complete translation (it has been done earlier), and we use only its label ($l(pr)$) (ln:4.2.3). An example of this case is the translation of the path connecting Courses to Instructors. Whilst we go from the former to the latter, the translation follows the reverse direction: "the name of instructors *that* teach *these* courses".

If the node v is RP (ln:2) with no μ edges, then we follow a direction from pr to rp (ln:5). pr has been fully translated before, so we use only its label (ln:5.1). Then, we pop out (x, y) edges from $path$ in a FIFO order (ln:5.2.1) and we translate both (x, y) and y (ln:5.2.2). Since y is met for first time, we fully translate it ($l_V(y)$); note that there is no case of y having a μ edge, so l_{MV} is obsolete. An example of this traversal happens for the path from Courses to Departments: "courses *that* are offered by departments whose name is CS". When the path has been translated, then we clear it (ln:6). Next, we proceed with the children of v, in a dfs style, until all nodes have been visited (ln:8-9). At the end, $cStr$ contains the MRP translation, which produces results as the one of the previous example.

Observe that that example is enriched with extra words that serve as coordinating conjunctions (e.g., "and"), conjunctions to noun clauses (e.g., "that"), and so on. For presentation simplicity, we have not overloaded Fig. 10 with such information as we did with INAF. For example, one could add the

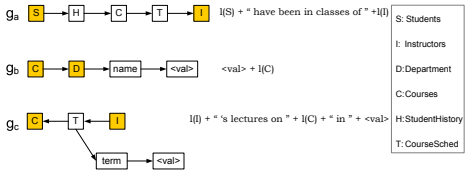


Fig. 11. Example graphs and their templates

expression " there " before $l(pr)$ in (ln:5.1) and before $l(x)$ in (ln:4.2.3). We have explained the use of special words in the previous algorithm (INAF). For MRP we have focused on the algorithmic part regarding the new translation strategy.

C. Template Selection

The previous query translation algorithms exploit generic templates on the edges of the query graph as they traverse the graph. Hence, their advantage is their ability to automatically generate a translation. If a designer has given some specific, i.e., more "intelligent", templates, that may also cover bigger parts of a graph (not just edges), then these algorithms cannot use them. Having templates for larger parts of a query rather than composing very simple templates allows us to have more natural and concise translations.

In this section, we present a flexible algorithm that can build on-the-fly the best combination of generic and specific templates for a query graph based on how templates can be "glued" together. To illustrate the basic idea of the algorithm, imagine the query graph as a puzzle that we have to fill (cover) and we have various pieces (i.e., templates) of various sizes. The objective is to use as few pieces that can be glued together as possible (few big pieces will make a clearer picture, while many small pieces would pixelize the result).

A generic template is automatically defined on an edge whereas a specific one, provided by a designer, may be defined over a subgraph. Therefore, we consider that a template is assigned to a *template graph* g, which is a DAG, and has a set $R(g)$ of reference points, which are nodes on g. The template provides a translation of the relationship involving the reference points on g.

Definition 7: Composeable templates. Two templates g, with reference points $R(g)$, and g', with reference points $R(g')$, are *composeable* if $R(g) \bigcap R(g') \neq \emptyset$.

In words, the reference points are the points where two templates can be glued together. Two templates are composeable if they share at least one reference point.

For instance, let us assume that for our example of Fig. 5, there are also some specific templates, shown in Fig. 11. On each graph, the colored nodes are the reference points. We observe that the graphs g_a, g_b are not composeable, since they refer to different things: students and instructors in the case of g_a vs. courses and departments for g_b. g_c is composeable with both g_a and g_b. Hence, the challenge is: given the fact that templates cannot be freely combined but they may still be combined if taken in the right order, then which templates to pick and in what order to "solve the puzzle".

Consequently, given a query graph $G_q(V_q, E_q)$ and a set of (both generic and specific) templates, we need to: (a) find the minimum set of composeable template graphs that cover the

Algorithm TS

Input: query graph $G_q(V_q, E_q)$, index I
Output: a minimum set of composeable graphs $\mathbf{g_t}$

Begin
0. initialize $M[][]$
1. **Foreach** e in E_q {
2. use I to retrieve $\mathbf{g_e}$;
3. **Foreach** $g \in \mathbf{g_e}$ {
3.1 $M[e][g] \leftarrow 1$;
3.2 } }
4. **Foreach** column g in M {
5. **If** $sum(M[][g]) = |E_q|$ {
5.1 $\mathbf{g_{con}}.push() \leftarrow g$;
5.2 $QP.push() \leftarrow (\{g\}, E_g, R(g))$;
5.3 }
6. **While** $(QP \neq \oslash)$ {
7. $(\mathbf{g_{com}}, E_{sat}, R_{\mathbf{g}}) \leftarrow QP.pop\_front()$;
8. **Foreach** $(g(V_g, E_g) \in \mathbf{g_{con}}, g \notin \mathbf{g_{com}}, R(g) \cap R_{\mathbf{g}} \neq \oslash)$ {
8.1 $\mathbf{g'_{com}} = \mathbf{g_{com}} \cup \{g\}$;
8.2 $E'_{sat} = E_{sat} \cup E_g$;
8.3 $R'_{\mathbf{g}} = R_{\mathbf{g}} \cup R(g)$;
8.4 **If** $(E'_{sat} = E_q)$ return $\mathbf{g'_{com}}$;
8.5 **Else** $QP.push() \leftarrow (\mathbf{g'_{com}}, E'_{sat}, R'_{\mathbf{g}})$;
8.6 } }
9. return $\oslash$;
End

Fig. 12. TS: algorithm for template selection.

query graph and (b) compose them based on the query graph and the template "composeability". A set $\{g_1, g_2, ...g_N\}$ of template graphs are composeable, if for each $g_i, i = 1...N$, there is a $g_j, j = 1...N, i \neq j$, s.t. g_i and g_j are composeable. We first describe the algorithm TS for template selection.

1) TS *algorithm:* Formally, the template selection problem is defined as follows: Given a query q and its query graph $G_q(V_q, E_q)$, we consider the set $\mathbf{g}$ of template graphs that are contained in $G_q(V_q, E_q)$, i.e.,:

$\mathbf{g} = \{g_i(V_i, E_i) | G_q$ is a supergraph of $g_i,\ i = 1..N\}$.

A set $\mathbf{g_k} \subseteq \mathbf{g}$ *covers* $G_q(V_q, E_q)$ iff $\bigcup_{g_x \in \mathbf{g_k}} E_x = E_q$ (query graphs are connected, hence this condition also implies $\bigcup_{g_x \in \mathbf{g_k}} V_x = V_q$.) All sets that cover the query graph can be ordered by their size, i.e., $\mathbf{g_k} > \mathbf{g_m} \Leftrightarrow |\mathbf{g_k}| > |\mathbf{g_m}|$. We are interested in the set $\mathbf{g_t} \subseteq \mathbf{g}$ of composeable template graphs s.t. $\nexists \mathbf{g_m} \subseteq \mathbf{g}$ of composeable graphs with $\mathbf{g_m} > \mathbf{g_t}$.

Fig. 12 provides the algorithm for template selection. First, we find the template graphs that are contained in the query graph. We keep an inverted index I over template graphs. Given a query graph $G_q(V_q, E_q)$, we probe the index with the edges of E_q. For each edge $e \in E_q$, the index returns the list $\mathbf{g_e}$ of graphs that contain e. A graph g is contained in G_q, if g is found in n lists returned for the edges in E_q and $n = |E_q|$. To identify the qualifying graphs, we keep a matrix $M[][]$ with rows mapping to edges and columns mapping to the template graphs returned by I for the query. We set $M[e][g]$ to 1 if the index returns g for e (ln:3). We keep only graphs that correspond to columns in the matrix with sum of 1's equal to $|E_q|$ (ln:5). These graphs are inserted into a list $\mathbf{g_{con}}$ in decreasing order of the graph size (number of edges).

The next step is to find the minimum set of composeable graphs from $\mathbf{g_{con}}$ that cover G_q. This is a set covering problem but not all combinations of template graphs are valid, since we are interested in composeable sets. For this reason, the algorithm's strategy is to build solutions by combining the largest composeable template graphs. Solutions that cannot extend to the whole query graph are pruned.

Algorithm TMT

Input: query graph $G_q(V_q, E_q)$, index I
Output: a clause $cStr$

Begin
0. $\mathbf{g_t} \leftarrow$ TS(G_q, I);
1. $E_{\mathbf{g_t}} = \cup_i E_{g_i}, g_i \in \mathbf{g_t}$;
2. **Foreach** relation r s.t. $\nexists\ edge\ (x, r) \in \{E_{g_t} - E^{\mu}_q\}, x \in V_q$;
3. $QP.push() \leftarrow r$;
4. **While** $(QP \neq \oslash)$ {
5. $r_i \leftarrow QP.pop\_front()$;
6. $V_{r_i} = \{\}$; $E_{r_i} = \{\}$; $leaves.push() \leftarrow r_i$;
7. **Foreach** $g \in \mathbf{g_t}$ with $root(g) \in leaves$ {
7.1 $V_{r_i}.push() \leftarrow R(g)$;
7.2 $E_{r_i}.push() \leftarrow g$;
7.3 $leaves.push() \leftarrow R(g) - \{root(g)\}$;
7.4 }
8. $L \leftarrow biased\_topological(G_r)$;
9. **While** $(L \neq \oslash)$ {
9.1 $g \leftarrow L.pop_f ront()$
9.2 $cStr_i$ += $l(g)$;
} }
10. $cStr$ += $cStr_i$;
11. return $cStr$;
End

Fig. 13. TMT: algorithm for specific template composition.

A candidate solution is represented as a tuple $(\mathbf{g_{com}}, E_{sat}, R_{\mathbf{g}})$, where $\mathbf{g_{com}}$ is a set of composeable graphs, E_{sat} is the set of edges covered by these graphs, and $R_{\mathbf{g}}$ is the union of their reference point sets. The size of a solution is the size of $\mathbf{g_{com}}$, i.e., the number of graphs in $\mathbf{g_{com}}$. TS keeps a list QP of candidate solutions in increasing order of size. Same size solutions are ordered in decreasing $|E_{sat}|$. At each round, it picks the head of QP (ln:7) and generates solutions (if any) that extend this one with a graph from $\mathbf{g_{con}}$ (ln:8). All solutions are inserted into QP unless one covers all edges of the query graph. Then it is a minimum solution, and the algorithm terminates.

2) TMT *algorithm:* The algorithm TMT (Fig. 13) uses the set $\mathbf{g_t}$ of composeable templates returned by TS to generates a query translation ($cStr$) for a query graph G_q. The challenge is to find how to compose the templates on the query graph. To illustrate, for the query of Fig. 5 and the specific templates shown in Fig. 11, TS would have found that these templates combined with generic templates for the parts of the query not covered can be used for translating the query. The result (using appropriate auxiliary phrases) would be:

> *"Find the gpa and name of students whose class is 2011 and have been in classes of instructors and find the name of these instructors, whose lectures on courses are in spring and find the title of these CS courses and the description of comments whose rating is greater than 3 given by these students."*

We observe that using specific templates may generate smaller and more natural text. On the other hand, since specific templates can be arbitrary, none of the previous query translation algorithms that read and translate edges on the query graph can be used. TMT uses a dynamic strategy to find in what order the templates should be read and how they must be combined. For example, the right order to read the specific templates is g_a, g_c, g_b.

TMT proceeds as follows. It finds a root r_i on the query graph that is a relation node and has no incoming edges

(except for possible membership edges) (ln:2). For example, Students is the only root for the templates above. With r_i as root, it builds a DAG $G_{r_i}(V_{r_i}, E_{r_i})$ by connecting template graphs found in $\mathbf{g_t}$ that can be composed with r_i (**ln:5-7**). Recall that each graph g is a DAG and can be seen as a "super edge" connecting the nodes in its set $R(g)$ of reference points (following the direction of the edges in g.) Hence G_{r_i} is composed of such "super edges" (which in the case of generic templates are edges on the query graph but in the case of specific templates may map to subgraphs.) In order to create this DAG, the algorithm gradually expands the graph (which initially contains only r_i) with graphs whose root is one of the current leaves of G_r.

When G_{r_i} is built, TMT performs a topological sort and stores G_{r_i}'s graphs (in the order produced) in a list L. The topological sort is biased to give from a relation priority to membership edges, then selection edges to values and finally all other cases (ln:8). Then, TMT pops g_is out of Q and builds a phrase $cStr_i$; if a g_i has more than one child, it uses appropriate coordinating conjunctions (e.g., 'and') (not shown in the figure for simplicity) (ln:9).

It is possible that there are more than one root r_i (ln:2), hence the algorithm constructs and translates a DAG G_r for each one of them, which may cover different parts of the graph, and at the end concatenates the partial translation results, $cStr_i$'s, to $cStr$ (ln:10).

D. Discussion

The algorithms presented so far, cover SPJ queries (paths, nested, etc.) as discussed in Section II. For simplicity, we left out of the discussion the grouping and ordering query parts. These two are handled separately, since they apply to the whole translation result. Thus, for both parts we work as in BST and create the phrases $gStr$ and $oStr$ by simply following the paths of γ or o edges, respectively. (A slightly different case involves nested queries, where these phrases may blend into the rest of the translated text; however, due to space considerations we have omitted this part from the descriptions of our algorithms.) Similarly, we work for r edges and functions f (also omitted from our discussion).

In most examples we used queries having conjunctive predicates. Nothing changes for disjunctive predicates. Extra care should be taken for the choice of the words responsible for coordinating phrases conjunction (e.g., apart from "and" we need "or" too). Operators' priority should be considered too.

An interesting issue concerns the "corporate" queries, which contain large chains of joins, and most importantly many projected attributes. Although, there is no inherent problem with the function of the proposed algorithms, there is a question regarding the usefulness of such translations. Clearly, the produced text is not pretty, but neither the queries themselves are. Since such queries usually are used by people with advanced technical skills, a translation might not be that useful. However, we can leverage the power of templates for producing "query summaries", which can be used as starting points; e.g., for facilitating query documentation. Using TMT and appropriate templates (with macros) we can put limits on the number of projected attributes in the result. [9] defines the notion of *heading* attribute, which represents the attribute that characterizes the most a relation (e.g., attribute $name$ for Students). Such attributes may be defined in the database graph, so when a query involving many projected attributes comes, we provide a first translation using the predefined attributes, so that the user would get insight into the query mechanism. The translated text for such attributes comes as a hyperlink pointing to their full-fledge translation.

As a final remark, TMT has been proven especially useful in the case of difficult for being translated queries [5]. For example, queries containing predicates like "having count(distinct year) = 1" and "where year $<$ all (<subquery>)", require extra knowledge for capturing their semantics. The first case implies "all" (e.g., as in "find students whose classes are *all* in the same year") and the second implies "earliest" (e.g., as in "find students who have taken courses in *the earliest* years that have been taught"). Clearly, this "impossible" queries as characterized in [5], can be resolved (whenever possible) only using specific templates and the logic of TMT.

V. Experiments

Before a query is translated, it needs to be parsed. We use General SQL Parser, an off-the-shelf tool that reads SQL queries and generates an XML-representation of the parse tree (http://www.sqlparser.com/index.php). This is the input to our query translation module that converts it to a query graph. The query translator is implemented in C++ and makes use of the Boost library for graphs (http://www.boost.org/doc/libs/1_39_0/libs/graph/doc/index.html). Our experimental study aims at shedding light on the *performance* as well as the *effectiveness* of the proposed methods changing various features of the queries:

- the *depth*: the ♯ of relations on the longest path in the query graph,
- the *out-degree*: the ♯ of edges emanating from a relation node pointing to other relations if query graph is converted to a DAG,
- the μ-*degree*: the total ♯ of membership edges,
- the σ-*degree*: the total ♯ of value nodes,
- the *compactness*: (♯ of relations)/(♯ of relations on the longest path in the query graph).

In addition, we studied the effect of: the query subject (on BST), the ♯ of reference points (on MRP) and the ♯ of templates (on TMT). We used the schema of the course database used in CourseRank comprising 20 relations with average number of fields around 5 [6].

A. Effectiveness

For these experiments, we recruited a few experts in SQL. We intentionally choose experts since they can judge whether a SQL query is translated well. We used different sets of queries, with the same features, for which we automatically generated query explanations with all algorithms. For MRP, we also set the default minimum distance between reference points to be 3 in order to ensure the use of reference points even when the query structure does not provide such points.

For TMT, we have provided sufficient templates to make sure that query translation can exploit them in order to leverage its expressivity. In addition, we asked two experts to write an explanation for each query (USER). Then, we involved the other experts in the following experiments. The queries used in each one of them were different in order to allow users judge the results without any recollection of queries seen before.

1) SQL → NL: The first set of experiments (Fig. 14) investigates the direction from SQL to text and it has two parts: the first part measures the effectiveness of some particular choices of the algorithms, namely the selection of a query subject, the use of reference points, and the use of templates. The benefits of reference points and specific templates are also discussed in other experiments, so we will focus on the query subject and summarize our findings for the other two due to space considerations. The second part of the experiments compares the various translation strategies.

Fig. 14(a) shows the effect of query subject. We consider path queries of *depth* equal to 10 with 6 of them being primary with one attribute projected and we generate their translation using BST with QS calculated by the algorithm and with alternative QS that are 1, 2, ..., hops away (denoted $QS-1$, $QS-2$,...). The experts were presented with the translation result for each QS at the same time per query and gave a rating from 1 to 10. The figure confirms the intuition behind the selection of QS: a central QS collects much more information around it and generates more balanced references to it.

For the second part of the experiment, each person was presented with the same set of SQL queries and all possible query explanations (BST, MRP, TMT, and USER), and we asked them to rate the explanations from 1 to 10 depending on their comprehensibility and naturality (10 is the best).

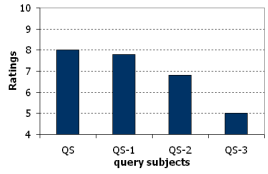
Fig. 14(b) shows ratings for queries as a function of the ♯ of relations (*depth*:2 to 7). First, let us observe that the ratings given to all query translations (even those user-generated) decrease as the *depth* increases. We observe similar trends when other aspects of the query (e.g., the μ-*degree* in Fig. 14(c)) change resulting in bigger, and more complex queries. Thus, the quality of translation is inevitably affected by the query size and complexity, which essentially means that even for humans it becomes very difficult to explain a query in concise and elegant way. On the other hand, for simple queries, all translation methods provide very satisfactory results.

Focusing now on the effect of the *depth* in Fig. 14(b), we observe that BST is the most sensitive, because the longer the paths on the query graph it translates, the more unnatural the translation result is. On the other hand, the quality of TMT's translation is more smooth because it can make use of specific templates that "explain" bigger parts of a graph and as a result while the query graph may grow, the algorithm can still find a translation combining fewer templates than the other algorithms. MRP's results provide a good compromise between TMT (which relies on human input) and BST (which is fully automated): it combats the "long-path" effect of BST by inserting intermediate reference points and breaking long paths to shorter segments. In a way, it tries to "mimic" the behavior of TMT by constructing templates (using of course generic ones) for bigger but digestible parts of the graph. A final note: it is worth noting that the USER translation results for small queries most of the times tended to follow a BST-like approach, while for bigger queries they approach MRP and finally, they adopt a TMT-like approach trying to simplify parts of the query in order to make its description shorter. We observed similar trends for other query parameters. We think that this provides an indication that such hybrid translation approach may be useful, and we intend to explore it as a continuation of this work.

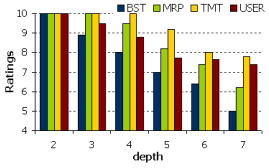
Fig. 14(c) shows user ratings for queries as a function of the ♯ of projections (μ-*degree*:2 to 10). We consider two projections per relation (which explains why in the figure μ-*degree* increases by increments of 2). We observe that TMT (although it starts with better translations), it is affected by μ-*degree* because, although we have specific templates for the main body of queries, i.e., for covering joins, for projections, we cannot do much improvement. On the other hand, BST seems more immune to μ-*degree* and we observe that for high values it has better results than the others which also coincide with USER. We observed in the user-generated texts that as queries had more projections they tend to adopt a BST strategy (i.e., first the describe the projections and at last the value selections).

Fig. 14(d) shows user ratings as a function of the σ-*degree*. We would like to highlight few points here. Overall, BST is the least affected simply because all value selections form a separate clause appended at the end of the query translation. For a certain number of value selections, MRP is not affected and actually it seems to blend them nicely in the query text. However, for many selections, the clean-cut solution of BST seems more preferable. We observe that USER ratings lie somewhere between BST and MRP ratings. We looked at the user-generated text and we saw that as σ-*degree* increases, the users were either trying to group selections at the end or they were trying a mixed strategy like MRP.

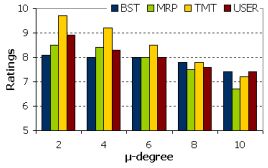
2) NL → SQL: This set of experiments looked at the inverse direction. Each person (except for those that provided query explanations) was presented in random order different explanations for the same set of SQL queries and was asked to write the SQL query. We measured the ♯ *of hits* (i.e., how many times they got the right SQL query). We also asked users to rate a text from 1 to 10 based on how easily they could build the corresponding SQL query (10 is the best rating). Fig. 15 and 16 show user ratings as a function of *depth* and μ-*degree*, resp. (For space considerations, we do not show results for the σ-*degree* since we observed very similar trends.) These figures reveal that interesting for the text generated by BST suits better the purpose of finding which SQL query is described. The difference is very obvious if we compare the figures 14(c) and 16. BST groups projections, joins, and selections in a query in separate clauses and dictates how to write the SQL query. MRP also allows to easily write the query but in the presence of several projections, it becomes harder to reconstruct the SQL query. TMT provides a higher



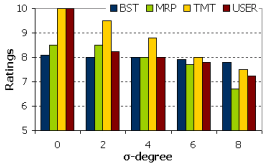
(a) d:10, o-$deg.$:1,μ-$deg.$:7, σ-$deg.$:0



(b) out-$deg.$:1, μ-$deg.$:1, σ-$deg.$:1



(c) dth:5, out-$deg.$:1, σ-$deg.$:1



(d) out-$deg.$:1, μ-$deg.$:1, d:5

Fig. 15. NL to SQL (out-$deg.$:1, μ-$deg.$:1, σ-$deg.$:1)

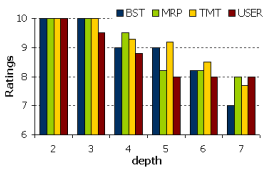


Fig. 16. NL to SQL ($depth$:5, out-$deg.$:1, σ-$deg.$:1)

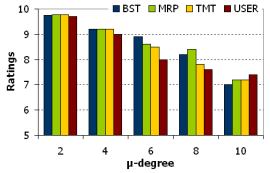
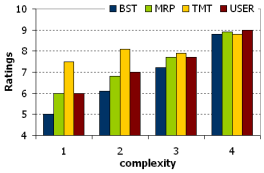


Fig. 17. NL to SQL ($depth$:12, μ-$deg.$:4, σ-$deg.$:4)



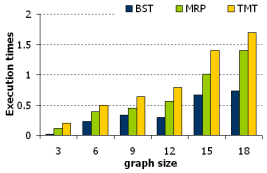


Fig. 18. Performance

level description of the query and makes it easier to catch the meaning but then one needs to make some work to map the semantic associations to real joins based on the underlying schema. It is also worth noting that (although not shown in the figures), we run experiments where we observed that reverse-engineering TMT text to SQL queries, may lead to equivalent but not exactly the same queries (e.g., in the case of nesting).

Fig. 17 shows the effect of *compactness* on the quality of query translations as expressed through user ratings. If it is equal to 1, then it shows a path query. The higher the compactness is the more branches the graph has. We considered queries of 12 relations of different complexity. Each subset of queries used for each complexity has 4 projections and four selections that are always distributed to the leave relations of the query graph. The purpose of this setting is to make it hard to pick a query subject on the query graph that is a central relation. (We have seen the effect of the query subject above.) We observe that the more compact the query graph becomes, BST translations improve thanks to the ability to select a more central query subject, and MRP translations are better due to the use of reference points and improve as they can also pick a better query subject. Finally, both generate equally good translations since for a very compact graph, MRP does not need to consider reference points. Interestingly, as the graph becomes compact, for our configuration, there were not too many specific templates to combine or they had large overlap.

Concluding: If one is willing to invest some effort on designing some specific templates, TMT can generate better translations. It can capture the important semantic associations between entities in the database providing an abstraction level that can hide the particularities of the schema, (such as normalization, re-structuring, etc). If an automated method is preferred, we could apply a different technique (BST or MRP), depending on the purpose the text will serve (explaining a query or helping a user write the query himself) and depending on the query characteristics.

B. Performance

Independent of the type of the nodes and edges in the query graph, our experiments have shown that execution times depend mainly on the graph size, which is ♯ *of relation nodes* + ♯ *of attribute nodes* + ♯ *of value nodes*. (Other parameters that affect performance include the number of templates TMT has to process but for our small template database we did not witness a significant overhead.) Fig. 18 shows times for the three algorithms in secs. BST is the most efficient since it only makes one pass of the graph. MRP it may traverse parts of the graph that correspond to joins to both directions as it goes forth to find a reference point and back to connect it to the previous reference point. TMT reads the query graph edges more than once in order to find candidate templates and to find how to compose them.

VI. Related Work

NL and DB. Earlier interaction of DB and NL processing has focused mainly on the opposite direction of the one studied here, such as NL Querying [4], NL and Schema Design [10], NL and Database interfaces [11], and Question Answering [12]. In the past, we have worked on translating small databases with content or query answers under certain constraints [9]. We have also discussed the usefulness of translating SQL queries into narratives and examined the space of the problem [5]. The problem of query translation that we study in this paper is more difficult than content translation because the size and complexity of a query are essentially arbitrary with no upper bounds (whereas database contents necessarily follow the schema structure, which is bounded).

Query graph representations. Query graphs have been proposed for query optimization purposes [7], [13], [8]. For instance, the query graph model (QGM) defines a conceptually more manageable representation of an SQL query [8]. These models form the key structure for representing information relevant to query optimization and processing, such as operations and data flows. We are not interested in the operational aspects of a query (i.e., "how" an answer will be generated) but more in its semantics (i.e., "what" the query describes). Our query graph model captures query semantics by identifying the elements of a query and capturing their semantic associations.

Graph and set problems. Our template selection problem is divided into a graph containment and a graph cover subproblem. Graph containment problems have recently gained attention and indexes and pruning methods have been proposed

for very large graph databases [14]. We follow an exact-match approach that works well for the size of (template) graph databases we consider. Our graph cover problem is: Given a (query) graph g and a set of subgraphs $\{g_1, g_2, ...\}$, find the min. subset of composeable subgraphs that cover g. Two subgraphs are composeable if they share specific nodes. This problem differs from graph decomposition [15], [16], where a graph g is decomposed into a set of subgraphs, that have disjoint sets of edges and keep the structural properties of g. Viewing graphs as sets (of edges), our problem can be seen as a set cover problem [17], [18]. However, in our case, sets cannot be freely combined, and a set cover for g may not be an acceptable solution. Our algorithm is designed to take these constraints into account and finds a graph cover.

VII. Conclusions and Future Work

In this paper, we explored a new problem, translating SQL queries to text. We have described a model for representing various forms of structured queries as directed graphs and we have captured query semantics by annotating the graph edges with template labels using an extensible mechanism. We have mapped the query translation problem to a graph problem and presented different graph traversal strategies for efficiently exploring these graphs and composing textual query descriptions. Among them is an algorithm that can capture important semantic associations between entities in the database providing an abstraction level over the db schema with very promising results as our experiments have indicated.

This is the first effort towards structured query translation and it is an open field for research. We are interested in an adaptive method that can follow different translation strategies depending on the query characteristics. A related problem is to apply techniques for finding interesting or frequent associations in queries (for example, by mining query logs) in order to recommend to a designer for template assignment.

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