HandsOn DB: Managing Data Dependencies involving Human Actions

Mohamed Eltabakh[1], Walid Aref[2], Ahmed Elmagarmid[3], Mourad Ouzzani[3]

[1] Worcester Polytechnic Institute, MA, USA, meltabakh@cs.wpi.edu
[2] Purdue University, IN, USA, aref@cs.wpi.edu
[3] Qatar Computing Research Institute, Qatar, {aelmagarmid, mouzzani}@qf.org.qa

Abstract—Consider two values, *x* and *y*, in the database, where *y* = *F(x)*. To maintain the consistency of the data, whenever *x* changes, *F* needs to be executed to re-compute *y* and update its value in the database. This is straightforward in the case where *F* can be executed by the DBMS, e.g., SQL or C function. In this paper, we address the more challenging case where *F* is a human action, e.g., conducting a wet-lab experiment, taking manual measurements, or collecting instrument readings. In this case, when *x* changes, *y* remains invalid (inconsistent with the current value of *x*) until the human action involved in the derivation is performed and its output result is reflected into the database. Many application domains, e.g., scientific applications in biology, chemistry, and physics, contain multiple such derivations and dependencies that involve human actions. In this paper, we propose *HandsOn DB*, a prototype database engine for managing dependencies that involve human actions while maintaining the consistency of the derived data. *HandsOn DB* includes the following features: (1) semantics and syntax for interfaces through which users can register human activities into the database and express the dependencies among the data items on these activities, (2) mechanisms for invalidating and revalidating the derived data, and (3) new operator semantics that alert users when the returned query results contain potentially invalid data, and enable evaluating queries on either valid data only, or both valid and potentially invalid data. Performance results are presented that study the overheads associated with these features and demonstrate the feasibility and practicality in realizing *HandsOn DB*.

Index Terms—Scientific databases, data dependency and consistency, human actions, query processing.

1 Introduction

In many application domains such as scientific experimentation in biology, chemistry, and physics, the derivations among the data items are complex and may involve sequences of human actions, e.g., conducting a wet-lab experiment, taking manual measurements, and collecting instrument readings. In traditional derived data that are stored inside the database, e.g., deriving age from the date-of-birth attribute, simple procedures internal to the database system can be coded and executed automatically to maintain the consistency of the data. In contrast, when the derivations among the data items involve human actions, these derivations cannot be coded within the database. Hence, updating a database value may render all dependent and derived values invalid until the required human actions are performed and their output results are updated back in the database.

Typical databases may contain multiple dependencies which may cascade and interleave with other dependencies that involve executable functions, e.g., SQL and C functions. Hence, a complex dependency graph is created among the database items. Since human actions may take long time to prepare for and perform, parts of the underlying database may remain inconsistent for long periods of time while the data still need to be made available for querying. Our focus in this paper is on managing dependencies that involve human actions or more generally, real-world activities, inside the database engine while maintaining the consistency of the derived data under update and query operations.

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Motivating Examples: Figure 1 illustrates an example, from the biology domain, of a pipeline collecting different pieces of information about genes/proteins and storing them in the database. As depicted in the figure, the initial sequence files stored in the database will be used as input to a set of procedures involving human actions in order to discover more information, e.g., the protein family, gene function, and the location of SNP (Single-Nucleotide Polymorphism). If the underlying sequence data is modified due to correction of sequencing errors or an improved assembly, then the corresponding output data from the procedures become potentially invalid and need to be re-verified. Another example of chemical reactions is illustrated in Figure 2 where chemists may store in the database descriptions of chemical reactions, e.g., substrates, reaction parameters, instruments settings, and products. Clearly, these chemical reactions require human intervention. If, for example, any of the substrates in the reaction are modified, then the products of the reaction may change as well, and hence they become invalid until the reaction is re-executed or the chemist verifies the old value.

The presence of potentially-invalid values in the database directly affects the correctness of the queries' answers as well as any decisions based on the results. For example, continuing with the biology pipeline (Figure 1) assume the database instance shown in Figure 3 where

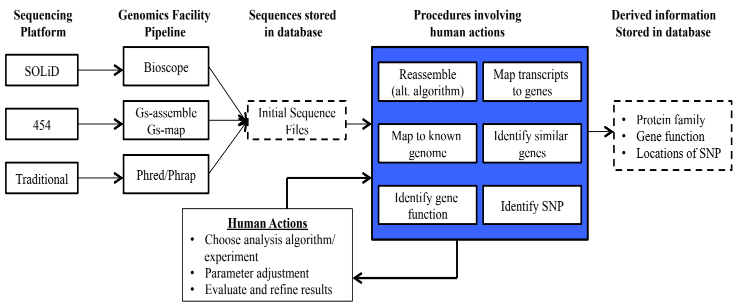


Fig. 1. Real-world dependencies in biological pipeline.

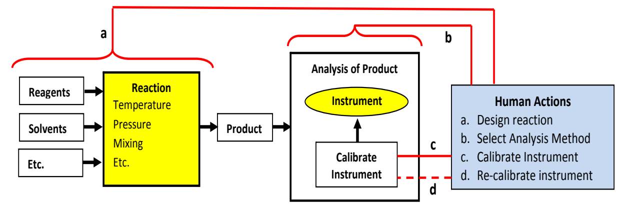


Fig. 2. Real-world dependencies in chemical reactions.

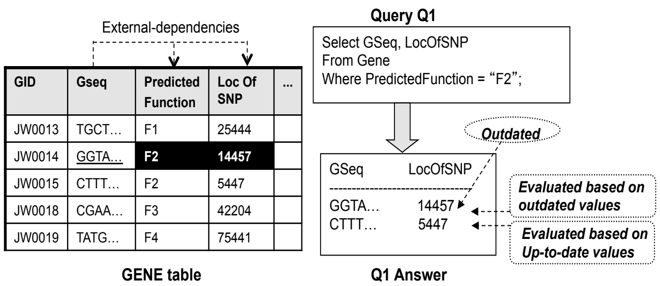


Fig. 3. Querying invalid values.

the sequence of gene *JW0014* has been updated, and hence the dependent values become invalid (marked as black table cells). Although the reported result from query *Q1* seems correct, it is missing crucial information, e.g., the reported value "14457" is potentially invalid and needs to be verified, and the first tuple in the answer matched the query predicate (*PredictedFunction = "F2"*) based on an invalid value *F2*, and hence its presence in the output is questionable.

Candidate Solutions with Current Technologies: While there are several existing technologies that may be used to solve our problem, all have limitations as compared to *HandsOn DB*. We discuss below three of these possible solutions.

The first possible approach is to store metadata information along with the data values, e.g., a version number or timestamp, to track whether values are up-to-date or outdated. However, this approach has several limitations including: (1) Without explicitly modeling the dependencies inside the DBMS, the maintenance of the auxiliary metadata is delegated to end-users which is both an overwhelming task and error prone. (2) Integrating the metadata information inside the query engine is problematic because users' queries have to incorporate the metadata information in their evaluation. For example, dependencies may span multiple tables, e.g., values in table R depend on values in tables S_i and S_j, and hence a query on only table R needs to be extended to also check tables S_i and S_j to decide whether R's values are up-to-date or outdated, which will make even simple queries very complex. (3) All curation operations, e.g., why certain values are invalid and how to re-validate them, and which external activities need to be performed and using which parameters, will be manually performed without any system support.

Another possible approach is to delay the updates to the database until all derived values are computed, i.e., keeping the partial results outside the database. Although feasible in some scenarios involving simple dependencies, it has several limitations as it does not scale with complex dependencies, and storing the data outside the database is not a preferred solution w.r.t. recovery, instant availability of results, and ensuring the consistency of the new values with other database values.

A third approach is in the context of workflow management, e.g., [27], [28], [29], where the external activities, dependencies, and the database updates are modeled as processes of a workflow. While attractive, this approach has two major limitations: (1) Since the dependencies are modeled at the workflow management level (i.e., outside the DB), directly querying the database without consulting the workflow system will not reflect such dependencies, and hence may reveal potentially-invalid values to end-users without notification, and (2) The advanced optimizations and features offered by *HandsOn DB*, such as extended querying capabilities and curation operators, will no longer be applicable because the external dependencies are not coherently integrated inside the database system. Supporting such optimizations and features at the workflow level will be much harder.

Contribution: The above limitations motivate the need for a more systemic mechanism and an end-to-end solution that enables scientists to focus on running their experiments and uploading the results, instead of tracking the dependencies among the data items and verifying their consistency. In this paper, we propose *HandsOn DB*, a prototype database engine for managing dependencies that involve real-world activities while maintaining the consistency of the derived data. *HandsOn DB* addresses all of the above limitations as it enables users to reflect the updates immediately into the database, i.e., instant availability of the data, while the DBMS keeps track of the derived data by marking them as *potentially invalid* (aka *outdated*) and reflecting their status in the query results, i.e., the consistency of the data is not compromised. *HandsOn DB* introduces extended query operators for evaluating users' queries on either valid data only, thus avoiding relying on any potentially invalid values (no false-positive tuples), or both valid and potentially invalid data (include false-positive tuples). *HandsOn DB* is a component in *bdbms* [1], [2], our proposed database system for scientific data management. We first highlighted the main research challenges involved in managing complex real-world dependencies in [3]. In this paper, we propose novel solutions to these challenges.

The contributions of this paper are as follows[1]:

- Proposing new SQL syntax and its corresponding semantics to register real-world activities into the database and to express the dependencies among data items using these activities.
- Introducing an extended relational algebra and new semantics for query operators to alert users of any potentially-invalid data in the query results, and to enable querying either valid data only or both valid and potentially-invalid data.
- Proposing new data manipulation and curation operations for invalidating and revalidating the data, and for keeping track of the real-world activities that need to be performed in order to revalidate the data.
- Experimentally evaluation the proposed features of *HandsOn DB* and demonstrating the system's practicality.

The rest of the paper is organized as follows. Section 2 overviews the related work. Section 3 presents the needed definitions. Sections 4 and 5 introduce the data manipulation operations as well as the new query operators, respectively. In Section 6, we present several design issues. The performance analysis is presented in Section 7. Section 8 contains concluding remarks.

2 Related Work

The theory of functional dependencies (FDs) in DBMSs, e.g., [5], [6], [7], is used to model dependencies among data items, infer keys, and systematically normalize database schemas to prevent several inconsistency problems, e.g., redundancy, and update and delete anomalies. However, FDs cannot solve the inconsistency problem raised in this paper mainly because the dependencies that involve real-world activities cannot be modeled or coded inside the database (E.g.,using triggers or user-defined functions) regardless of how well the schema is designed or normalized. The existence of such external activities that cannot be handled by DBMSs triggered the research in long-running transactions, e.g., [8], [9], where a database transaction may involve external activities, e.g., getting a manager's signature to complete a purchase transaction. Systems for long-running transactions took the approach of loosening the ACID properties, using optimistic concurrency control techniques, and using compensating transactions in the case of failures. The key objective of these systems is to keep track of the derived data that are already modified by the transaction to roll them back if needed (compensating transactions). However, long-running transactions do not keep track of the derived data that are still awaiting to be updated and are currently inconsistent, and hence they delegate this inconsistency issue to the end-user without any system support. More importantly, the currently inconsistent values are subject to querying—possibly for long periods of time— without any special query processing or notification mechanisms.

Active databases [10], [11], [12] provide mechanisms (through triggers) to respond automatically to events taking place either inside or outside the database. The outside events are ultimately mapped to operations that the DBMS can capture, e.g., insertion, deletion, or calling of a user-defined function. Unlike *active databases*, in *HandsOn DB*, a change inside the database, e.g., updating the gene sequence in Figure 3, may trigger the execution of a real-world activity outside the database to update the derived data. Until this activity is performed, the system needs to keep track of all potentially invalid data items, reflect their status over query results, and provide mechanisms for re-validating these invalid items. Active databases do not address these challenges.

Multi-version systems and databases, e.g., [13], [14], [15], maintain the old and new values of updated data. However, like snapshot databases (which is the focus of this paper), multi-version databases model only the computable dependencies among the data items. And hence, the provided isolation level and consistency degree are based on the traditional notion of transactions. For example, if value v_j depends on value v_i through an external activity, then a transaction updating v_i to v_i' would create a newer version of the database where both v_i' and v_j are viewed as consistent and up-to-date values. Although this is correct with the traditional notion of transactions, it is semantically incorrect because the external dependency is not taken into account. Extending the proposed techniques in the context multi-version databases is left as future work, and in this case, the history of dependencies changing over time can be also maintained.

Some systems such as checkout\checkin systems [16] consider querying an old consistent version of the data while updating an *off-line* version until all required changes to all dependent data items have been performed. Then, the off-line version is released as the newer consistent version. The drawbacks of this approach include violating the need for making users' updates available as early as possible, hiding possible data corrections for unbounded long delays, and resolving any consistency issues outside the DBMS, i.e., data conflicts are resolved at the checkin time using version-control systems outside the DBMS. *HandsOn DB* resolves all these issues within the database system.

Probabilistic and fuzzy database systems (PDBMSs), e.g., [17], [18], [19], [20], overlap with *HandsOn DB* assuming that data invalidation introduces uncertainty to the data, e.g., *potentially invalid* values can be viewed as *unknown* values. However, the focus of the two systems is different. In *HandsOn DB* a change in the state of a database value, i.e., being valid or invalid, is triggered by database operations, while in PDBMSs the uncertainty is inherent to the data and is given as external input. These uncertainties do not change over time unless users

1. The correctness of execution of *HandsOn DB* is theoretically proven in [4], but the proof is not included in this paper due to space limitations.

manually modify them. Therefore, PDBMSs do not address several challenges, that are the core of *HandsOn DB*, such as modeling the dependencies among the data items, keeping track of when and why a data item becomes uncertain (invalid), and keeping track of how to revalidate a data item to become certain (valid).

Provenance management, e.g., [20], [21], [22], [23], follows two main approaches; *inversion-based* and *annotation-based*. Inversion-based techniques are not applicable to the problem at hand since we deal with external activities that cannot be executed by the DBMS in the first place. Annotation-based techniques [21], [24], [25], [26] lack the ability of modeling and integrating real-world activities inside the database system, and hence the dependency graph involving these external activities cannot be constructed. Annotations, therefore, can neither maintain the consistency of the derived data items (computable or non-computable) nor keep track of pending activities that need to be performed to re-validate the data. Provenance has been also studied extensively in the context of scientific workflows, e.g., [27], [28], [29], [30] where workflow systems are instrumented to capture and store the provenance information. In these systems, a database can be a single component within a bigger workflow. However, as discussed in Section 1, modeling the external dependencies at the workflow management level has several limitations and does not actually guarantee the desired consistency level. Nevertheless, *HandsOn DB* can still be used in conjunction with workflow systems to achieve stronger consistency of the data.

3 MODELING ACTIVITIES & DEPENDENCIES

In this section, we present the formal definitions of activities and dependencies, and show how to model them inside the database. We assume a relational database model, and we use the term *"database cell"* to refer to an attribute value in a single tuple. The value itself can be primitive, e.g., integer or string, or complex, e.g., arrays or bit maps.

Definition **(Real-world Activity):** *A real-world activity (RWA, for short) is an activity that requires human intervention, and hence cannot be executed by the DBMS. RWA takes one or more input parameters and produces one or more output parameters.*

Since real-world activities are very close in definition to functions, we define the concept of a *real-world activity function* that maps a real-world activity to a nondeterministic function inside the database. RWA functions are nondeterministic since RWAs such as lab experiments may not generate the same exact output given the same input parameters.

Definition **(Real-world Activity Function):** *A real-world activity function RWA-F is a nondeterministic function inside the database that represents a real-world activity. RWA-F is of type 'real-world activity' and has a signature that specifies the function name and the input and output types. RWA-F has no associated code.*

Similar to defining SQL, C, or Java functions inside the database, we extend the SQL *Create Function* command to define real-world activity functions as follows:

```
Create Function <activity_name> (<input_types>)
 Returns (<output_types>) As real-world activity;
```

Once real-world activity functions are defined in the database, users can create dependencies among the data items using these functions. Users can also create dependencies among the data items using executable functions, e.g., SQL or C functions. Each dependency defines the function name involved in the dependency, the input parameters to the function (the order of the inputs matters only if the function is executable), and the output parameters from the function.

Definition **(Dependency Instance):** *A dependency instance DI is a dependency between a set of input parameters (database cells) and a set of output parameters (database cells) through a specific execution of a function. A dependency instance is defined as* DI= (F, SP, DP)*, where:*

- ***F:*** The function name involved in the dependency.
- ***SP (Source Parameters):*** A set of database cells that are the input parameters to F.
- ***DP (Destination Parameters):*** A set of database cells that are the output parameters from F.

If F is of type *real-world activity*, then *DI* is called *real-world dependency*, otherwise, *DI* is called *computable dependency*. The dependency of *DP* on *SP* is complete in the sense that each database cell in *DP* depends on all database cells in *SP*.

Dependency instances are conceptually defined at the cell level, i.e., they capture the dependencies between the database table cells. Such fine-granular level of expressing the dependencies may sometimes involve high overhead as reported in [35]. In *HandsOn DB*, we introduce a higher level of abstraction using the *Add Dependency* construct, by which users may define dependencies over one cell, multiple cells, or even entire columns at once. Dependencies are created in (or dropped from) the database using the *Add Dependency* (or *Drop Dependency*) constructs that are augmented to the SQL *Create Table* and *Alter Table* commands as follows:

```
Create Table <R>
(
  <columns_definitions >
   ....
 Add Dependency [<dependency_id>]
 Using <func_name>
 Source <T1.c1[, T2.c2, ...] >
 Destination <R.c'1 [, R.c'2, ...]>
 [Where <predicates>]
);
```

```
Alter Table <R>
Add Dependency [<dependency_id>]
Using <func_name>
Source <T1.c1[, T2.c2, ...] >
Destination <R.c'1 [, R.c'2, ...]>
[Where <predicates>]
[Invalidate Destination] ;

Alter Table <R>
Drop Dependency <dependency_id>
[Invalidate Destination] ;
```

A new dependency is defined over Table R that contains the destination attributes $R.c'_1$, $R.c'_2$, ... of the dependency. The *dependency_id* is a unique id that is either defined by the user or generated automatically by the system. If the dependency applies to multiple destination tables, then it is defined over each of these tables with different *dependency_id*. The optional *Where* clause contains join and selection predicates over the source and destination tables to specify the exact table cells that are linked together. Examples 1 and 2 below illustrate defining dependencies over single and multiple tables.

Example 1: Single-table dependency

```
Create Table Gene(
  GID text  primary key,
  GSeq text,
  GDirection char,
  GFunction text,
  …
  ADD Dependency
  Using GeneFunExp
  Source GSeq, GDirection
  Destination GFunction);
```

__Description:__ Each gene function is inferred from the corresponding gene's sequence and direction using *GeneFunExp*.

Example 2: Cross-table dependency

```
Create Table Protein(
  PID text primary key,
  GID text references Gene(GID),
  PSeq text,
  PFunction text,
  …
  ADD Dependency Using A-Prediction
  Source Gene.GSeq, Gene.GDirection
  Destination Protein.PSeq
  Where Protein.GID = Gene.GID
  And Gene.GFunction = 'F1',
  ADD Dependency Using B-Prediction
  Source Gene.GSeq
  Destination Protein.PSeq
  Where Protein.GID = Gene.GID
  And Gene.GFunction != 'F1');
```

__Description:__ For proteins whose gene functions = 'F1', the protein sequence is inferred from the corresponding gene's sequence and direction using *A-Prediction*. Otherwise, the protein sequence is inferred from only the gene's sequence using *B-Prediction*.

In Example 1, the *Where* clause is omitted which indicates that the source and destination table cells belong to the same tuple. In this example, The dependency definition applies to all tuples in table `GENE`. In Example 2, the dependencies are defined between the two tables, `GENE` and `PROTEIN`. In this case, the *Where* clause contains a join between the two tables. Join predicates are mandatory for cross-table dependencies and are restricted to only equality joins between a foreign key in the destination table, e.g., *Protein.GID*, and the primary key in the source table, e.g., *Gene.GID*. This restriction ensures that each destination table cell is attached to unique source table cells. Notice that the predicates of the two *Add Dependency* constructs in Example 2 are not disjoint, i.e., one tuple may have the gene function equals *"F1"* and the start position greater than 10000. In this case, the destination table cell of that tuple, i.e., the protein sequence, follows the definition of the second dependency (the most recent one) as will be explained using the *overriding* property in Section 4.

4 Data Manipulation Operations

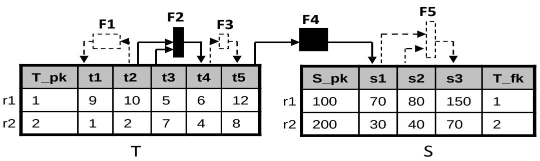
In this section, we present the data manipulation operations in *HandesOn DB* and define how they affect the value and status of the database cells. These operations represent the interfaces through which the dependency graph—created from the user-defined real-world and computable dependencies—is manipulated. Conceptually, each table cell has a status (0 = up-to-date, 1 = outdated) in addition to the cell value. That is, Relation R having n attributes is represented as: $R = \{r =< (C_1.value, C_1.status), ..., (C_n.value, C_n.status) >\}$.

We define five data manipulation operations, namely, *insert(t)*, *delete(t)*, *update(c)*, *invalidate(c)*, and *validate(c)*, where t is a tuple and c is a database cell. In Figure 4, we demonstrate a sequence of cumulative operations over two sample tables T and S. Tuples in S reference the tuples in T using the foreign and primary keys $S.T\_fk$, and $T.T\_pk$, respectively. The dependencies among the two tables are depicted in Figure 4(a), where the dashed and solid lines represent computable and real-world dependencies, respectively. The semantics of each dependency are presented in Figure 4(b). Figure 4(c) gives the state of the database after performing each operation. The black-marked table cells represent the outdated values while the red-marked ones represent modified or newly inserted values.

Throughout this section, we use the following shorthand notations for a given database cell c. The database cells from which c is derived are called *InputParameters(c)*. The database cells that are derived from c through real-world and computable dependencies are called *RealworldOutputs(c)*, and *ComputableOutputs(c)*, respectively.

- **invalidate(c):** invalidates c and all database cells that depend on c recursively, i.e., database cells in *ComputableOutputs(c)* and *RealworldOutputs(c)*. For example, when Operation 1 in Figure 4 invalidates the database cell (t4,r1) because of the existence of the real-world activity *F2*, the invalidation propagates recursively to the dependent database cells (t5,r1), (s1,r1), and (s3, r1).
- **validate(c):** validates c only if *InputParameters(c)*, are all up-to-date. If c is validated, then the *validate* procedure is called recursively on the database cells in *ComputableOutputs(c)*. The database cells in *RealworldOutputs(c)* are not validated automatically because they are waiting on real-world activities to be performed. Referring to Operation 2 in Figure 4, when Activity *F2* is externally performed and its result (value 13) is updated in (t4, r1), the dependent table cell (t5, r1) is re-computed and validated automatically through the computable dependency involving *F3*. However, the validation does not propagate to (s1, r1) because *F4* is a real-world activity.
- **update(c):** updates the value of c as well as the values of *ComputableOutputs(c)*. If c is currently invalid, then c is validated only if *InputParameters(c)* are all valid. Otherwise, the status of c remains unchanged. Moreover, since the value of c is modified, the database cells in *RealworldOutputs(c)* are invalidated. For example, Operation 1 in Figure 4 re-computes and modifies the value of (t1, r1) from '9' to '3' while maintaining its status valid. In contrast, the value in (t4, r1) is invalidated through the real-world dependency involving *F2*. Similarly, Operation 3 results in re-computing the value in (s3,r1) to be '90' instead of '150' through *F5*. However, this update does not validate (s3,r1) because one of its input parameters, i.e., (s1,r1), is still outdated.
- **delete(t):** If the values in t are neither source nor destination parameters to any dependency, then t is deleted without any further processing. The same rule applies if the values in t are only destination parameters to some existing dependencies. However, if the values in t are source parameters to some existing dependencies, then either the deletion of t is rejected, or t is deleted and the destination parameters of these dependencies are invalidated. The default behavior in the system is to reject the deletion of t. This behavior can be altered at the table level using the following command:

```
Alter Table <tableName> Add Constraint <constName>
  On Delete Propagate Invalidation;
```



(a) User-defined dependencies over sample tables T and S

Dependency function	Type	Description	Source(s)	Dest.	Predicate(s)
F1	Computable	Subtract one from the source	T.t2	T.t1	None
F2	Real-world	Wet-lab experiment	T.t2, T.t3	T.t4	None
F3	Computable	Multiply the source by 2	T.t4	T.t5	None
F4	Real-world	Wet-lab experiment	T.t5	S.s1	S.T_fk = T.T_pk
F5	computable	Sum the sources	S.s1, S.s2	S.s3	None
F6 (in Op# 7)	Real-world	Wet-lab experiment	S.s1	S.s3	None

(b) Dependencies details

Op.#	Operation	Triggering event	Consequence
1	Update cell (t2,r1) from 10 to 4	---	-Update cell (t1,r1) with value 3 -Invalidate cell (t4,r1) -Invalidate cell (t5, r1) -Invalidate cell (s1,r1) -Invalidate cell (s3,r1)
2	Update cell (t4,r1) from 6 to 13	Activity *F2* is conducted using the current values of cells (t2,r1) and (t3,r1). The output value is 13	-Validate cell (t4, r1) -Update cell (t5,r1) with value 26 -Validate cell (t5,r1)
3	Update cell (s2,r1) from 80 to 20	---	-Update cell (s3,r1) with value 90
4	Insert into T tuple r3	---	---
5	Update cell (t3,r3) from 4 to 8	---	-Invalidate cell (t4,r3) -Invalidate cell (t5, r3)
6	Insert into S tuple r3	---	-Invalidate cell (s1,r3) -Invalidate cell (s3,r3)
7	Alter Table S Add Dependency Using F6 Source S.s1 Destination S.s3 Invalidate destination;	The derivation mechanism of Column S.s3 is modified.	-For each database cell c in S.s3 -Invalidate (c) -For each database cell c in S.s3 -The new dependency overrides the old one

Database state after the operation

Op. 1

	T_pk	t1	t2	t3	t4	t5
r1	1	3	4	5	6	12
r2	2	1	2	7	4	8

	S_pk	s1	s2	s3	T_fk
r1	100	70	80	150	1
r2	200	30	40	70	2

Op. 2

	T_pk	t1	t2	t3	t4	t5
r1	1	3	4	5	13	26
r2	2	1	2	7	4	8

	S_pk	s1	s2	s3	T_fk
r1	100	70	80	150	1
r2	200	30	40	70	2

Op. 3

	T_pk	t1	t2	t3	t4	t5
r1	1	3	4	5	13	26
r2	2	1	2	7	4	8

	S_pk	s1	s2	s3	T_fk
r1	100	70	20	90	1
r2	200	30	40	70	2

Op. 4

	T_pk	t1	t2	t3	t4	t5
r1	1	3	4	5	13	26
r2	2	1	2	7	4	8
r3	3	8	9	4	7	14

	S_pk	s1	s2	s3	T_fk
r1	100	70	20	90	1
r2	200	30	40	70	2

Op. 5

	T_pk	t1	t2	t3	t4	t5
r1	1	3	4	5	13	26
r2	2	1	2	7	4	8
r3	3	8	9	8	7	14

	S_pk	s1	s2	s3	T_fk
r1	100	70	20	90	1
r2	200	30	40	70	2

Op. 6

	T_pk	t1	t2	t3	t4	t5
r1	1	3	4	5	13	26
r2	2	1	2	7	4	8
r3	3	8	9	8	7	14

	S_pk	s1	s2	s3	T_fk
r1	100	70	20	90	1
r2	200	30	40	70	2
r3	300	3	13	16	3

Op. 7 (F6)

	T_pk	t1	t2	t3	t4	t5
r1	1	3	4	5	13	26
r2	2	1	2	7	4	8
r3	3	8	9	8	7	14

	S_pk	s1	s2	s3	T_fk
r1	100	70	20	90	1
r2	200	30	40	70	2
r3	300	3	13	16	3

(c) Sequence of database operations and their effect on the database (dark cells represent invalid values)

Fig. 4. Examples of database operations under a set of user-defined dependencies.

- **insert(t):** One of the restrictions on the *Add Dependency* construct is that the destination table has to contain foreign keys that reference the primary keys in the source tables (Refer to Section 3). This restriction ensures the uniqueness of the source table cells for a given destination table cell. It also simplifies the insertion procedure since it ensures that at the insertion time of t, there cannot be destination parameters in the database that depend on t. The default action is to insert t into the database with all its values up-to-date and no further processing is needed. The only exception is when the values of t are destination parameters to some existing dependencies. In this case, for each database cell c in t, if any of the *InputParameters(c)* is invalid, then c is invalidated. For example, Operation 4 in Figure 4 inserts a new tuple *T.r3* with all its values up-to-date. In contrast, Operation 6 inserts tuple *S.r3* (which references tuple *T.r3*) and invalidates the value in (s1,r3) because this value is inferred from (t5,r3), which is currently invalid.

Other operations that may affect the status of the database items are adding and dropping dependencies. When a new dependency, say DI, is added to the database, we need to address two issues: (1) whether or not DI will form a cycle with other existing dependencies, and (2) whether or not DI will override other existing dependencies.

A cycle among a set of user-defined dependencies indicates that the derivations among the destination and source parameters of these dependencies may loop indefinitely. Cycles are not allowed in *HandsOn DB* according to the following definitions— Recall that $DI.DP$ and $DI.SP$ correspond to the destination and source parameters of dependency DI, respectively.

Definition **(Cycle Formation):** *Dependency instances* DI_1, DI_2, ..., DI_n *form a cycle if* $DI_i.DP \cap DI_{i+1}.SP \neq \phi$, *for* $1 \leq i < n$, *and* $DI_n.DP \cap DI_1.SP \neq \phi$.

Property **(Cycle-Free Dependency Graph):** *A newly defined dependency instance* DI_i *is rejected by the system if* $\exists$ *dependency instances* DI_j, DI_k, ..., DI_n $\mid$ $DI_i \cup DI_j$, DI_k, ..., DI_n *form a cycle.*

The algorithm for detecting and preventing cycles among the dependencies is discussed in Section 6.1.

Since the derivations among the data items may change over time, the user-defined dependencies may change over time as well, i.e., new dependencies may *override* other existing dependencies. For example, if a database cell c is a destination parameter to dependency DI_j and a new dependency DI_i is defined where c is its destination parameter, then DI_i overrides DI_j w.r.t. c. Now c is being derived according to DI_i instead of DI_j. Dependencies DI_i and DI_j may or may not be of the same type (real-world or computable). The overriding property is defined as follows:

Definition **(Dependency Overriding)** *Dependency instance DI_i is said to override dependency instance DI_j w.r.t destination parameters $DP' \neq \phi$ if $DI_i.DP \cap DI_j.DP = DP'$ and DI_i is defined (chronologically) after DI_j.*

The dependency overriding mechanism creates flexibility in the system by allowing derivations of values to change over time while making sure that any database cell c can be a destination parameter to at most one dependency instance at any given time. Hence, there is exactly one way to derive or infer c (if any). This guarantees the deterministic behavior of *HandsOn DB*, otherwise the system cannot determine which function derives a given value.

- **Adding/Dropping dependencies:** A new dependency is added to the database using either the extended *Create Table* or *Alter Table* commands (See Section 3). If an added (or dropped) dependency is defined using the *Alter Table* command including the optional *Invalidate Destination* clause, then the destination table cells that satisfy the dependency predicates are invalidated. Otherwise, the destination table cells remain valid. Newly added dependencies may override existing ones. For example, Operation 7 in Figure 4 defines a new dependency indicating that the values in column $S.s3$ are new derived from the RWA-F *F6* instead of the computable dependency involving *F5*. The overriding mechanism is described in detail in Section 6.1.

5 Extended Querying Mechanism

Initially, all values in *HandsOn DB* have a *valid* status. However, as users perform database updates, parts of the underlying database will become *potentially invalid* (under re-evaluation). Thus, it is crucial for end-users to get alerted when their queries touch or depend on potentially invalid values. In this section, we introduce extended semantics for the query operators to annotate the query results with the status information and to enable evaluating queries on either valid data only (avoid getting false positive tuples), or both valid and potentially invalid data (include false positive tuples).

5.1 Predicate Evaluation

A predicate evaluation over a tuple typically results in a boolean value True or False. With the status of each value in the database being up-to-date or outdated, we extend the predicate evaluation to return one of four possible values (4-valued logic): True (T), False (F), Potentially false positive (+ve), and Potentially false negative (-ve). The value *True* indicates that the tuple qualifies the predicate based on only up-to-date values, and hence, the tuple is certainly part of the answer (e.g., the 2^{nd} tuple

OID	Attr-1	Attr-2	…	Attr-N
1	a1	b1	…	v1
2	a2	b2	…	v2
3	a3	b3	…	v2
4	a4	b4	…	v4
5	A5	b5	…	v5
6	a3	b6	…	v7

(a) Example of Database Instance.
*Black-marked values are potentially-invalid.

Predicate 1	Predicate 2
Attr-N = "v2"	Attr-N = "v2" AND Attr-1= "a3"
F	F
T	-ve
+ve	+ve
F	F
-ve	F
F	F

(b) Predicate Evaluation.

Fig. 5. Examples of predicate evaluation.

against Predicate1 in Figure 5). The value *False* indicates that the tuple disqualifies the predicate based on only up-to-date values, and hence, the tuple is certainly not part of the answer (e.g., the 1^{st} tuple against Predicate1 in Figure 5). The value *Potentially false positive* indicates that the tuple qualifies the predicate but based on outdated values, and hence, the tuple is potentially a false positive (e.g., the 3^{rd} tuple against Predicate1 in Figure 5). The value *Potentially false negative* indicates that the tuple disqualifies the predicate based on outdated values, and hence, the tuple is potentially a false negative (e.g., the 5^{th} tuple against Predicate1 in Figure 5). Although it seems easier to set the potentially-invalid values to Null and use the 3-valued logic supported by most DBMSs, i.e., True, False, and IS NULL, the proposed 4-valued logic has several advantages: (1) Columns in the database may be defined as *Not NULL* and hence the Null value may not be allowed in the first place. (2) Null values are known to be problematic to work with as they mandate the use of special functions, e.g., IS NULL or NVL, when comparing values to avoid nondeterministic evaluation. Nevertheless the complexity of manipulating Null values by query operators such as joins and grouping. (3) Under the 3-valued logic, the query operators still need to be extended to differentiate between the user-inserted Null values and the system-generated Null values, otherwise, simple operation like reporting the potentially-invalid values in a given column cannot be performed.

In Figure 6(a), we present the rules for evaluating binary predicates (*Column <op> Column*)— rules for evaluating unary predicates (*Column <op> constant*) are trivial. As an example, a predicate P over Columns c_i and c_j evaluates to *+ve* if the values of c_i and c_j satisfy P while at least one of the two values is outdated. The truth tables for evaluating multiple predicates are presented in Figure 6(b).

5.2 Query Operators

In this section, we present extended semantics for the query operators. Our goal is that the output produced from the query operators should be both semantically meaningful and easily interpretable by end-users. We extended the selection and join operators with three different semantics to enable retrieving tuples that evaluate the predicate(s) to either T, +ve, or -ve. The semantics of the other operators, e.g., duplicate elimination and set operators, have been also extended to take both the status

$$P = \begin{cases} T & \text{if } P(c_i.\text{value}, c_k.\text{value}) = \text{True } \& \ (c_i.\text{status} = 0 \ \& \ c_k.\text{status} = 0) \\ F & \text{if } P(c_i.\text{value}, c_k.\text{value}) = \text{False } \& \ (c_i.\text{status} = 0 \ \& \ c_k.\text{status} = 0) \\ +ve & \text{if } P(c_i.\text{value}, c_k.\text{value}) = \text{True } \& \ (c_i.\text{status} = 1 \ || \ c_k.\text{status} = 1) \\ -ve & \text{if } P(c_i.\text{value}, c_k.\text{value}) = \text{False } \& \ (c_i.\text{status} = 1 \ || \ c_k.\text{status} = 1) \end{cases}$$

*Up-to-date → Status = 0
*Outdated → Status = 1

(a) Binary predicate *P* over columns c_i and c_k

	T	+ve	-ve	F
T	T	+ve	-ve	F
+ve		+ve	-ve	F
-ve			-ve	F
F				F

Conjunction

	T	+ve	-ve	F
T	T	T	T	T
+ve		+ve	+ve	+ve
-ve			-ve	-ve
F				F

Disjunction

T	+ve	-ve	F
F	-ve	+ve	T

Negation

(b) Truth tables for multiple predicates

Fig. 6. Predicate evaluation rules.

and the value of the database items into account while comparing them. The following notations are used in the rest of this section: R and S are relation names, r and s are individual tuples in R and S, respectively, and c_i is a column name. When ambiguous, we use $r.c_i$ to refer to Column c_i in Tuple r.

• ***Selection*:** Tuples that evaluate the selection predicate to *T*, *+ve*, or *-ve* are of interest since they either satisfy or have the potential to satisfy the query. However, returning these tuples altogether from one operator can be very misleading and hard to interpret. In *HandsOn DB*, we define three types of selection operators, namely, *True Selection* (σ_T), *False-positive Selection* (σ_+), and *False-negative Selection* (σ_-), that return tuples that evaluate to each of *T*, *+ve*, or *-ve*, respectively. The algebraic expressions of the selection operators are as follows.

***True Selection*($\sigma_{T,P}$):** Selects tuples that evaluate Predicate P to T.

$$\sigma_{T,P}(R) = \{r =< (c_1.value, c_1.status), ..., (c_n.value, c_n.status) >, \\ |P(r) = T\}$$

***False-positive Selection*($\sigma_{+,P}$):** Selects tuples that evaluate Predicate P to *+ve*.

$$\sigma_{+,P}(R) = \{r =< (c_1.value, c_1.status), ..., (c_n.value, c_n.status) >, \\ |P(r) = +ve\}$$

***False-negative Selection*($\sigma_{-,P}$):** Selects tuples that evaluate Predicate P to *-ve*.

$$\sigma_{-,P}(R) = \{r =< (c_1.value, c_1.status), ..., (c_n.value, c_n.status) >, \\ |P(r) = -ve\}$$

• ***Inner Join*:** The evaluation of a join predicate over a pair of tuples r and s results in one of four possible values, i.e., *T*, *+ve*, *-ve*, or *F*. Join predicates are binary predicates and hence they follow the evaluation rules presented in Figure 6(a). Similar to the *selection* operator, we define three types of join operators, namely, *True Join*, *False-positive Join*, and *False-negative Join*, that return tuples that evaluate to each of the values *T*, *+ve*, *-ve*, respectively. The algebraic expression of the *True Join* operator is as follows.

***True Join*($R \bowtie_{T,P} S$):** Returns the joined tuples r and s that evaluate predicate P to T.

X	Y	Z
a	β	2
a	β	3
a	α	1
b	β	2
b	β	5
b	α	4

Data table

Grouping(X)	COUNT(Z)
a	2
a	1
b	3

(a) Single-column Grouping

Grouping(X,Y)		SUM(Z)
a	β	5
a	α	1
b	β	7
b	α	4

(b) Multiple-column Grouping

* Dark table cells contain outdated values

Fig. 7. Example of grouping and aggregation.

$$R \bowtie_{T,P} S = \{z =< (r_1.value, r_1.status), ..., (s_1.value, s_1.status), \\ ..., (s_m.value, s_m.status) > |P(z) = T\}$$

The algebraic expressions of the *False-positive* ($\bowtie_{+,P}$) and *False-negative* ($\bowtie_{-,P}$) join operators are similar to that of the *True* join operator with the exception of having Join Predicate *P(z)* evaluates to *+ve* and *-ve*, respectively.

• ***Duplicate Elimination* & *Set operations*:** Two tuples are considered identical iff they share the same value and status for all their attributes. More formally, tuples r and s are considered identical w.r.t. Columns c_1, c_2, ..., c_n iff: $(r.c_i.value = s.c_i.value \ and \ r.c_i.status = s.c_i.status) \ \forall \ i \in \{1, 2, ..., n\}$. Duplicate elimination and set operators, i.e., union, intersect, and except, are extended based on this semantics. Note that it is possible that two identical and invalid tuples may be invalid for different reasons. However, since no extra information, e.g., the reason of invalidation, is carried out with these tuples in the output, then reporting all of the instances to users can be very confusing and unjustified. Instead, we opt to implement the standard semantics and report only one instance of such identical tuples. In Section 5.3, we will present a set of curation operators that enable users to track the reasons of tuples' invalidations and report their dependencies.

• ***Grouping*($\gamma(R)$):** Consistent with the semantics of identical tuples, tuples that have the same values and status in the grouping columns are added to the same group. Therefore, two identical values with different status will form two different groups with different status as well. For example, the grouping over column X in Figure 7(a) results in producing two groups for value a; one up-to-date and one outdated.

• ***Aggregation*($\eta(R)$):** An aggregate function, e.g., SUM, AVG, COUNT, aggregates a set of up-to-date and outdated values and returns a single value. The question is: What will the status of the returned value be? We categorize the aggregate functions into two categories, *value-insensitive* and *value-sensitive* aggregators. A value-insensitive aggregator, e.g., COUNT, always returns a value with an up-to-date status. The reason is that the result from a value-insensitive aggregator does not depend on the actual values in the aggregated set. For example, the group corresponding to value b in Figure 7(a) has *count(Z)* equals 3 with up-to-date status although one of the values are outdated. In contrast, a value-sensitive aggregator, e.g., SUM, AVG, MIN, or MAX, returns a value with an up-to-date status only if all the values in the aggregated set are up-to-date, otherwise the returned value will have an outdated status. For example, the group corresponding to the pair (b, β) in Figure 7(b) has *sum(Z)* equals 7 with outdated status since the sum depends on the outdated value 5.

We extend the SQL *select* statement to include the newly proposed operators. A comparison operator may be suffixed with '+', or '-' to indicate a *false-positive* or *false-negative* evaluation, respectively.

Example: Consider the following extended query:

```
Select GSeq, PSeq From GENE G, PROTEIN P
 Where G.GID =+ P.GID And GFunction =- 'F2';
```

where =+, and =- correspond to *false-positive* and *false-negative* equality operators, respectively. The query is equivalent to the algebraic expression: $\pi_{GSeq,PSeq}(\sigma_{-,GFunction='F2'}(GENE \bowtie_{+,G.GID=P.GID} PROTEIN))$.

5.3 Curation Operators

HandsOn DB provides a set of curation operators that help users managing and tracing the dependencies among the data. The query and curation operators are complementary to each other where the former operators allow users to seamlessly query the data, the latter operators allow users to track why certain tuples/values are invalid and how to validate them. In this section, we present three of these curation operators, i.e., dependency tracking (*DTrack*), hierarchical dependency tracking (*HDTrack*), and dependency roots (*DRoots*). All the operators execute over the output from an SQL *select* statement as depicted below.

```
[DTrack | HDTrack | DRoots] (
        Select *
        From <table name>
        Where <predicates> );
```

For each output tuple *t* from the select statement, the *DTrack* operator reports for each attribute value *v* in *t*, the status of *v*, the dependency id to which *v* is a destination, and the source table cells on which *v* depends. *DTrack* starts by retrieving the *c_dependency_id* values stored in *t* and then based on the dependency definitions, it executes a reverse query to retrieve the source table cells. The *HDTrack* operator executes in a similar way as *DTrack* except that it reports the complete hierarchy of dependencies until it reaches values with no further dependencies, i.e., *HDTrack* recursively executes *DTrack* until no further dependencies can be found. Both *DTrack* and *HDTrack* help users to trace the dependencies upward in order to re-validate certain values. *DRoots*, on the other hand, reports all invalid values within the selected tuples that depend only on all up-to-date values—and hence they are the ones to start re-validating (the roots). To find the roots in a given set of tuples, *DRoots* scans the *Pending Activity* table (Refer to Section 6.2) for records with pending status and no compensating counterparts. The destination table cells in these records are the set of roots in the database which will then be filtered based on the user's selection.

6 Design Issues

Since the dependency graph may grow massively, materializing and storing it inside the database may involve unnecessary and substantial overhead. Therefore, *HandsOn DB* utilizes the powerful triggering mechanism in database systems by dynamically generating triggers that enforce the user-defined dependencies and propagate the (in)validation operations accordingly (Section 6.1). The maintenance of the real-world activities pending execution is presented in Section 6.2.

Storage Scheme: For each dependency, we store in catalog tables the dependency definition, the names of the source and destination tables and columns, the type of the dependency as either *computable* or *real-world*, and a unique identifier (dependency_id) that is assigned to the dependency at the creation time (See the *Add Dependency* construct in Section 3). For each table cell c, in addition to c's value, we keep two additional system-maintained fields *c_status* and *c_dependency_id*, where *c_status* indicates whether c is up-to-date (*status* = 0) or outdated (*status* = 1), and *c_dependency_id* stores the id of the most recent dependency to which c is a destination parameter (if dependency_id is *null*, then c does not depend on other values in the database). When a new dependency having dependency_id, say v_i, is added to the database, all destination table cells belonging to this dependency will have their dependency_id field updated to v_i.

6.1 Realization of Dependencies using Triggers

When a new dependency is added to the database, the system extracts the predicates from the *Add Dependency* construct and automatically generates triggers that enforce the dependency. The processing of a given *Add Dependency* construct involves four steps: (1) detecting whether or not the new dependency forms a cycle with the already existing dependencies, (2) assigning a unique id v_i to the dependency, (3) generating a set of triggers over the source and destination tables to enforce the dependency, and (4) overriding other existing dependencies by modifying the *dependency_id* field of the destination parameters of the new dependency to v_i. Regarding the scalability of the triggering mechanism, we experimented with few thousands of triggers in PostgreSQL over 5 to 10 tables and did not observe any bottleneck due to the number of triggers. Yet, one simple approach to even scale better is to merge multiple triggers together — This is straightforward since triggers are automatically generated by the system. Another approach is to consider more advanced indexing techniques for triggers as proposed in [36].

Formation of cycles: Testing the formation of a cycle among the user-defined dependencies can be very expensive if performed at the cell level. *HandsOn DB*, therefore, detects cycles in two phases; *filter* (column_level test) and *refine* (cell_level test). The intuition is that if no dependency is found between columns $T.c_i$ and $T.c_j$, then there is no need to check the values in these columns (the filter phase). If a dependency is found between $T.c_i$ and

$T.c_j$, then we need to perform the more-expensive step and check which exact table cells have the dependencies (the refine phase). In the filter phase, we maintain a *precedence graph* among the database columns, where an edge is added from column $T.c_i$ to column $S.c_j$ if $T.c_i$ and $S.c_j$ are source and destination columns in a given dependency, respectively. If the new dependency will not form a cycle in the *precedence graph*, then the dependency is added to the database. Otherwise, we move to the more-expensive refine phase in which we check whether the candidate cycle at the column level forms a real cycle at the cell level. In the refine phase, we form a temporary table, say $Temp_i(Src,\ Dest)$, for each dependency, say D_i, involved in the column-level cycle. $Temp_i$ contains the tuple ids of the source and destination table cells for dependency D_i (temporary tables can be expressed as queries without materializing them). The temporary tables are then joined so that $Temp_i.Dest = Temp_{i+1}.Src$, where $1 \leq i \leq n-1$, and $Temp_n.Dest = Temp_1.Src$ (assuming the column-level cycle is of length n). If the query returns any results, then there exists a cell-level cycle, and the new dependency is rejected. Otherwise, the new dependency is added to the database. Notice that if the new dependency passes the refine phase, then any insertions or updates to the base tables involved in the column-level cycle need to be checked to ensure that they will not form a cycle in the future. This check is not expensive since it will be performed only for the newly inserted or updated tuple.

In principle, given a new dependency definition, *HandsOn DB* creates automatically several triggers to enforce the dependency and to propagate the status to dependent values. In Figures 8(a) and (b), we present the *After Update* code templates for *real-world*, and *computable* dependencies, respectively. Consider the template in Figure 8(a). The trigger fires when an update occurs to a tuple, say t, in Table T_i. Column c_i is the source column in the dependency. Lines 1 and 2 retrieve the source and destination table cells involved in the dependency. If the *dependency_id* value of the destination table cell does not match with the id value assigned to the dependency when defined (v_i), then the trigger terminates because the destination cell is no longer a destination parameter to this dependency (Lines 3-5). Lines 7-11 handle the case when the value of c_i is updated while its status remains the same. If the status of c_i as well as all other source parameters of the dependency are up-to-date, then a request record is inserted into the *PendingActivity* table (See Section 6.2) to indicate that the involved real-world activity should be performed based on the new value of c_i (Line 9). In Line 11, the destination table cell of the dependency is marked *outdated*. The *PendingActivity* table is maintained and populated automatically to help users identify which *real-world* activities are ready for execution as will be presented in Section 6.2. Lines 12-15 handle the case when the value is updated and the status is modified from *outdated* to *up-to-date*. In this case, a request record is inserted into *PendingActivity* only if all other source cells are up-to-date (Line 14). Notice that *dest_cell* remains outdated until the real-world activity is performed.

```
1  src_list = the set of all source cells involved in the dependency other than Ti.ci;
2  dest_cell = the destination cell of the dependency;
3  IF (dest_cell.dependency_id ≠ vi) THEN
4      Return;
5  END IF;
6  IF ((dest_cell != null) and (ci.old != ci.new)) THEN
7      IF (ci_Status.old = ci_Status.new = "up-to-date") THEN
8          IF (status of all cells in src_list is "up-to-date") THEN
9              -- Insert a pending record into PendingActivity to request an
                      execution of function F using src_list and Ti.ci as inputs;
10         END IF
11         -- Update the status of dest_cell to "outdated";
12     ELSE IF (ci_Status.old = "outdated" and ci_Status.new = "up-to-date") THEN
13         IF (status of all cells in src_list is "up-to-date") THEN
14             -- Insert a pending record into PendingActivity to a request an
                      execution of function F using src_list and Ti.ci as inputs;
15         END IF
16     END IF
17 ELSE IF ((dest_cell != null) and (ci_Status.old != ci_Status.new)) THEN
18     IF (ci_Status.old = "up-to-date" and ci_Status.new = "outdated") THEN
19         IF (dest_cell.status = "outdated") THEN
20             IF (status of all cells in src_list is "up-to-date") THEN
21                 -- Insert a compensating record into PendingActivity
22             END IF;
23         ELSE
24             -- Update the status of dest_cell to "outdated";
25         END IF;
26     ELSE IF (ci_Status.old = "outdated" and ci_Status.new = "up-to-date") THEN
27         IF (status of all cells in src_list is "up-to-date") THEN
28             -- Insert a pending record into PendingActivity to request an
                      execution of function F using src_list and Ti.ci as inputs;
29         END IF
30     END IF
31 END IF
```

(a) Template for *real-world activity* function *F* over source column $T_i.c_i$

```
1  src_list = the set of all source cells involved in the dependency other than Ti.ci;
2  dest_cell = the destination cell of the dependency ;
3  IF (dest_cell.dependency_id ≠ vi) THEN
4      Return;
5  END IF;
6  IF ((dest_cell != null) and (ci.old != ci.new)) THEN
7      Call function F using src_list and Ti.ci as inputs to update dest_cell.value;
8      IF (status of all cells in src_list is "up-to-date") THEN
9          -- Update the status of dest_cell to "up-to-date";
10     END IF
11 ELSE IF ((dest_cell != null) and (ci_Status.old != ci_Status.new)) THEN
12     IF (ci_Status.old = "up-to-date" and ci_Status.new = "outdated") THEN
13         -- Update the status of dest_cell to "outdated";
14     ELSE IF (status of all cells in src_list is "up-to-date") THEN
15         -- Update the status of dest_cell to "up-to-date";
16     END IF
17 END IF
```

(b) Template for *computable* function *F* over source column $T_i.c_i$

Fig. 8. Templates for *Add Dependency* constructs.

The second part of the template (Lines 17-31) handles a change in the status of c_i without changing its value. In the case when the status of c_i is modified from *up-to-date* to *outdated*, *dest_cell* is marked *outdated* if it is currently up-to-date (Line 24). However, if *dest_cell* is currently outdated and all the other source table cells are up-to-date, then a previous request must have been inserted into *PendingActivity* to validate *dest_cell*. This request can no longer validate *dest_cell* because c_i is now invalid. For this reason, we insert a *compensating* record (Line 21) into *PendingActivity* to prevent the previous request from validating *dest_cell* as will be discussed in Section 6.2. In the case when the status of c_i is modified from *outdated* to *up-to-date*, then a request record is inserted into *PendingActivity* only if all other source cells are up-to-date (Line 28).

The *computable-function* template in Figure 8(b) is a simplified version of that in Figure 8(a). An important difference to note is that since the function involved in the dependency is computable, the trigger executes this function automatically to update *dest_cell* whenever the

```
1  IF (the request status is "completed", "overwritten", or "compensating") THEN
2      Return;
3  END IF;

4  IF (there exist previous pending requests for the same destination table cell) THEN
5      IF (cascade flag is False) THEN
6          Return;
7      ELSE
8          update the status of these previous requests to "overwritten";
9      END IF;
10 END IF;

11 IF (there exist more recent requests for the same destination cell) THEN
12     update the value of the destination table cell without validating it;
13 ELSE
14     update the value of the destination table cell and mark it as "up-to-date";
15 END IF;

16 Update the status of the request to "completed";
```

Fig. 9. Processing the *PendingActivity* records.

value of c_i is modified (Line 7). Another key difference is that whenever all the source parameters become up-to-date, the destination parameter is automatically marked as up-to-date (Lines 9, 15). This is unlike the case of the real-world dependencies in which a request record is inserted into *PendingActivity*.

6.2 Logging and Resuming Pending Activities

When a real-world activity function F has all its source parameters up-to-date but its destination parameter outdated, a request record (of type *pending*) for F is inserted into the *PendingActivity* table (Lines 9, 14, and 28 in Figure 8(a)). Before serving that request, i.e., executing F and reflecting its output value into the database, the source parameters of F may change again, or may get invalidated. In the former case, more *pending* requests for executing F are inserted into *PendingActivity*. Users have the option to either serve these requests sequentially or serve only the last request (See the *Resume Function* command below). In the latter case, a *compensating* record is inserted into *PendingActivity* (Line 21 in Figure 8(a)) to indicate that any previous pending requests for executing F can still be served to update the value of the destination table cell but without validating it.

The schema of the *PendingActivity* table consists of: a unique request id, the function name F to be externally executed, the input arguments to F, an update statement that updates the destination table cell once the new results from F are known, and a status field that shows the status of the request. The status field takes one of the following values: *pending*, *completed*, *overwritten*, or *compensating*. When F is performed and its output result is available, the result is passed to the system using the following command:

```
Resume Function <func_name> Value <func_output>
  References <RequestId> [Cascade];
```

where $RequestId$ references the unique request id that is assigned to each request in *PendingActivity*. The procedure for executing the *Resume Function* command is presented in Figure 9. If the request has a status of either *completed*, *overwritten*, or *compensating*, then the procedure terminates without further processing (Lines 1-3). If there are previous pending requests targeting the same destination table cell and the optional *Cascade* keyword is not specified, then the procedure terminates because, in this case, requests have to be served in order (Line 6). If *Cascade* is included, then any previous pending requests are marked as *overwritten* and the current request is served (Line 8). Lines 12 and 14 update the value of the destination table cell, and depending on whether or not there are requests more recent than the one currently at hand, the destination table cell either remains invalid (Line 12) or gets validated (Line 14).

7 Performance Analysis

We implemented *HandsOn DB* via extensions to PostgreSQL that include: (1) adding new SQL syntax for creating the real-world activity functions and modeling the dependencies, (2) adding new data manipulation operations, i.e., *invalidate()* and *validate()*, (3) augmenting mechanisms for automatically creating (or deleting) triggers when dependencies are added (or deleted), (4) introducing new query operators in PostgreSQL with the semantics presented in Section 5, and (5) adding the *Resume Function()* command for resuming pending activities. In this section, we study the overheads associated with these extensions and demonstrate the feasibility and practicality of *HandsOn DB*.

***Datasets*:** We use three datasets: *Genobase*, a real biological database of size approximately 40MB, *PubChem-substance*, a real chemical database of size approximately 300MB, and a synthetic dataset of size approximately 450MB. *Genobase* stores the gene details of the Ecoli organism along with different mutation types. *PubChem-substance* stores information about chemical substances, e.g., substance_ids, sources, synonyms, compounds, and atoms. The synthetic dataset is designed primarily to stress on the cascading effect of the dependencies as will be explained later. It consists of 10 tables, i.e., R_1, ..., R_{10}. Each table consists of ten attributes, i.e., c_1, c_2, ..., c_{10}, in addition to the primary and foreign keys. Each table R_{i+1} contains two foreign keys that point to the primary keys of tables R_i and R_{i-1}.

***Storage*:** In Figure 10, we study the storage overhead imposed from adding the *status* (one bit) and *dependency_id* (two-bytes integer) columns for each database column. The figure illustrates that the storage overhead ranges from 2% to 7% of the database size. As expected, the storage overhead is relatively insignificant. The reason is that scientific databases typically store many large-size attributes such as text and sequence fields that dominate the storage overhead. *PubChem-substance* shows the highest storage overhead because the average length of its attributes is smaller than those of the other two databases.

***Adding Dependency*:** In Figure 11, we study the average time needed for adding a new dependency. This time involves detecting whether or not a cycle exists, and creating the required triggers. In this experiment, we vary the number of generated dependencies from 2^5 to 2^{11} (the X-axis) distributed over 5 tables with an average cascading length of 2. One half of the generated dependencies has a single source table while the other half

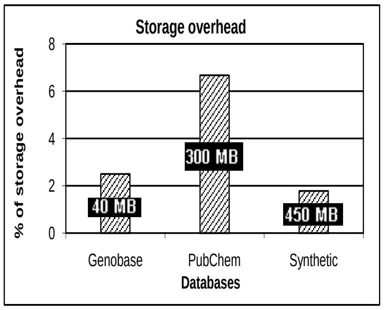


Fig. 10. Storage overhead

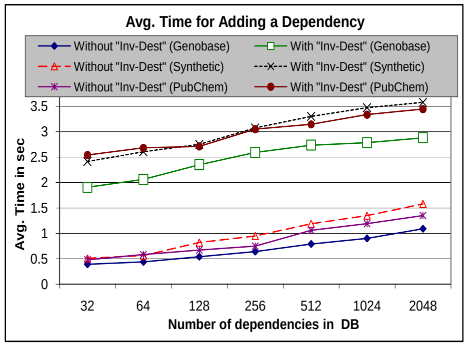


Fig. 11. Adding dependency

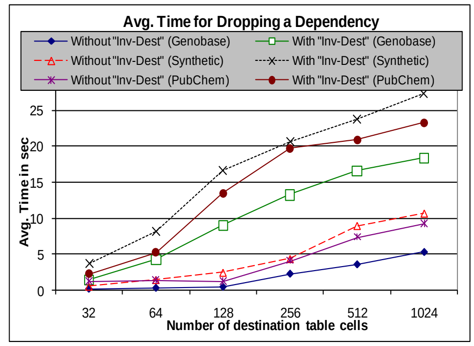


Fig. 12. Dropping dependency

has two source tables. To create multiple non-overlapping dependencies over a single destination attribute, we divide this attribute into disjoint subsets and assume that each subset is inferred or computed using a different function. In the experiment, we study the two cases where the newly defined dependency either invalidates the destination table cells (labeled as 'With Inv-Dest') or keeps them as valid (labeled as 'Without Inv-Dest'). Figure 11 illustrates that the size of the database does not significantly affect the execution time. The reason is that the time taken to detect whether or not a cycle exists and to create the required triggers is not influenced much by the size of the underlying database. Also, the figure illustrates that the average time taken in the case of invalidating the destination table cells is higher than that where the destination table cells are kept valid. The reason is that invalidating the destination table cells will propagate this invalidation to all dependent data items which may span multiple tables.

***Dropping Dependency*:** In Figure 12, we measure the average time required for dropping a dependency. In this experiment, we vary the number of destination table cells that belong to the dropped dependency from 2^5 to 2^{10} (the X-axis) and measure the required time under the cases where the destination cells are either invalidated (labeled as 'With Inv-Dest') or validated (labeled as 'Without Inv-Dest'). The measured performance depends on the initial status of the database cells, e.g., invalidating table cells that are already invalid is less expensive than invalidating up-to-date cells, and the same applies for validation. Therefore, we compute each point in the figure as the average over five runs each with a different percentage of the outdated values in the destination column, i.e., {0%, 5%, 10%, 15%, 20%}. Figure 12 illustrates that dropping a dependency can be an expensive operation especially when invalidating a large number of destination table cells. The overhead associated with invalidating the destination parameters of the dropped dependency is around three or four times higher than that associated with validating the destination parameters. The reason for this difference is that most of the data items in the database are already valid, and hence the validation procedure is not as expensive as the invalidation procedure. In general, dropping a dependency is expected to be an infrequent operation especially when the number of associated destination table cells is large. Otherwise, the overhead involved in re-verifying and re-validating these destination table cells would probably dominate the overhead of the *Drop Dependency* operation.

***Manipulation Operations*:** The performance of the data manipulation operations is presented in Figure 13. In this experiment, we use only the synthetic database that is designed primarily to enable creating long cascading paths among the database tables. Each of the ten tables contains a number of tuples that varies from 1,000 to 50,000. Each table R_i contains the following dependency types among its attributes: (1) computable dependency from c_1 to c_2, (2) real-world dependency from c_2 and c_3 to c_4, and (3) computable dependency from c_4 to c_5. Each defined dependency targets a small subset of the destination column, and hence multiple dependencies can be defined over the destination column without overriding each other. The database contains also cross-table dependencies defined as follows: (1) computable dependency from $R_i.c_5$ to $R_{i+1}.c_1$, and (2) real-world dependency from $R_i.c_2$ to $R_{i+1}.c_7$. Using this database design, the length of a cascading path varies from 0 to 40 operations. In Figure 13, we study the average time needed to perform each of the *update*, *invalidate*, *validate*, or *Resume Function* operations. For the first three operations, each measurement represents the average over 50 randomly-selected table cells (five from each table). The figure illustrates that the *update* operation involves the highest cost. The reason is that the update procedure performs extra processing (including calling the user-defined functions involved in the computable dependencies) regardless of whether the updated table cell is up-to-date or outdated. This is unlike the invalidate and validate procedures that may take no actions if the table cell is already invalid or valid, respectively. The cost of the *invalidate* operation is less than that of the *update* operation because if the invalidated table cell is already outdated, then the procedure terminates without any further processing. Otherwise, it involves the cost of invalidating all dependent data items.

***Query Operators*:** With respect to data querying, we define extended semantics for the comparison operators, e.g., =, =+, and =-, correspond to the true, false-positive, and false-negative evaluation of the equality operators, respectively. Other operators, e.g., >, <, and <>, are extended in the same way. Queries that involve the extend

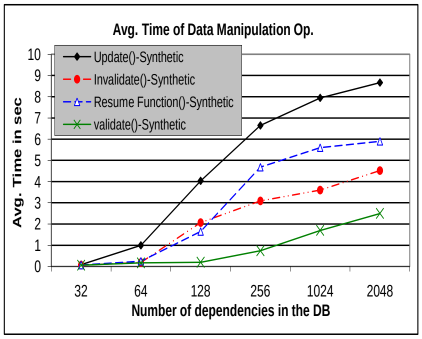


Fig. 13. Manipulation operation

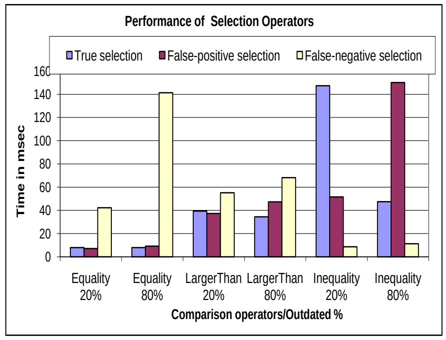


Fig. 14. Selection performance

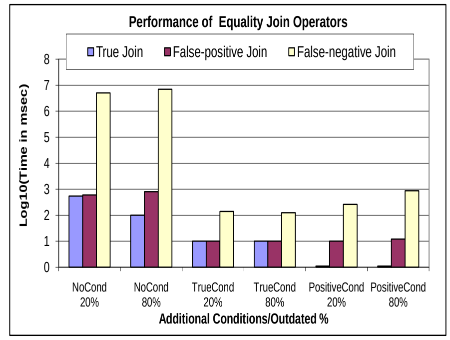


Fig. 15. Join performance

operators are re-written using the standard operators according to the re-writing rules presented in Figure 16.

In Figure 14, we study the performance of the three types of selection operators over a table consisting of 50,000 tuples from the synthetic database. The select statement is in the form of `Select * From R Where R.a OP <const>`, where *OP* is one of the extended selection operators. The values in the selection column *R.a* have a duplication factor that varies uniformly over the range from 1 to 10. Since the performance of the selection operators depends on the percentage of the outdated values in $R.a$, we run each experiment over two different percentages of the outdated values, 20% and 80%, as illustrated in Figure 14. We build B+-tree indexes over both the data column involved in the *where* clause, i.e., $R.a$, and $R.a$'s corresponding status column, i.e., $R.a\_status$. In the experiment, we consider three different types of comparison operators: equality, larger than, and inequality. In the case of equality, the *true* and *false-positive* selections have relatively lower overhead (compared to *false-negative*) because they make use of the index on the value columns to find the matching values. The *false-negative* operator utilizes the index on the status field (in the case of 20% outdated values), but performs a full-scan (in the case of 80% outdated values) which explains the difference in the execution time illustrated in Figure 14. The inequality comparison has the inverse behavior of the equality comparison.

With respect to joins, we focus on studying the performance of the three types of equality joins as depicted in Figure 15. We use two relations *R* and *S* from the synthetic database, each consisting of 50,000 tuples. The Select statement is in the form of `Select * From R, S Where R.a OP S.b And <ExtraCond>`, where *OP* is one of the extended equality join operators. The values in the join attributes *R.a* and *S.b* are randomly generated over the range from 1 to 10,000 with a duplication factor that varies uniformly over the range from 1 to 10. Both columns and their corresponding status attributes have B+-tree indexes. In Figure 15, we consider three different scenarios that trigger different query plans: (1) the scenario where there are no extra conditions in the select statement, called *NoCond*, (2) the scenario where there is a *true* equality selection condition on *R.a*, called *TrueCond*, and (3) the scenario where there is a *false-positive* equality selection condition on *R.a*, called *PositiveCond*. Each scenario is evaluated under 20% and 80% percentages of outdated values in the joined columns, i.e., *R.a* and *S.b*. The Y-axis in the figure is a logarithmic scale.

	Extended operator	Re-writing rule
Unary operators	R.a = <*constant*>	R.a = <*constant*> and R.a_status = 0
	R.a =+ <*constant*>	R.a = <*constant*> and R.a_status = 1
	R.a =- <*constant*>	R.a <> <*constant*> and R.a_status = 1
Binary operators	R.a = S.b	R.a = S.b and (R.a_status = 0 and S.b_status = 0)
	R.a =+ S.b	R.a = S.b and (R.a_status = 1 or S.b_status = 1)
	R.a =- S.b	R.a <> S.b and (R.a_status = 1 or S.b_status = 1)

∗Other comparison operators, e.g., '>', '<', '<>', have similar rules

Fig. 16. Re-writing rules of the extended operators

In the case where the query includes only the join condition (*NoCond* case), the *true* and *false-positive* join operators use a hash-based join algorithm since the join condition is an equality between *R.a* and *S.b*. The *true* join has less execution time in the case where the outdated percentage is 80% because the query optimizer uses the index on the *status* column to retrieve only the 20% up-to-date values that can contribute to the join. In contrast, the *false-negative* join operator uses a nested-loops join and that is why it involves high overhead. In the case where the query includes a *true* equality selection on *R.a*(*TrueCond*), the values from *R.a* that satisfy the selection predicate are all up-to-date. Hence, for the *false-positive* and *false-negative* joins, the values from *S.b* column have to be outdated. In this case, the re-written predicates for the *false-positive* and *false-negative* joins will only contain conjunctive predicates. In the case where the query includes a *false-positive* equality selection on *R.a*(*PositiveCond*), the values from *R.a* that satisfy the selection predicate are all outdated. Hence, the result set from the *true* join is always empty because the *true* join requires the joined values to be both up-to-date. This explains the very low overhead involved in this join type.

8 Conclusion

In this paper, we proposed *HandsOn DB* system for supporting dependencies that involve real-world activities while maintaining the consistency of derived data under update and query operations. *HandsOn DB* addresses several challenges that include: (1) keeping track of the potentially invalid data items and reflecting their status in the query results, (2) introducing new semantics for query operators that enable evaluating queries on either valid data only (no false-positives), or both valid and potentially-invalid data (include false-positives), (3) proposing new mechanisms for invalidating, revalidating, and curating the data items, and (4) proposing dynamic techniques through database triggers for enforcing the dependencies without materializing them. We also evaluated experimentally the performance of *HandsOn DB* and demonstrated the feasibility and practicality of its operations.

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Mohamed Eltabakh is a professor of computer science at Worcester Polytechnic Institute (WPI). His research interest is in the broad area of Database Management Systems and Information Management. In particular, his work is in the areas of query processing and optimization, indexing techniques, scientific data management, and large-scale data analytics. Eltabakh received his Ph.D. degree in Computer Science from Purdue University in May 2010, and he received his MSc. and BSc degrees from Purdue University in May 2005 and Alexandria University, Egypt in May 1999, respectively. Prof. Eltabakh is a member of ACM and IEEE.

Walid Aref is a professor of computer science at Purdue. His research interests are in extending the functionality of database systems in support of emerging applications, e.g., spatial, spatio-temporal, multimedia, biological, and sensor databases. He is also interested in query processing, indexing, data mining, and geographic information systems (GIS). Professor Aref's research has been supported by the National Science Foundation, the National Institute of Health, Purdue Research Foundation, CERIAS, Panasonic, and Microsoft Corp. Professor Aref is a member of Purdue's CERIAS and Discovery Park Cyber Center. He is a senior member of the IEEE, and a member of the ACM.

Ahmed Elmagarmid is the inaugural executive director of the Qatar Computing Research Institute at Qatar Foundation. Before joining Qatar Foundation in 2010, he was founder and director of both the Cyber Center in Discovery Park and the Indiana Center for Database Systems at Purdue University. He was a full professor of computer science at Purdue, where he had been actively involved in teaching and research for 22 years. Early in his career he received the National Science Foundations Presidential Young Investigator award from President Ronald Reagan. The University of Dayton and Ohio State University have both named him among their distinguished alumni. He is an IEEE fellow and an ACM distinguished scientist and is a member of Sigma Xi American Association for the Advancement of Science (AAAS). Dr. Elmagarmid received his B.S. in computer science from the University of Dayton and his M.S. and Ph.D from Ohio State University. He has held faculty positions at Pennsylvania State University, the University of Padova, and Purdue University.

Mourad Ouzzani is a Senior Scientist with the Qatar Computing Research Institute (QCRI), Qatar Foundation. He is interested in research and development related to data management and scientific data and how they enable discovery and innovation in science and engineering. He conducts research in data integration, data quality, spatio temporal data management, and database systems for scientific data. He is the architect of several cyberinfrastructure platforms to support multidisciplinary research. Mourad received the Purdue University Seeds of Success Award in 2010. Mourad received his PhD degree from Virginia Tech and his BS and MS degrees both from USTHB, Algeria.