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SMARTINT: using mined attribute dependencies to integrate fragmented web databases

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Abstract Many web databases can be seen as providing partial and overlapping information about entities in the world. To answer queries effectively, we need to integrate the information about the individual entities that are fragmented over multiple sources. At first blush this is just the inverse of traditional database normalization problem—rather than go from a universal relation to normalized tables, we want to reconstruct the universal relation given the tables (sources). The standard way of reconstructing the entities will involve joining the tables. Unfortunately, because of the autonomous and decentralized way in which the sources are populated, they often do not have Primary Key–Foreign Key relations. While tables may share attributes, naive joins over these shared attributes can result in reconstruction of many spurious entities thus seriously compromising precision. Our system, SMARTINT is aimed at addressing the problem of data integration in such scenarios. Given a query, our system uses the Approximate Functional Dependencies (AFDs) to piece

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together a tree of relevant tables to answer it. The result tuples produced by our system are able to strike a favorable balance between precision and recall.

Keywords Web databases · Loss of PK/FK · Information integration

1 Introduction

With the advent of web, data available online is rapidly increasing, and an increasing portion of that data corresponds to large number of web databases populated by web users. Web databases can be viewed as providing partial but overlapping information about entities in the world. Conceptually, each entity can be seen as being fully described by a universal relation comprising of all its attributes. Individual sources can be seen as exporting parts of this universal relation. This picture looks very similar to the traditional database set-up. The database administrator (who ensures lossless normalization) is replaced by *independent data providers*, and specialized users (who are aware of database querying language) are replaced by *lay users*. These changes have two important implications:

- **Ad hoc normalization by providers**: Primary key-Foreign key (PK-FK) relationships that are crucial for reconstructing the universal relation are often missing from the tables. This is in part because partial information about the entities are independently entered by data providers into different tables, and synthetic keys (such as vehicle ids, model ids, employee ids) may not be uniformly preserved across sources. (In some cases, such as public data sources about people, the tables may even be explicitly forced to avoid keeping such key information.)
- **Imprecise queries by lay users**: Most users accessing these tables are lay users and are often not aware of all the attributes of the universal relation. Thus their queries may be "imprecise" (Nambiar and Kambhampati 2006) in that they may miss requesting some of the relevant attributes about the entities under consideration.

Thus a core part of the source integration on the web can be cast as the problem of reconstructing the universal relation in the absence of primary key–foreign key relations, and in the presence of lay users. Our main aim in this paper is to provide solution to this problem. One reason this problem has not received much attention in the past is that it is often buried under the more immediate problem of attribute name heterogeneity: In addition to the loss of PK-FK information, different tables tend to rename their columns.[1] While many reasonable schema mapping solutions have been developed to handle the schema heterogeneity problem (c.f. Melnik et al. 2002; Doan et al. 2003; Li and Clifton 1995; Larson et al. 1989), we are not aware of any effective solutions for the reconstruction problem. In this paper (as well as in our implemented system) we will simply assume that the attribute name change problem can be handled by adapting one of the existing methods. This allows us to focus on the central problem of reconstruction of universal relation in the absence of primary key–foreign key relationships.

[1] In other words, web data sources can be seen as resulting from an *ad hoc* normalization followed by the attribute name change.

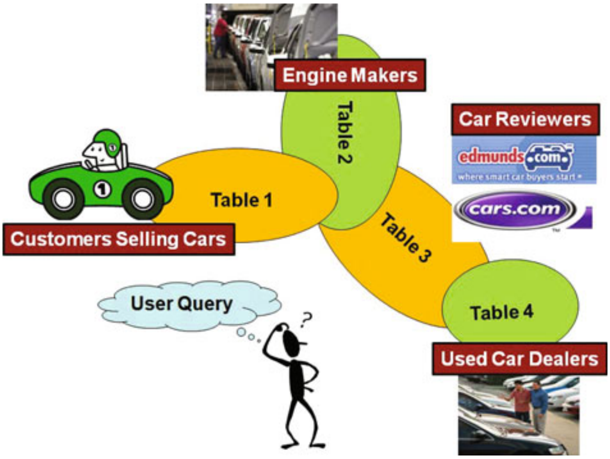


Fig. 1 Overlapping tables in the database

1.1 Motivating scenario

As a motivating scenario, let us consider a set of tables (with different schema) populated in a Vehicle domain (Fig. 1). The universal schema of entity 'Vehicle' can be described as follows: *Vehicle (VIN, vehicle-type, location, year, door-count, model, make, review, airbags, brakes, year, condition, price, color, engine, cylinders, capacity, power, dealer, dealer-address)*

Let us assume that the database has the following tables: *Table* 1 *with Schema S1*—populated by normal web users who sell and buy cars, *Table* 2 *with Schema S2*—populated by crawling reviews of different vehicles from websites, *Table* 3 *with Schema S3*—populated by engine manufacturers/vendors with specific details about vehicle engines and *Table* 4 *with Schema S4*. The following shows the schema for these tables and the corresponding schema mappings among them: *S1—(make, model_name, year, condition, color, mileage, price, location, phone), S2—(model, year, vehicle-type, body-style, door-count, airbags, brakes, review, dealer), S3—(engine, mdl, cylinders, capacity, power) and S4—(dealer, dealer-address, car-models)*.

The following attribute mappings are present among the schema: *(S1: model_name = S2: model = S3: mdl, S2: dealer = S4: dealer)* The italicized attribute *MID (Model ID)* refers to a *synthetic primary key* which would have been present if the users shared understanding about the entity which they are populating. If it is present, entity completion becomes trivial because you can simply use that attribute to join the tables. There can be a variety of reasons why that attribute is not available: (1) In autonomous databases, users populating the data are not aware of all the attributes and may end up missing the 'key' information. (2) Since each table is

Table 1 Schema 1—cars (S_1)

MID	Make	Model_name	Price	Other attrbs
HACC96	Honda	Accord	19,000	...
HACV08	Honda	Civic	12,000	...
TYCRY08	Toyota	Camry	14,500	...
TYCRA09	Toyota	Corolla	14,500	...

Table 2 Schema 2—reviews (S_2)

Model	Review	Vehicle-type	Dealer	Other attrb
Corolla	Excellent	Midsize	Frank	...
Accord	Good	Fullsize	Frank	...
Highlander	Average	SUV	John	...
Camry	Excellent	Fullsize	Steven	...
Civic	Very good	Midsize	Frank	...

autonomously populated, though each table has a key, it might not be a shared attribute. (3) Because of the decentralized way the sources are populated, it is hard for the sources to agree on "synthetic keys" (that sometimes have to be generated during traditional normalization). (4) The primary key may be intentionally masked, since it describes sensitive information about the entity (e.g. social security number).

Consider the following representative queries (that SmartInt is aimed at handling):

Q1:
```
SELECT make, model
WHERE price < $15,000 AND cylinders = '4'.
```
Q2:
```
SELECT make, vehicle-type
WHERE price < $15,000 AND cylinders = '4'.
```
Q3:
```
SELECT *
WHERE price < $15,000 AND cylinders = '4'.
```

The first thing to note is that all these queries are *partial* in that they do not specify the exact tables over which the query is to be run. Furthermore, note that both the query constraints and projected attributes can be are *distributed over multiple tables*. In Q1, the constraint on price can only be evaluated over the first table, while the constraint on the number of cylinders can only be evaluated on Table 3. In Q2, the projected attributes are also distributed across different tables. Finally, Q3 is an imprecise (entity completion) query, where the user essentially wants all the information–spread across different tables–on the entities that satisfy the constrains. Before we introduce our approach, let us examine the limitations of two obvious approaches to answer these types of queries in our scenario:

Answering from a single table The first approach is to answer the query from the single table which conforms to the most number of constraints mentioned in the query and provides maximum number of attributes. In the given query since 'make', 'model' and 'price' map onto Table 1, we can directly query that table by ignoring the constraint on the 'cylinders'. The resulting tuples are shown in Table 5. The second

Table 3 Schema 3—engine (S_3)

MID	Mdl	Engine	Cylinders	Other attrb
HACC96	Accord	K24A4	6	...
TYCRA08	Corolla	F23A1	4	...
TYCRA09	Corolla	155 hp	4	...
TYCRY09	Camry	2AZ-FE I4	6	...
HACV08	Civic	F23A1	4	...
HACV07	Civic	J27B1	4	...

Table 4 Schema 4—dealer info (S_4)

Dealer	Address	Other attrb
Frank	1011 E Lemon St, Scottsdale, AZ	...
Steven	601 Apache Blvd, Glendale, AZ	...
John	900 10th Street, Tucson, AZ	...

tuple related to ‘Camry’ has 6 cylinders and is shown as an answer. Hence ignoring constraints would lead to erroneous tuples in the final result set which do not conform to the query constraints.

Direct (naive) join The second and a seemingly more reasonable approach is joining the tables using whatever shared attribute(s) are available. The result of doing a direct join based on the shared attribute (‘model’) is shown in Table 6. If we look at the results, we can see that even though there is only one ‘Civic’ in Table 1, we have two Civics in the final results. The same happens for ‘Corolla’ as well. The absence of Primary Key–Foreign Key relationship between these two tables has lead to spurious results.

1.2 The SmartInt approach

As we saw, the main challenge we face is handling query constraints as well as projected attributes that are spread across tables, in the absence of primary key–foreign key dependencies. Broadly speaking, our approach is to start with a “base table” on which most of the query constraints can be evaluated. The remaining query constraints, i.e., those that are over attributes not present in the base table, are *translated onto the base table*—i.e., approximated by constraints over the base table attributes. The tuples in the base table that conform to the constraints (both native to the table, and those that are translated onto it) are the base tuples. After this “**constraint translation**” phase, we enter a “**tuple expansion**” phase where the base tuples are expanded by predicting values of any (projected or other) attributes that are not part of the base table. Both the constraint translation and tuple expansion phases are facilitated by inter-attribute correlations called “approximate functional dependencies”, as well as accompanying value associations that we mine (learn) from samples of the database tables.

As an illustration of the idea, suppose the following simple AFDs (to be formally defined in Section 3) are mined from our tables (note that the actual mined AFDs can have multiple attributes on the left hand side): (1) $S_2 : \{model\} \rightarrow vehicle\_type$, (2) $S_2 : \{model\} \rightarrow review$, (3) $S_3 : \{model\} \rightarrow cylinders$. Suppose we start with Table 1 as the base table. Rule 3 provides us a way to translate the constraint on the number of cylinders into a constraint on the model (which is present in the first table). Rules

Table 5 Results of query Q1 just from table T_1

Make	Model	Price
Honda	Civic	12,000
Toyota	Camry	14,500
Toyota	Corolla	14,500

Table 6 Results of query Q3 using direct-join ($T1 \bowtie T3$)

Make	Model	Price	Cylinder	Engine	Other attrbs
Honda	Civic	12,000	4	F23A1	...
Honda	Civic	12,000	4	J27B1	...
Toyota	Corolla	14,500	4	F23A1	...
Toyota	Corolla	14,500	4	155 hp	...

1 & 2 provide information on vehicle type and review for a given model, and hence provide more information in response to the query. They allow us to expand partial information about the car model into more complete information about vehicle type, review and cylinders. The results using attribute dependencies are shown in Table 7 and conform to the constraints and are more informative compared to other approaches.

As shown in Fig. 2, the operation of SmartInt can thus be understood in terms of (1) mining AFDs and value association statistics from different tables and (2) actively using them to propagate constraints and retrieve attributes from other non-joinable tables. Figure 2 shows the SmartInt system architecture. When the user submits a query, the source selector first selects the most relevant 'tree' of tables from the available set of tables. The tree of tables provides information about the base table (onto which constraints will be translated), and additional tables from which additional attributes are predicted. Source selector uses the source statistics mined from the tables to pick the tree of tables. The tuple expander module operates on the tree of tables provided by the source selector and then generates the final result set. Tuple expander first constructs the expanded schema using the AFDs learned by AFDMiner and then populates the values in the schema using source statistics.

Contributions The specific contributions of SmartInt system can be summarized as follows: (1) We have developed a query answering mechanism that utilizes attribute dependencies to recover entities fragmented over tables, even in the absence of primary key–foreign key relations. (2) We have developed a source selection method using novel relevance metrics that exploit the automatically mined AFDs to pick the most appropriate set of tables. (3) We have developed techniques to efficiently mine approximate attribute dependencies. We provide comprehensive experimental results to evaluate the effectiveness of SmartInt as a whole, as well as its AFD-mining sub-module. Our expeirments are done on data from Google Base, and show that SmartInt is able to strike a better balance between precision and recall than can be achieved by relying on single table or employing direct joins.

Organization The rest of the paper is organized as follows. Section 2 discusses related work about current approaches for query answering over web databases. Section 3 discusses some preliminaries. Section 4 proposes a model for source selection and query answering using attribute dependencies. Section 5 provides

Table 7 Results of query Q3 using attribute dependencies

Make	Model	Price	Cylinders	Review	Dealer	Address
Honda	Civic	12,000	4	Very good	Frank	1011 E St
Toyota	Corolla	14,500	4	Excellent	Frank	1011 E St

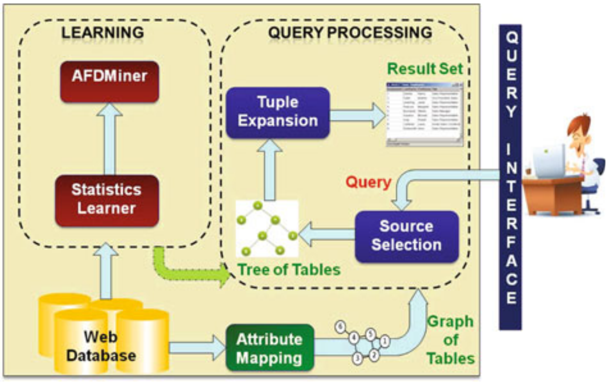


Fig. 2 Architecture of SMARTINT system

details about the methods for learning attribute dependencies. Section 6 presents a comprehensive empirical evaluation of our approach on data from GOOGLE BASE. Section 7 provides conclusion and future work. A prototype of SMARTINT system has been demonstrated at ICDE 2010 (Gummadi et al. 2010).

2 Related work

Data integration The standard approaches investigated in the database community for the problem recovering information split across multiple tables is of course data integration (Lenzerini 2002; Halevy 2001; Kambhampati et al. 2004). The approaches involve defining a global (or mediator) schema that contains all attributes of relevance, and establishing mappings between the global schema and the source schemas. This latter step can be done either by defining global schema relations as views on source relations (called GAV approach), or defining the source relations as views on the global schema (called LAV approach). Once such mappings are provided, queries on the global schema can be reformulated as queries on the source schemas. While this methodology looks like a hand-in-glove solution to our problem, its impracticality lies in the fact that it requires manually or semi-automatically established mappings between global and source schemas. This is infeasible in our context where lay users may not even know the set of available tables, and even if they do, the absence of PK-FK relations makes establishment of sound and complete mappings impossible. In contrast, our approach does not depend on the availability of GAV/LAV mappings.

Entity identification/resolution The Entity Identification problem in heterogeneous databases is matching object instances from different databases that represent same real world entities. Instance Level Functional Dependencies (Lim et al. 1993) are used to derive missing extended key information for joining the tuples. Virtual attributes (DeMichiel 1989) are found to map databases in different databases. However, both these approaches require the tables to have initial key information. Also, it involves manual mappings from the domain experts to an extent. As opposed to this, SmartInt predicts values for attributes that are not present in the table using mined AFDs.

Keyword search on databases The entity completion queries handled in SmartInt are similar in spirit to keyword queries over databases. This latter has received significant attention (Hristidis and Papakonstantinou 2002; Balmin et al. 2004; Bhalotia et al. 2002). The work on Kite system extends keyword search to multiple databases as well (Sayyadian et al. 2007). While Kite doesn't assume that PK-FK relations are pre-declared, it nevertheless assumes that the columns corresponding to PK-FK relations are physically present in the different tables if only under different names. In the context of our running example, Kite would assume that the model id column is present in the tables, but not explicitly declared as a PK-FK relation. Thus Kite focuses on identifying the relevant PK-FK columns using key discovery techniques (c.f. Huhtala et al. 1999). Their techniques do not work in the scenarios we consider where the key columns are simply absent (as we have argued in our motivating scenario).

Handling incomplete databases & imprecise queries Given a query involving multiple attributes, SmartInt starts with a base table containing a subset of them, and for each of the tuples in the base table, aims to predict the remaining query attributes. In this sense it is related to systems such as QPIAD (Wolf et al. 2007). However, unlike QPIAD which uses AFDs learned from a single table to complete null-valued tuples, SmartInt uses AFDs both for translating constraints onto the base table, and for expanding tuples in the base table by predicting query attributes not in the base table. Viewed this way, the critical challenge in SmartInt is the selection of base table, which in turn is based on the confidences of the mined AFDs (see Section 4.1). The constraint translation mechanism used by SmartInt also has relations to constraint relaxation approaches used by the systems aimed at handling imprecise queries (e.g. Nambiar and Kambhampati 2006).

Learning attribute dependencies Though rule mining is popular in the database community, the problem of AFD mining is largely under explored. Earlier attempts were made to define AFDs as an approximation to FDs (Ilyas et al. 2004; Huhtala et al. 1999) with few error tuples failing to satisfy the dependency. In these lines, CORDs (Ilyas et al. 2004) introduced the notion of Soft-FDs. But, the major shortcoming of their approach is, they are restricted to rules of the type $C1 \rightarrow C2$, where C1 and C2 are only singleton sets of attributes. TANE (Huhtala et al. 1999) provides an efficient algorithm to mine FDs and also talks about a variant of the FD-mining algorithm to learn approximate dependencies. But, their approach is restricted to minimal pass rules (Once a dependency of type ($X \rightsquigarrow Y$) is learnt, the search process stops without generating the dependencies of the type ($Z \rightsquigarrow Y$), where $X \subset Z$. Moreover, these techniques are restricted to a single table, but we are interested in learning AFDs from multiple tables and AFDs involving shared attributes. In this paper, we provide a learning technique that treats AFDs as a condensed representation of association rules (and not just approximations to FDs), define appropriate metrics, and develop efficient algorithms to learn all the intra and inter-table dependencies. This unified learning approach has an added advantage of computing all the interesting association rules as well as the AFDs in a single run.

3 Preliminaries

Our system assumes that the user does not have knowledge about different tables in the database and has limited knowledge about attributes he is interested in querying. This is a reasonable assumption, since most web databases do not expose the tables to the users. So we model the query in the following form where the user just needs to specify the attributes and constraints: $\mathcal{Q} =< \bar{A}, \bar{C} >$ where $\bar{A}$ are the projected attributes which are of interest to the user and $\bar{C}$ are the set of constraints (i.e. attribute-label, value pairs)

Attribute dependencies are represented in the form of approximate functional dependencies. A **functional dependency (FD)** is a constraint between two sets of attributes in a relation from a database. Given a relation R, a set of attributes X in R is said to functionally determine another attribute Y, also in R, (written X → Y) if and only if each X value is associated with precisely one Y value. Since the real world data is often noisy and incomplete, we use approximate dependencies to represent the attribute dependencies. An **Approximate Functional Dependency (AFD)** is an approximate determination of the form $X \rightsquigarrow A$ over relation R, which implies that **attribute set X, known as the determining set**, approximately determines **A, called the determined attribute.** An AFD is a functional dependency that holds on all but a small fraction of tuples. For example, an AFD $model \rightsquigarrow body\_style$ indicates that the value of a car model usually (but not always) determines the value of $body\_style$.

Graph of tables The inter-connections between different tables in the database are modeled as a graph. Each attribute match is represented as an undirected edge and any PK-FK relationship is represented as a directed edge pointing towards the table containing the primary key.

4 Query answering

In this section, we describe our query answering approach. We assume that attribute dependencies are provided upfront for the system. We outline our approach in terms of solutions to challenges identified earlier in Section 1:

1) **Information distributed across tables needs to be integrated**: The information needs to be integrated since both answering queries with attributes spanning over multiple tables and providing additional information to the user needs horizontal integration of the tuples across tables. In the absence of PK-FK relationships, performing meaningful joins to integrate data is not feasible (as illustrated in Section 1). Instead we start with a 'base set of tuples' (from a designated base table chosen by the source selector) and successively expand those tuples horizontally by appending attribute values predicted by the attribute dependencies. This expansion is done recursively until the system cannot chain further or it reconstructs the universal relation. We use attribute determinations along with attribute mappings to identify attributes available in other tables, whose values can be predicted using values of the selected attributes.
2) **Constraints need to be translated**: The base table provides a set of tuples, i.e. tuples which conform to the query constraints. Generation of 'base set of tuples' requires taking into account constraints on non-base tables. We use

attribute mappings and attribute determinations for translating constraints onto the base table. Basically, we need to translate the constraint on a non-base table attribute to a base table attribute through attribute determinations. In the example discussed in Section 1, suppose T_1 is designated as a base table and T_3 is a non-base table which has an AFD (model $\rightsquigarrow$ vehicle-type). If the query constrains the attribute vehicle-type to be 'SUV', then this constraint can be evaluated over the base table, if information about the likelihood of a model being an 'SUV' is given. Attribute determinations provide that information.

Now we explain how these solution approaches are embedded into SmartInt framework. Query answering mechanism involves two main stages: Source Selection and Tuple Expansion. We explain these in detail in the next few sections.

4.1 Source selection

In a realistic setting, data is expected to be scattered across a large number of tables, and not all the tables would be equally relevant to the query. Hence, we require a source selection strategy aimed at selecting the top few tables most relevant to the query. Given our model of query answering, where we start with a set of tuples from the base table which are then successively expanded, it makes intuitive sense for tuple expansion to operate over a tree of tables. Therefore source selection aims at returning the most relevant tree of tables over which the Tuple Expander operates. Given a user query, $\mathcal{Q} =< \bar{A}, \bar{C} >$ and a parameter 'k' (the number of relevant tables to be retrieved and examined for tuple expansion process), we define source selection as selecting a tree of tables of maximum size k which has the highest relevance to the query. The source selection mechanism involves the following steps: (1) Generate a set of candidate tables $T_c = \{\mathcal{T} \in T | relevance(\mathcal{T}) \geq threshold\}$.This acts as a pruning stage, where tables with low relevance are removed from further consideration. (2) Not all tables have a shared attribute. We need to pick a connected sub-graph of tables, G_c, with highest relevance. (3) Select the tree with the highest relevance, among all the trees possible in G_c. This step involves generating and comparing the trees in G_c, which can be computationally expensive if G_c is large. We heuristically estimate the best tree with the highest relevance to the query among all the trees. The relevance metrics used are explained below.

We will explain how source selection works in the context of the example described in introduction. In order to answer the query Q, `SELECT make,model WHERE price < $15,000 AND cylinders = '4'`, we can observe that the projected attributes *make*, *model* and constraint *price* < \$15,000 are present in Table 1 and constraint *cylinders* = '4' is present in Table 3. Given this simple scenario, we can select either Table 1 or Table 3 as the base table. If we select Table 3 as the base table, we should translate the constraint *price* < \$15,000 from Table 1 to Table 3 using the AFD, *model* $\rightsquigarrow$ *price*. On the other hand if we designate Table 1 as base table, we would need to translate the constraint *cylinders* = '4' from Table 3 to Table 1 using the AFD, *model* $\rightsquigarrow$ *cylinders*. Intuitively we can observe that the AFD *model* $\rightsquigarrow$ *cylinders* generalizes well for a larger number of tuples than *model* $\rightsquigarrow$ *price*. Source selection tries to select the table which emanates high quality AFDs as the base table and hence yield more precise results.

Here we discuss the different *relevance functions* employed by the source selection stage:

Relevance of a table The relevance of a table $\mathcal{T}$ depends on two factors: (1) the fraction of query-relevant attributes present in the table–we can view this as "horizontal relevance" and (2) the fraction of tuples in the table that are expected to conform to the query—we can view this as "vertical relevance". We evaluate relevance as follows:

$$relevance(\mathcal{T}, q) \approx \frac{|A_{\mathcal{T}} \cap \bar{A}|}{|\bar{A}|} * P_{\mathcal{T}}(\bar{C}) * tupleCount_{\mathcal{T}}$$

where the first factor is measuring the horizontal relevance and the other two estimate the vertical relevance. Specifically, $P_{\mathcal{T}}(\bar{C})$ is the probability that a random tuple from $\mathcal{T}$ conforms to constraints $\bar{C}$, $tupleCount_{\mathcal{T}}$ is the number of tuples in $\mathcal{T}$, and $A_{\mathcal{T}}$ is the set of attributes in $\mathcal{T}$.[2]

Relevance of a tree While selecting the tree of relevant tables, the source selection stage needs to estimate the relevance of tree. The relevance of tree takes into account the confidence of AFDs emanating out of the table. Relevance of a tree T_r rooted at table $\mathcal{T}$ w.r.t query $Q < \bar{A}, \bar{C} >$ can be expressed as: $relevance(T_r, q) = relevance(\mathcal{T}, q) + \sum_{a \in \bar{A} - A_b} pred\_accuracy(a)$ where A_b are the set of attributes present in the base table, and $pred\_accuracy(a)$ gives the accuracy with which the attribute a can be predicted. When the attribute is in the neighboring table it is equal to the confidence of AFD and when its not in the immediate neighbor its calculated the same way as in AFD chaining (Explained in Section 5).

The above relevance functions rely on the conformance probability $P_{\mathcal{T}}(C) = \Pi_i P_{\mathcal{T}}(C_i)$. $P_{\mathcal{T}}(C_i)$ denotes the probability that a random tuple from $\mathcal{T}$ conforms to the constraint C_i (of the form $X = v$), and is estimated as:

- $P_{\mathcal{T}}(C_i) = P_{\mathcal{T}}(X = v), if X \in A_{\mathcal{T}}$, where $A_{\mathcal{T}}$ is the set of attributes in $\mathcal{T}$
- $P_{\mathcal{T}}(C_i) = \sum_i P_{\mathcal{T}}(Y = v_i) * P_{\mathcal{T}'}(X = v | Z = v_i)$, if $\mathcal{T} : Y = \mathcal{T}' : Z$, i.e. $\mathcal{T}$'s neighboring table $\mathcal{T}'$ provides attribute X. (These probabilities are learnt as source statistics.)
- $P_{\mathcal{T}}(C_i) = \epsilon$ (small non-zero probability), otherwise. (We use ϵ as a smoothing factor so the probability is not set to zero just because it couldn't be computed).

In this section we explained the source selection mechanism. We discuss how the tuple expansion mechanism answers the query from the selected sources in the next section.

4.2 Tuple expansion

Source selection module gives a tree of tables which is most relevant to the query. Tuple expansion operates on the tree of tables given by that module. One of the key contributions of our work is returning the result tuples with schema as close to

[2] Presently we give equal weight to all the attributes in the system, this can be generalized to account for attributes with different levels of importance.

Algorithm 1 Source Selection

Require: Query q, Threshold τ, Number of tables k, Set of AFDs $\bar{A}$

$T_c = \{\emptyset\}$
for all table $\mathcal{T}$ in T **do**
  if relevance($\mathcal{T}$, q) $\geq \tau$ **then**
    add $\mathcal{T}$ to T_c
G_c := Set of connected graphs over T_c up to size k
$Trees = \{\emptyset\}$
for all $g \in G_c$ **do**
  $Trees_g$ = Set of trees from graph g
  add $Trees_g$ to $Trees$
$tree_{sel} = \arg\max_{tree \in Trees} relevance(tree, q)$
return $tree_{sel}$

the universal relation as possible. We need to first construct the schema for the final result set and then populate tuples that correspond to that particular schema from other tables. These steps are described in detail in the sections that follow.

4.2.1 Constructing the schema

One important aspect of tuple expansion is that it is a hierarchical expansion. The schema grows in the form of a tree because attributes retrieved from other tables are relevant only to the determining attribute(s) (refer to the definition of AFD in Section 3). This module returns a hierarchical list of attributes, *AttrbTree*, rather than a flat list. This is more clearly illustrated by the attribute tree generated for query discussed in Section 1 shown in Fig. 3. The base table (T_1) contains attributes *Make, Model, Price*. Tables T_1, T_2 and T_3 share the attribute *Model*. In table T_2, we have the AFDs *Model* $\rightsquigarrow$ *Cylinders* and *Model* $\rightsquigarrow$ *Engine*. These two determined attributes are added to the base answer set, but these are only relevant to the attribute 'model', so they form a branch under the attribute 'model'. Similarly, *review, dealer* and *vehicle type* form another branch under 'Model'. In the next level, T_3 and T_4 share 'dealer-name' attribute. 'Dealer-Name' is a key in T_4, therefore all the attributes in

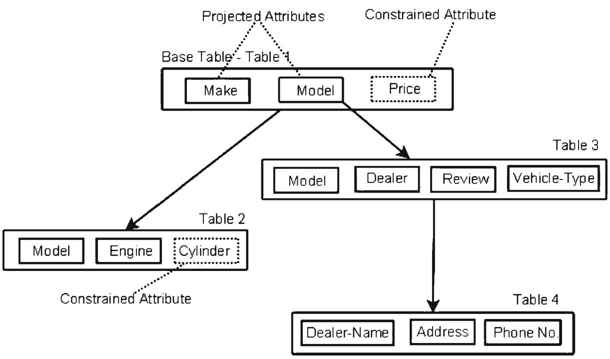


Fig. 3 Expanded attribute tree for the query

T_4 ('dealer-address', 'phone-number' etc) are attached to the *AttrbTree*. The final attribute tree is shown in the Fig. 3.

4.2.2 Populating the tuples

The root of the selected tree of tables given by the source selection is designated as the *base table*. Once the attribute hierarchy is constructed, the system generates a 'base set' of tuples from the base table which form the 'seed' answers. We refer to this base set as the *most likely tuples* in the base table which conform to the constraints mentioned in the query. We call them 'most likely' tuples because when constraints are specified on one of the children of the base table, we propagate constraints from child to base table. But since we have approximate dependencies between attributes, the translated constraints do not always hold on the base set. To clearly illustrate this, let us revisit the example of *Vehicle* domain from Section 1. We assume that Table 1 has been designated as the base table. The constraint *price* < \$15,000 is local for the base table and hence each tuple can be readily evaluated for conformance. The constraint *cylinders* = *'4'*, on the other hand, is over Table 3 and needs to be translated on to the base table. Notice that these two tables share the attribute 'model' and this attribute can approximately determine *cylinder* in Table 3 ($model \rightsquigarrow Cylinders$). ($model \rightsquigarrow Cylinders$) implies that the likelihood of a model having certain number of cylinders can be estimated, which can be used to estimate the probability that a tuple in Table 1 would conform to the constraint *Cylinders* = '4'. We can see that model 'Civic' is more likely to be in the base set than 'Accord' or 'Camry'.

Once the base tuple set has been generated, each of those tuples are expanded horizontally by predicting the values for the attributes pulled from children tables. Given a tuple from the base set, all the children tables (to the base table) are looked up for determined attributes, and the most likely value is used to expand the tuple. Further, values picked from the children tables are used to pick determined attributes from their children tables and so on. In this way, the base tuple set provided by the root table is expanded using the learned value dependencies from child tables.

In tuple expansion, if the number of shared attributes between tables is greater than one, getting the associated values from other tables would be an interesting challenge. For instance, in our running example, Table 1 also had the year attribute and Table 2 is selected as the base table. We need to predict the value of price from Table 1. If we consider both Model and Year to predict the price, results would be more accurate, but we do not have the values of all combinations of Model and Year in Table 1 to predict the price. However, if we just use Model to predict the price, the precision might go down. Another interesting scenario where taking multiple attributes might not boost the prediction accuracy is the following: $Model, Number\_tires \rightsquigarrow Price$ is no better than $Model \rightsquigarrow Price$. In order to counter this problem, we propose a *fall back* approach of the AFDs to ensure high precision and recall.

This method can be formally described as this: If $\mathcal{X}$ is the set of shared attributes between two tables T_1 and T_2, where T_1 is the base table and T_2 is the child table. We need to predict the values of attribute Y from T_2 and populate the result attribute tree. If the size of $\mathcal{X}$ is equal to n ($n \geq 1$), we would first start with AFDs having n attributes in determining set and 'significantly higher' confidence than any of their AFDs. We need 'significantly higher' confidence because if the additional attributes

Algorithm 2 Tuple Expansion

Require: Source-table-tree $\mathcal{S}_t$; Result-attribute-tree $\mathcal{A}_t$, Set of AFDs $\bar{A}$
$R := \{\emptyset\}$ {Initializing the result set with schema $\mathcal{A}_t$ }
$b := Root(\mathcal{S}_t)$ {Setting the base table}
Translate the constraints onto base table
Populate all the attributes in level 0 of $\mathcal{A}_t$ from b
for all child c in $\mathcal{A}_t$ **do**
  if b and c share n attributes **then**
    fd = AFDs with n attrbs in detSet
    while $n > 0$ **do**
      if c has the specified combination **then**
        Populate R using predicted values using fd from c
        break
      fd = Pick AFDs with $n - 1$ attributes in detSet
return Result Set R

do not boost the confidence much, they will not increase the accuracy of prediction as well. If the AFDs do not find matching values between two tables to predict values, we 'fall back' to the AFDs with smaller determining set. We do this until we would be able to predict the value from the other table. Algorithm 2 describes it.

5 Learning attribute dependencies

We have seen in the previous section how attribute dependencies within and across tables help us in query answering by discovering related attributes from other tables. But it is highly unlikely that these dependencies will be provided up front by autonomous web sources. In fact, in most cases the dependencies are not apparent or easily identifiable. We need an automated learning approach to mine these dependencies.

As we have seen in the Section 4, we extensively use attribute-level dependencies (AFDs). The notion of mining AFDs as condensed representations of association rules is discussed in detail in Kalavagattu (2008). Our work adapts the same notion, since it helps us in learning dependencies both at attribute and value level.

The following sections describe how rules are mined within the table and how they are propagated across tables.

5.1 Intra-table learning

In this subsection we describe the process of learning AFDs from a single table. It is easy to see that the number of possible AFDs in a database table is exponential to the number of attributes in it, thus AFD mining is in general expensive. But, only few of these AFDs are useful to us. To capture this, we define two metrics *confidence* and *specificity* for an AFD, and focus on AFDs that have high *confidence* and low *specificity* values.

5.1.1 Confidence

If an Association rule is of the form $(\alpha \rightsquigarrow \beta)$, it means that if we find all of α in a row, then we have a good chance of finding β. The probability of finding β for us to accept this rule is called the confidence of the rule. Confidence denotes the conditional probability of head given the body of the rule.

Generalizing to AFDs, the confidence of an AFD should similarly denote the chance of finding the value for the dependent attribute, given the values of the attributes in the determining set. We define *confidence* in terms of the confidences of the underlying association rules. Specifically, we define it in terms of picking the best association rule for every distinct value-combination of the body of the association rules. For example, if there are two association rules (Honda $\rightsquigarrow$ Accord) and (Honda $\rightsquigarrow$ Civic), given Honda, the probability of occurrence of Accord is greater than the probability of occurrence of Civic. Thus, (Honda $\rightsquigarrow$ Accord) is the best association rule, for (Make $=$ Honda) as the body. The support is defined as $support(\alpha_i) = count(\alpha_i)/N$, where N is the number of tuples in the training set.

$$confidence\ (X \rightsquigarrow A) = \sum_{x}^{N'} \arg \max_{y \in [1, N_j]} (support\,(\alpha_x) \times Confidence(\alpha_x \rightsquigarrow \beta_y))$$

Here, N' denotes the number of distinct values for the determining set X in the relation. This can also be written as,

$$Confidence\ (X \rightsquigarrow A) = \sum_{x}^{N'} \arg \max_{y \in [1, N_j]} (support\,(\alpha_x) \rightsquigarrow \beta_y)$$

Example: For the database relation displayed in Table 8, Confidence of the AFD $(Make \rightsquigarrow Model) =$ Support $(Make : Honda \rightsquigarrow Model : Accord) +$ Support $(Make : Toyota \rightsquigarrow Model : Camry) = \frac{3}{8} + \frac{2}{8} = \frac{5}{8}$.

5.1.2 Specificity-based pruning

The distribution of values for the determining set is an important measure to judge the "usefulness" of an AFD. For an AFD $X \rightsquigarrow A$, the fewer distinct values of X and the more tuples in the database that have the same value, potentially the more relevant possible answers can be retrieved through each query, and thus a better recall. To quantify this, we first define the *support of a value* α_i of an attribute set X,

Table 8 Fragment of a car database

ID	Make	Model	Year	Body Style
1	Honda	Accord	2001	Sedan
2	Honda	Accord	2002	Sedan
3	Honda	Accord	2005	Coupe
4	Honda	Civic	2003	Coupe
5	Honda	Civic	1999	Sedan
6	Toyota	Sequoia	2007	SUV
7	Toyota	Camry	2001	Sedan
8	Toyota	Camry	2002	Sedan

$support(\alpha_i)$, as the occurrence frequency of value α_i in the training set. The support is defined as $support(\alpha_i) = count(\alpha_i)/N$, where N is the number of tuples in the training set.

Now we measure how the values of an attribute set X are distributed using *specificity*. *specificity* is defined as the information entropy of the set of all possible values of attribute set X: $\{\alpha_1, \alpha_2, \ldots, \alpha_m\}$, normalized by the maximal possible entropy (which is achieved when X is a key). Thus, *specificity* is a value that lies between 0 and 1.

$$specificity\ (X) = \frac{-\sum_1^m support(\alpha_i) \times \log_2(support(\alpha_i))}{\log_2(N)}$$

When there is only one possible value of X, then this value has the maximum support and is the least specific, thus we have *specificity* equal to 0. When all values of X are distinct, each value has the minimum support and is most specific. In fact, X is a key in this case and has *specificity* equal to 1.

Now we overload the concept of *specificity* on AFDs. The *specificity* of an AFD is defined as the *specificity* of its determining set. i.e. $specificity\ (X \rightsquigarrow A) = specificity\ (X)$. The lower *specificity* of an AFD, potentially the more relevant possible answers can be retrieved using the rewritten queries generated by this AFD, and thus a higher recall for a given number of rewritten queries.

Intuitively, *specificity* increases when the number of distinct values for a set of attributes increases. Consider two attribute sets X and Y such that Y $\supset$ X. Since Y has more attributes than X, the number of distinct values of Y is no less than that of X, *specificity* (Y) is no less than *specificity* (X).

Definition 1 (Monotonicity of *specificity*) For any two attribute sets X and Y such that Y$\supset$X, *specificity* (Y) $\geq$ *specificity* (X). Thus, adding more attributes to the attribute set X can only increase the *specificity* of X. Hence, *specificity* is monotonically increasing w.r.t increase in the number of attributes.

This property is exploited in pruning the AFDs during the mining, by eliminating the search space of rules with *specificity* less than the given threshold.

Algorithms for mining AFDs face two costs: the combinatorial cost of searching the rule space and the cost of scanning the data to calculate the required metrics for the rules. In query processing the AFDs which we are mostly interested are the ones with the shared attributes in determining set of the rule. If $X \rightsquigarrow A$ is an AFD, we are interested in rules where $X \in S$, where S is the set of shared attributes between two tables. Since number of such attributes is typically small, we can use this as one of the heuristics to prune away irrelevant rules.

5.1.3 AFDMiner algorithm

The problem of mining AFDs can be formally defined as follows: Given a database relation **r**, and user-specified thresholds *minConf* (minimum confidence) and *maxspecificity* (maximum *specificity*), generate all the Approximate Functional Dependencies (AFDs) of the form ($X \rightsquigarrow A$) from r for which *confidence* (X$\rightsquigarrow$ A) $\geq$ *minConf* and *specificity* (X) $\leq$ *maxspecificity*

To find all dependencies according to the definition above, we search through the space of non-trivial dependencies and test the validity of each dependency. We follow a breadth first search strategy and perform a level-wise search in the lattice of attributes, for all the required AFDs. Bottom-up search in the lattice starts with singleton sets and proceeds upwards level-wise in the lattice, searching bigger sets. For AFDs, the level-wise bottom-up algorithm has a powerful mechanism for pruning the search space, especially the pruning based on *specificity*.

Search starts from singleton sets of attributes and works its way to larger attribute sets through the set containment lattice level by level. When the algorithm is processing a set X, it tests AFDs of the form $X \setminus A \rightsquigarrow A$, where A ∈ X.

Algorithm 3 AFDMiner: Levelwise search of dependencies

```
1: L_0 := {∅}
2: L_1 := {{A} | A ∈ R}
3: ℓ := 1
4: while L_ℓ ≠ ∅ do
5:     ComputeDependenciesAtALevel(L_ℓ)
6:     PRUNE(L_ℓ)
7:     L_{ℓ+1} := GenerateNextLevel(L_ℓ)
8:     ℓ := ℓ + 1
```

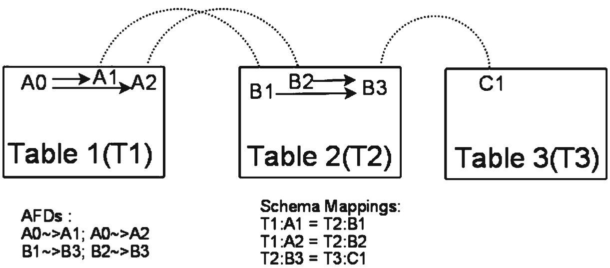
Algorithm 3 briefly presents the main *AFDMiner* algorithm. In it, GenerateNextLevel computes the level $L_{\ell+1}$ from L_ℓ. The level $L_{\ell+1}$ will contain only those attribute sets of size $\ell + 1$ which have all their subsets of size ℓ in L_ℓ. (ComputeDependenciesAtALevel(L_ℓ)) computes all the AFDs that hold true at the given level of the lattice. In this process, it computes the confidence of each association rule constituting the AFDs. PRUNE(L_ℓ) implements the pruning strategies and prunes the search space of AFDs. It computes the *specificity* of each rule, and if it is less than the specified threshold, eliminates all the rules whose determining sets are supersets of it. Thus, level $L_{\ell+1}$ will contain an attribute set only if all its subsets of length ℓ are in level L_ℓ. The bottom-up approach of intelligently pruning rules at higher levels in *AFDMiner* is motivated from the Apriori algorithm (Agrawal and Srikant 1994) used in computing association rules from itemsets. Apriori uses the frequency of itemsets to eliminate infrequent itemsets at higher levels, where as, *AFDMiner* uses *specificity* of attribute sets to prune AFDs at higher levels.

5.2 Learning source statistics

Storing association rules The probabilities which we used extensively in the query answering phase are nothing but the confidence of the association rules. So we store all the association rules mined during the process of AFD mining (specifically, in ComputeDependenciesAtALevel(L_ℓ))) and use them at query time. This saves us the additional cost of having to compute the association rules separately by traversing the whole lattice again.

Here we describe the value level source statistics gathered by the system, which are employed by the query answering module for constraint propagation and attribute value prediction. As mentioned earlier, AFD mining involves mining the underlying association rules. During association rule mining, following statistics are

Fig. 4 Inter-table learning



gathered from each source table $\mathcal{T}$: (1) $P_{\mathcal{T}}(X = x_i)$: Prior probabilities of distinct values for each attribute X in $A_{\mathcal{T}}$ (2) $P_{\mathcal{T}}(X = x_i | Y = y_j)$: Conditional probabilities for distinct values of each attribute X conditioned on those of attribute Y in $A_{\mathcal{T}}$. Recall that this is nothing but the confidence of an association rule. Only the shared attributes are used as evidence variables, since value prediction and constraint propagation can only be performed across shared attributes.

5.3 Inter-table chaining

After learning the AFDs within a table, we need to use them to derive inclusion dependencies which are used in query answering phase. In order to combine AFDs from different tables, we need anchor points. These anchor points are provided by the attribute mappings across tables, so we extend our attribute dependencies using them. When two AFDs between neighboring tables are combined, the resultant AFD would have a confidence equal to the product of the two confidences.

But when we are combining dependencies between tables which are not directly connected, we need to consider all the possibilities. Let us consider the scenario in Fig. 4, with three tables T_1, T_2 and T_3. T_1 and T_2 have mappings between attributes $A_1 - B_1$ and $A_2 - B_2$. Similarly T_2 and T_3 have mapping between $B_3 - C_1$. If we want to get the most likely value of C_1 for A_0, we have more than one chaining to consider. We need to consider the confidences of AFDs, $A_0 \rightsquigarrow A_1$, $A_0 \rightsquigarrow A_2$ as well as the confidences of AFDs, $B_1 \rightsquigarrow B_3$, $B_2 \rightsquigarrow B_3$. We cannot greedily pick the AFD with higher confidence in either T_1 or T_2. We need to pick a combination of the AFDs which have higher *cumulative* confidence.[3]

6 Experimental evaluation

A prototype of SmartInt system, as described in this paper, has been implemented. The prototype supports automatic mining of approximate functional dependencies and value associations in an off-line phase. It also ranks the answer tuples it returns in terms of the overall confidence associated with each tuple. The prototype system has been demonstrated at ICDE 2010 (Gummadi et al. 2010).

Our intent is to evaluate the effectiveness of SmartInt in terms of precision and recall measures. The following explains how precision and recall measures are computed to take into account the fact that SmartInt's answers can differ from

[3]Cumulative Confidence is defined as product of the confidences of all the dependencies in a chain.

ground truth(provided by the master table) both in terms of how many answers it returns and how correct and complete each answer is.

- **Correctness of a tuple** (cr_t): If the system returns a tuple with m attributes of n attributes in the universal relation, the correctness of a tuple is defined as the ratio of total number of correct values in the tuple to number of attributes returned.

$$cr_t = \frac{\text{Number of correct values in the tuple}}{\text{Number of attributes in 'returned result set' (m)}}$$

- **Precision of the result set** (P_{rs}): Precision of the result set is defined as the average of correctness of a tuple in the result set.

$$P_{rs} = \frac{\Sigma cr_t}{\text{Total number of tuples in 'returned result set'}}$$

- **Completeness of a tuple**(cp_t): If the system returns a tuple with m attributes of n attributes in universal relation, the correctness of a tuple is defined as the ratio of total number of correct values in the tuple to number of attributes in universal relation.

$$cp_t = \frac{\text{Number of correct values in the tuple}}{\text{Number of attributes in 'master table' (n)}}$$

- **Recall of the result set** (R_{rs}): is defined as the ratio of the cumulative completeness of the tuples returned by the system to the total number of answers.

$$R_{rs} = \frac{\Sigma cp_t}{\text{Number of tuples retrieved from 'master table'}}$$

- **F-measure of the result set** (F_{rs}): is defined as the harmonic mean of precision and recall of the answer set.

$$F_{rs} = 2.\frac{P_{rs}.R_{rs}}{P_{rs} + R_{rs}}$$

Experimental setup To evaluate the SmartInt system, we used Vehicles database. We used around 350,000 records probed from **Google Base** for the experiments. We created a *master table* with 18 attributes. We divided this *master table* into multiple child tables with overlapping attributes. This helps us in evaluating the returned 'result set' with respect to the results from master table and establish how our approach compares with the ground truth.We have divided the master table into 5 different tables with the following schema

- *Vehicles_Japanese: (condition, price_type, engine, model, VIN, vehicle_type, payment,door_count, mileage, price, color, body_style, make)*
- *Vehicles_Chevrolet: (condition, year, price, model, VIN, payment, mileage, price, color, make),*
- *Vehicles_Chevrolet_Extra: (Model, Door Count, Type, Engine)*
- *Vehicles_Rest: (condition, year, price, model, VIN, payment, mileage, price, color, make)*
- *Vehicles_Rest_Extra: (Engine, Model, Vehicle Type, door count, body style)*

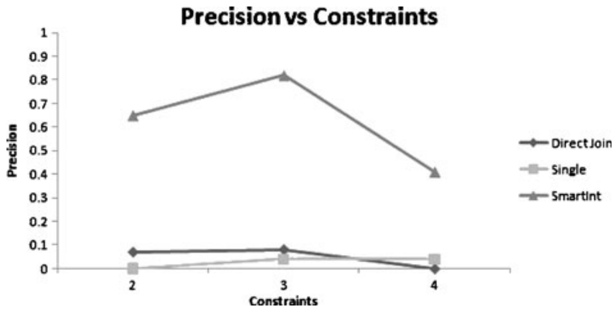


Fig. 5 Precision *vs.* number of constraints

The following (implicit) attribute overlaps were present among the fragmented tables.

- *Vehicles_Chevrolet:Model* ↔ *Vehicles_Rest:Model*
- *Vehicles_Chevrolet:Year* ↔ *Vehicles_Rest:Year*
- *Vehicles_Rest:Year* ↔ *Vehicles_Rest_Extra:Year*
- *Vehicles_Chevrolet_Extra:Model* ↔ *Vehicles_Rest_Extra:Model.*

The following are the input parameters which are changed: (1) Number of Attributes and (2) Number of Constraints. We measured the value of precision and recall by taking the average of the values for different queries. While measuring the value for a particular value of a parameter we varied the other parameter. While we are measuring precision for 'Number of attributes = 2', we posed queries to the system with 'Number of constraints = 2, 3 and 4' and took the average of all these values and plotted them. Similarly, we varied the 'Number of attributes' while we are measuring the Precision for each value of 'Number of constraints'. The same process is repeated for measuring the recall as well.

Comparison with 'sngle table' and 'direct join' approaches In this section, we compare the accuracy of SmartInt with 'Single table' and 'Direct join' approach which we discussed in Section 1 and analyze them. Recall that in the single table approach, results are retrieved from a single table which has maximum number of attributes/constraints mentioned in the query mapped on it. The direct join approach involves joining the tables based on the shared attributes. As explained in the

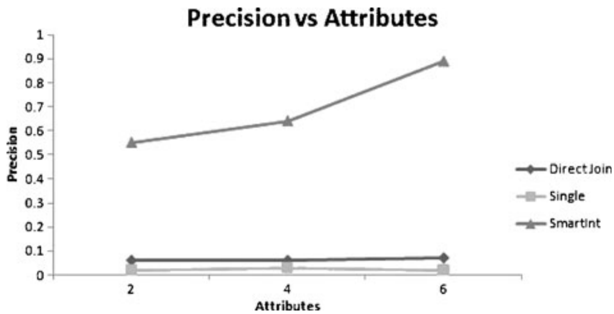
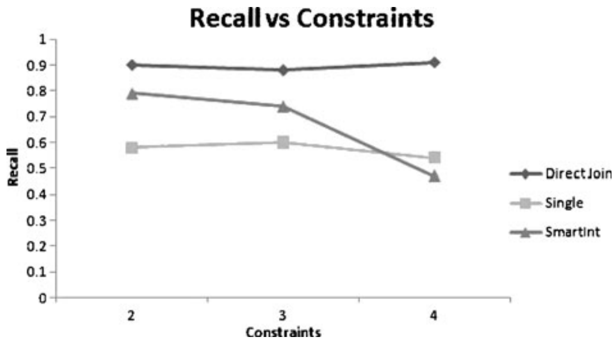


Fig. 6 Precision *vs* number of attributes

Fig. 7 Recall *vs* number of constraints



introduction, the latter approach tends to generate spurious entities, while the former also fails to draw together the connected information about the entity.

In the simple case of queries mapping on to a single table, the precision and recall values are independent of attribute dependencies, since query answering does not involve constraint propagation or tuple expansion through attribute value prediction.

In cases where queries span multiple tables, some of the attribute values have to be predicted and constraints have to be propagated across tables. Availability of attribute dependency information allows accurate prediction of attributes values and hence boosts precision. As shown in Figs. 5 and 6, our approach scored over the other two in precision. Direct join approach, in absence of primary-foreign key relationships, ends up generating non-existent tuples through replication, which severely compromises the precision. In cases where query constraints span over multiple tables, single table approach ends up dropping all the constraints except the ones mapped on to the selected best table. This again results in low precision.

In terms of recall (Figs. 7 and 8), performance is dominated by the direct join approach, which is not surprising. Since direct join combines partial answers from selected tables, the resulting tuple set contains most of the real answers, subject to completeness of individual tables. Single table approach, despite dropping constraints, performs poorly on recall. The selected table does not cover all the query attributes, and hence answer tuples are low on completeness, which affects recall.

When accurate attribute dependencies are available, our approach processes the distributed query constraints effectively and hence keeps the precision fairly high. At the same time, it performs chaining across tables to improve the recall. Figures 9

Fig. 8 Recall *vs* number of attributes

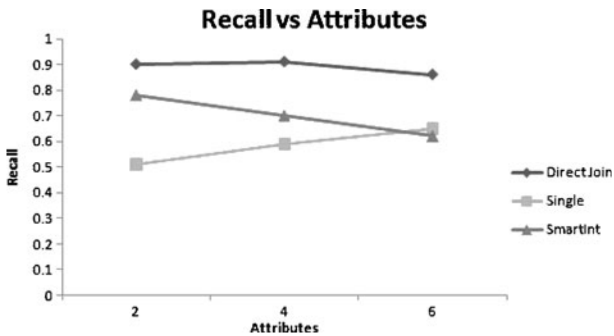
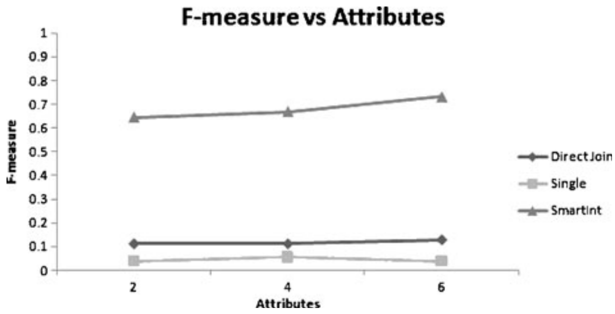


Fig. 9 F-measure *vs* number of attributes

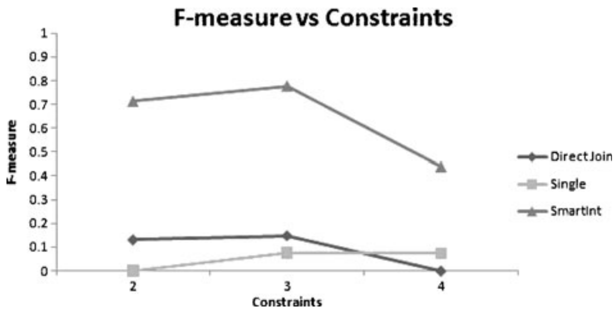


and 10 show that our approach scores higher on F-measure, hence suggesting that it achieves a better balance between precision and recall.

Comparison with multiple join paths In the previous evaluation the data model had one shared attribute between the tables, but there can be multiple shared attributes between the tables. In such scenarios, direct join can be done based on any combination of the shared attributes. Unless one of the attribute happens to be a key column the precision of the joins is low. In order to illustrate this, we considered the data model with more than one shared attribute and measured the precision and recall for all the possible join paths between the tables. The experimental results (See Fig. 11) show that SmartInt had higher F-measure than all possible join paths.

Tradeoffs in number vs. completeness of the answers Normal query processing systems are only concerned about retrieving top-k results since the width(number of attributes) of the tuple is fixed. But SmartInt chains across the tables to increase the extent of completion of the entity. This poses an interesting tradeoff: In a given time, the system can retrieve more tuples with less width or fewer tuples with more width. In addition to this, if user is only interested high confidence answers, each tuple can expand to variable width to give out high precision result set. We analyze how precision and recall varies with w (the number of attributes to be shown). The Fig. 12 shows how precision, recall and F-measure varies as more number of attributes are predicted for a specific result set (the query constraints are make = 'BMW' and year = '2003'). In scenarios, when SmartInt has to deal with infinite width tuples, F-measure can be used to guide SmartInt when to stop expanding.

Fig. 10 F-measure *vs* number of constraints



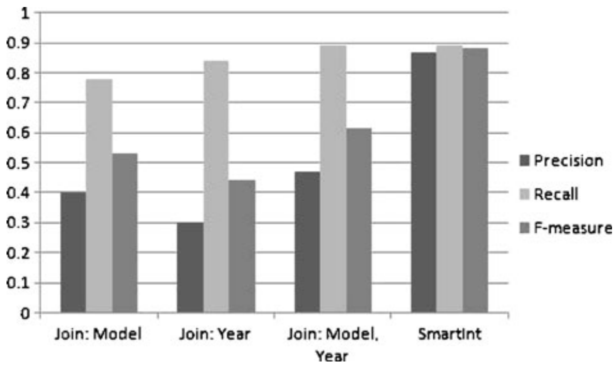


Fig. 11 SmartInt *vs* multiple join paths

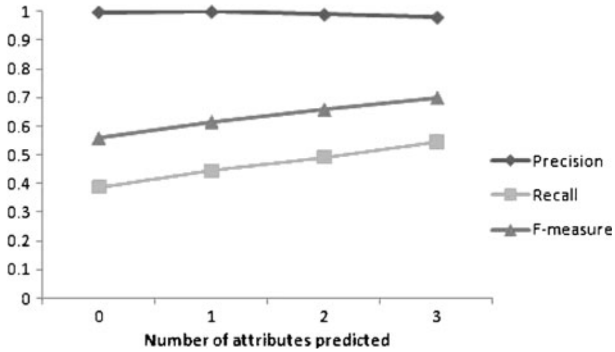


Fig. 12 Precision, recall and F-measure *vs* tuple width

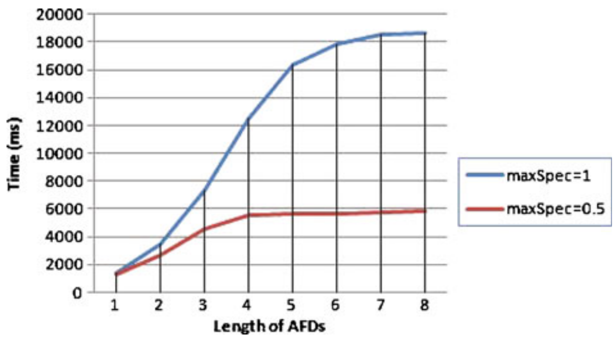


Fig. 13 Time taken by AFDMiner *vs* length of AFD

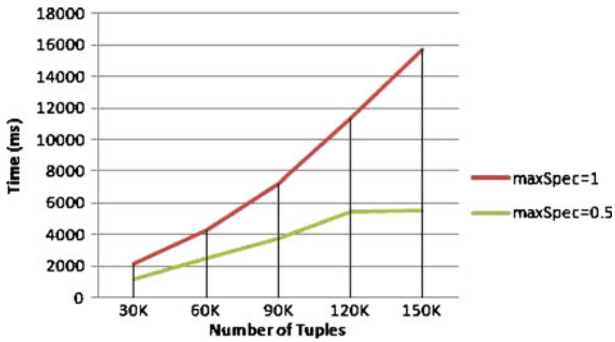


Fig. 14 Time taken by AFDMiner *vs* no. of tuples

Learning time (AFDMiner) We invoke AFDMiner to learn the association rules and the AFDs. But this is done offline before query processing starts. So learning time usually does not directly affect the performance of the system. Nevertheless, the current implementation of AFDMiner uses several optimizations and data preprocessing to keep learning time low. In fact, *AFDMiner takes only about 4 s for mining the rules used in the current experimental setup*. Figures 13 and 14 show the comparison between the time taken for AFDMiner with specificity threshold set to 0.5 and 1, with varying tuplesize and the length of the AFD respectively.[4] We see that *specificity* metric results in faster learning times. For a detailed experimentation on AFDMiner, refer to Kalavagattu (2008).

7 Conclusion and future work

Our work is an attempt to provide better query support for web databases having tables with shared attributes using learned attribute dependencies but missing primary key–foreign key relationship. We use learned attribute dependencies to make up for the missing PK-FK information and recover entities spread over multiple tables. Our experimental results demonstrate that approach used by SmartInt is able to strike a better balance between precision and recall than can be achieved by relying on single table or employing direct joins.

We are currently exploring a variety of extensions to the SmartInt system. These include (1) differentiating the importance of the attributes in tuple expansion (2) allowing variable width answers, and assessing the diminishing rewards of additional information using a discounted reward model and (3) considering vertical fragmentation of tables in addition to horizontal fragmentation (which will involve operating with a set of base tables rather than a single one).

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[4] At first blush, pruning highly specific AFDs seems to hurt the precision, but in the current set of experiements *specificity* based pruning reduced the total running time and did not effect the accuracy.

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