ExpressQ: Identifying Keyword Context and Search Target in Relational Keyword Queries

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ABSTRACT

Keyword search in relational databases has gained popularity due to its ease of use. However, the challenge to return query answers that satisfy users' information need remains. Traditional keyword queries have limited expressive capability and are ambiguous. In this work, we extend keyword queries to enhance their expressive power and describe an semantic approach to process these queries. Our approach considers keywords that match meta-data such as the names of relations and attributes, and utilizes them to provide the context of subsequent keywords in the query. Based on the ORM schema graph which captures the semantics of objects and relationships in the database, we determine the objects and relationships referred to by the keywords in order to infer the search target of the query. Then, we construct a set of minimal connected graphs called query patterns, to represent user's possible search intentions. Finally, we translate the top-k ranked query patterns into SQL statements in order to retrieve information that the user is interested in. We develop a system prototype called ExpressQ to process the extended keyword queries. Experimental results show that our system is able to generate SQL statements that retrieve user intended information effectively.

Categories and Subject Descriptors

H.3.3 [**Information Storage and Retrieval**]: Information Search and Retrieval—Search process

Keywords

Keyword Query; Relational Database; Semantic Approach

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1. INTRODUCTION

Designing effective query mechanisms for users to query large and complex databases easily has been one of the most elusive goals of the database research community. Traditional structured query models such as SQL for relational databases provide functionalities to query databases precisely. However, they require users to be knowledgeable about database schemas and query languages. Keyword queries have gained popularity due to their ease of use. However, they are inherently ambiguous and it is difficult to determine the users' search intention.

The traditional approach to evaluate a keyword query first materializes the database as a graph where each node represents a tuple and each edge represents a foreign key-key reference, and then finds the minimal connected subgraphs that contain all the keywords [8, 9, 6, 15]. But this is computationally expensive as the number of subgraphs is huge. Another approach translates a keyword query into a set of SQL statements, and leverages on relational DBMSs to evaluate the statements and retrieve answers [1, 7, 5, 12, 13]. However, these works do not analyze the users' search intention, and often returns an overwhelming amount of answers, many of which are complex and not easily understood.

Recently, [2] exploits the relative positions of keywords in a query along with auxiliary external knowledge to make an educated guess of the users' search intention. They measure the likelihood of mapping from a keyword to the database structure (a relation, an attribute, or a tuple), and generate the most probable mappings for the query keywords.

We observe that a relational database is essentially a repository of objects that interact with each other via relationships that are embedded in the foreign key-key references. When a user issues a query, s/he must have some particular search intention in mind. If we can determine the keywords that refer to the same object or relationship in the database, we would be able to infer the search target of the user. These keywords can also provide the context of subsequent query keywords that impose conditions on the search target.

Figure 1 shows a sample company database. Suppose a user issues a keyword query {Employee Brown}. The keyword Brown can refer to an employee name or a department address. However, since the keyword Employee matches the name of the *Employee* relation, we deduce that the user is more likely to be interested in an employee called Brown

than the address of a department. In other words, a keyword that matches a relation name specifies a target object or relationship, while a keyword that matches an attribute name indicates the information that the user wants to retrieve for the target object/relationship. Keywords that match tuple values impose restrictions on the object/relationship.

Employee

Eid	Name	Salary	Deptid	JoinDate
e1	Smith	3.5k	d1	2010
e2	Green	4.2k	d1	2009
e3	Brown	5.5k	d1	2006

EmployeeSkill

Eid	Skill
e1	Java
e2	SQL
e3	Java
e3	PhP

EmpProj

Eid	Pid	JoinDate
e1	p1	2010
e2	p1	2009
e2	p2	2010
e3	p2	2007
e3	p3	2008

Project

Pid	Name	Budget
p1	XML	40k
p2	RDB	50k
p3	Survey	30k

ProjDept

Pid	Deptid
p1	d1
p2	d1
p3	d2

Department

Deptid	Name	Address
d1	computing	Brown Street
d2	marketing	Queen Street

Figure 1: Example company database

In this work, we extend the expressive power of keyword queries so that users can better express their search intentions. We design a semantic approach to process these extended keyword queries. Our approach considers keywords that match meta-data e.g., names of relations and attributes, and utilizes them to provide the context of subsequent keywords in the query. We discover the various ways objects in a database interact with each other, and construct query patterns to denote user's possible search intentions. We propose a ranking scheme that takes into account the search targets of the query as well as the number of objects captured in a query pattern. The top-k ranked query patterns are used to generate SQL statements. We develop a prototype system called ExpressQ to process extended keyword queries. Experimental results on two databases demonstrate the effectiveness of ExpressQ in generating SQL statements to retrieve relevant information for users.

2. PRELIMINARIES

The work in [16] classifies the relations in a database into object relations, relationship relations, mixed relations and component relations. An object (relationship) relation captures the information of objects (relationships), i.e., the single-valued attributes of an object class (relationship type). Multivalued attributes are captured in the component relations. A mixed relation contains information of both objects and relationships, which occurs when we have a many-to-one relationship.

In our example database in Figure 1, relations *Project* and *Department* are object relations as they contain single-valued attributes of project and department objects respectively. Relations *EmpProj* and *ProjDept* are relationship relations. *Employee* is a mixed relation as it captures information of employee objects and the many-to-one relationships between employee and department objects. The relation *EmployeeSkill* is a component relation containing the multivalued attribute of employees.

We can model the relational schema with an undirected graph called *Object-Relationship-Mixed (ORM) schema graph* $G = (V, E)$ [16]. Each node $v \in V$ comprises of an object/relationship/mixed relation and its component relations, and is associated with a $v.type \in \{object, relationship, mixed\}$. Two nodes u and v are connected via an edge $e(u, v) \in E$ if there exists a foreign key-key constraint from the relations in u to that in v.

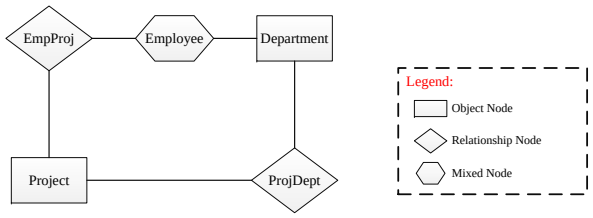


Figure 2: ORM schema graph of Figure 1

Figure 2 shows the ORM schema graph of the database in Figure 1. It has two object nodes (rectangle), two relationship nodes (diamond) and one mixed node (hexagon). The node Department is an object node that comprises of the object relation *Department*, while the node Employee is a mixed node that comprises of the mixed relation *Employee* and component relation *EmployeeSkill*. These two nodes are connected via an edge because there is a foreign key-key constraint from the relation *Employee* to the relation *Department*.

Suppose a user issues the keyword query {Smith Green}. Both keywords match some employee name in the *Employee* relation. Based on the ORM schema graph in Figure 2, these two employees are possibly related via the relationship EmpProj, the many-to-one relationship with departments, and a combination of these relationships. Thus, some of the possible interpretations of the query are:

a. Find information on the project in which both employees Green and Smith are involved.

b. Find information on the department in which both employees Green and Smith work.

c. Find information on the department which conducts a project that involves the employee Green and the employee Smith works in.

Existing works would consider all the above query interpretations and retrieve the corresponding information from the database. Consequently, the user is often overwhelmed by a huge number of answers, many of which are complex and not easily understood.

In order to reduce the ambiguity of keyword queries, we propose to allow users to explicitly indicate his/her search intention whenever possible. This can be achieved by augmenting the query with additional keywords that match the names of relations and attributes. For example, if the user would like to find the information on the department that both the employee Smith and the employee Green work in, s/he can express the query as {Department Employee Smith Employee Green}. The keyword Department matches the name of the *Department* relation, indicating that the user is interested in the information of the department. While the keyword Employee matches the name of the *Employee* relation, giving the context that the keywords Smith and Green refer to names of two employees.

DEFINITION 1. *An extended keyword query consists of a sequence of keywords* $Q = \{k_1\ k_2\ \cdots\ k_n\}$ *such that each keyword* k *matches a relation name, or an attribute name or a tuple value.*

3. KEYWORD QUERY EVALUATION

Given an extended keyword query, we want to generate a set of SQL statements that best capture the user's search intention. This entails the following steps:

1. **Query analysis.** We parse each keyword in the query and utilize the ORM schema graph of the database to determine the object or relationship that a keyword refers to. The semantic information of each keyword is captured in a tag, and the tags that refer to the same object or relationship are grouped together.
2. **Query interpretation.** Based on the groups of tags, we generate a set of minimal connected graphs called query patterns, that represent the possible search intentions of the query, and rank these patterns.
3. **SQL statement generation.** The top-k ranked query patterns are used to generate SQL statements to retrieve results from the relational database.

The following sections give the details of each of these steps.

3.1 Query Analysis

Given an extended keyword query $Q = \{k_1\ k_2\ \cdots\ k_n\}$, we will determine the interpretation(s) of each keyword in Q. We capture each keyword interpretation in a tag $T = (label, attr, cond)$, where *label* is the name of the object or relationship, *attr* is the attribute name, and *cond* is the restriction on the object or relationship. The restriction occurs in the form of a value. The tag(s) for a keyword k is generated depending on the following type of matches:

a. k matches the name of some object/mixed/relationship relation.

   This indicates that k refers to some object or relationship. The name of the object is given by the corresponding object or mixed node in the ORM schema graph, while the name of the relationship can be obtained from the corresponding relationship node in the graph. We capture this keyword interpretation by creating a tag $(k, null, null)$ for this keyword.

b. k matches the name of a component relation or an attribute name.

   This implies that k refers to the attribute of the some object or relationship l, and we create a tag $(l, k, null)$ for this keyword.

c. k matches some tuple value.

   Clearly, k refers to the value of some attribute a of an object or relationship l, and we create a tag (l, a, k) for this keyword.

EXAMPLE 1. *Consider the keyword queries in Table 1. Table 2 shows the sequence of tags generated for these queries. For query Q_1, we know that the keyword* Department *matches an object relation, while the keyword* Employee *matches a mixed relation from the ORM schema graph in Figure 2. Hence, these keywords refer to the names of department and employee objects in the database, and we capture their interpretations in the corresponding tags. On the other hand, the keywords* Smith *and* Green *match the Name attribute values of some tuples in the Employee relation, and we capture these information in their tags T_{13} and T_{15}.*

Query Q_2 contains the keyword Skill *that matches an attribute name. From the ORM schema graph, we see that this attribute belongs to the component relation EmployeeSkill which is associated with the mixed node* Employee*. Hence, we know that skill is a multivalued attribute of the employee object and we capture this interpretation in the tag T_{23}. Further, the keywords* Java *and* PhP *match the Skill attribute values of some tuples.*

Note that Q_3 contains the keyword Brown *that matches the Name attribute value of some tuple in Employee relation, as well as the Address attribute value of some tuple in Department relation. In this case, we create a tag for each matching. The tag T_{34} in Table 2 captures the interpretation that keyword* Brown *refers to an employee name, while the tag T'_{34} captures the interpretation that* Brown *refers to a department address. Hence, we see that Q_3 has two sequences of tags, denoting two different query interpretations.* □

Table 1: Example Queries

Q_1	Department Employee Smith Employee Green
Q_2	Project Employee Skill Java PhP
Q_3	Project Employee Green Brown

After creating a sequence of tags for the keywords in the query, we group the tags that refer to the same object or relationship together. Clearly, tags that do not have the same *label* are placed into different groups since their keywords refer to different objects/relationships. However, keywords with tags that have the same *label* do not necessarily refer to the same object/relationship.

EXAMPLE 2. *Consider query Q_1 in Table 1 and its tags in Table 2. All these tags except T_{11} have the same label* Employee*. However, their keywords actually refer to different objects: keywords* Employee *and* Smith *refer to the employee named* Smith*, while keywords* Employee *and* Green *refer to the employee named* Green*.* □

This example demonstrates the need to process the tags of keywords in a keyword query in sequence, and examine the objects or relationships referred to by the current and preceding keywords.

Let $\mathcal{T}$ be the sequence of tags for a query Q. We put a tag $T_i \in \mathcal{T}$ into a new group to denote a different object/relationship if one of these following cases is true:

Case 1. T_i has a different *label* from all the tags $T_j \in \mathcal{T}$, $j \in [1, i-1]$.

Case 2. T_i has the same *label* as $T_j \in \mathcal{T}$ for some $j \in [1, i-1]$, and the *attr* and *cond* of T_i are *null*.

Case 3. T_i has the same *label* and *attr* as $T_j \in \mathcal{T}$ for some $j \in [1, i-1]$, and *attr* is not a multivalued attribute.

A tag that satisfies Case 2 indicates that its keyword refers to a *new* object/relationship and provides the context for the next keyword in the query. Hence, we create a new group for this tag. On the other hand, a tag that satisfies Case 3 indicates that both its keyword and the preceding keyword refer to the same single-valued attribute of an object/relationship or its values. Since an object/relationship cannot have a single-valued attribute with two values, the keyword of this tag must refer to a *new* object/relationship.

EXAMPLE 3. *Let us consider the sequence of tags for Q_1. Tags T_{11} and T_{12} belong to two different groups g_1 and g_2*

Table 2: Sequence of tags generated for the queries in Table 1

Q_1	T_{11} = (Department,null,null), T_{12} = (Employee,null,null), T_{13} = (Employee,Name,Smith), T_{14} = (Employee,null,null), T_{15} = (Employee,Name,Green)
Q_2	T_{21} = (Project,null,null), T_{22} = (Employee,null,null), T_{23} = (Employee,Skill,null), T_{24} = (Employee,Skill,Java), T_{25} = (Employee,Skill,PhP)
Q_3	T_{31} = (Project,null,null), T_{32} = (Employee,null,null), T_{33} = (Employee,Name,Green), T_{34} = (Employee,Name,Brown) T_{31} = (Project,null,null), T_{32} = (Employee,null,null), T_{33} = (Employee,Name,Green), T'_{34} = (Department,Address,Brown)

since they have different labels. Since tag T_{13} has the same label Employee *as its preceding tag T_{12}, it is placed in the same group g_2. T_{14} is put in a new group g_3 because its attr and cond are null and it refers to a different employee object (Case 2). Since T_{15} has the same label as T_{14}, it is put in g_3. Note that we cannot put T_{15} in g_2 because* Name *is a single valued attribute of employees, and it is not possible for the same employee to have two different names (Case 3). In other words, the keywords* Smith *and* Green *are the names of two different employees. Hence, the tags for Q_1 are grouped as follows:*

- $g_{11} = \{T_{11}\}$ *refers to some department object,*
- $g_{12} = \{T_{12}, T_{13}\}$ *refers to an employee named* Smith*,*
- $g_{13} = \{T_{14}, T_{15}\}$ *refers to an employee named* Green*.*□

The following example illustrates a query involving multivalued attributes.

Example 4. *Consider query Q_2 and its sequence of tags in Table 2. The tags T_{22}, T_{23}, and T_{24} have the same label and are put in the same group. Note that T_{24} and its preceding tag T_{23} have the same label and attr. They are put in the same group because the attribute* Skill *is a multivalued attribute. In other words, the keywords* Java *and* PhP *refer to the values of the multivalued attribute* Skill*, and the user is interested in an employee who knows both* Java *and* PhP*. Hence, the tags for Q_2 are grouped as follows:*

- $g_{21} = \{T_{21}\}$ *refers to some project object,*
- $g_{22} = \{T_{22}, T_{23}, T_{24}\}$ *refers to an employee with skills* Java *and* PhP*.* □

3.2 Query Interpretation

After grouping the tags of a query, the next step is to generate *query patterns*. Each query pattern is a minimal connected graphs that represents one possible search intention of the query. Intuitively, we construct a query pattern by creating a node to represent each object/relationship referred to by each group of tags. These nodes will correspond to nodes in the ORM schema graph and we can connect them based on the edges in the graph.

Let $S = \{g_1, g_2, \cdots, g_m\}$ be a set of tag groupings, and $G = (V, E)$ be the ORM schema graph. A query pattern $P = (V', E')$ is constructed as follows. For each group of tags $g_i \in S$, $1 \leq i \leq m$, we create a node u_i to denote the object/relationship referred to by g_i. The corresponding object class or relationship type is given by a node v_i in G. We say that u_i corresponds to v_i.

Let $D' = \{u_1, u_2, \cdots, u_m\}$ and $D = \{v_1, v_2, \cdots, v_m\}$. We first insert the nodes in D' into the query pattern P. If $|D'| = 1$, then all the tags in the query are in one group which refers to the same object/relationship. Hence, the query pattern P has only a single node. However, if we have $|D'| > 1$, then we need to use the schema graph G to connect these nodes. We have two cases to handle:

Case A. The object class or relationship type of every object/relationship is distinct.

In this case, all the nodes in D' correspond to distinct nodes in D, i.e., $|D'| = |D|$. We find a minimal subgraph H of G that connects all the nodes in D. For each intermediate node x in H, we create a node x' that corresponds to x and insert it into P. For each edge $e(x, y)$ in H, we create an edge $e(x', y')$ in P.

Case B. The object class or relationship type of every object/relationship is *not* distinct.

In this case, some objects (or relationships) have the same object class (or relationship type). In other words, two or more nodes in D' correspond to the same node in G, i.e., $|D'| > |D|$. We cluster the nodes in D' according to their object classes, and connect the nodes between the clusters. We try to find a node $u \in D'$ such that u can connect to the other nodes in D' based on the paths between their corresponding nodes in the ORM schema graph. If no such node exists, we create a node x' that corresponds to some node $x \in G$ to connect all the nodes in D'.

The following examples illustrate the above cases.

Example 5. *Let us consider the set of tag groupings $S = \{g_{21}, g_{22}\}$ obtained for query Q_2 in Example 4. We create two nodes u_1 and u_2 to represent g_{21} and g_{22} respectively. Nodes u_1 and u_2 correspond to the nodes* Project *and* Employee *in the ORM schema graph in Figure 2 respectively (Case A). Since the* Employee *and* Project *nodes can be connected via the* EmpProj *node in the ORM schema graph, we create a new node u_3 that corresponds to the* EmpProj *node to connect u_1 and u_2, and output the graph as a query pattern (see Figure 3). This query pattern captures the user's intention to find the information on the project that involves the employees with both skills* Java *and* PhP*.* □

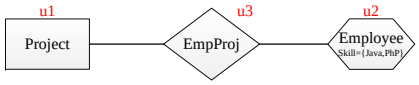
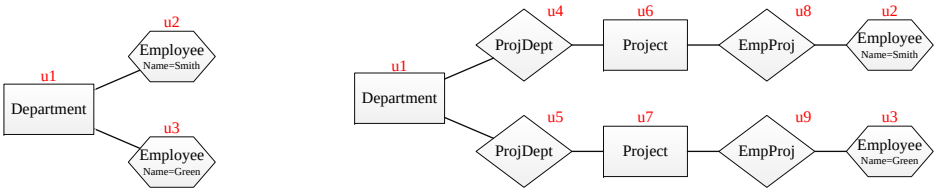


Figure 3: Query pattern in Example 5

Example 6. *Consider the 3 groups of tags g_{11}, g_{12} and g_{13} obtained for Q_1 in Example 3. We create a set of nodes $D' = \{u_1, u_2, u_3\}$ for these groups, and $D = \{$*Employee*,* Department*$\}$. Note that the corresponding object classes of the nodes in D' are not distinct (Case B). Node u_1 corresponds to the* Department *node in the ORM schema graph, while both nodes u_2 and u_3 correspond to the* Employee *node. We cluster the nodes in D' according to their object classes, and connect the nodes between the clusters, i.e., $c_1 = \{u_1\}$ and $c_2 = \{u_2, u_3\}$, and we try to connect u_1 to u_2 and u_3. Based on the ORM schema graph, the* Department *node can connect to the* Employee *node directly. Hence, we create two edges to connect u_1 to u_2 and u_3 respectively. Figure 4(a) shows the query pattern P_1 obtained which indicates that the user wants to find information on the department that both employees* Smith *and* Green *work in.*



(a) P_1 (b) P_2

Figure 4: Query patterns for query Q_1 = {Department Employee Smith Employee Green} in Example 6

Further, we observe that the Department node can also connect to the Employee node via the path Department − ProjDept − Project − EmpProj − Employee in the ORM schema graph. By creating nodes u_4 and u_5 (correspond to ProjDept), u_6 and u_7 (correspond to Project), u_8 and u_9 (correspond to EmpProj), we obtain the query pattern P_2 in Figure 4(b). This pattern indicates that the user is interested in the department with projects involving both employees Smith and Green. □

3.3 Query Pattern Ranking

After generating the various query patterns, the next step is to rank them. The standard method typically ranks graphs based on the number of nodes, i.e., a smaller graph is more easily understood and is ranked higher than a larger complex graph. This approach does not consider the semantics of objects and relationships in the graphs. For example, a query to find an employee who have both skills Java and PhP will have a graph with 3 nodes (EmployeeSkill − Employee − EmployeeSkill), each of which denotes a relation tuple. However, all 3 nodes refer to the same employee object. It should not be ranked equally as a graph with 3 nodes such as Employee − EmpProj − Project, where nodes Employee and Project refer to two different objects.

We observe that when a user issues a query, s/he must have some particular search intention in mind. We refer to the objects/relationships that meet the user's interest in the search intention as the search targets of the query. Our proposed ranking scheme aims to take into account the search targets of the query as well as the number of object/mixed nodes in the query patterns.

In order to identify the search targets of a query, we classify the nodes that correspond to the tag groups into target nodes and condition nodes since they denote the objects and relationships that the user is interested in. A target node specifies the search target of the query, while a condition node indicates the search conditions of the query. In our Example 6, u_1 is a target node since the user is interested in the information on a department. On the other hand, u_2 and u_3 are condition nodes as they specify two particular employees by their names. We define target nodes and condition nodes formally as below:

DEFINITION 2. *Let u be an object/relationship node referred to by a tag group g. We say u is a **condition node** if $\exists\ T \in g$ such that $T.cond \neq null$. Otherwise, u is a **target node** if:*

1. *$\forall\ T \in g$, we have $T.cond = null$ or*
2. *$\exists\ T \in g$ such that $T.attr \neq null$ and $\nexists\ T' \in g$ where $T'.attr = T.attr$*

The first condition indicates that the user is interested in the information of an object/relationship, while the second condition indicates that the user is interested in obtaining information on an object/relationship attribute.

Note that a node can be both a target node and a condition node. Suppose we have the following group of tags:

T_1 = (Department,null,null)
T_2 = (Department,Address,Queen)
T_3 = (Department,Name,null)

This group of tags refers to a department object node that is both a target and a condition node since the semantics of the tags indicates that the user is interested in the name of the department in Queen street.

Let X be the set of target nodes, Y be the set of condition nodes, and N be the number of object and mixed nodes in a query pattern P. We compute a score for P by counting the number of objects involved in the query pattern and the average distance between the target and condition nodes. We define the score of a query pattern P as:

$$score(P) = \frac{1}{N * \sum_{u \in X, v \in Y} \frac{dist(u,v,P)}{|X|*|Y|}}$$

where $dist(u, v, P)$ is the total number of object and mixed nodes in the path connecting two nodes u and v in P.

Query patterns with fewer object/mixed nodes, and a shorter average distance between target nodes and condition nodes will be scored higher.

EXAMPLE 7. *Figure 5 shows two query patterns P_1 and P_2 for the query Q_3 = {Project Employee Green Brown}. P_1 indicates that the user wants to find the information on the project that involves both the employees Green and Brown, while P_2 indicates that the user is interested in the project involving the employee Green who works in the department in Brown street. Both these query patterns have 3 object/mixed nodes. Besides, node u_1 is a target node while nodes u_2 and u_3 are condition nodes. We compute the average distance between the target node (u_1) and the condition nodes (u_2 and u_3) for both query patterns. P_1 has an average distance of $\frac{2+2}{2} = 2$, while P_2 has an average distance of $\frac{2+3}{2} = 2.5$. Thus, we have $score(P_1) = \frac{1}{6}$ and $score(P_2) = \frac{2}{15}$, and P_1 will be ranked higher than P_2.*

We see that this ranking complies with human intuition that both the employees Green and Brown are "closely" related to the target project in P_1. In contrast, the department in Brown street is related to the target project just because it has some employee (Green) involves in the project in P_2. On the other hand, using standard method which ranks graphs based on the number of nodes will give P_1 a lower rank than P_2, as P_1 consists of 5 nodes while P_2 consists of 4 nodes. □

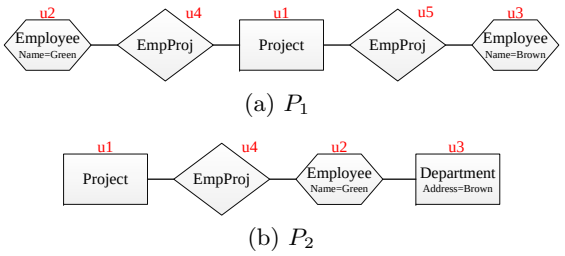


Figure 5: Query patterns in Example 7

Note that a query may not contain keywords that explicitly indicate the search targets. For example, none of the keywords in the query {Project XML Project RDB} indicate the search targets explicitly. In this case, we will need to infer the target nodes.

The work in [11] defines the centric distance of a node u as the longest distance between u and any node in the graph. Further, the radius of the graph is the minimal value among the centric distances of every node. A query answer is a graph whose radius is not larger than a specified value. Here, we use the radius of query patterns to determine the target nodes.

We define the centric distance of a node u in P as the longest distance between u and any node v in P, that is,

$$centric(u, P) = max_{v \in P} \ \ dist(u, v, P)$$

Then the radius of P is given by the shortest centric distance among all the nodes in P. We infer that a node u is a target node if its centric distance is equal to the radius of P.

EXAMPLE 8. *Figure 6 shows a query pattern for the query* {*Project XML Project RDB*} *with 3 object nodes. Both the nodes* u_1 *and* u_2 *correspond to the* Project *node in the ORM schema graph and are condition nodes. There is no target node in the pattern according to Definition 2. Thus, we will look for a node whose centric distance is equal to the radius of the query pattern. This gives us* u_4 *as the target node, indicating that the user is interested in the department that conducts both projects* XML *and* RDB*. We compute the average distance between the target node* u_4 *and the condition nodes* u_1 *and* u_2*, and obtain a score of* $\frac{1}{6}$ *for this pattern.* □

Figure 6: Query pattern in Example 8

3.4 SQL Statement Generation

Finally, we generate a set of SQL statements based on the top-k query patterns. These SQLs statements are used to retrieve results from the relational database. The results are then returned as answers to the extended keyword query.

For each query pattern P, we generate an SQL statement as follows:

SELECT clause. For each target node u in P, if u specifies a search target via the object or relationship name (Condition 1 in Definition 2), then we include all the attributes of the relations of u in the SELECT clause. Otherwise, if u specifies a search target via an attribute name (Condition 2 in Definition 2), then we include only the corresponding attribute of the relations of u in the SELECT clause. If u is inferred from the radius of P, then we assume that user is interested in all of information of u and include all the attributes of the relations of u in the SELECT clause.

FROM clause. The FROM clause contains the relations of all the nodes in P.

WHERE clause. The WHERE clause joins the relations in the FROM clause based on the foreign key-key constraints. Further, for each condition node u in P, we check the group of tags that refer to the object/relationship denoted by u. For each tag T such that $T.cond \neq null$, we include the condition "$T_k.label.attr$ contains $T_k.val$" in the WHERE clause.

EXAMPLE 9. *Consider the query pattern* P_1 *in Figure 4(a). Node* u_1 *is a target node and denotes a department object, while nodes* u_2 *and* u_3 *are condition nodes that denote the employee objects named* Smith *and* Green *respectively. We will generate the following statement for the query pattern:*

```
SELECT D.Deptid,D.Name,D.Address
FROM Department D,Employee E1,Employee E2
WHERE D.Deptid=E1.Deptid AND D.Deptid=E2.Deptid AND
    E1.Name contains 'Smith' AND E2.Name contains 'Green'
```
□

4. EXPRESSQ SYSTEM PROTOTYPE

We design a system called ExpressQ which enables users to query the database using extended keyword queries. Figure 7 shows the main components in ExpressQ: (a) Query Analyzer, (b) Query Interpreter, and (c) SQL Generator.

Given a query Q and the ORM schema graph G, we first call the Query Analyzer to produce a list of sets of tag groupings. Since a keyword in an extended keyword query may be ambiguous, and may be associated with multiple tags, we enumerate the different sequence of tags for a query. For each sequence of tags, the Query Analyzer produces a set of tag groupings. Then we call the Query Interpreter to generate a list of query patterns for each set of tag groupings. We compute the scores of the query patterns and output the *top-k* patterns. Finally, we generate the SQL statements for the *top-k* ranked query patterns. The results of these SQLs are returned as the answers of Q.

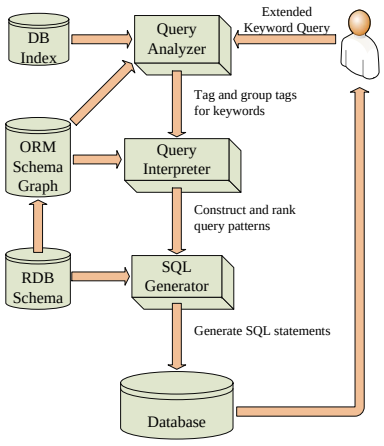


Figure 7: Architecture of ExpressQ

Algorithm 1: *QueryAnalyzer*

Input: $Q = \{k_1 \ \cdots \ k_n\}$, ORM schema graph G
Output: list of sets of tag groupings L

```
1  L ← ∅;
2  for i = 1 to n do
3  |  TagList_i = createTags(k_i, G);
4  foreach tag sequence {T_1, ··· , T_n}, T_i ∈ TagList_i do
5  |  S ← ∅;
6  |  Let g = {T_1}, glabel = T_1.label, newg = false;
7  |  for i = 2 to n do
8  |  |  if T_i.label ≠ glabel then
9  |  |  |  newg = true;
10 |  |  else if T_i.attr = null ∧ T_i.cond = null then
11 |  |  |  newg = true;
12 |  |  else if T_i.attr is not multivalued ∧∃j ∈ [i − |g|, i − 1]
   |  |  such that T_j.attr = T_i.attr then
13 |  |  |  newg = true;
14 |  |  if newg is true then
15 |  |  |  S = S ∪ {g}; g ← ∅;
16 |  |  |  g = g ∪ {T_i}; glabel = T_i.label;
17 |  |  else
18 |  |  |  g = g ∪ {T_i};
19 |  S = S ∪ {g};
20 |  Insert S into L;
```

Algorithm 1 describes the details of the Query Analyzer. We first create a list of tags for each keyword in the query (Lines 2-3). For each sequence of tags, we group the tags that refer to the same object or relationship. We initialize S and put the tag of the first keyword T_1 into a group g (Lines 5-6). Next, we check whether the tags of the subsequent keywords can be put into the same group g (Lines 8-13), and create new groups if needed (Lines 14-19). Finally, we insert S into the list L (Line 20).

Algorithm 2 gives the details of the Query Interpreter. For each group of tags g_i in S, we create a node u_i to denote the object/relationship referred to by g_i. We add u_i into set D' and its corresponding node v_i in the ORM graph into set D. Then we insert u_i into the query pattern P (Lines 3-7).

If D' has only one node, we simply add P into $Plist$ (Lines 8-9). Otherwise, we compare the number of nodes in D' and D. If $|D'| = |D|$, we find the minimal subgraph H of G that connects all the nodes in D. For each intermediate node x in H, we create a node x' that corresponds to x and insert it into P. For each edge $e(x, y)$ in H, we create an edge $e(x', y')$ in P. Then we add P into $Plist$ (Lines 10-16).

If $|D'|$ is larger to $|D|$, we divide the nodes in D' into clusters $c_1, c_2, \cdots, c_m$ such that the nodes in each c_i corresponds to a node v_i in D, and $|c_i| \leq |c_{i+1}|$, $\forall i \in [1, m-1]$.

If the smallest cluster c_1 has only one node u_1, then we connect u_1 to the nodes in $c_2, c_3, \cdots, c_m$. Let H be the path that connect v_1 and v_i in G. We connect u_1 to the nodes in c_i based on H (Lines 17-25).

On the other hand, if c_1 has more than one node, then we will use a node x' that corresponds to some node $x \in G - D$ to connect all the nodes in $c_1, c_2, \cdots, c_m$. For each object or mixed node x in $G - D$, we first create a copy P' of P, and insert a node x' that corresponds to x into P'. Again, let H be the path that connect x and v_i in G. We connect x' to the nodes in c_i based on H. After all the nodes in D' are connected, we add P' into $Plist$ (Lines 26-34).

Algorithm 2: *QueryInterpreter*

Input: set of tag groupings S, ORM schema graph G
Output: list of query patterns $Plist$

```
1  Plist ← ∅; D' ← ∅; D ← ∅;
2  Let P be a query pattern;
3  for i = 1 to |S| do
4  |  Create a node u_i for group of tags g_i;
5  |  Let u_i corresponds to v_i in G;
6  |  D' = D' ∪ {u_i}; D = D ∪ {v_i};
7  |  Insert u_i into P;
8  if |D'| = 1 then
9  |  Add P into Plist;
10 else if |D'| = |D| then
11 |  H = findSubgraph(D, G);
12 |  foreach intermediate node x in H do
13 |  |  Create a node x' and insert it into P;
14 |  foreach edge e(x, y) in H do
15 |  |  Create an edge e(x', y') in P;
16 |  Add P into Plist;
17 else if |D'| > |D| then
18 |  Let D' = c_1 ∪ c_2 ··· ∪ c_m, |c_i| ≤ |c_{i+1}|, i ∈ [1, m − 1];
19 |  if |c_1| = 1 then
20 |  |  Let u_1 be the node in c_1;
21 |  |  for i = 2 to m do
22 |  |  |  Let H be the path that connects v_1 and v_i in G;
23 |  |  |  for j = 1 to |c_i| do
24 |  |  |  |  Connect u_1 to u_{i,j} in c_i based on H;
25 |  |  Add P into Plist;
26 |  else
27 |  |  foreach object/mixed node x in G − D do
28 |  |  |  P' = P;
29 |  |  |  Create a node x' and insert it into P';
30 |  |  |  for i = 1 to m do
31 |  |  |  |  Let H be the path that connects x and v_i in G;
32 |  |  |  |  for j = 1 to |c_i| do
33 |  |  |  |  |  Connect x' to u_{i,j} in c_i based on H;
34 |  |  |  Add P' into Plist;
```

5. PERFORMANCE STUDY

In this section, we evaluate the effectiveness and efficiency of the ExpressQ system. We implement the algorithms in Java and carry out experiments on an 3.40GHz CPU with 8GB RAM. We use two relational databases in our experiments: the TPC-H database (TPCH) and the ACM Digital Library publication (ACMDL).

We construct 7 queries for each database. Tables 3 and 4 show the queries and the corresponding descriptions (or search intentions). The keywords of these queries may match relation names, attribute names and tuple values.

5.1 Effectiveness Experiments

One of the advantages of ExpressQ is its ability to identify the context of keywords and the search target of a query to retrieve user's intended information. We verify its effectiveness by comparing ExpressQ with Spark [13], an existing relational keyword search engine that does not consider keyword contexts or search targets.

Spark finds the relations whose tuples matches the query keywords, and constructs a set of minimal connected graphs called candidate networks based on these relations. The candidate networks are ranked according to their size, and SQL statements are generated from the top-k networks.

5.1.1 Results for the TPCH Database

Table 5 shows the generated SQL statements that best match the descriptions of the queries for the TPCH database. We see that although both ExpressQ and Spark generate the same SQL statement for query $T1$, they differ greatly for the rest of the queries.

Queries $T2$ to $T4$ show that ExpressQ is more selective in its retrieval of information as it identifies the search target in the query. ExpressQ retrieves only the retail price of the part

Table 3: Queries for the TPCH database

#	Query	Description
$T1$	part type nickel	find the information of the parts with type 'nickel'
$T2$	part retailprice name rose	find the retail price of the part 'rose'
$T3$	customer phone mktsegment automobile	find the phone of the customers who are in 'automobile' market segment
$T4$	orders date priority high China	find the date of the orders that have 'high' priority and come from 'China'
$T5$	supplier Canada	find the information of the suppliers in 'Canada'
$T6$	supplier part cornflower	find the information of the suppliers who supply part 'cornflower'
$T7$	customer name lineitem ship rail	find the name of the customers who order lineitems by 'ship' and 'rail'

Table 4: Queries for the ACMDL database

#	Query	Description
$A1$	author "Tok Wang Ling"	find the information of the author "Tok Wang Ling"
$A2$	paper "keyword search"	find the information of the papers on "keyword search"
$A3$	author Jagadish affiliation	find the affiliations of the author 'Jagadish'
$A4$	publisher code proceeding SIGMOD	find the code of the publisher for the 'SIGMOD' proceedings
$A5$	paper title author Hristidis	find the title of the papers authored by 'Hristidis'
$A6$	editor name proceeding EDBT ICDT	find the names of the common editors for the proceedings 'EDBT' and 'ICDT'
$A7$	author name paper "query processing" "data integration"	find the name of the authors with both papers "query processing" and "data integration"

'rose' for $T2$, whereas Spark overwhelms the user by retrieving all the attributes of this part. This is because ExpressQ has identified retailprice as the search target in $T2$. Similarly, ExpressQ retrieves only the customer phone and order date information for $T3$ and $T4$ respectively, while Spark retrieves all the attributes of the relations in the FROM clause.

Queries $T5$ to $T7$ demonstrate that by considering the context of keywords, ExpressQ is able to generate SQL statements to retrieve information that the user is interested in. ExpressQ uses the context provided by the keyword supplier in both $T5$ and $T6$ to correctly generates SQL statements that retrieve supplier information.

In contrast, Spark generates SQL statements to retrieve information on the nation 'Canada' for $T5$, and part information for $T6$. We see that this does not match the query descriptions of $T5$ and $T6$. Similarly, for $T7$, the SQL statement obtained from ExpressQ retrieves the intended customer information, while Spark retrieves item information instead.

5.1.2 Results for the ACMDL Database

Table 6 gives the results for the ACMDL database. Both ExpressQ and Spark generate the same SQL statements for queries $A1$ and $A2$ because these are relatively straightforward keyword queries. However, for query $A3$, ExpressQ correctly retrieves the affiliation of the author 'Jagadish' while Spark retrieves all the attributes of the author. This is because Spark is unable to identify that affiliation is the search target of a query.

Queries $A4$ to $A7$ show that the context of keywords is important and enables ExpressQ to correctly generate SQL statements that retrieves the intended information: publisher information for $A4$, paper information for $A5$, editor information for $A6$, and author information for $A7$. On the other hand, we observe that Spark retrieves information that clearly do not match the query descriptions, e.g., proceedings for $A4$, and authors for $A5$.

The results of this set of experiments clearly indicate that identifying the keyword context and search target of queries greatly enhances the evaluation of keyword queries and leads to the retrieval of appropriate information.

5.2 Efficiency Experiments

Finally, we compare the time taken by ExpressQ and Spark to generate SQL statements for the queries. Figure 8 shows the results for both TPCH and ACMDL queries in Tables 3 and 4 on cold cache.

We observe that Spark is faster than ExpressQ when the number of nodes in the candidate network/query pattern is small. This is because Spark does not analyze the search intention of the queries but only finds candidate networks containing all the keywords that match tuple values.

However, Spark is slower than ExpressQ for queries $T4$, $T7$, $A6$ and $A7$. This is because the number of nodes in the candidate networks for these queries is large, and Spark needs more time to enumerate the networks in a breadth-first traversal manner. For example, Spark generates 339 intermediate graphs before finding the top 3 candidate networks for query $T7$. In contrast, ExpressQ finds the path customer−lineitem−orders in the ORM schema graph, and builds the query pattern based on this path directly.

Figure 9 compares the time taken by ExpressQ to generate SQL statements, and the time needed to execute these statements over the databases. We see that the execution of SQL statements dominates the overall processing time (in seconds), indicating that the extra time taken by ExpressQ to analyze the queries (in ms) to identify the search intention of the user is a good tradeoff. We note that the execution time of SQL statements varies significantly with the number of results retrieved and the number of joins. For example, the SQL statement for query $T7$ takes more than 30 minutes to join 5 relations, while the SQL statement for query $T5$ takes only 78 ms to retrieve 412 results.

6. RELATED WORK

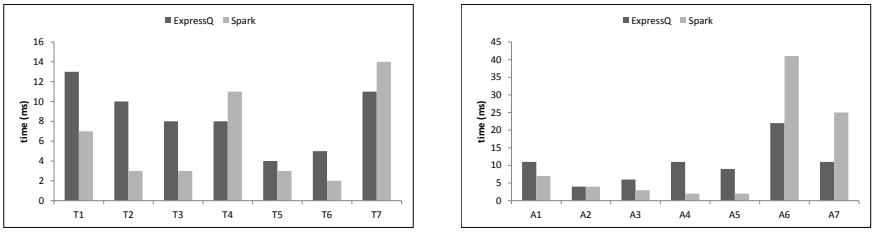
Existing works in relational keyword search typically use a schema graph or a data graph to process a keyword query. The schema graph approach models the database schema as an undirected graph where each node represents a relation and each edge represents a foreign-key key constraint. Early works such as DBXplorer [1] and DISCOVER [7] propose a breadth-first traversal on the schema graph to generate a set of SQL statements. The output tuples of each SQL contain

Table 5: SQL statements generated for the TPCH database

#	ExpressQ	Spark
$T1$	select R1.partkey, R1.name... from part R1 where match(R1.type) against ('nickel' in boolean mode);	select R1.partkey, R1.name... from part R1 where match(R1.type) against ('nickel' in boolean mode);
$T2$	**select R1.retailprice** from part R1 where match(R1.name) against ('rose' in boolean mode);	**select R1.partkey, R1.name, R1.mfgr, R1.brand, R1.type, R1.size...** from part R1 where match(R1.name) against ('rose' in boolean mode);
$T3$	**select R1.phone** from customer R1 where match(R1.mktsegment) against ('automobile' in boolean mode);	**select R1.custkey, R1.name, R1.address...** from customer R1 where match(R1.mktsegment) against ('automobile' in boolean mode);
$T4$	**select R1.date** from orders R1, customer R2, nation R3 where R1.custkey=R2.custkey and R2.nationkey=R3.nationkey and match(R1.priority) against ('high' in boolean mode) and match(R3.name) against ('China' in boolean mode);	**select R1.orderkey, R1.custkey, ..., R2.custkey, R2.name...** from orders R1, customer R2, nation R3 where R1.custkey=R2.custkey and R2.nationkey=R3.nationkey and match(R1.priority) against ('high' in boolean mode) and match(R3.name) against ('China' in boolean mode);
$T5$	select R2.suppkey, R2.name, R2.address... **from nation R1, supplier R2** where R2.nationkey=R1.nationkey and match(R1.name) against ('Canada' in boolean mode);	select R1.nationkey, R1.name, R1.regionkey, R1.comment **from nation R1** where match(R1.name) against ('Canada' in boolean mode);
$T6$	select R3.suppkey, R3.name... **from part R1, partsupp R2, supplier R3** where R2.suppkey=R3.suppkey and R2.partkey=R1.partkey and match(R1.name) against ('cornflower' in boolean mode);	select R1.partkey, R1.name... R1.comment **from part R1** where match(R1.name) against ('cornflower' in boolean mode);
$T7$	**select R1.name from customer R1, orders R2, lineitem R3, orders R4, lineitem R5** where R2.custkey=R1.custkey and R3.orderkey=R2.orderkey and R4.custkey=R1.custkey and R5.orderkey=R4.orderkey and match(R3.shipmode) against ('ship' in boolean mode) and match(R5.shipmode) against ('rail' in boolean mode);	**select R1.orderkey, R1.partkey, ..., R2.orderkey, R2.custkey... from lineitem R1, orders R2, lineitem R3** where R1.orderkey=R2.orderkey and R3.orderkey=R2.orderkey and match(R1.shipmode) against ('ship' in boolean mode) and match(R3.shipmode) against ('rail' in boolean mode);

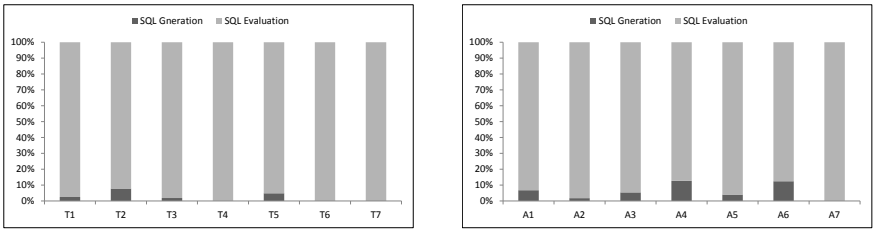
Table 6: SQL statements generated for the ACMDL database

#	ExpressQ	Spark
$A1$	select R1.author_id, R1.name from author R1 where match(R1.name) against ("'Tok Wang Ling"' in boolean mode);	select R1.author_id, R1.name from author R1 where match(R1.name) against ("'Tok Wang Ling"' in boolean mode);
$A2$	select R1.paper_id, ..., R1.title... from paper R1 where match(R1.title) against ("'keyword search"' in boolean mode);	select R1.paper_id, ..., R1.title... from paper R1 where match(R1.title) against ("'keyword search"' in boolean mode);
$A3$	**select R11.affiliation from author R1, author_aff_history R11** where R11.author_id=R1.author_id and match(R1.name) against ('Jagadish');	**select R1.author_id, R1.name from author R1** where match(R1.name) against ('Jagadish' in boolean mode);
$A4$	**select R2.code from proceeding R1, publisher R2** where R1.publisher_id=R2.publisher_id and match(R1.acronym) against ('SIGMOD' in boolean mode);	**select R1.proc_id, R1.publisher_id, R1.acronym, R1.description, R1.class, R1.title, R1.volume, R1.isbn13... from proceeding R1** where match(R1.acronym) against ('SIGMOD' in boolean mode);
$A5$	**select R3.title from author R1, author_paper R2, paper R3** where R2.paper_id=R3.paper_id and R2.author_id=R1.author_id and match(R1.name) against ('Hristidis' in boolean mode);	**select R1.author_id, R1.name from author R1** where match(R1.name) against ('Hristidis' in boolean mode)
$A6$	**select R1.name from editor R1, edit_proceeding R2, proceeding R3, edit_proceeding R4, proceeding R5** where R2.proc_id=R3.proc_id and R2.editor_id=R1.editor_id and R4.proc_id=R5.proc_id and R4.editor_id=R1.editor_id and match(R3.acronym) against ('EDBT' in boolean mode) and match(R5.acronym) against ('ICDT' in boolean mode);	**select R1.proc_id, ..., R2.publisher_id, ..., R3.proc_id from proceeding R1, publisher R2, proceeding R3** where R1.publisher_id=R2.publisher_id and R3.publisher_id=R2.publisher_id and match(R1.acronym) against ('EDBT' in boolean mode) and match(R3.acronym) against ('ICDT' in boolean mode);
$A7$	**select R1.name from author R1, author_paper R2, paper R3, author_paper R4, paper R5** where R2.paper_id=R3.paper_id and R2.author_id=R1.author_id and R4.paper_id=R5.paper_id and R4.author_id=R1.author_id and match(R3.title) against ("'query processing"' in boolean mode) and match(R5.title) against ("'data integration"' in boolean mode);	**select R1.paper_id, R1.proc_id, ..., R2.citing, R2.cited, R3.paper_id, R3.proc_id... from paper R1, paper_citation R2, paper R3** where R2.citing=R1.paper_id and R2.cited=R3.paper_id and match(R1.title) against ("'query processing"' in boolean mode) and match(R3.title) against ("'data integration"' in boolean mode);



(a) TPCH (b) ACMDL

Figure 8: Comparison of the time taken by ExpressQ and Spark to generate SQL statements



(a) TPCH (b) ACMDL

Figure 9: Comparison of the SQL generation time by ExpressQ and the SQL execution time

all the query keywords. [5] incorporates an IR-style ranking strategy to evaluate the relevance of query results and proposes two algorithms to compute the top-k results. [12] improves the effectiveness of [5] by normalizing the ranking factors. [13] avoids the side effect of overly rewarding contributions of the same keyword in [5] and [12].

The data graph approach models the database as an undirected graph where each node represents a tuple and each edge represents a foreign key-key reference. BANKS [8] proposes a backward expansion search to find the Steiner trees that contain all the keywords, and evaluates the relevance of a Steiner tree based on its root and leaf nodes. [9] improves the efficiency of BANKS by using a bidirectional expansion search to reduce the search space. [3] employs a dynamic programming technique by identifying top-k minimal group Steiner trees. CI-Rank [15] considers the importance of nodes, as well as the cohesiveness of the tree structure.

To improve the usability of keyword search, [10] summarizes the results of keyword queries so that users can refine their search based on these summaries. [14] finds co-occurring terms of keywords to provide users relevant information to refine the answers. [4] generates a list of object summaries. None of these works consider the context of keywords and search target in the queries.

7. CONCLUSION

In this paper, we have examined the problem of enhancing the expressive power and evaluation of relational keyword queries. This is achieved by extending the keyword queries in two aspects. First, we consider keywords that match meta-data e.g., names of relations and attributes, and utilize them to provide the context of subsequent keywords in the query. Second, we use the ORM schema graph to enrich the semantics of the keywords, and identify sets of keywords that refer to the same object/relationship in the database, in order to infer the search target of the query. The proposed approach is implemented in a prototype system called ExpressQ that analyzes keyword query to identify user's search intention and generates SQL statements to retrieve relevant information. Experimental results demonstrate that the effectiveness of ExpressQ.

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