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Polymorphic queries for P2P systems

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When a query is posed on a centralized database, if it refers to attributes that are not defined in the database, the user is warranted to get either an error or an empty set. In contrast, when a query is posed on a peer in a P2P system and refers to attributes not found in the local database, the query should not be simply rejected if the relevant information is available at other peers. This paper proposes a query model for unstructured P2P systems to answer such queries. (a) We introduce a class of polymorphic queries, a revision of conjunctive queries by incorporating type variables to accommodate attributes not defined in the local database. (b) We define the semantics of polymorphic queries in terms of horizontal and vertical object expansions, to find attributes and tuples, respectively, missing from the local database. We show that both expansions can be conducted in a uniform framework. (c) We develop a top-K algorithm to approximately answer polymorphic queries. (d) We also provide a method to merge tuples collected from various peers, based on matching keys specified in polymorphic queries. Our experimental study verifies that polymorphic queries are able to find more sensible information than traditional queries supported by P2P systems, and that these queries can be evaluated efficiently.

1. Introduction

Consider a centralized database D specified by schema S. When D is a centralized database and a query Q is posed on D, if Q refers to attributes not found in S, then the user is warranted to get either an error or an empty set. This is also the semantics adopted by current query models for P2P systems [1–10]: when Q is posed on D residing at a peer P, Q is not allowed to refer to any attributes that are not defined in S.

However, while the information about an attribute cannot be found in D, it may be available at other peers in the P2P system. One would expect that P2P systems could do better than centralized database systems. Indeed, as illustrated below, P2P systems may be able to find missing attributes at other peers, and hence, should not simply reject Q. After all it is to share data that P2P systems are developed in the first place.

Example 1.1. Alice is interested in John Denver's albums that received a good rating. She wants to query a P2P system and find information about the price, label and release of those albums. She has only access to peer P_0. The database at P_0 is specified by schema

review(album,artist,rating).

As shown in Fig. 1(a), a review relation collects albums by various artists, and with each album it associates an average rating in the scale [0, 4]. To this end Alice poses an SQL query Q_0 on the database residing at P_0:

select	album, price, label, release
from	review
where	artist = "Denver, J" **and** rating = "4"

Observe that Q_0 refers to attributes price, label and release, which are not defined in the local schema review.

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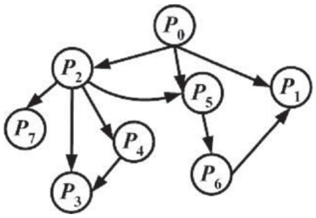
a

An instance of *review* at peer P_0

	album	artist	rating
t_1:	Almost Heaven	Denver,J	3
t_2:	Greatest Hits	Denver,J	4

b

Peer P_0 and its neighboring peers



c

An instance of *sale* at P_2

	album	artist	price	label	rating
t_3:	Almost Heaven	Denver, J	7.99	Dancing Bull	good
t_4:	Take Me Home	Denver, J	5.97	Windstar	high
t_5:	Greatest Hits	Denver, J	8.36	BMG	high
t_6:	Diana	Anka, P	5.98	Magic	fair

d

An instance of *CD* at P_3

	title	artist	label	release	rank
t_7:	Almost Heaven	Denver, J	Dancing Bull	12/05/2005	2,175
t_8:	Take Me Home	Denver, J	Windstar	03/07/2006	1,654

e

Answer to query Q_0 posed on peer P_0

	album	price	label	release
s_1:	Greatest Hits	8.36	BMG	null
s_2:	Take Me Home	5.97	Windstar	03/07/2006

Fig. 1. Example data and answer to query Q_0.

If Q_0 were posed on a centralized database system, Alice would get either an error or an empty set.

However, while price, label and release are not provided by peer P_0, they may be available at other peers in the P2P system. As depicted in Fig. 1(b), P_0 has a neighboring peer P_2 with a database of schema sale(album, artist, price, label, rating), which in turn has a neighbor P_3 with a database of schema CD(title, artist, label, release, rank). Instances of sale and CD are shown in Figs. 1(c) and (d), respectively.

Provided these, the system has got enough information to answer Q_0. (1) For the album "Greatest Hits" found at P_0, we can find its price and label from P_2. That is, we can "horizontally" expand the object by including missing attributes found at other peers. In addition, (2) from P_2 an album "Take Me Home" is found (when 'high' indicates a good rating), which is missing from P_0. The answer to Q_0 can be "vertically" expanded by including the album, which is further expanded at P_3 by adding release. Taken together, the answer to Q_0 contains tuples shown in Fig. 1(e). □

Several query models have been put forward for unstructured P2P systems, based on, *e.g.*, schema mapping and certain query answering [1–3], information retrieval [4], mapping (concordance) tables [5], approximate query processing [7,8], dynamic construction of group schemas [9,10], and query expansion via synonym rules [11] (see [12] for a recent survey). However, we are not aware of any P2P query models that allow queries to explicitly retrieve attributes not defined in a local schema, such as the query Q_0 given above. This highlights the need for a new P2P query model to support such queries.

Contributions. To explore the data sharing nature of P2P systems, we propose a query model for unstructured, schema-heterogeneous P2P systems. The model consists of (1) a revision of conjunctive (SPC) queries that may refer to attributes not defined in the local schema, (2) the semantics of the queries in terms of object expansions, (3) an efficient top-K algorithm for approximately answering the queries, and (4) a method for merging tuples from various peers that represent the same real-world object.

(1) We introduce a class of queries for P2P systems, referred to as *polymorphic queries*. Polymorphic queries extend SPC queries by supporting: (a) *type variables* to specify, explicitly or implicitly, attributes that are not defined in a local schema, and (b) *matching keys* to guide how tuples retrieved from various peers are merged. For example, query Q_0 can be expressed as a polymorphic query.

Polymorphic queries are based on the notion of extensible records, which have proved extremely useful in functional programming (see, *e.g.*, [13]). An extensible record carries *unknown* fields with type variables, in addition to a set of known fields with fixed types. It allows one to build an object *incrementally* by adding a finite number of fields and instantiating their type variables accordingly. Along the same lines, we use type variables to cope with attributes found at other peers that are "unknown" to the local peer.

(2) We define the semantics of polymorphic queries in terms of two forms of expansions: (a) *horizontal expansion*, to augment an object by incorporating additional attributes of the object found at various peers in the P2P system, and (b) *vertical expansion*, to enrich query answer by including tuples missing from the local peer but found at other peers in the system.

Referring to query Q_0, horizontal and vertical expansions yield tuples s_1 and s_2 of Fig. 1(e) in the answer to Q_0, respectively. Most P2P query models typically support vertical expansion only.

We provide a conceptual evaluation strategy for polymorphic queries, conducting horizontal and vertical expansions in a uniform framework based on a notion of *contextual foreign keys* (CFKs). CFKs extend foreign keys that reference primary keys, by incorporating patterns of semantically related data values. They specify correspondences between *attributes* and between *values* across different peers. They can express lexical semantic relations as found in, *e.g.*, WordNet (see http://en.wikipedia.org/wiki/WordNet). Instead of assuming the existence of schema mapping [2,3] or mapping tables [5], we show that CFKs between neighboring peers suffice to rewrite queries for vertical expansion and to collate tuples for horizontal expansion.

(3) To reduce the communication cost of the conceptual evaluation strategy, we develop a top-K algorithm to approximately answer polymorphic queries. The algorithm decides whether a query and relevant objects should be forwarded from one peer to another, based on a *quality model*. The model takes into account of the local data at the peer and the statistics of the data at its neighboring peers. Given a query Q and predefined numbers K and m, the algorithm returns K top tuples in the answer to Q, with a performance guarantee: at each peer it forwards at most K tuples to at most m neighbors. In addition, we present optimization methods to further reduce network traffic.

(4) Tuples collected from various peers may represent the same real-world object. We provide a method to merge such tuples, an issue that has not been well explored for P2P systems [14]. We approach this based on a notion of matching keys, which may be optionally specified in a polymorphic query. To identify tuples from different sources, a matching key specifies what attributes to compare and how to compare them, in terms of equality or similarity operators.

(5) We experimentally verify that polymorphic queries and their evaluation techniques are capable of finding far more relevant information than the traditional approach based on schema mapping (*e.g.*, [2]), without substantial degradation in performance. Indeed, the conceptual evaluation strategy constantly retrieves 5 times more results than the mapping-based approach, and the top-K algorithm finds 1.42 times more than the traditional approach (when $K \geq 40$ and $m = 3$). When top K tuples are concerned, the top-K algorithm finds up to 84.78% of the results of the conceptual strategy, and 253% more than that of the mapping approach, with significantly less network traffic. Moreover, both the conceptual strategy and the top-K algorithm scale well with the number of peers and the size of data. We also find that our tuple merging method is effective: it constantly identifies over 19% of tuples returned by the traditional approach that refer to the same object.

Organization. We discuss related work in Section 2. Polymorphic queries are introduced in Section 3, followed by CFKs in Section 4. The semantics of polymorphic queries is defined in Section 5 by giving the conceptual evaluation strategy based on object expansions. The top-K algorithm is developed in Section 6, followed by a method for tuple merging in Section 7. The experimental study is presented in Section 8, followed by conclusions in Section 9.

2. Related work

Several query models have been studied for unstructured P2P systems (*e.g.*, [1–5,9–11]). Piazza [2] interprets P2P queries based on schema mappings (query rewriting) and certain query answering. A variation was proposed in [3] in terms of epistemic FO (First-Order logic). This approach is effective when neighboring peers do not have radically different schemas. However, successive rewritings often reduce information that a query is to retrieve, when *e.g.*, attributes at one peer do not find a match at its neighbors. To tackle this problem, automated construction of group schemas was studied in [9,10]. PeerDB [4] is based on information retrieval techniques. Heptox [1] uses rules to translate queries. These models support vertical expansion, but not horizontal expansion. They do not expand objects by adding relevant *attributes* retrieved from other peers.

Closer to this work is Hyperion, based on mapping tables [5]. A mapping table maintains value and name correspondences between data in neighboring peers, which is similar to CFKs. Hyperion evaluates a query Q by traversing peers, translating Q to a set of queries based on mapping tables, and collecting relevant objects found by those translated queries. It simply puts these objects together via outer union, but considers neither extending existing objects with additional attributes nor conflict resolution.

A notion of query expansion has been explored for P2P queries [6]. It is to enhance queries with vague or surrounding concepts of pre-defined keywords, when users are unable to identify precise keywords. This is quite different from object expansion: query expansion aims to find more relevant results of fixed keywords, and is developed mostly for keyword queries [15,16]; in contrast, object expansion is to enrich objects with new relevant attributes, for SPC queries.

To the best of our knowledge, no previous P2P models allow queries to explicitly refer to attributes that are not defined at the local peer, such as Q_0 of Example 1.1.

Quality models have been proposed in, *e.g.*, [7,8] to select peers, based on certain metrics of information completeness. Top-K algorithms have also been studied for various applications (see [17] for a survey). The quality model proposed in this work differs from prior models in that it takes into account not only new information retrieved via vertical expansion, but also the amount of new information associated with attributes added via horizontal expansion.

Conflict resolution has been studied for data integration (*e.g.*, [18–20]) and uncertain data (*e.g.*, [21,22]). There has also been a host of work on record matching (see [23] for a survey). As observed in [14], however, few P2P query models deal with conflicts. This work is among the first efforts to explore these issues for P2P queries.

There has also been work on polymorphic type inference for relational algebra [24]. The focus is to determine on what schema a query Q is well defined, and to infer the "principle" (most generic) type for Q. This is studied for centralized systems. In contrast, given a query Q that is *not* well defined at the local peer in the standard semantics, this work studies how to evaluate the query based on object expansion. This also involves object merge and conflict handling, which are not encountered in polymorphic type inference.

3. Polymorphic queries

We next present the syntax of polymorphic queries. To simplify the discussion we define polymorphic queries as an extension of SPC queries, and defer the study of more general polymorphic queries to future work.

SPC queries. An SPC query [25] is defined on a relational schema $\mathcal{R}$ in terms of the *selection* (σ), *projection* (π) and *Cartesian product* ($\times$) operators. It is of the form:

$$\pi_L(\sigma_F(E_c)) \quad \text{where } E_c = R_1 \times \cdots \times R_n.$$

Here (a) for each $j \in [1,n]$, we assume w.l.o.g. that R_j is a relation atom in $\mathcal{R}$ such that the attributes in R_j and R_l are disjoint if $j \neq l$; (b) F is a predicate built from equality atoms such as $A = B$ and $A =$ 'a' for a constant a in the domain of A, by closing under conjunction (and) and disjunction (or); and (c) let Q_c denote $\sigma_F(E_c)$, then in the projection $\pi_L(Q_c)$, L is a list of attributes *appearing* in Q_c.

Note that we allow disjunction in F and hence, support certain SPCU queries defined with union.

Polymorphic queries. We define an extension of SPC, referred to as *polymorphic queries* and denoted by SPC*, by supporting (1) a *polymorphic projection* operator Π with type variables, and (2) an optional list MK of matching keys:

$$\Pi_L(Q_c) \text{ group\_by MK} \quad \text{where } L = (L_1; L_2; \alpha).$$

Here (a) $Q_c = \sigma_F(E_c)$ is the same as above, (b) L_1 is a list of attributes appearing in Q_c, but in contrast, (c) L_2 is a list of attributes *not* appearing in Q_c, and (d) α is an optional variable, which, if present, is to be instantiated with a list of attributes appearing in neither L_1 nor L_2. Intuitively,

- L_2 denotes attributes that the user *explicitly* wants to find from a P2P system, although they are not defined in the local schema; while the labels of these attributes are known, their *types* are *unknown* and are represented by type variables; and
- α indicates that other relevant attributes are also demanded, if any. The user needs to know neither the *labels* nor the *types* of these attributes.

We refer to L_1 attributes as *local attributes*, and L_2 as *explicit attributes*. We refer to attributes that instantiate α as *implicit* attributes. Note that both L_2 and α carry type variables, along the same lines as extensible records [13].

We denote by sch(Q) *the output schema* of an SPC* query Q, *i.e.*, the schema of the answer to Q in a P2P system. Here sch(Q) consists of local, explicit and implicit attributes.

Example 3.1. The query Q_0 described in Example 1.1 can be expressed as an SPC* query $Q = \Pi_{(L_1;L_2)}(\sigma_F(E_c))$, where (a) F is a conjunction of equality atoms artist = "Denver, J" and rating = "4"; (b) E_c is the review relation schema at the local peer P_0; (c) L_1 = [album] and L_2 = [price , label, release], which are the attributes appearing in sch(Q_0).

As another example, Alice may want to retrieve other relevant attributes, although she does not know the labels of those attributes. To this end she may write query Q_1 by adding α to Q_0: $\Pi_{(L_1;L_2;\alpha)}(\sigma_F(E_c))$. When Q_1 is evaluated in the P2P system described in Example 1.1, α will be instantiated with attributes found in the system, including but not limited to rank from P_3. The output schema sch(Q_1) consists of all these attributes and those in L_1 and L_2, with type variables instantiated with the corresponding domains.

Extending the SQL syntax, Q_1 can be written as:

```
select*  album; price, label, release;  X
from     review
where    artist = "Denver, J" and rating = "4"
```

Here X indicates the variable α in the SPC* query. □

Remark. (1) Just like SPC queries, when writing an SPC* query, a user does not need to know anything *beyond* the local schema. She may declaratively request other attributes of interest, no matter whether she knows their labels or not, as if they were defined in the local schema. As will be seen shortly, it is the polymorphic query model that automatically retrieves those "external" attributes across the entire system. This provides the user with the flexibility and expressive power to share data in the P2P system.

(2) When an SPC query Q' is posed on a centralized database D, the output schema of Q' is uniquely determined by Q' and the schema of D. In contrast, we cannot *statically determine* sch(Q) of an SPC* query Q in a P2P system based on Q and the local schema alone. Referring to Example 1.1, for instance, one cannot determine the types of price, label, and release based on Q_0 and the schema review at compile time. The output schema is "open-ended" and is *incrementally completed* when the query is evaluated by traversing the linked peers, along the same lines as extensible records.

(3) SPC queries are a special case of SPC* queries: when L_2 is empty, and when α and MK are absent.

(4) To simplify the discussion we have assumed that distinct type variables for attributes in L_2 are automatically generated. Following extensible records of functional programming [13], this model can be extended by allowing multiple attributes to share the same type variable. For instance, if firstname and lastname are attributes in L_2, we may require firstname and lastname to carry the same type variable τ, *i.e.*, the two attributes will bear the same type no matter how τ is instantiated. As will be seen in Section 7, such typing constraints can be enforced in the tuple merging phase, which resolves typing conflicts for tuples collected from different peers.

Matching keys. In an SPC* query Q, if MK is specified, it is of the form $\phi_1, \ldots, \phi_m$. Each ϕ_j ($j \in [1,m]$) is a *matching key* specified by a set of attribute-operator pairs: $((A_1,\text{op}_1), \ldots, (A_l,\text{op}_l))$. Here for each $i \in [1,l]$, A_i is an attribute in L_1 or L_2, and op_i is either a *similarity* operator '$\approx$' or an equality '='.

A matching key expresses a matching rule of [26]. We assume a set Θ of similarity metrics such as q-grams, Jaro distance or edit distance [23]. For each $\approx$ in Θ and for values x and y, $x \approx y$ yields true iff x and y are "close" enough in the similarity metric $\approx$ *w.r.t.* a predefined threshold.

Tuples s_1 and s_2 *satisfy* ϕ_j if $s_1[A_i]\ \text{op}_i\ s_2[A_i]$ for all $i \in [1,l]$, *i.e.*, the attributes of ϕ_j in s_1 and s_2 pairwise "match" *w.r.t.* the corresponding similarity operators. Intuitively, if s_1 and s_2 satisfy ϕ_j then they represent the same object.

Example 3.2. Consider a tuple s_3: (album = "The Greatest Hits", price = 9.99, label = "BMG", release = 01/07/2002), found at, *e.g.*, P_4 (Fig. 1(b)). Then s_3 and s_1 of Fig. 1(e) represent the same album. However, $s_1 \neq s_3$ if one attempts to compare them pairwise *w.r.t.* all attributes in sch(Q_0).

Suppose that a matching key ϕ for query Q_0 is specified: ((album, $\approx$), (label, $=$)), where $\approx$ is a similarity metric such that "The Greatest Hits" $\approx$ "Greatest Hits". Then s_1 and s_3 satisfy ϕ and can be identified, although some of their attributes, *e.g.*, price, are radically different. □

Intuitively, matching keys are an extension of traditional relational keys by incorporating similarity operators to accommodate errors or different representations in tuple matching. They allow us to group (cluster) tuples in the answer to Q by attributes in the keys, such that tuples in the same group are identified to represent the same real-world object.

4. Contextual foreign keys

To give the semantics of SPC* queries, we first define contextual foreign keys, an extension of foreign keys.

Foreign keys (FKs). Recall [25] that a foreign key fk from relation R_1 to R_2 is of the form $R_1[X] \subseteq R_2[Y]$, where X,Y are attribute lists in R_1, R_2, respectively, and Y is a key of R_2. Note that fk specifies a pair of constraints: (a) a key Y for R_2, and (b) an inclusion dependency from R_1 to R_2.

Given instances (D_1, D_2) of (R_1, R_2), fk asserts that Y is a key of D_2 and furthermore, for any tuple t_1 of D_1, there is a tuple t_2 of D_2 such that $t_1[X] = t_2[Y]$, *i.e.*, $t_1[X]$ references the tuple t_2 identified by $t_2[Y]$.

One may want to use FKs to specify schema matching and data concordance across peers. However, FKs (even inclusion dependencies) are not powerful enough, as illustrated below.

Example 4.1. Recall relations review, sale and CD from Example 1.1. Suppose that (album, artist) is the primary key of review and sale, and (title, artist) is the primary key of CD. One might want to specify FKs from review to sale, and from sale to CD as follows:

review(album, artist) $\subseteq$ sale(album, artist)
sale(album, artist) $\subseteq$ CD(title, artist)

These FKs do not make sense if (a) the review relation contains information about all albums while sale contains only albums that received a rating above "poor"; and (b) the CD relation contains only albums from either Windstar or DancingBull. In light of this, the correspondences from review to sale and from sale to CD cannot be expressed as traditional FKs or even as more general inclusion dependencies. □

Contextual foreign key (CFKs). The limitations of traditional FKs motivate us to propose CFKs.

A CFK φ from relation R_1 to R_2 is of the form

$(R_1[X] \subseteq R_2[Y],\ t_p[X_p, Y_p])$,

where (a) X, X_p (resp. Y, Y_p) are two disjoint lists of attributes in R_1 (resp. R_2); (b) $R_1[X] \subseteq R_2[Y]$ is an FK, where X (resp. Y) is a *primary key* of R_1 (resp. R_2); (c) t_p is the *pattern tuple* of φ with attributes in X_p and Y_p, such that for each attribute B in X_p (or Y_p), $t_p[B]$ is a constant in B's domain. We refer to $t_p[X_p]$ (resp. $t_p[Y_p]$) as the X_p (resp. Y_p) *pattern* of φ.

Instances (D_1, D_2) of (R_1, R_2) *satisfy* φ if X (resp. Y) is the primary key of D_1 (resp. D_2) and moreover, for *each* tuple t_1 in D_1, if $t_1[X_p] = t_p[X_p]$, then there exists a tuple t_2 in D_2 such that $t_1[X] = t_2[Y]$ and $t_2[Y_p] = t_p[Y_p]$.

Intuitively, the X_p *pattern* of φ identifies a subset of D_1 that matches $t_p[X_p]$, and the traditional FK $R_1[X] \subseteq R_2[Y]$ is enforced on this subset rather than on the entire D_1. Further, for each tuple t_2 in D_2 that is referenced by $t_2[Y]$ (*i.e.*, $t_1[X]$), the Y_p *pattern* is enforced, *i.e.*, $t_2[Y_p] = t_p[Y_p]$.

Example 4.2. The constraints described in Example 4.1 can be expressed as CFKs as follows:

φ_1: (review(album, artist) $\subseteq$ sale(album, artist), (review(rating) = "4", sale(rating) = "high"))
φ_2: (review(album, artist) $\subseteq$ sale(album, artist), (review(rating) = "3", sale(rating) = "good"))
φ_3: (sale(album, artist) $\subseteq$ CD(title, artist), (sale(label) = "Windstar"))
φ_4: (sale(album, artist) $\subseteq$ CD(title, artist), (sale(label) = "DancingBull"))

Here CFK φ_1 asserts that for each tuple t_i ($i \in [1,2]$) in the review relation, if t_i[rating] = " 4" , then there must be a tuple t_j in the sale relation such that t_i and t_j agree on their (album, artist) attributes and moreover, t_j[rating] = " high" ; similarly for φ_2. These two CFKs ensure that review tuples can be mapped to sale tuples if and only if their ratings are above 2, and moreover, that a rating of "4" (resp. "3") in review corresponds to "high" (resp. "good") in sale.

The CFKs φ_3 and φ_4 assure that sale tuples can find a match in the CD relation only for those albums from either Windstar or DancingBull. Note that no Y_p patterns are specified for CD in φ_3 and φ_4. □

Remark. Observe the following. (1) Traditional FKs are a special case of CFKs with empty X_p and Y_p, when X (resp. Y) is the primary key of R_1 (resp. R_2). (2) CFKs are a variation of conditional inclusion dependencies (CINDs) studied in [27]. A CFK specifies three constraints: (a) X is the primary key of R_1, (b) Y is the primary key of R_2, and (c) an inclusion dependency from R_1 to R_2 with a pattern. In contrast, CINDs specify (c) alone without requiring (a) or (b). (3) CFKs can express lexical semantic relations (*e.g.*, WordNet).

We shall give the semantics of polymorphic queries in terms of CFKs in the next section. More specifically, we use CFKs to collate information about the same object for horizontal expansion, and to rewrite queries for vertical expansion. This is a departure from previous P2P models based on schema mapping [3,2,8], as illustrated by the example below.

Example 4.3. Consider schemas review and sale given in Example 1.1, for databases at peers P_0 and P_2, respectively. Suppose that one wants to specify "peer mapping" [2] from P_0 to P_2 as schema mapping $Q_{(0,2)}$, *i.e.*, $Q_{(0,2)}$ is a query from instances of review to instances of sale. By treating review as a "mediated schema" and sale as a "data source", $Q_{(0,2)}$ is a *local-as-view* (LAV) mapping [2,28]. One can see the following. (1) The instance D_2 of sale at peer P_2 cannot be an exact view [28] of the instance D_0 of review at peer P_0, no matter what query $Q_{(0,2)}$ is considered. Indeed, as we can see from Figs. 1(a) and (c), tuples t_4 and t_6 of D_2 cannot find a match in D_0, and moreover, although t_3 and t_5 of D_2 have a match in D_0, their price and label attributes are not mapped from tuples in D_0. (2) One might want to consider a combination of *global-as-view* (GAV) and LAV as suggested in [2], *i.e.*, a pair $Q_{(0,2)}$ and $Q_{(2,0)}$ of queries such that $Q_{(0,2)}(D_0)$ = $Q_{(2,0)}(D_2)$. However, it is nontrivial to find such mappings. Indeed, schema mapping is often derived from schema matching, which is in turn computed from inclusion dependencies across peers [29]. Deriving schema mapping from dependencies is itself a computationally intractable problem [30]. (3) Even when schema mappings from review to sale are in place, they do not tell us how to answer query Q_0 posed on peer P_0. Indeed, the mappings do not specify how tuple t_2 of D_0 is related to tuples of D_2, such that t_2 can be horizontally expanded by including attributes price and label. Neither query rewriting nor query unfolding helps here.

There has also been recent work on data exchange, *a.k.a.* schema mapping (see [31] for a recent survey). Data exchange is often specified in terms of constraints, such as tuple generating dependencies (TGDs). However, data exchange aims to materialize a target instance using data from a data source, *e.g.*, to generate a sale instance from the instance D_0 of review. It is not for answering queries posed on D_0 with data in D_2. Furthermore, while TGDs are more expressive than CFKs, they do not tell us whether a tuple in D_0 and another in D_2 refer to the same entity, as opposed to CFKs. That is, the increased expressive power of TGDs does not help when it comes to horizontal expansion, not to mention the extra complexity when reasoning about TGDs. □

Table 1
A summary of notations.

Notation	Name	Definition
SPC*	Polymorphic queries	$\Pi_L(Q_c)$ group_by MK
Local attributes L_1; explicit and implicit attributes L_2 and α with type variables		
MK	Matching keys	$((A_1, \approx_1), \ldots, (A_l, \approx_l))$
Rules for identifying tuples by comparing attributes A_i via similarity operators $\approx_i$		
CFK	Contextual foreign keys	$(R_1[X] \subseteq R_2[Y],\ t_p[X_p, Y_p])$
Foreign keys with patterns $t_p[X_p, Y_p]$, for horizontal and vertical expansions		

For the ease of reference we summarize various notations in Table 1.

5. The semantics of SPC* queries

We now present the semantics of polymorphic queries in a P2P system based on CFKs. To focus on the main idea of horizontal and vertical expansions, we first give a conceptual evaluation strategy that may not be efficient, and defer the presentation of optimization techniques to Section 5.5.

5.1. A conceptual query evaluation strategy

Consider an unstructured P2P system $\mathcal{P} = (P_0, \ldots, P_n)$, where P_j is a peer. For each $j \in [0,n]$, the peer P_j is specified by:

- the relational schema S_j of its local database D_j, such that on each relation R in S_j, a primary key is defined; and
- for those $i \in [0,n]$ such that P_i is a neighboring peer of P_j, a set $\Sigma_{(j,i)}$ of CFKs from relations of S_j to relations of S_i, stored at peer P_i.

Remark. We do *not* require that (D_j, D_i) satisfy $\Sigma_{(j,i)}$. Indeed, we simply use the CFKs to specify how *attributes* and *data values* across different peers are mapped to each other, at the schema level. These CFKs can be either explicitly specified or automatically discovered when a new peer joins the system. The maintenance cost for the CFKs is no larger than its counterparts for schema mapping or mapping tables. As shown in Example 4.3, it is less demanding to assume CFKs $\Sigma_{(j,i)}$ rather than schema mapping.

To simplify the exposition, we assume that all CFKs defined on a relation R of S_j in $\Sigma_{(j,i)}$ reference a unique R' in S_i, *i.e.*, each R is mapped to at most one relation in S_i via CFKs, as often assumed in schema mapping. Note that there may exist multiple CFKs from R to R' in $\Sigma_{(j,i)}$, and there may be CFKs from R to distinct R''s in $\Sigma_{(j,l)}$ for $l \neq i$.

Evaluation. Consider an SPC* query $Q = \Pi_L(Q_c)$ group_by MK, where $L = (L_1; L_2; \alpha)$. Suppose that Q is posed on peer P_0, referred to as *the local peer*. Then as depicted in Fig. 2, Q is evaluated in the P2P system $\mathcal{P}$ as follows.
Initial answer. Upon receiving Q, local peer P_0 generates a set ans_0 of objects as follows. (a) It first rewrites Q into a normal SPC query Q' on its local database D_0. (b) It then extracts a set $ans_0 = Q'(D_0)$ of tuples. (c) Finally, it forwards Q and ans_0 to all of its neighboring peers for expansion.
Expand and forward. When peer P_i receives query Q_j and a set ans_j of tuples from peer P_j, where Q_j is a rewriting of Q and is defined on the database D_j, P_i expands ans_j horizontally and vertically as follows:

- *horizontal:* leveraging CFKs in $\Sigma_{(j,i)}$, P_i extends tuples in ans_j by adding relevant attributes available at P_i;
- *vertical:* it extracts new tuples from its database D_i. More specifically, using $\Sigma_{(j,i)}$, it first rewrites Q_j into query Q_i that is defined on D_i. It then executes Q_i on D_i, and expands ans_j with new tuples in $Q_i(D_i)$.

As shown in Fig. 2, P_i generates two sets of tuples: (a) new_i consisting of tuples not in ans_j that are added by vertical expansion, and those tuples in ans_j extended with new attributes by horizontal expansion; and (b) $ans_i = new_i \cup ans_j$.

Peer P_i sends new_i back to the local peer P_0 as part of the answer to Q in the P2P system. Meanwhile it forwards Q_i and ans_i to its neighboring peers for further expansions, which forms "forward and expand" paths.

As will be seen in Section 5.5, both new_i and ans_i can be significantly reduced based on our optimization techniques. That is, the "expand and forward" step does not necessarily incur heavy network traffic.

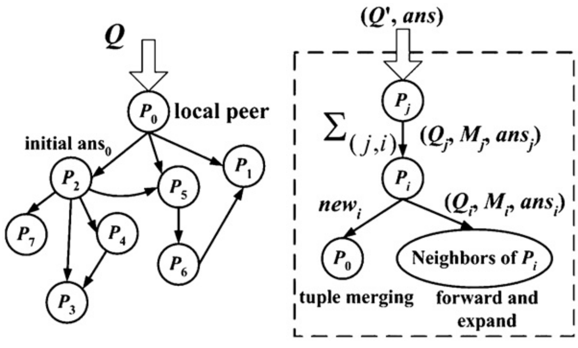


Fig. 2. Polymorphic query evaluation.

Tuple merging. The expansion process proceeds until no more attributes or tuples are sent to P_0. Then the local peer P_0 identifies and merges tuples representing the same real-world object, and handles conflicts based on matching keys. At this stage it instantiates the type variables of L_2 attributes as well as implicit attributes (if α is specified). Here L_2 attributes may be null, and α may be instantiated to an empty list, as shown in Fig. 1(e). The result is returned as the answer to query Q.

Remark. The complete answer to Q in the P2P system is the inflational fixpoint of its expansions, which is guaranteed to be reached when the system is relatively "static" (see *e.g.*, [25] for discussions of fixpoint).

Like all other P2P query models in use, one may adopt "time to live (TTL)" (*e.g.*, [32]): the merging step starts when TTL expires. That is, we can use TTL to compute approximate query answers and strike a balance between the complete answer set and the overhead.

Example 5.1. Recall SPC* query Q_0 given in Example 1.1, the P2P system shown in Fig. 1, the CFKs of Example 4.2, and the matching keys of Example 3.2. To give an overview of the evaluation strategy, we show how the answers to Q_0 in the system are generated in various stages. We shall present detailed algorithms and examples in the rest of the section.

When Q_0 is posed on the local peer P_0, the initial answer consists of s_0, which is extracted from t_2 of relation review:

	album	artist	rating
s_0:	Greatest Hits	Denver, J	4

The initial answer is forwarded to peer P_2 and expanded there:

	album	artist	price	label	rating
s_1:	Greatest Hits	Denver, J	8.36	BMG	high
s_2:	Take Me Home	Denver, J	5.97	Windstar	high

Here s_1 is horizontally expanded by including attributes price and label extracted from t_5 of relation sale, and s_2 is added by vertical expansion with tuple t_4 of sale. The answer set is then forwarded to peer P_3 and expanded there as follows:

	album	artist	price	label	rating	release
s_1:	Greatest Hits	Denver, J	8.36	BMG	high	null
s_2:	Take Me Home	Denver, J	5.97	Windstar	high	03/07/2006

Here s_2 is horizontally expanded by adding attribute release of t_8. Observe that s_1 is not expanded at P_3 since it does not find a matching tuple in relation CD.

Suppose that peer P_4 has a tuple s_3 = (album = "The Greatest Hits", price = 9.99, label = "BMG", release = 01/07/2002) (see Example 3.2). Then s_3 is added to the answer set via vertical expansion at P_4.

Taken together, the answer set to Q_0 becomes

	album	artist	price	label	rating	release
s_1:	Greatest Hits	Denver, J	8.36	BMG	high	null
s_2:	Take Me Home	Denver, J	5.97	Windstar	high	03/07/2006
s_3:	The Greatest Hits	Denver, J	9.99	BMG	null	01/07/2002

Finally, the tuples are merged by using matching keys at the local peer:

	album	price	label	release
s_1:	{Greatest Hits, The Greatest Hits}	{8.36, 9.99}	BMG	01/07/2002
s_2:	Take Me Home	5.97	Windstar	03/07/2006

This is final answer set to Q_0 in the P2P system. □

In the rest of the section we provide the details of initial answer generation, horizontal and vertical expansions, as well as optimization techniques for reducing communication cost. We defer the discussion of tuple merging to Section 7.

5.2. Generating initial answer

The local peer P_0 generates an initial answer ans_0 to query Q by extracting data from its local database D_0. As shown in Fig. 2, the set ans_0 of tuples is forwarded to and expanded at other peers in the P2P system.

Procedure Normalize

Input: An SPC* query $Q = \Pi_{L_1;L_2;\alpha}(\sigma_F(R_1 \times \ldots \times R_l))$.
Output: A set ans_0 of tuples, and a renaming table M_0.

$M_0 := \emptyset;\quad L := L_1;$
for each relation R in $R_1, \ldots, R_l$ with primary key Z **do**
  $M_0 := M_0 \cup \{(R, Z) \mapsto (R, Z)\};$
  $L := L \cup \mathsf{attr}(R);$
$Q' := \pi_L(\sigma_F(R_1 \times \ldots \times R_l));$
$ans_0 := Q'(D_0);$
return $(ans_0, M_0);$

Fig. 3. Algorithm Normalize.

The SPC* query Q may be defined with attributes not in D_0, and thus cannot be directly executed against D_0. Hence we rewrite Q to a normal SPC query Q' defined on D_0, and let $ans_0 = Q'(D_0)$. Query Q' returns tuples with local attributes L_1 and moreover, the set attr(R) of all attributes in each relation R that appear in Q. As will be seen shortly, we need the additional attributes to decide whether a tuple matches X_p patterns of CFKs, for horizontal expansion.

The set ans_0 is generated by Algorithm Normalize, shown in Fig. 3. In addition to ans_0, Normalize also creates an initial *renaming* table M_0. We generate a renaming table M_i at each peer P_i visited, which keeps track of the keys of relations at the local peer. As will be seen in Section 7, the keys help us merge tuples. Table M_i consists of entries of the form $(R_1(X) \mapsto R(Z))$, where Z is the primary key of a relation R at the local peer P_0, and X is the primary key of R_1 at P_i. Normalize produces the initial table M_0, which maps the primary key Z of each relation R to itself.

After ans_0 and M_0 are generated, P_0 forwards them to its neighboring peers, along with the SPC* query Q.

5.3. Horizontal expansion

Using CFKs $\Sigma_{(j,i)}$ from P_j to P_i, one can extend tuples in ans_j by including relevant attributes found at P_i. Indeed, if a tuple t at P_j identifies a tuple t' at P_i via a CFK in $\Sigma_{(j,i)}$, then the attributes of t' are also properties of t. Hence we can extend t by adding those attributes of t' not found in t.

Example 5.2. Consider tuple t_2 of Fig. 1(a) at peer P_0 and CFK φ_1 of Example 4.2 from P_0 to P_2. Note that t_2 matches the X_p pattern of φ_1, *i.e.*, t_2[review(rating)] = 4, That is, t_2 references a sale tuple at P_2. Indeed, t_5 of Fig. 1(c) is the tuple: t_2[review(album,artist)] = t_5[sale(album,artist)]. Thus we can expand t_2 by adding sale attributes price, label and rating, carrying the corresponding values of t_5. □

This motivates us to develop an algorithm for horizontal expansion, referred to as HExpansion and shown in Fig. 4. The algorithm takes as input ans_j, $\Sigma_{(j,i)}$ and a renaming table M_j forwarded from P_j. It returns as output a set $\mathcal{Q}_{(i,h)}$ of queries for computing ans_i, and a revised renaming table M_i at P_i.

Procedure HExpansion

Input: An answer set ans_j, a set $\Sigma_{(j,i)}$ of CFKs, and a renaming table M_j.
Output: A set $\mathcal{Q}_{(i,h)}$ of queries, and a renaming table M_i.

$\mathcal{Q}_{(i,h)} := \emptyset;\quad M_i := \emptyset;$
for each CFK $\varphi = (R_1[X] \subseteq R_2[Y],\ t_p[X_p, Y_p]) \in \Sigma_{(j,i)}$ **do**
  if $(R_1(X) \mapsto R(Z)) \in M_j$ **then**
    $Q_\varphi :=$ "$(\sigma_{X_p = t_p[X_p]} ans_j) \bowtie^l_{R_1[X]=R_2[Y]} R_2$";
    $\mathcal{Q}_{(i,h)} := \mathcal{Q}_h \uplus Q_\varphi;$ /* outer union */
    $M_i := M_i \cup \{R_2(Y) \mapsto R(Z)\};$
return $(\mathcal{Q}_{(i,h)}, M_i);$

Fig. 4. Algorithm HExpansion.

Queries. For each $\varphi = (R_1[X] \subseteq R_2[Y],\ t_p[X_p,Y_p])$ in $\Sigma_{(j,i)}$, a query Q_φ is generated (line 4 of Fig. 4):

$$Q_\varphi = (\sigma_{X_p = t_p[X_p]} ans_j) \bowtie^{l}_{R_1[X] = R_2[Y]} R_2,$$

where $\bowtie^{l}_{C}$ denotes left outer join with condition C.

Query Q_φ first selects those tuples t in ans_j such that $t[X_p] = t_p[X_p]$, and then identifies R_2 tuple t' in D_i such that $t[X] = t'[Y]$. It expands t by adding $t[B] = t'[B]$ for all attributes B that are not yet in t. Observe that such t' is *unique* if it exists, since Y is the primary key of R_2. As mentioned earlier, t carries additional attributes found at peer P_j in order to determine whether it matches the X_p pattern of φ.

Example 5.3. For the CFK φ_1 given in Example 4.2, Algorithm HExpansion generates query Q_{φ_1} as follows:

select	album, artist, price, label, rating
from	*ans*$_0$ *t* LEFT OUTER JOIN sale *s* on
	t[rating] = 4 **and** *t*.album=*s*.album **and** *t*.artist=*s*.artist

Similarly for φ_2 of Example 4.2, Q_{φ_2} is generated. □

Answer sets. Define $Q_{(i,\ h)}$ to be the outer union of all the queries in $\mathcal{Q}_{(i,h)}$, *i.e.*, $Q_{(i,h)} = \uplus_{\varphi \in \Sigma_{(j,i)}} Q_\varphi$. When executed on database D_i at P_i, $Q_{(i,\ h)}$ produces a set $Q_{(i,\ h)}(D_i)$. Using table M_j, we rename attributes of the tuples in $Q_{(i,\ h)}(D_i)$ to generate two sets of tuples: new_i to be sent back to the local peer P_0, and ans_i to be forwarded to P_i's neighbors.

The set new_i includes those tuples in $Q_{(i,\ h)}(D_i)$ with newly added non-null attributes. Further, we restore the names of the local attributes in L_1 by applying M_i to new_i, in order to facilitate tuple merging.

To generate ans_i, we need to rename the attributes of the tuples in $Q_{(i,\ h)}(D_i)$. For each tuple t in $Q_{(i,\ h)}(D_i)$, we rename its attributes by substituting $R_2[Y]$ for $R_1[X]$ if t is generated by $Q_\varphi(D_i)$, with the CFK $\varphi = (R_1[X] \subseteq R_2[Y],\ t_p[X_p,Y_p])$. The set ans_i includes the renamed tuples. We also create renaming table M_i at peer P_i (line 6 of Fig. 4).

5.4. Vertical expansion

Suppose that Q_j is a rewriting of Q on D_j. Based on $\Sigma_{(j,i)}$, we can further rewrite Q_j into an SPC* query Q_i that can be normalized as an SPC query defined on the database D_i at peer P_i. When the SPC query is evaluated on D_i, it may find new tuples missing from the local peer P_0.

Example 5.4. Recall query Q_0 of Example 1.1, posed on peer P_0 of Fig. 1(b). Using CFKs φ_1 and φ_2 of Example 4.2 from P_0 to P_2, one can rewrite Q_0 into SPC* query Q_2:

select	album; price, label; release
from	sale
where	artist="Denver, J" **and** rating="high"

Query Q_2 can be rewritten into SPC query $Q_2{}'$ that is defined on the sale relation, using a variation of Algorithm Normalize of Fig. 3. When $Q_2{}'$ is evaluated on the sale data of Fig. 1(c) at P_2, it returns t_4, a tuple not found by Q_0 at P_0. □

Indeed, CFKs specify contextual schema matching of [30], which is an extension of conventional schema matching. Below we outline an algorithm for query rewriting based on CFKs, extending the method of [30].

The algorithm, denoted as VExpansion, is given in Fig. 5. Suppose that $Q_j = \Pi_L(Q_c)$, where $Q_c = \sigma_F(E_c)$ and $E_c = R_1 \times \cdots \times R_l$. We ignore MK here since the matching keys are only needed for tuple merging, the final step to be done at the local peer. The rewriting consists of two steps.

(1) *Relation atoms*. For each relation atom R in E_c and each CFK $\phi = (R[X] \subseteq R'[Y],\ t_p[X_p,Y_p])$ from R to R' in $\Sigma_{(j,i)}$, we generate a query $q_\phi = \sigma_{F_\phi} R'$, where F_ϕ involves only equality atoms defined in terms of attributes in R, replaced with their counterparts in R' (line 3 of Fig. 5).

More specifically, for each $A =$ 'a' in F such that A is an attribute of R, if $A \in X$ and A corresponds to $B \in Y$ via ϕ, then we substitute B for A. If $A \notin X$ but $t_p[X_p]$ entails $A =$ 'a', then we replace $A =$ 'a' with $Y_p = t_p[Y_p]$. Query q_ϕ is well defined if σ_{F_ϕ} does not contain any attributes of R after the substitutions. Similarly $A = B$ is rewritten if both A and B are R attributes.

Example 5.5. Query Q_2 of Example 5.4 is q_{φ_1}. In particular, rating="4" is replaced with rating="high" since the X_p pattern of φ_1 entails rating="4", and its Y_p pattern is rating="high". In contrast, q_{φ_2} is not well defined, since the X_p pattern of φ_2 does not entail rating="4" and the review attribute rating cannot be removed from Q_{φ_2}. □

Procedure VExpansion

Input: Query $Q_j = \Pi_L(\sigma_F(R_1 \times \ldots \times R_l))$, and a set $\Sigma_{(j,i)}$ of CFKs.
Output: A rewriting Q_i of Q_j defined on D_i.

1. **for** each R in $(R_1, \ldots, R_l)$ **do**
2. $\quad F_R :=$ true;
3. $\quad$ **for** each CFK $\phi = (R[X] \subseteq R'[Y],\ t_p[X_p, Y_p]) \in \Sigma_{(j,i)}$ **do**
4. $\qquad$ **if** F_ϕ is defined **then** $F_R :=$ "$F_R \vee F_\phi$";
5. $\quad Q_R :=$ "$\sigma_{F_R} R'$";
6. $Q_i :=$ "$\Pi_L(\rho(\sigma_{F_i}(Q_{R_1} \times \ldots \times Q_{R_l})))$";
7. **if** Q_i is well-defined **then return** Q_i;
8. **else return** "Undefined";

Fig. 5. Algorithm VExpansion.

Recall that for each relation R in S_j, there exists at most one relation R' in S_i such that $\Sigma_{(j,i)}$ contains CFKs from R to R'. Let Σ_R denote the set of CFKs from R to R' in $\Sigma_{(j,i)}$. Define query $Q_R = \sigma_{F_R} R'$, where $F_R = \vee_{\phi \in \Sigma_R} F_\phi$ (line 5 of Fig. 5) which is equivalent to the union of well-defined q_φ's.

(2) *Query* Q_i. We write Q_i as $\Pi_L(\rho(\sigma_{F_i}(Q_{R_1} \times \cdots \times Q_{R_l})))$, where F_i consists of equality of the form $R.A = R'.B$ for distinct R and R', renamed with attributes in D_i. Attributes corresponding to the primary keys of the local peer are renamed by ρ (derived from renaming table M_i), along the same lines as described above. Query Q_i is well defined if so is every Q_{R_s}, and if F_i does not contain attributes in D_j.

Example 5.6. Given Q_0 and φ_1,φ_2 described in Example 5.4, Algorithm VExpansion returns the query Q_2 given in Example 5.4.

In contrast, given Q_2 and CFKs φ_3,φ_4 of Example 4.2 from P_2 to P_3, VExpansion does not return any well-defined query. Indeed, Q_2 cannot be rewritten to a query that is defined on the CD database at peer P_3, since the attribute rating does not find a counterpart in CD, and hence, equality atom rating = "4" in the where clause of Q_2 cannot be translated. □

Observe the following. (a) There is a simple procedure to check whether Q_i is well defined, in quadratic time in the sizes of the query Q_i and the schema S_i (details omitted). (b) Query Q_i can be readily converted to an SPC* query of the form given in Section 3, in linear-time in the size of Q_i. Indeed, for each $i \in [1,l]$, suppose that R_i in S_j is mapped to R_i' in S_i via the CFKs. Then Q_i can be rewritten as $\Pi_L(\rho(\sigma_{F_i'}(R_1' \times \cdots \times R_l')))$, where F_i' is the conjunction of F_i and F_{R_i} for all $i \in [1,l]$. We refer to this SPC* query also as Q_i.

Answer sets. When Q_i is well-defined, it can be rewritten to an SPC query Q_i' defined on D_i, along the same lines as Algorithm Normalize. The tuples returned by $Q_i'(D_i)$ are added to ans_i and new_i. As shown in Fig. 2, peer P_i sends new_i back to the local peer P_0; it forwards the SPC* query Q_i, table M_i and the answer set ans_i to its neighbors.

5.5. Optimization

To simplify the discussion we have so far included entire tuples in ans_i and new_i. This is often unnecessary. Below we present optimization methods to reduce the communication cost by removing redundancies from new_i and ans_i.

(1) *Reducing* new_i. Whenever a new tuple t is found at P_i, we generate a unique id(t) (by associating the id of P_i with it), which is sent to the local peer P_0 and neighbors of P_i. When new attributes are found for t later at some peer P_r, we do not include the entire tuple in new_i; instead, it suffices to send only id(t) and the new attributes to P_0.

(2) *Reducing* ans_i. This set is needed for horizontal expansion at neighboring peers P_r, via queries $\mathcal{Q}_{(i,r)}$. As will be seen shortly, $\mathcal{Q}_{(i,r)}$ can be generated at peer P_i. Recall from Fig. 4 that each query in $\mathcal{Q}_{(i,r)}$ is of the form $(\sigma_{X_p = t_p[X_p]} ans_i) \bowtie^l_{R_1[X] = R_2[Y]} R_2$. The condition $X_p = t_p[X_p]$ can be checked earlier at P_i. Hence, we only need to send to P_r a subset T_ϕ of ans_i, consisting of those tuples of ans_i that satisfy this condition, *i.e.*, those tuples of ans_i that can be possibly expanded at P_r instead of ans_i. Better still, for each t of these tuples, we only send id(t) and attributes $t[X]$, rather than the entire tuple. Accordingly the query above can be simplified to $T_\phi \bowtie^l_{R_1[X] = R_2[Y]} R_2$.

6. A top-K algorithm for evaluating polymorphic queries

The conceptual evaluation strategy given in Section 5 is based on search by flooding: each peer P_i forwards its answer set ans_i to all of its neighboring peers. When ans_i is large, it may incur high communication cost. In practice, however, one often wants only top K tuples in the answer [17].

In light of these, we next develop a top-K algorithm for evaluating polymorphic queries. For predefined numbers K and m, and given an SPC* query Q, the algorithm evaluates Q in a P2P system $\mathcal{P}$ and returns K high-quality tuples as the answer to Q. Instead of search by flooding, each peer P_i sends at most K tuples to at most m neighboring peers, selected based on a quality model. As will be verified by our experimental results, this algorithm significantly reduces the communication cost and is still able to find quality answers.

Below we present the quality model, the strategy for selecting peers and tuples, and the top-K algorithm.

6.1. A quality model for search

Consider a peer P_i at which a set ans_i is already computed. Let $\mathcal{P}_i$ denote the set of neighboring peers of P_i. We want to (a) select a set $\mathcal{P}_i^s$ of at most m peers from $\mathcal{P}_i$, and (b) for each peer $P_r \in \mathcal{P}_i^s$, choose a set $ans_{(i,r)}$ of at most K tuples from ans_i to forward to P_r, such that these peers maximally expand the chosen tuples horizontally and vertically.

To determine $\mathcal{P}_i^s$ and $ans_{(i,\ r)}$, we introduce a quality model, based on certain statistics of neighboring peers.

Statistics. Consider the P2P system $\mathcal{P}$ described in Section 5. For each neighbor P_r of P_i, we assume that the following information about P_r is stored at P_i: (a) the schema S_r of the database D_r at P_r, (b) the set $\Sigma_{(i,r)}$ of CFKs from P_i to P_r, and (c) statistics about D_r: for each attribute B, the cardinality $|\mathsf{adom}(B)|$ of its active domain in relation R_B where B appears, and the cardinality $|R_B|$ of R_B; we estimate the selectivity $B\%$ of B by $|\mathsf{adom}(B)|/|R_B|$.

Given these, at peer P_i we derive query Q_r for vertical expansions at peer P_r, by algorithm VExpansion of Fig. 5. Let the SPC* query Q_i be $\Pi_L(Q_c)$, where $L = (L_1; L_2; \alpha)$.

Quality model. We denote by score(r) the amount of new information (attributes and tuples) that P_r may add to ans_i:

$$\mathsf{score}(r) = \mathsf{score}(r,h) + \mathsf{score}(r,\nu),$$

where (a) score(r,h) assesses explicit attributes in L_2 and implicit attributes for α (if specified) added by horizontal expansion queries $\mathcal{Q}_{(r,h)}$, associated with weights w_e and w_α, respectively; and (b) score(r,ν) estimates new tuples found by vertical expansion query Q_r, with weight w_ν.

(a) We calculate score(r,h) using ans_i and $\Sigma_{(i,r)}$. For each tuple $t \in ans_i$ and each CFK $\varphi = (R_1[X] \subseteq R_2[Y],\ t_p[X_p,Y_p])$ in $\Sigma_{(i,r)}$, we define score$(t,\varphi) = w_e * n_e + w_\alpha * n_\alpha$ if $t[X_p] = t_p[X_p]$, and let score(t,φ) be 0 otherwise. Here n_e is the number of R_2 attributes in L_2 of Q_i, and n_α is the number of R_2 attributes in neither L_1 nor L_2. Since Y is a key of R_2, if $t[X_p] = t_p[X_p]$, there exists at most one R_2 tuple t' referenced by t.

We define score$(t) = \text{Sum}_{\varphi \in \Sigma_{(i,r)}}$score$(t,\varphi)$, the sum of score$(t,\varphi)$ when φ ranges over all CFKs in $\Sigma_{(i,r)}$.

We pick K tuples t from ans_i with the highest nonzero score(t), and let $ans_{(i,r)}$ be the set of these tuples. We define

$$\text{score}(r,h) = \text{Sum}_{t \in ans_{(i,r)}}\text{score}(t).$$

(b) We compute score(r,v) based on vertical expansion query Q_r and the statistics about D_r. Recall from Fig. 5 that $Q_r = \Pi_L(\rho(\sigma_{F_r}(Q_{R_1} \times \cdots \times Q_{R_l})))$, where each Q_{R_s} is an SPC query $\sigma_{F_R}(R_s')$, derived from CFKs in $\Sigma_{(i,r)}$.

We define score(Q_{R_s}) and score(r,v) as follows:

$$\text{score}(Q_{R_s}) = (w_e * n_e + w_\alpha * n_\alpha) * |R_s'| * \text{Product}_{B \in F_{R_S}} B\%,$$

$$\text{score}(r,v) = w_v * \text{Product}_{C \in F_r} C\% * \text{Product}_{s \in [1,l]}\text{score}(Q_{R_s}).$$

Here n_e and n_α are the numbers of new attributes in R_s' as described above, B ranges over attributes in condition F_{R_S}, and $\text{Product}_{B \in F_{R_S}} B\%$ estimates the probability that F_{R_S} is satisfied by the multiplication of the selectivity of the attributes in F_{R_S}. Intuitively, score(r,v) estimates the number of tuples returned by Q_r, assessed by attributes added.

The larger score(r) is, the more new information P_r may contribute and thus the higher its ranking is.

Example 6.1. Referring to Fig. 1(b), let us consider peer selection at P_2. As shown in Examples 5.2 and 5.4, the answer set at P_2 consists of s_1 (a combination of t_2 and t_5) and s_2 (*i.e.*, t_4). Assume that P_3 and P_7 allow horizontal expansion only, vertical only at P_5, and horizontal and vertical expansions at P_4. Let $w_e = 0.7$, $w_\alpha = 0.2$. and $w_v = 0.1$.

By checking the CFKs, we get (s_2, 1, 1, P_3), indicating that P_3 can expand s_2 with n_e=1 (attribute *release*) and $n_\alpha = 1$(*rank*). Similarly for (s_1, 1, 0, P_4), (s_1, 1, 0, P_7), (s_1, 0, 0, P_3), (s_2, 0, 0, P_4), and (s_2, 0, 0, P_7). Then at P_3, score$(s_2) = (0.7*1+0.2*1) = 0.9$ and score$(s_1) = 0$. Similarly we get scores for s_1 and s_2 at P_4 and P_7. Then for horizontal expansion, score$(P_3,h) =$ 0.9, score$(P_4,h) = 0.7$, and score$(P_7,h) = 0.7$. Peer P_2 next calculates the scores for vertical expansion. By checking the statistics of the data at its neighbors, P_2 gets (P_4, 100, 1, 1, 0.01, 0.2), indicating that P_4 has a relation of 100 tuples with n_e=1, $n_\alpha = 1$, 1% of the tuples satisfying artist="Denver, J", and 20% with a rate of "high". Similarly we get (P_5, 200, 0, 2, 0.02, 0.3). The scores are score$(P_3,v) = 0$, score$(P_4,v) = 0.1*100*(0.7*1+0.2*1)*1\%*20\% = 0.018$, score$(P_5,v) = 0.048$, and score$(P_7,v) = 0$.

Taking these together, we have that score$(P_3) =$ score$(P_3,h)+$score$(P_3,v) = 0.9$, score$(P_4) = 0.718$, score$(P_5) =$ 0.048 and score$(P_7) = 0.7$. □

To simplify the discussion we assume minimal statistics about neighboring peers. The quality model and algorithms can be readily improved if P_i collects statistics about peers that can be reached within h hops, for a constant $h > 1$.

Peer and tuple selection. Based on the quality model, we develop an algorithm for selecting a set $\mathcal{P}_i^s$ of m peers and for each $P_r \in \mathcal{P}_i^s$, a set $ans_{(i,r)}$ of K tuples. The algorithm, denoted by SelectPeers, is shown in Fig. 6. For each

Procedure SelectPeers

Input: $K, m, ans_i, \mathcal{P}_i$ and for each neighbor P_r, $\Sigma_{(i,r)}$, Q_r and $\mathcal{Q}_{(r,h)}$.
Output: m peers $\mathcal{P}_i^s$ and for each $P_r \in \mathcal{P}_i^s$, K tuples $ans_{(i,r)}$.

```
1.  for each peer P_r ∈ 𝒫_i do
2.      for each t ∈ ans_i do      /* for horizontal expansion */
3.          for each φ ∈ Σ_(i,r) do
4.              compute score(t, φ);
5.          score(t) := Sum_{φ∈Σ_(i,r)} score(t, φ);
6.      ans_(i,r) := the set of K tuples t in ans_i with the highest
        nonzero score(t);
7.      score(r, h) := Sum_{t∈ans_(i,r)} score(t);
    /* for vertical expansion */
8.      for each Q_{R_s} in Q_r do
        /* Q_r = Π_L(ρ(σ_{F_r}(Q_{R_1} × ... × Q_{R_l})) */
9.          score(Q_{R_s}):=(w_e * n_e + w_α * n_α)* |R'_s| * Product_{B∈F_{R_S}} B%;
10.     score(r, v) := w_v * Product_{B∈F_r} B% * Product_{s∈[1,l]} score(Q_{R_s});
11.     score(r) := score(r, h) + score(r, v);
12. 𝒫_i^s := the set of m peers P_r with the highest nonzero score(r);
13. return 𝒫_i^s and the set ans_(i,r) for each P_r ∈ score(r);
```

Fig. 6. Algorithm SelectPeers.

neighbor P_r of P_i, it computes $ans_{(i,r)}$,score(r,h) (lines 2–7), score(r,v) (lines 8–10) and score(r) (line 11) as described above. It then selects m peers with the highest nonzero scores, and builds the set $\mathcal{P}_i^s$ with these peers (line 12). It returns $\mathcal{P}_i^s$ and a set $ans_{(i,r)}$ for each P_r in $\mathcal{P}_i^s$ (line 13).

Example 6.2. When $m=2$ and $K=2$, SelectPeers selects P_3 and P_4 at peer P_2 based on the scores computed in Example 6.1. The sets of tuples to be sent to its neighbors P_3 and P_4 are $\{s_2\}$ and $\{s_1\}$, respectively. □

6.2. A top-K algorithm

We next present the top-K algorithm, which revises the conceptual evaluation strategy by leveraging the quality model and Procedure SelectPeers.

Initial answer. Upon receiving Q and a predefined TTL, the local peer P_0 does the following. (1) It generates ans_0 by using Algorithm Normalize of Fig. 3. (2) For each neighbor P_r, it generates queries $\mathcal{Q}_{(r,h)}$ and Q_r for horizontal and vertical expansions, by HExpansion and VExpansion of Figs. 4 and 5, respectively. (3) By Algorithm SelectPeers, it selects at most m neighbors and forwards at most K tuples to each of these peers. Also forwarded are queries $\mathcal{Q}_{(r,h)}$ and Q_r, and renaming table M_0. It also decreases TTL by 1 and forwards it to the selected neighbors.

In contrast to the conceptual strategy, the queries for expansions at the neighbors of P_0 are generated at P_0. Further, at most K tuples are forwarded to at most m selected peers, instead of search by flooding.

Expand and forward. When peer P_i receives tuples ans_j and queries $\mathcal{Q}_{(i,h)}$ and Q_i from P_j, it does the following.

1. It executes $\mathcal{Q}_{(i,h)}$ and Q_i against its local database D_i, to expand ans_j horizontally and vertically, as described in its counterpart of the conceptual strategy.
2. It generates sets new_i and ans_i of tuples, and sends new_i back to the local peer P_0.
3. If TTL=0, no more expansion is conducted. Otherwise it produces expansion queries for its neighbors, selects at most m peers, forwards the queries and at most K tuples to these neighbors along with renaming table M_i, as described in steps (2) and (3) of the initial answer stage. TTL is decreased by 1 and is also forwarded to its selected neighbors.

As described in Section 5.5, only necessary parts of new_i and ans_i are sent to P_0 and selected neighbors, respectively.

Tuple merging. When TTL expires or when the local peer P_0 receives no more new tuples or attributes for a certain period of time, P_0 merges tuples and handles conflicts as will be described in Section 7. It then selects K tuples as follows. (1) For each tuple t collected by P_0, define

$$\text{ranking}(t) = w_e * n_e + w_\alpha * n_\alpha,$$

where n_e and n_α are the numbers of its explicit (L_2) attributes and implicit (α) attributes with non-null values in the input query Q, respectively, and w_e and w_α are weights described in Section 6.1. (2) Peer P_0 selects K tuples with the highest ranking scores (or all the tuples if there exist less than K tuples), and returns them as the answer to query Q.

Example 6.3. We show how Algorithm TopKPoly evaluates the SPC* query Q_0 of Example 1.1 in the P2P system of Fig. 1(b). Let K=2, m=2 and TTL=2. Upon receiving Q_0, the local peer P_0 finds $ans_0=\{t_2\}$ by Normalize. It then generates queries for horizontal and vertical expansions at its neighbors P_2,P_5 and P_1, including Q_{φ_1} (Example 5.3) and Q_2 (Example 5.4) for expansions at P_2. Assume that P_2 is the only peer selected by SelectPeers. Then P_0 decreases TTL by 1 and sends (Q_{φ_1}, Q_2, M_0, ans_0, TTL=1) to P_2.

When P_2 receives the request from P_0, it evaluates Q_{φ_1} and Q_2 against its local database sale, and gets the set ans_2:

	album	artist	price	label	rating
s_1:	Greatest Hits	Denver, J	8.36	BMG	high
s_2:	Take Me Home	Denver, J	5.97	Windstar	high

where s_1 is found by horizontally expanding t_2 with attributes in t_5 via Q_{φ_1}, and s_2 by vertical expansion via Q_2. The newly added tuples and attributes are sent back to P_0 as new_2.

Peer P_2 then produces expansion queries for P_3, P_4, P_5, P_7. For example, horizontal expansion query Q_{φ_3} at P_3 is

select title, artist, label, release
from ans_2 t LEFT OUTER JOIN CD s on
t[label]= Windstar **and** t. album=s.title **and** t. artist=s.artist

As shown in Example 6.2, Algorithm SelectPeers selects P_3 and P_4 as the top 2 peers. Then P_2 sends the corresponding expansion queries to P_3 and P_4, along with the renaming table M_2. Here M_2={sale(album)↦review (album), sale(artist)↦review(artist)}. It sends tuple s_2 to P_3 and s_1 to P_4 for expansions. It also decreases TTL by 1 and sends TTL=0 to P_3 and P_4.

Given Q_{φ_3} and ans_2, peer P_3 evaluates Q_{φ_3} against its CD relation, and extends tuple s_2 in ans_2 by adding a *release* attribute taken from t_8 (Fig. 1(d)). It sends the newly added attribute back to P_0 as new_3. Similarly, expansion queries are evaluated at P_4. Note that at P_3 and P_4, TTL=0 and thus no further expansion is needed.

The answer set at P_0 consists of

	album	artist	price	label	release
s_1:	Greatest Hits	Denver, J	8.36	BMG	null
s_2:	Take Me Home	Denver, J	5.97	Windstar	03/07/2006
s_3:	The Greatest Hits	Denver, J	9.99	BMG	01/07/2002

where s_3 is found at P_4, by vertical expansion (the *rating* attribute is omitted). As will be seen in Section 7, the tuples are merged to produce the final answer to Q_0 in the P2P system. □

Remark. The choice of TTL, K and m values are application dependent, adapted to strike a balance between the completeness of query answer and the cost for computing the answer. The study of TTL in traditional P2P models is also applicable to polymorphic query processing (see, *e.g.*, [32]). For an unstructured P2P network of size n, where each peer has at most p neighbors, TTL is usually the minimal integer t satisfying that $1+p+p^2+\cdots+p^t \geq n$. In this way, each peer has a chance to be visited before TTL expires. Accordingly, m is an integer between 1 and p, and the value is decided based on individual application domains.

7. Merging tuples and resolving conflicts

A polymorphic query may have attributes specified with type variables, namely, explicit (L_2) attributes and implicit (α) attributes. Moreover, attributes or tuples collected from different peers may refer to the same real-world object but may have *typing conflicts* and *data conflicts*. We now present methods for instantiating type variables, merging tuples representing the same object, and for handling conflicts.

An example. We illustrate our methods using a query

$Q_0' = \Pi_{(L_1;L_2)}(\sigma_F(E_c))$ group_by ϕ,

where $\Pi_{(L_1;L_2)}(\sigma_F(E_c))$ is query Q_0 given in Example 3.1, which is to find the album (L_1), and price, label, release (L_2) of John Denver's albums that received a good rating. Here ϕ is the matching key ((album, $\approx$), (label, $=$)) given in Example 3.2.

Query Q_0' is posed on peer P_0 of the P2P system depicted in Fig. 1(b). As shown in Example 6.3, a set of tuples is found and returned to P_0, denoted by *ans*, including:

	album	artist	price	label	release
s_1:	Greatest Hits	Denver, J	8.36	BMG	null
s_3:	The Greatest Hits	Denver, J	9.99	BMG	01/07/2002

These tuples represent the same real-world object.

Method. Our tuple merging method consists of two steps:

- partition *ans* into groups, such that tuples in the same group represent the same real-world object; and
- develop a single succinct representation for each group, and instantiate type variables and null attributes.

We next present the details of these steps.

Grouping tuples. We partition *ans* such that each tuple s in *ans* is in a group, denoted by eq(s). When two tuples s and s' are identified to represent the same object, we merge eq(s) and eq(s') into the same group. We identify tuples based on primary keys and matching keys, as follows.

(1) Recall from Figs. 3 and 4 that we keep track of the primary key of each relation at the local peer throughout the horizontal expansion process, by propagating renaming tables. These keys are also carried by each tuple in *ans*, *e.g.*, s_1 and s_3 above retain the key (album, artist) of relation review at P_0. The keys allow us to identify tuples that are horizontal expansions of the same tuple. Indeed, when two tuples s and s' in *ans* have the same primary key for each of the base relations, we can merge eq(s) and eq(s').

(2) Primary keys, however, typically do not help when matching tuples resulted from vertical expansion. For example, s_1 and s_3 cannot be identified by primary key since s_1[album]$\neq s_3$[album]. In contrast, we can identify s_1 and s_3 by using matching key ϕ as shown in Example 3.2, and merge eq(s_1) and eq(s_3). Now s_1 and s_3 are in the same group eq(s_1). Putting these together, we use matching keys to identify tuples found by vertical expansion, and primary keys to match tuples resulted from horizontal expansion.

Tuples s and s' in the same group can be merged if for each attribute A, either $s[A]=s'[A]$ or one of them is null. In the latter case $s[A]$ takes the non-null value.

If after the merging process, each group has a single tuple, then there is no data conflict. However, conflicts are commonly found in practice. For instance, after the merging process, eq(s_1) remains $\{s_1,s_3\}$ and cannot be further reduced: s_1 and s_3 differ in their album and price attributes.

Representing groups. Several methods have been studied to resolve data conflicts in data integration. A naive method is to set conflicting attributes to null. A better way is to use resolution functions such as ANY, FIRST, LAST, MIN, MAX, AVG, DISCARD (*e.g.*, [18,33,19]). Given a list Val of values with the same data type, ANY draws a random value from Val, FIRST returns the first one, LAST returns the last one; MIN, MAX and AVG return the minimum, maximum and average values, respectively, when Val consists of numerical values; DISCARD returns null if Val contains more than one value, and it returns the only value in Val otherwise. The user may choose one of these functions.

We adopt another approach, based on OR-sets proposed in [21,22] for managing incomplete information. An OR-set is a disjunction of a set of data values. For instance, eq(s_1) is represented as OR-set:

album	artist	price	label	release
{Greatest Hits, The Greatest Hits}	Denver, J	{8.36, 9.99}	BMG	01/07/2002

indicating an album of J. Denver known as either "Greatest Hits" or "The Greatest Hits", released on 01/07/2002 by BMG, with a price of 8.36 or 9.99.

More specifically, we cope with data conflicts by representing each group as a single OR-set. Compared to other resolution methods, OR-sets provide a succinct representation for all the relevant data, *without loss of information*.

To resolve typing conflicts, for each attribute A in L_2 (or α), we cast the types of the values of the A column of *ans* into a uniform type τ_A by leveraging an automatic type casting mechanism, such that the type variable for A is instantiated with τ_A. When multiple attributes are explicitly required to share the same type variable (see Section 3), such typing constraints are enforced at this stage so that these attributes have the same type. Techniques for type inference in functional programming [13] and relational queries [24] can also be incorporated when resolving typing conflicts.

Preparing final answer. If α is not specified in the query, we need to remove redundant attributes from the groups. For instance, for query Q_0', we remove artist from eq(s_1):

album	price	label	release
{Greatest Hits, The Greatest Hits}	{8.36, 9.99}	BMG	01/07/2002

We sort the groups based on the number of non-null attributes in L_2 (and α if it is specified), as described in Section 6.2. In an OR-set, an attribute is non-null if its value contains a value that is not null. The groups with the highest ranking scores are returned as the answer to the query.

8. Experimental study

In this section we present an experimental study of the following three approaches to evaluating queries in P2P systems: (a) flooding, the conceptual evaluation strategy for SPC* queries presented in Section 5, (b) TopK, the top-K algorithm developed in Section 6, and (c) mapping, the approach based on schema mapping. We focus on the impact of the size of P2P system (the number of peers) and the sizes of databases on the quality of query answers and the communication cost of these approaches. Furthermore, we evaluate the effectiveness of the tuple merging method developed in Section 7.

8.1. Experimental setting

We performed the experiments on a cluster of 32 Linux machines, each with a 2.00 GHz Intel(R) Xeon(R) Dual-Core processor and 8 GB of memory. A commercial DBMS was installed on each of these machines. These machines were connected with a local area network. We implemented all the algorithms (flooding, TopK, mapping) in Java. For each of flooding and TopK, we implemented two versions: one with the optimization described in Section 5.5 by shipping partial answers to neighboring peers, and the other without.

Data and CFKs. We implemented a data generator to produce (logical) peers, schemas, data and CFKs. The input of the generator consists of the following: (a) #peer, the number of peers, (b) #neighbor, the average number of neighbors for each peer, (c) #col, the average arity (number of attributes) of a schema, (d) #size, the average number of tuples in an instance of the schema, and (e) #CFK, the average number of CFKs in $\Sigma_{(j,i)}$ between neighboring peers P_j and P_i.

For each $i \in$ [1, #peer], a relation schema R_i was generated at peer P_i, with #col attributes in average. For each pair of neighboring peers P_j and P_i, a set $\Sigma_{(j,i)}$ of CFKs was produced, with $|\Sigma_{(j,i)}| \leq$ #CFK. Each CFK is of the form

$$(R_j(\mathsf{key}_j) \subseteq R_i(\mathsf{key}_i), t_p[\overline{A}, \overline{B}])$$

where $t_p[\overline{A}] = R_j[\overline{A}] = \overline{r},\ t_p[\overline{B}] = R_i[\overline{B}] = \overline{s}$.

Here key_j (resp. key_i) is the primary key of R_j (resp. R_i), $\overline{A}$ (resp. $\overline{B}$) denotes randomly selected attributes from R_j (resp. R_i), and $\overline{r}$ and $\overline{s}$ are randomly generated constants.

Queries. We generated a number of SPC* queries of the form $\Pi_{(L_1;L_2;\alpha)}(\sigma_F(R_0))$ for testing, where (a) L_1 consists of local attributes of R_0, (b) L_2 is a set of explicit attributes not in R_0, randomly selected from the schemas at other peers, (c) α is to be instantiated with a list of attributes appearing in neither L_1 or L_2, and (d) F consists of equality atoms defined with the attributes in L_1 and constants in their corresponding domains. These queries were converted to normal SPC queries by dropping the L_2 attributes when being evaluated by mapping.

Evaluation. We conducted four sets of experiments. The first three sets evaluated the impact of the following factors on the performance of the three algorithms: #peer ranging from 10 to 100, #size from 5k to 50k tuples, and K from 10 to 100 for TopK. As observed in [12], efficient *query processing* in "PDMS with tens of peers tends to be intractable". In light of this, we opt to evaluate the performance of SPC* queries (rather than keyword search) on unstructured P2P networks with up to 100 nodes, and defer the experimental study on larger P2P systems to future work.

In each of these experiments, we evaluated the quality of query results and the communication cost of each of the three algorithms, measured by the following: (a) #attr, the number of relevant non-null attributes in final answer sets and in top K tuples, merged by matching keys, and (b) #bytes, the number of bytes that were transferred to answer a query.

The last set of experiments evaluated the effectiveness of our tuple merging techniques on identifying tuples in the query answers returned by flooding, TopK and mapping.

When not stated otherwise, we used #peer=30, #neighbor=4, TTL=4, #size=20k, #CFK=10, #col=10, $K=20$, and $m=3$ in our experiments, where m is the number of selected neighbors in TopK. The weights for horizontal expansion and vertical expansion were set as $w_e=0.7$, $w_\alpha=0.2$, and $w_v=0.1$ (see Section 6). Each set of experiments was run 5 times and the average is reported here.

8.2. Experimental results

Below we report our findings from the experiments.

Varying P2P network size. To evaluate the scalability and the quality of query answers of the algorithms, we varied #peer from 10 to 100. We report the number of relevant non-null attributes (#attr) in Figs. 7(a) and (b). As shown in Fig. 7(a), flooding found about 5.51 times more relevant attributes than mapping. We also compared the results of TopK with *the top K tuples* that ranked the highest in the results of flooding and mapping. In this setting, Fig. 7(b) shows that TopK found over 59.47% of the information returned by flooding and 216% more than that of mapping.

We report the communication cost (#bytes) in Fig. 7(c), which shows that TopK had almost constant communication cost, far smaller than those of flooding and mapping. This is because TopK trades the size of answer for efficiency. The results also tell us that both TopK and flooding scale well with #peer. Moreover, our optimization methods (Section 5.5) substantially reduces network traffic (by 92.87% for flooding and 78.71% for TopK), without hampering the quality of query answers. Among other things, with optimization the network traffic of flooding is comparable to that of mapping.

Varying the data size. To evaluate the impact of data size on the performance of the algorithms, we varied $|DB|$ from 5k to 50k at each peer. The results on #attr are shown in Figs. 7(d) and (e), and on #bytes in Fig. 7(f). The results are consistent with those reported above: in average, flooding found 5.13 times more relevant non-null attributes than mapping (Fig. 7(d)); and when top K tuples are concerned, TopK found up to 84.78% of the result of flooding, and outperformed mapping by 2.53 times (Fig. 7(e)).

As shown in Fig. 7(f), the communication cost of TopK was much smaller than those of flooding and mapping, and was far less sensitive to the data size. Moreover, flooding with optimization does not incur substantial overhead compared to mapping; this again verifies the effectiveness of the optimization techniques proposed in Section 5.5. The results also show that flooding and TopK scale well with $|DB|$.

Varying K. To evaluate the impact of K and m on the top-K algorithm, we varied K from 10 to 100, while m was set to 2 or 3. The results of TopK were compared with *all the non-null attributes* found by flooding and mapping, respectively, rather than the top K tuples. As depicted in Fig. 7(g), the larger K and m were, the more relevant attributes were found by TopK, as expected. Better still, TopK outperformed mapping when K was sufficiently large, *e.g.*, when $K \geq 40$ and $m=3$ (resp. $K \geq 60$ and $m=2$). On average, the relevant non-null attributes found by TopK were 12.94% of that of flooding, and were 1.42 times more than that of mapping. As shown in Fig. 7(h), TopK constantly incurred far less network traffic than flooding and mapping, and it scaled well with K.

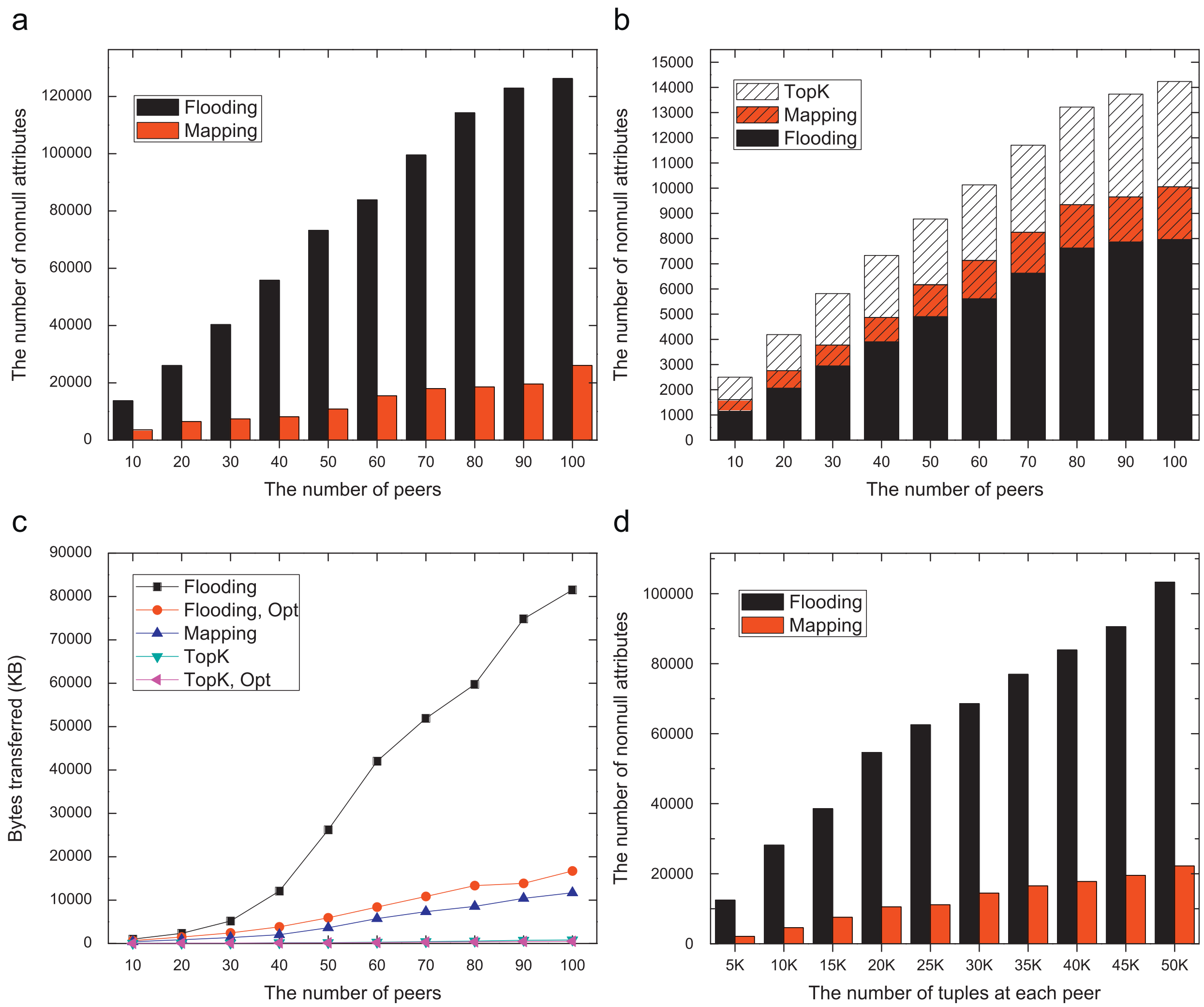


Fig. 7. Experimental results on the quality of query answers and the communication cost. (a) #attr retrieved vs. #peer; (b) #attr (top K) vs. #peer; (c) #bytes shipped vs. #peer; (d) #attr retrieved vs. $|DB|$; (e) #attr (top K) vs. $|DB|$; (f) #bytes shipped vs. $|DB|$; (g) #attr retrieved vs. K; (h) #bytes shipped vs. K.

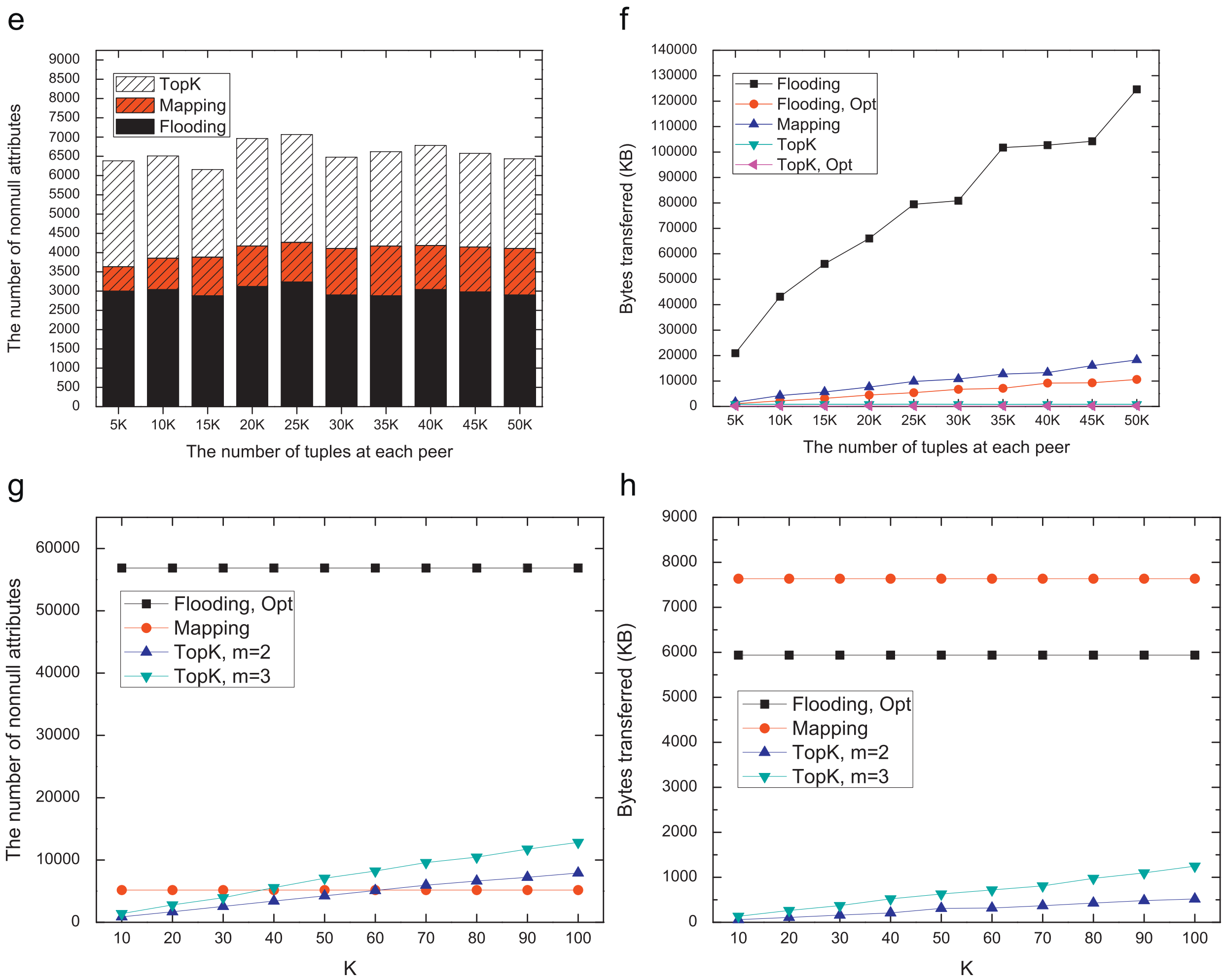


Fig. 7. (*Continued*)

Tuple merging. We also evaluated the effectiveness and scalability of our tuple merging method, varying the number of peers from 10 to 100. Fig. 8 compared the following for flooding, mapping, and TopK, respectively: (a) the number of relevant non-null attributes (#attr) in the answer sets before merging, and (b) the number of relevant non-null attributes in the sets after merging by traditional keys and by matching keys. We can see that the more peers in the network, the more #attr were merged. Fig. 8(a) shows that 71.01% of #attr in flooding were merged by traditional keys. In addition, 17.43% of these attributes were merged by matching keys (totally 83.39% of the initial answers). Fig. 8(b) tells us that on average, 17.55% of #attr in mapping were merged by traditional keys, and further, 13.19% by matching keys (*i.e.*, 19.86% of the initial answers). Fig. 8(c) shows that #attr merged from the results of TopK was the minimum of the three, which was only 0.18% of that of flooding (resp. 6.39% against that of mapping). This is because that TopK took care to remove redundant tuples when processing the data, and thus incurred far less redundancies than its flooding and mapping counterparts.

Summary. From the experimental results we find the following. (a) flooding constantly outperforms the traditional mapping approach in the quality of query answers by over 5 times. In addition, when K and m are reasonably large (*e.g.*, K=40 and m=3), the result quality of TopK is also better than that of mapping: it finds 142% more relevant non-null attributes. These verify that polymorphic queries and their evaluation techniques are able to find more relevant information than the traditional approach. (b) Both flooding and TopK scale well with the size of P2P network and data size. In addition, TopK scales well with K. (c) TopK substantially reduces the communication cost, while it is still able to find about 84.78% of the results of flooding, and 253% more than that of mapping in average, when top K tuples that ranked the highest are concerned. (d) The optimization methods effectively reduce the communication cost, constantly by 92.87% for flooding and 78.71% for TopK. With optimization the communication cost of flooding is comparable to that of mapping. (e) The tuple merging strategy substantially improves the quality of query results, up to 83.39% for flooding and 19.86% for mapping.

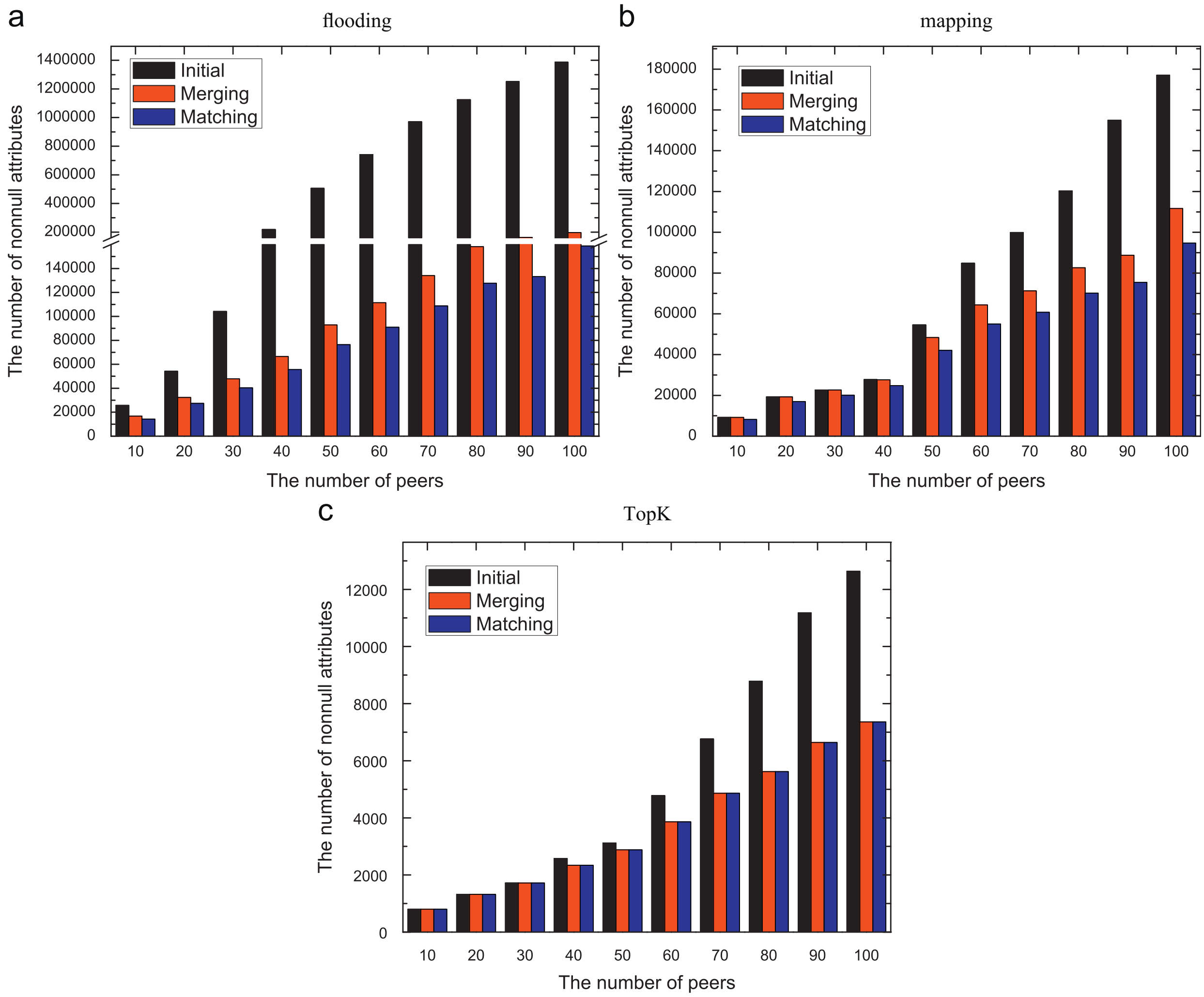


Fig. 8. The effectiveness of merging.

9. Conclusion

We have proposed a query model for P2P systems. Its novelty consists in the following: (a) polymorphic queries (SPC*) to explicitly retrieve attributes even when they are not defined at the local peer; (b) horizontal and vertical expansions, to find not only tuples but also attributes missing from the local peer; (c) CFKs to support horizontal and vertical expansions in a uniform framework; (d) a top-K algorithm for SPC*, based on a quality model for peer and tuple selections; and (e) matching keys for identifying tuples and handling conflicts. As verified by our experimental study, SPC* queries are able to find more relevant information than traditional SPC queries in P2P systems, without incurring high communication cost.

Several issues need further investigation. First, we are currently experimenting with larger datasets and more peer nodes. Second, we aim to extend SPC* to polymorphic relational algebra. Third, we are exploring optimization techniques for polymorphic queries, with performance guarantees on both the efficiency and the quality of query answers. In particular, we plan to leverage semantics indices (*e.g.*, [34]) in order to efficiently locate peers of interest.

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