Data acquisition, extraction, and storage

Provenance in Databases: Principles and Applications

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ÉCOLE NORMALE SUPÉRIEURE | PSL

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Provenance management

- Data management all about query evaluation

Provenance management

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- What if we want something more than the query result?
    - Where does the result come from?
    - Why was this result obtained?
    - How was the result produced?
    - What is the probability of the result?
    - How many times was the result obtained?
    - How would the result change if part of the input data was missing?
    - What is the minimal security clearance I need to see the result?
    - What is the most economical way of obtaining the result?
    - How can a result be explained in layman terms?

Provenance management

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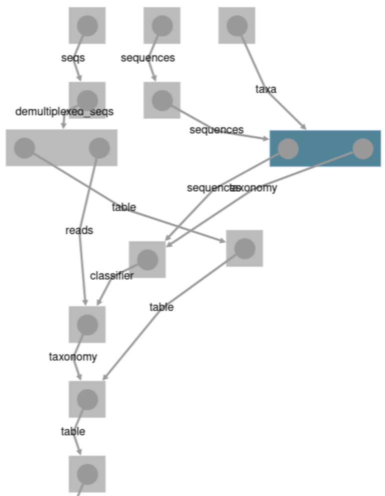
  - How can a result be explained in layman terms?
- Provenance management: along with query evaluation, record additional bookkeeping information allowing to answer the questions above

Workflow provenance vs fine-grained provenance

qiime2view File: l6-ancom-subject.qzv Visualization Details Provenance

Provenance Graph Citations



Action Details

▾ execution:
uuid: "ecd33371-3fef-4a8e-b462-9ef2ab7294be"
▾ runtime:
start: 2021-04-21T17:31:07.414Z
end: 2021-04-21T17:32:22.665Z
duration: "1 minute, 15 seconds, and 250599 microseconds"
▾ action:
type: "method"
plugin: "environment:plugins:rescript"
action: "dereplicate"
▾ inputs:
▾ 0:
sequences: "b00dd907-5ae2-4e86-ab91-e8911889ac06"
▾ 1:
taxa: "6d0c1726-2a4c-4bdc-a23d-9334f813bbfd"
▾ parameters:
▾ 0:
mode: "uniq"
▾ 1:
perc_identity: 1
▾ 2:
threads: 1
▾ 3:
rank_handles: "greengenes"
▾ 4:
derep_prefix: false
output-name: "dereplicated_sequences"
▾ citations:
0: "action|rescript:2021.4.0.dev0+6.g073ccf0|method:dereplicate|0"

Workflow provenance vs fine-grained provenance

Workflow provenance

[Davidson et al., 2007]

- Uniquely identifies datasets used and produced
- Documents every action carried out (date, tool, version, parameters, inputs, outputs, etc.)
- Typically has a simple directed graph structure

Workflow provenance vs fine-grained provenance

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[Davidson et al., 2007]

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- Documents every action carried out (date, tool, version, parameters, inputs, outputs, etc.)
- Typically has a simple directed graph structure

Data (fine-grained) provenance

[Buneman et al., 2001]

- At the level of a single data item (a record, a data value, a node in a graph, etc.)
- Documents how this particular data item was produced
- Possibly a rich mathematical structure
- Support for a limited set of data operations

Outline

Data model

- Relational data model: data decomposed into relations, with labeled attributes. . .

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name	position	city	classification
John	Director	New York	unclassified
Paul	Janitor	New York	restricted
Dave	Analyst	Paris	confidential
Ellen	Field agent	Berlin	secret
Magdalen	Double agent	Paris	top secret
Nancy	HR director	Paris	restricted
Susan	Analyst	Berlin	secret

Data model

- Relational data model: data decomposed into relations, with labeled attributes...
- ... with an extra provenance annotation for each tuple (think of it first as a tuple id)

name	position	city	classification	prov
John	Director	New York	unclassified	t_1
Paul	Janitor	New York	restricted	t_2
Dave	Analyst	Paris	confidential	t_3
Ellen	Field agent	Berlin	secret	t_4
Magdalen	Double agent	Paris	top secret	t_5
Nancy	HR director	Paris	restricted	t_6
Susan	Analyst	Berlin	secret	t_7

Relations and databases

Formally:

- A relational schema $\mathcal{R}$ is a finite sequence of distinct attribute names; the arity of $\mathcal{R}$ is $|\mathcal{R}|$
- A database schema is a mapping from relation names to relational schemas, with finite support
- A tuple over relation schema $\mathcal{R}$ is a mapping from $\mathcal{R}$ to data values; each tuple comes with a provenance annotation
- A relation instance (or relation) over $\mathcal{R}$ is a finite set of tuples over $\mathcal{R}$
- A database instance (or database) over database schema $\mathcal{D}$ is a mapping from the support of $\mathcal{D}$ mapping each relation name R to a relation instance over $\mathcal{D}(R)$

Queries

- A query is an arbitrary function that maps databases over a fixed database schema $\mathcal{D}$ to relations over some relational schema $\mathcal{R}$
- The query does not consider or produce any provenance annotations; we will give semantics for the provenance annotations of the output, based on that of the input
- In practice, one often restricts to specific query languages:
  - Monadic-Second Order logic (MSO)
  - First-Order logic (FO) or the relational algebra
  - SQL with aggregate functions
  - etc.

Outline

Boolean provenance [Imieliński and Lipski, 1984]

- $\mathcal{X} = \{x_1, x_2, \ldots, x_n\}$ finite set of Boolean events
- Provenance annotation: Boolean function over $\mathcal{X}$, i.e., a function of the form: $(\mathcal{X} \to \{\bot, \top\}) \to \{\bot, \top\}$
- Interpretation: possible-world semantics
  - every valuation $\nu : \mathcal{X} \to \{\bot, \top\}$ denotes a possible world of the database
  - the provenance of a tuple on ν evaluates to $\bot$ or $\top$ depending whether this tuple exists in that possible world
  - for example, if every tuple of a database is annotated with the indicator function of a distinct Boolean event, the set of possible worlds is the set of all subdatabases

Example of possible worlds

name	position	city	classification	prov
John	Director	New York	unclassified	t_1
Paul	Janitor	New York	restricted	t_2
Dave	Analyst	Paris	confidential	t_3
Ellen	Field agent	Berlin	secret	t_4
Magdalen	Double agent	Paris	top secret	t_5
Nancy	HR director	Paris	restricted	t_6
Susan	Analyst	Berlin	secret	t_7

$$\nu: \quad \begin{array}{ccccccc} t_1 & t_2 & t_3 & t_4 & t_5 & t_6 & t_7 \\ \top & \top & \top & \top & \top & \top & \top \end{array}$$

Example of possible worlds

name	position	city	classification	prov
John	Director	New York	unclassified	t_1
Dave	Analyst	Paris	confidential	t_3
Magdalen	Double agent	Paris	top secret	t_5
Susan	Analyst	Berlin	secret	t_7

$$\nu: \quad \begin{array}{ccccccc} t_1 & t_2 & t_3 & t_4 & t_5 & t_6 & t_7 \\ \top & \bot & \top & \bot & \top & \bot & \top \end{array}$$

Boolean provenance of query results

- $\nu(D)$: the subdatabase of D where all tuples whose provenance annotation evaluates to $\bot$ by ν are removed
- The Boolean provenance $\mathrm{prov}_{q,D}(t)$ of tuple $t \in q(D)$ is the function:

$$\nu \mapsto \begin{cases} \top \text{ if } t \in q(\nu(D)) \\ \bot \text{ otherwise} \end{cases}$$

Example (What cities are in the table?)

name	position	city	classification	prov
John	Director	New York	unclassified	t_1
Paul	Janitor	New York	restricted	t_2
Dave	Analyst	Paris	confidential	t_3
Ellen	Field agent	Berlin	secret	t_4
Magdalen	Double agent	Paris	top secret	t_5
Nancy	HR director	Paris	restricted	t_6
Susan	Analyst	Berlin	secret	t_7

city	prov
New York	$t_1 \vee t_2$
Paris	$t_3 \vee t_5 \vee t_6$
Berlin	$t_4 \vee t_7$

What now?

- How to compute Boolean provenance for practical query languages? What complexity?
- What can we do with provenance?
- How should we represent provenance annotations?
- How can we implement support for provenance management in a relational database management system?

Outline

Commutative semiring $(K, \mathbb{0}, \mathbb{1}, \oplus, \otimes)$

- Set K with distinguished elements $\mathbb{0}$, $\mathbb{1}$
- $\oplus$ associative, commutative operator, with identity $\mathbb{0}_K$:
  - $a \oplus (b \oplus c) = (a \oplus b) \oplus c$
  - $a \oplus b = b \oplus a$
  - $a \oplus \mathbb{0} = \mathbb{0} \oplus a = a$
- $\otimes$ associative, commutative operator, with identity $\mathbb{1}_K$:
  - $a \otimes (b \otimes c) = (a \otimes b) \otimes c$
  - $a \otimes b = b \otimes a$
  - $a \otimes \mathbb{1} = \mathbb{1} \otimes a = a$
- $\otimes$ distributes over $\oplus$:

$$a \otimes (b \oplus c) = (a \otimes b) \oplus (a \otimes c)$$

- $\mathbb{0}$ is annihilating for $\otimes$:

$$a \otimes \mathbb{0} = \mathbb{0} \otimes a = \mathbb{0}$$

Example semirings

- $(\mathbb{N}, 0, 1, +, \times)$: counting semiring
- $(\{\bot, \top\}, \bot, \top, \vee, \wedge)$: Boolean semiring
- $(\{\textit{unclassified}, \textit{restricted}, \textit{confidential}, \textit{secret}, \textit{top secret}, \textit{unavailable}\}, \textit{unavailable}, \textit{unclassified}, \min, \max)$: security semiring
- $(\mathbb{N} \cup \{\infty\}, \infty, 0, \min, +)$: tropical semiring
- $(\{\text{Boolean functions over } \mathcal{X}\}, \bot, \top, \vee, \wedge)$: semiring of Boolean functions over $\mathcal{X}$
- $(\mathbb{N}[\mathcal{X}], 0, 1, +, \times)$: semiring of integer-valued polynomials with variables in $\mathcal{X}$ (also called How-semiring or universal semiring, see further)
- $(\mathcal{P}(\mathcal{P}(\mathcal{X})), \emptyset, \{\emptyset\}, \cup, \Cup)$: Why-semiring over $\mathcal{X}$ $(A \Cup B := \{a \cup b \mid a \in A, b \in B\})$

Semiring provenance [Green et al., 2007]

- We fix a semiring $(K, \mathbb{0}, \mathbb{1}, \oplus, \otimes)$
- We assume provenance annotations are in K
- We consider a query q from the positive relational algebra (selection, projection, renaming, cross product, union; joins can be simulated with renaming, cross product, selection, projection)
- We define a semantics for the provenance of a tuple $t \in q(D)$ inductively on the structure of q

Selection, renaming

Provenance annotations of selected tuples are unchanged

Example ($\rho_{\text{name}\to\text{n}}(\sigma_{\text{city}=\text{“New York”}}(R))$)

name	position	city	classification	prov
John	Director	New York	unclassified	t_1
Paul	Janitor	New York	restricted	t_2
Dave	Analyst	Paris	confidential	t_3
Ellen	Field agent	Berlin	secret	t_4
Magdalen	Double agent	Paris	top secret	t_5
Nancy	HR director	Paris	restricted	t_6
Susan	Analyst	Berlin	secret	t_7

n	position	city	classification	prov
John	Director	New York	unclassified	t_1
Paul	Janitor	New York	restricted	t_2

Projection

Provenance annotations of identical, merged, tuples are $\oplus$-ed

Example ($\pi_{\text{city}}(R)$)

name	position	city	classification	prov
John	Director	New York	unclassified	t_1
Paul	Janitor	New York	restricted	t_2
Dave	Analyst	Paris	confidential	t_3
Ellen	Field agent	Berlin	secret	t_4
Magdalen	Double agent	Paris	top secret	t_5
Nancy	HR director	Paris	restricted	t_6
Susan	Analyst	Berlin	secret	t_7

city	prov
New York	$t_1 \oplus t_2$
Paris	$t_3 \oplus t_5 \oplus t_6$
Berlin	$t_4 \oplus t_7$

Union

Provenance annotations of identical, merged, tuples are $\oplus$-ed

Example

$$\pi_{\text{city}}(\sigma_{\textit{ends-with}(\text{position},\text{“agent”})}(R)) \cup \pi_{\text{city}}(\sigma_{\text{position}=\text{“Analyst”}}(R))$$

name	position	city	classification	prov
John	Director	New York	unclassified	t_1
Paul	Janitor	New York	restricted	t_2
Dave	Analyst	Paris	confidential	t_3
Ellen	Field agent	Berlin	secret	t_4
Magdalen	Double agent	Paris	top secret	t_5
Nancy	HR director	Paris	restricted	t_6
Susan	Analyst	Berlin	secret	t_7

city	prov
Paris	$t_3 \oplus t_5$
Berlin	$t_4 \oplus t_7$

Cross product

Provenance annotations of combined tuples are $\otimes$-ed

Example

$$\pi_{\text{city}}(\sigma_{\textit{ends-with}(\text{position},\text{“agent”})}(R)) \bowtie \pi_{\text{city}}(\sigma_{\text{position}=\text{“Analyst”}}(R))$$

name	position	city	classification	prov
John	Director	New York	unclassified	t_1
Paul	Janitor	New York	restricted	t_2
Dave	Analyst	Paris	confidential	t_3
Ellen	Field agent	Berlin	secret	t_4
Magdalen	Double agent	Paris	top secret	t_5
Nancy	HR director	Paris	restricted	t_6
Susan	Analyst	Berlin	secret	t_7

city	prov
Paris	$t_3 \otimes t_5$
Berlin	$t_4 \otimes t_7$

What can we do with it?

counting semiring: count the number of times a tuple can be derived, multiset semantics

Boolean semiring: determines if a tuple exists when a subdatabase is selected

security semiring: determines the minimum clearance level required to get a tuple as a result

tropical semiring: minimum-weight way of deriving a tuple (think shortest path in a graph)

Boolean functions: Boolean provenance, as previously defined

integer polynomials: universal provenance, see further

Why-semiring: Why-provenance [Buneman et al., 2001], set of combinations of tuples needed for a tuple to exist

Example of security provenance

$$\pi_{\text{city}}(\sigma_{\text{name}<\text{name2}}(\pi_{\text{name,city}}(R) \bowtie \rho_{\text{name}\to\text{name2}}(\pi_{\text{name,city}}(R))))$$

name	position	city	prov
John	Director	New York	unclassified
Paul	Janitor	New York	restricted
Dave	Analyst	Paris	confidential
Ellen	Field agent	Berlin	secret
Magdalen	Double agent	Paris	top secret
Nancy	HR director	Paris	restricted
Susan	Analyst	Berlin	secret

city	prov
New York	restricted
Paris	confidential
Berlin	secret

Notes [Green et al., 2007]

- Computing provenance has a PTIME data complexity overhead
- Semiring homomorphisms commute with provenance computation: if there is a homomorphism from K to K', then one can compute the provenance in K, apply the homomorphism, and obtain the same result as when computing provenance in K'
- The integer polynomial semiring is universal: there is a unique homomorphism to any other commutative semiring that respects a given valuation of the variables
- This means all computations can be performed in the universal semiring, and homomorphisms applied next
- Two equivalent queries can have two different provenance annotations on the same database, in some semirings

Outline

Semirings with monus [Amer, 1984, Geerts and Poggi, 2010]

- Some semirings can be equipped with a $\ominus$ verifying:
  - $a \oplus (b \ominus a) = b \oplus (a \ominus b)$
  - $(a \ominus b) \ominus c = a \ominus (b + c)$
  - $a \ominus a = \mathbb{0} \ominus a = \mathbb{0}$
- Boolean function semiring with $\wedge\neg$, Why-semiring with $\setminus$, counting semiring with truncated difference...
- Most natural semirings (but not all semirings [Amarilli and Monet, 2016]!) can be extended into semirings with monus
- Sometimes strange things happen [Amsterdamer et al., 2011a]: e.g, $\otimes$ does not always distribute over $\ominus$
- Allows supporting full relational algebra with the $\setminus$ operator, still PTIME
- Semantics for Boolean function semiring coincides with that of Boolean provenance

Difference

Provenance annotations of diff-ed tuples are $\ominus$-ed

Example

$$\pi_{\text{city}}(\sigma_{\textit{ends-with}(\text{position},\text{“agent”})}(R)) \setminus \pi_{\text{city}}(\sigma_{\text{position}=\text{“Analyst”}}(R))$$

name	position	city	classification	prov
John	Director	New York	unclassified	t_1
Paul	Janitor	New York	restricted	t_2
Dave	Analyst	Paris	confidential	t_3
Ellen	Field agent	Berlin	secret	t_4
Magdalen	Double agent	Paris	top secret	t_5
Nancy	HR director	Paris	restricted	t_6
Susan	Analyst	Berlin	secret	t_7

city	prov
Paris	$t_5 \ominus t_3$
Berlin	$t_4 \ominus t_7$

Provenance for aggregates

[Amsterdamer et al., 2011b, Fink et al., 2012]

- Trickier to define provenance for queries with aggregation, even in the Boolean case
- One can construct a K-semimodule $K * M$ for each monoid aggregate M over a provenance database with a semiring in K
- Data values become elements of the semimodule

Example ($\text{count}(\pi_{\text{name}}(\sigma_{\text{city}=\text{``Paris''}}(R)))$)

$$t_3 * 1 + t_5 * 1 + t_6 * 1$$

Provenance in XML databases

[Foster et al., 2008]

Data: Trees (with different kinds of nodes, with data values on leaves…)

Queries: XPath, XQuery, expressing in particular tree-pattern queries

Provenance annotations: on nodes of the tree; a node "inherits" annotations of its ancestors

Boolean and semiring provenance extend quite naturally to this setting, cf. works on Probabilistic XML [Abiteboul et al., 2009] and Annotated XML [Foster et al., 2008].

Provenance in graph databases
[Ramusat et al., 2018]

Data: Graphs (with properties on nodes, edges...)

Queries: Graph query languages (such as Cypher), especially Regular Path Queries

Provenance annotations: on nodes or edges of the graphs

Semiring provenance extends to this setting, but queries inherently recursive, so need for technical conditions on semiring (e.g., ω-continuity [Green et al., 2007], absorptivity [Deutch et al., 2014], existence of a * operator [Ramusat et al., 2018]) for provenance to be definable and for specific algorithms.

Provenance in triple stores

[Damásio et al., 2012]

Data: Triples (subject, predicate, object) in an open world

Queries: SPARQL (including negation capabilities, e.g., optionality)

Provenance annotations: on triples

Provenance definition extends, but need for negation support, so m-semiring provenance; additional axioms need to be satisfied for compatibility with SPARQL semantics [Geerts et al., 2016]

Outline

Application: Probabilistic databases
[Green and Tannen, 2006, Suciu et al., 2011]

- Tuple-independent database: each tuple t in a database is annotated with independent probability $\Pr(t)$ of existing
- Probability of a possible world $D' \subseteq D$:

$$\Pr(D') = \prod_{t \in D'} \Pr(t) \times \prod_{t \in D' \setminus D} (1 - \Pr(t'))$$

- Probability of a tuple for a query q over D:

$$\Pr(t \in q(D)) = \sum_{\substack{D' \subseteq D \\ t \in q(D')}} \Pr(D')$$

- If $\Pr(x_i) := \Pr(t_i)$ where x_i is the provenance annotation of tuple t_i then $\Pr(t \in q(D)) = \Pr(\mathrm{prov}_{q,D}(t))$
- Computing the probability of a query in probabilistic databases thus amounts to computing Boolean provenance, and then computing the probability of a Boolean function
- Also works for more complex probabilistic models

Example of probability computation

name	position	city	classification	prov	prob
John	Director	New York	unclassified	t_1	0.5
Paul	Janitor	New York	restricted	t_2	0.7
Dave	Analyst	Paris	confidential	t_3	0.3
Ellen	Field agent	Berlin	secret	t_4	0.2
Magdalen	Double agent	Paris	top secret	t_5	1.0
Nancy	HR director	Paris	restricted	t_6	0.8
Susan	Analyst	Berlin	secret	t_7	0.2

city	prov
New York	$t_1 \vee t_2$
Paris	$t_3 \vee t_5 \vee t_6$
Berlin	$t_4 \vee t_7$

Example of probability computation

name	position	city	classification	prov	prob
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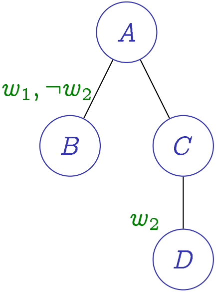
Paul	Janitor	New York	restricted	t_2	0.7
Dave	Analyst	Paris	confidential	t_3	0.3
Ellen	Field agent	Berlin	secret	t_4	0.2
Magdalen	Double agent	Paris	top secret	t_5	1.0
Nancy	HR director	Paris	restricted	t_6	0.8
Susan	Analyst	Berlin	secret	t_7	0.2

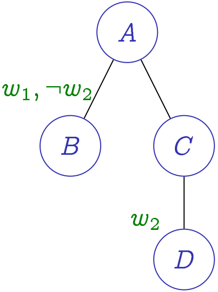
city	prov	prob
New York	$t_1 \vee t_2$	$1-(1-0.5)\times(1-0.7)=0.85$
Paris	$t_3 \vee t_5 \vee t_6$	1.00
Berlin	$t_4 \vee t_7$	$1-(1-0.2)\times(1-0.2)=0.36$

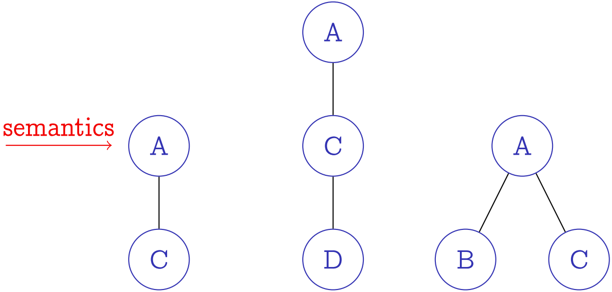
Application: Probabilistic XML



Event	Prob.
w_1	0.8
w_2	0.7

Application: Probabilistic XML





$p_1 = 0.06$ $p_2 = 0.70$ $p_3 = 0.24$

Event	Prob.
w_1	0.8
w_2	0.7

Outline

Views

- Views are named queries
- They are used in the same way as tables within other queries
- Semantics: one replaces the view by the result of the evaluation of the corresponding query

Virtual and materialized views

- A view may be virtual or materialized
- No semantic difference
- Operational difference, with an impact on the efficiency of query evaluation:

  virtual view: the query defining the view is evaluated each time the view is used in a query

  materialized view: the query defining the view is evaluated when the view is created and the result is stored in an auxiliary table; this table is directly used each time the view is used in another query

Why using views?

Logical independence: an application can access views, without the need to know how data is effectively organized in the database (the organization can change in a transparent manner, by just redefining the views)

Access control: different access rights can be given to base tables and to views, so that a given user or application only has access to a restricted subset of the content of the database

Data integration: views can be defined to gather data from multiple sources with different schemas

Optimization: materialized views can be defined for frequent queries or subqueries, so that they do not need to be evaluated each time they are used

Views and updates

Views interact in complex ways with updates (insertions, modifications, deletions).

View maintenance: when an update is performed on base tables, this update should be reflected in the views

- Nothing to do for virtual views
- More complex for materialized views, that need to be maintained in terms of the updates

Views and updates

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View update: one wants in some settings to perform an update directly on a view, which causes appropriate updates on base tables

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- Nothing to do for virtual views
- More complex for materialized views, that need to be maintained in terms of the updates

View update: one wants in some settings to perform an update directly on a view, which causes appropriate updates on base tables

How to do it? With provenance! At least for deletions

View maintenance for deletions

- Just use Boolean provenance!
- Remove all tuples whose provenance annotation evaluates to $\perp$

View maintenance for deletions

- Just use Boolean provenance!
- Remove all tuples whose provenance annotation evaluates to $\bot$

name	position	city	prov
John	Director	New York	t_1
Paul	Janitor	New York	t_2
Dave	Analyst	Paris	t_3
Ellen	Field agent	Berlin	t_4
Magdalen	Double agent	Paris	t_5
Nancy	HR director	Paris	t_6
Susan	Analyst	Berlin	t_7

city	prov
New York	$t_1 \wedge t_2$
Paris	$t_3 \wedge t_5 \vee t_3 \wedge t_6 \vee t_5 \wedge t_6$
Berlin	$t_4 \wedge t_7$

If t_1 disappears

View maintenance for deletions

- Just use Boolean provenance!
- Remove all tuples whose provenance annotation evaluates to $\bot$

name	position	city	prov
John	Director	New York	t_1
Paul	Janitor	New York	t_2
Dave	Analyst	Paris	t_3
Ellen	Field agent	Berlin	t_4
Magdalen	Double agent	Paris	t_5
Nancy	HR director	Paris	t_6
Susan	Analyst	Berlin	t_7

city	prov
New York	$t_1 \wedge t_2$
Paris	$t_3 \wedge t_5 \vee t_3 \wedge t_6 \vee t_5 \wedge t_6$
Berlin	$t_4 \wedge t_7$

If t_1 disappears, New York disappears from the result of the view.

View update for deletions [Buneman et al., 2002]

- Use case for Why-provenance!
- To delete a tuple t in the result of a view, select a minimal subset of tuples (in terms of size, or in terms of side effects on other tuples of the deleted view) whose annotation appears in every set of annotations of the Why-provenance of t
- NP-complete in general

View update for deletions [Buneman et al., 2002]

- Use case for Why-provenance!
- To delete a tuple t in the result of a view, select a minimal subset of tuples (in terms of size, or in terms of side effects on other tuples of the deleted view) whose annotation appears in every set of annotations of the Why-provenance of t
- NP-complete in general

name	position	city	prov
John	Director	New York	t_1
Paul	Janitor	New York	t_2
Dave	Analyst	Paris	t_3
Ellen	Field agent	Berlin	t_4
Magdalen	Double agent	Paris	t_5
Nancy	HR director	Paris	t_6
Susan	Analyst	Berlin	t_7

ville	prov
New York	$\{\{t_1, t_2\}\}$
Paris	$\{\{t_3, t_5\}, \{t_3, t_6\}, \{t_5, t_6\}\}$
Berlin	$\{\{t_4, t_7\}\}$

To delete Paris

View update for deletions [Buneman et al., 2002]

- Use case for Why-provenance!
- To delete a tuple t in the result of a view, select a minimal subset of tuples (in terms of size, or in terms of side effects on other tuples of the deleted view) whose annotation appears in every set of annotations of the Why-provenance of t
- NP-complete in general

name	position	city	prov
John	Director	New York	t_1
Paul	Janitor	New York	t_2
Dave	Analyst	Paris	t_3
Ellen	Field agent	Berlin	t_4
Magdalen	Double agent	Paris	t_5
Nancy	HR director	Paris	t_6
Susan	Analyst	Berlin	t_7

ville	prov
New York	$\{\{t_1, t_2\}\}$
Paris	$\{\{t_3, t_5\}, \{t_3, t_6\}, \{t_5, t_6\}\}$
Berlin	$\{\{t_4, t_7\}\}$

To delete Paris, delete two tuples among t_3, t_5, t_6.

Outline

Using provenance for explanation

- Semiring provenance can be used to provide a user with explanation on the query result:
  - How-provenance (provenance polynomials) explains precisely how a result has been computed: often too fine-grained
  - Why-provenance explains why a particular result is generated by providing combinations of tuples required for a tuple to be produced
- Provenance often too long and complex, (imperfect) summarization may be required [Ainy et al., 2015]
- Still far from a natural language explanation!
- Why-not provenance: why a result was not produced. Expressible with m-semirings, but requires dedicated techniques [Chapman and Jagadish, 2009] for compact explanations

Where-provenance [Buneman et al., 2001]

- Different form of provenance: captures from which database values come which output values
- Bipartite graph of provenance: two attribute values are connected if one can be produced from the other
- Axiomatized in [Buneman et al., 2001, Cheney et al., 2009]
- Cannot be captured by provenance semirings [Cheney et al., 2009], because of renaming (does not keep track of relation attributes), projection (does not remember which attribute values still exist), join (in a join, an output value comes from two different input values)

Outline

Provenance

Applications

Implementing Provenance Support

- Representation Systems for Provenance
- Systems

Conclusion

Representation systems

- In the Boolean semiring, the counting semiring, the security semiring: provenance annotations are elementary
- In the Boolean function semiring, the universal semiring, etc., provenance annotations can become quite complex
- Needs for compact representation of provenance annotations
- Lower the provenance computation complexity as much as possible

Provenance formulas

- Quite straightforward
- Formalism used in most of the provenance literature
- PTIME data complexity
- Expanding formulas (e.g., computing the monomials of a $\mathbb{N}[\mathcal{X}]$ provenance annotation) can result in an exponential blowup

Example

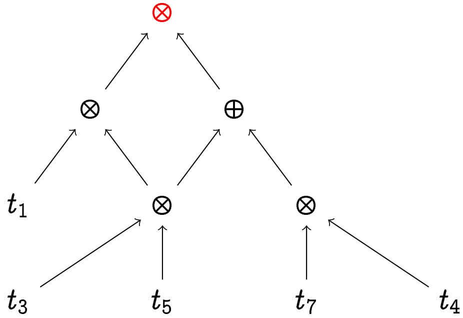
Is there a city with both an analyst and an agent, and if Paris is such a city, is there a director in the agency?

$$((t_3 \otimes t_5) \oplus (t_4 \otimes t_7)) \otimes ((t_3 \otimes t_5) \otimes t_1)$$

Provenance circuits [Deutch et al., 2014, Amarilli et al., 2015]

- Use arithmetic circuits (Boolean circuits for Boolean provenance) to represent provenance
- Every time an operation reuses a previously computed result, link to the previously created circuit gate
- Allow linear-time data complexity of provenance computation when restricted to bounded-treewidth databases [Amarilli et al., 2015] (MSO queries for Boolean provenance, positive relational algebra queries for arbitrary semirings)
- Formulas can be quadratically larger than provenance circuits for MSO formulas, $(\log \log)$-larger for positive relational algebra queries [Wegener, 1987, Amarilli et al., 2016]

Example provenance circuit



OBDD and d-DNNF

- Various subclasses of Boolean circuits commonly used:
  - OBDD: Ordered Binary Decision Diagrams
  - d-DNNF: deterministic Decomposable Negation Normal Form
- OBDDs can be obtained in PTIME data complexity on bounded-treewidth databases [Amarilli et al., 2016]
- d-DNNFs can be obtained in linear-time data complexity on bounded-treewidth databases
- Application: probabilistic query evaluation in linear-time data complexity on bounded-treewidth databases (d-DNNF evaluation is in linear-time)

Outline

Desiderata for a provenance-aware DBMS

- Extends a widely used database management system
- Easy to deploy
- Easy to use, transparent for the user
- Provenance automatically maintained as the user interacts with the database management system
- Provenance computation benefits from query optimization within the DBMS
- Allow probability computation based on provenance
- Any form of provenance can be computed: Boolean provenance, semiring provenance in any semiring (possibly, with monus), aggregate provenance, where-provenance, on demand

ProvSQL: Provenance within PostgreSQL (1/2)

[Senellart et al., 2018]

- Lightweight extension/plugin for PostgreSQL $\geq$ 10 (tested against all versions – upgrade to a new version typically takes a couple of hours)
- Provenance annotations stored as Universally Unique Identifiers (UUIDs), in an extra attribute of each provenance-aware relation
- UUIDs of base tuples randomly generated; UUIDs of query results generated in a deterministic manner
- A provenance circuit relating UUIDs of elementary provenance annotations and arithmetic gates stored in shared memory of the DBMS (or on disk)
- All computations done in the universal semiring (more precisely, with monus, in the free semiring with monus; for where-provenance, in a free term algebra)

ProvSQL: Provenance within PostgreSQL (2/2)

[Senellart et al., 2018]

- Query rewriting (after parsing, before planning) to automatically compute output provenance attributes in terms of the query and input provenance attributes:
  - Duplicate elimination (DISTINCT, set union) results in aggregation of provenance values with $\oplus$
  - Cross products, joins results in combination of provenance values with $\otimes$
  - Difference rewritten in a join, with combination of provenance values with $\ominus$
- Additional circuit gates on projection, join for support of where-provenance
- Probability computation from the provenance circuits, via various methods (naive, sampling, compilation to d-Ds, tree decomposition)
- (Expected) Shapley value computation

Challenges

- Low-level access to PostgreSQL data structures in extensions
- No simple query rewriting mechanism
- SQL is much less clean than the relational algebra
- Multiset semantics by default in SQL
- SQL is a very rich language, with many different ways of expressing the same thing
- Inherent limitations: e.g., no aggregation within recursive queries
- Implementing provenance computation should not slow down the computation
- User-defined functions, updates, etc.: unclear how provenance should work

ProvSQL: Current status

- Supported SQL language features:
  - Regular SELECT-FROM-WHERE queries (aka conjunctive queries with multiset semantics)
  - JOIN queries (regular joins and outer joins; semijoins and antijoins are not currently supported)
  - SELECT queries with nested SELECT subqueries in the FROM clause
  - GROUP BY queries
  - SELECT DISTINCT queries (i.e., set semantics)
  - UNION's or UNION ALL's of SELECT queries
  - EXCEPT queries
  - Aggregate queries (terminal, for simple aggregates)
- Try it (and see a demo) from `https://github.com/PierreSenellart/provsql`

Other databases with provenance management

- Older probabilistic database systems can compute some forms of provenance (especially, Boolean provenance); but tied to a specific version of PostgreSQL, hard to deploy

  Trio: `http://infolab.stanford.edu/trio/` [Benjelloun et al., 2006]

  MayBMS: `http://maybms.sourceforge.net/` [Huang et al., 2009]

- Perm `https://github.com/IITDBGroup/perm` [Glavic and Alonso, 2009] now obsolete system for provenance management; also tied to a specific version of PostgreSQL
- GProM `http://www.cs.iit.edu/~dbgroup/projects/gprom.html` [Arab et al., 2018] is similar to ProvSQL (though no probabilistic database capabilities, and limited semiring support), with some extra features; implemented as a middleware

Outline

Provenance

Applications

Implementing Provenance Support

Conclusion

Database Provenance [Senellart, 2017]

- Quite rich foundations of provenance management:
  - Different types of provenance
  - Semiring formalism to unify most provenance forms
  - (Partial) extensions for difference, recursive queries, aggregation, updates [Bourhis et al., 2020]; to other data models
  - Compact provenance representation formalisms
- ProvSQL: aim at building concrete, efficient, usable implementation
- Wide variety of applications are made possible by provenance: probabilistic query evaluation, computation of power indices, but also enumeration of query results, sampling of results...

Tutorial

https://github.com/PierreSenellart/provsql/tree/master/doc/tutorial

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