Provenance in Databases

Principles and Applications

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Reasoning Web Summer School 2019

Provenance management

- Data management all about query evaluation

Provenance management

- Data management all about query evaluation
- 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?

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  - What is the most economical way of obtaining the result?
  - 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

Outline

Data management

Numerous applications (standalone software, Web sites, etc.) need to manage data:

- Structure data useful to the application
- Store them in a persistent manner (data retained even when the application is not running)
- Efficiently query information within large data volumes
- Update data without violating some structural constraints
- Enable data access and updates by multiple users, possibly concurrently

Often, desirable to access the same data from several distinct applications, from distinct computers.

Role of a DBMS

Database Management System

Software that simplifies the design of applications that handle data, by providing a unified access to the functionalities required for data management, whatever the application.

Database

Collection of data (specific to a given application) managed by a DBMS

Major types of DBMSs

Relational (RDBMS). Tables, complex queries (SQL), rich features

XML. Trees, complex queries (XQuery), features similar to RDBMS

Graph/Triples. Graph data, complex queries expressing graph navigation

Objects. Complex data model, inspired by OOP

Documents. Complex data, organized in documents, relatively simple queries and features

Key–Value. Very basic data model, focus on performance

Column Stores. Data model in between key–value and RDBMS; focus on iteration and aggregation on columns

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NoSQL

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Outline

Classical relational DBMSs

- Based on the relational model: decomposition of data into relations (i.e., tables)
- A standard query language: SQL
- Data stored on disk
- Relations (tables) stored line after line
- Centralized system, with limited distribution possibilities

Relational schema

We fix countably infinite sets:

- $\mathcal{L}$ of labels
- $\mathcal{V}$ of values
- $\mathcal{T}$ of types, s.t., $\forall \tau \in \mathcal{T}, \tau \subseteq \mathcal{V}$

Definition

A relation schema (of arity n) is an n-tuple $(A_1, \dots, A_n)$ where each A_i (called an attribute) is a pair (L_i, τ_i) with $L_i \in \mathcal{L}$, $\tau_i \in \mathcal{T}$ and such that all L_i are distinct

Definition

A database schema is defined by a finite set of labels $L \subseteq \mathcal{L}$ (relation names), each label of L being mapped to a relation schema.

Example database schema

- Universe:
  - $\mathcal{L}$ the set of alphanumeric character strings starting with a letter
  - $\mathcal{V}$ the set of finite sequences of bits
  - $\mathcal{T}$ is formed of types such as `INTEGER` (representation as a sequence of bits of integers between -2^{31} and $2^{31}-1$), `REAL` (representation of floating-point numbers following IEEE 754), `TEXT` (UTF-8 representation of character strings), `DATE` (ISO8601 representation of dates), etc.
- Database schema formed of 2 relation names, `Guest` and `Reservation`
- `Guest`: $((\texttt{id}, \texttt{INTEGER}), (\texttt{name}, \texttt{TEXT}), (\texttt{email}, \texttt{TEXT}))$
- `Reservation`: $((\texttt{id}, \texttt{INTEGER}), (\texttt{guest}, \texttt{INTEGER}), (\texttt{room}, \texttt{INTEGER}), (\texttt{arrival}, \texttt{DATE}), (\texttt{nights}, \texttt{INTEGER}))$

Database

Definition

An instance of a relation schema $((L_1, \tau_1), \ldots, (L_n, \tau_n))$ (also called a relation on this schema) is a finite set $\{t_1, \ldots, t_k\}$ of tuples of the form $t_j = (v_{j1}, \ldots, v_{jn})$ with $\forall j \forall i \; v_{ji} \in \tau_i$.

Definition

An instance of a database schema (or, simply, a database on this schema) is a function that maps each relation name to an instance of the corresponding relation schema.

Note: Relation is used somewhat ambiguously to talk about a relation schema or an instance of a relation schema.

Example

Guest

id	name	email
1	John Smith	john.smith@gmail.com
2	Alice Black	alice@black.name
3	John Smith	john.smith@ens.fr

Reservation

id	guest	room	arrival	nights
1	1	504	2017-01-01	5
2	2	107	2017-01-10	3
3	3	302	2017-01-15	6
4	2	504	2017-01-15	2
5	2	107	2017-01-30	1

Variant: bag semantics

- A relation instance is defined as a (finite) set of tuples. One can also consider a bag semantics of the relational model, where a relation instance is a multiset of tuples.
- This is what best matches how RDBMSs work…
- … but most of relational database theory has been established for the set semantics, more convenient to work with
- We will mostly discuss the set semantics in this lecture

Outline

The relational algebra

- Algebraic language to express queries
- A relational algebra expression produces a new relation from the database relations
- Each operator takes 0, 1, or 2 subexpressions
- Main operators:

Op.	Arity	Description	Condition
R	0	Relation name	$R \in \mathcal{L}$
$\rho_{A \to B}$	1	Renaming	$A, B \in \mathcal{L}$
$\Pi_{A_1 \ldots A_n}$	1	Projection	$A_1 \ldots A_n \in \mathcal{L}$
σ_φ	1	Selection	φ formula
$\times$	2	Cross product	
$\cup$	2	Union	
$\setminus$	2	Difference	
$\bowtie_\varphi$	2	Join	φ formula

Relation name

Guest

id	name	email
1	John Smith	john.smith@gmail.com
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Reservation

id	guest	room	arrival	nights
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4	2	504	2017-01-15	2
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Expression: `Guest`

Result:

id	name	email
1	John Smith	john.smith@gmail.com
2	Alice Black	alice@black.name
3	John Smith	john.smith@ens.fr

Renaming

Guest

id	name	email
1	John Smith	john.smith@gmail.com
2	Alice Black	alice@black.name
3	John Smith	john.smith@ens.fr

Reservation

id	guest	room	arrival	nights
1	1	504	2017-01-01	5
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3	3	302	2017-01-15	6
4	2	504	2017-01-15	2
5	2	107	2017-01-30	1

Expression: $\rho_{\texttt{id}\to\texttt{guest}}(\texttt{Guest})$

Result:

guest	name	email
1	John Smith	john.smith@gmail.com
2	Alice Black	alice@black.name
3	John Smith	john.smith@ens.fr

Projection

Guest

id	name	email
1	John Smith	john.smith@gmail.com
2	Alice Black	alice@black.name
3	John Smith	john.smith@ens.fr

Reservation

id	guest	room	arrival	nights
1	1	504	2017-01-01	5
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3	3	302	2017-01-15	6
4	2	504	2017-01-15	2
5	2	107	2017-01-30	1

Expression: $\Pi_{\mathtt{email},\mathtt{id}}(\mathtt{Guest})$

Result:

email	id
john.smith@gmail.com	1
alice@black.name	2
john.smith@ens.fr	3

Selection

Guest

id	name	email
1	John Smith	john.smith@gmail.com
2	Alice Black	alice@black.name
3	John Smith	john.smith@ens.fr

Reservation

id	guest	room	arrival	nights
1	1	504	2017-01-01	5
2	2	107	2017-01-10	3
3	3	302	2017-01-15	6
4	2	504	2017-01-15	2
5	2	107	2017-01-30	1

Expression: $\sigma_{\texttt{arrival}>2017\text{-}01\text{-}12\wedge\texttt{guest}=2}(\texttt{Reservation})$

Result:

id	guest	room	arrival	nights
4	2	504	2017-01-15	2
5	2	107	2017-01-30	1

The formula used in the selection can be any Boolean combination of comparisons of attributes to attributes or constants.

Cross product

Guest

id	name	email
1	John Smith	john.smith@gmail.com
2	Alice Black	alice@black.name
3	John Smith	john.smith@ens.fr

Reservation

id	guest	room	arrival	nights
1	1	504	2017-01-01	5
2	2	107	2017-01-10	3
3	3	302	2017-01-15	6
4	2	504	2017-01-15	2
5	2	107	2017-01-30	1

Expression: $\Pi_{\texttt{id}}(\texttt{Guest}) \times \Pi_{\texttt{name}}(\texttt{Guest})$

Result:

id	name
1	Alice Black
2	Alice Black
3	Alice Black
1	John Smith
2	John Smith
3	John Smith

Union

Guest

id	name	email
1	John Smith	john.smith@gmail.com
2	Alice Black	alice@black.name
3	John Smith	john.smith@ens.fr

Reservation

id	guest	room	arrival	nights
1	1	504	2017-01-01	5
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3	3	302	2017-01-15	6
4	2	504	2017-01-15	2
5	2	107	2017-01-30	1

Expression: $\Pi_{\texttt{room}}(\sigma_{\texttt{guest}=2}(\texttt{Reservation})) \cup \Pi_{\texttt{room}}(\sigma_{\texttt{arrival}=\text{2017-01-15}}(\texttt{Reservation}))$

Result:

room
107
302
504

Union

Guest

id	name	email
1	John Smith	john.smith@gmail.com
2	Alice Black	alice@black.name
3	John Smith	john.smith@ens.fr

Reservation

id	guest	room	arrival	nights
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5	2	107	2017-01-30	1

Expression: $\Pi_{\texttt{room}}(\sigma_{\texttt{guest}=2}(\texttt{Reservation})) \cup \Pi_{\texttt{room}}(\sigma_{\texttt{arrival}=\text{2017-01-15}}(\texttt{Reservation}))$

Result:

room
107
302
504

This simple union could have been written $\Pi_{\texttt{room}}(\sigma_{\texttt{guest}=2\vee\texttt{arrival}=\text{2017-01-15}}(\texttt{Reservation}))$. Not always possible.

Difference

Guest

id	name	email
1	John Smith	john.smith@gmail.com
2	Alice Black	alice@black.name
3	John Smith	john.smith@ens.fr

Reservation

id	guest	room	arrival	nights
1	1	504	2017-01-01	5
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3	3	302	2017-01-15	6
4	2	504	2017-01-15	2
5	2	107	2017-01-30	1

Expression: $\Pi_{\texttt{room}}(\sigma_{\texttt{guest}=2}(\texttt{Reservation})) \setminus \Pi_{\texttt{room}}(\sigma_{\texttt{arrival}=\text{2017-01-15}}(\texttt{Reservation}))$

Result:

room
107

Difference

Guest

id	name	email
1	John Smith	john.smith@gmail.com
2	Alice Black	alice@black.name
3	John Smith	john.smith@ens.fr

Reservation

id	guest	room	arrival	nights
1	1	504	2017-01-01	5
2	2	107	2017-01-10	3
3	3	302	2017-01-15	6
4	2	504	2017-01-15	2
5	2	107	2017-01-30	1

Expression: $\Pi_{\texttt{room}}(\sigma_{\texttt{guest}=2}(\texttt{Reservation})) \setminus \Pi_{\texttt{room}}(\sigma_{\texttt{arrival}=2017\text{-}01\text{-}15}(\texttt{Reservation}))$

Result:

room
107

This simple difference could have been written $\Pi_{\texttt{room}}(\sigma_{\texttt{guest}=2 \wedge \texttt{arrival} \neq 2017\text{-}01\text{-}15}(\texttt{Reservation}))$. Not always possible.

Join

Guest

id	name	email
1	John Smith	john.smith@gmail.com
2	Alice Black	alice@black.name
3	John Smith	john.smith@ens.fr

Reservation

id	guest	room	arrival	nights
1	1	504	2017-01-01	5
2	2	107	2017-01-10	3
3	3	302	2017-01-15	6
4	2	504	2017-01-15	2
5	2	107	2017-01-30	1

Expression: $\texttt{Reservation} \bowtie_{\texttt{guest}=\texttt{id}} \texttt{Guest}$

Result:

id	guest	room	arrival	nights	name	email
1	1	504	2017-01-01	5	John Smith	john.smith@gmail.com
2	2	107	2017-01-10	3	Alice Black	alice@black.name
3	3	302	2017-01-15	6	John Smith	john.smith@ens.fr
4	2	504	2017-01-15	2	Alice Black	alice@black.name
5	2	107	2017-01-30	1	Alice Black	alice@black.name

The formula used in the join can be any Boolean combination of comparisons of attributes of the table on the left to attributes of the table on the right.

Note on the join

- The join is not an elementary operator of the relational algebra (but it is very useful)
- It can be seen as a combination of renaming, cross product, selection, projection
- Thus:

$$\begin{aligned}&\texttt{Reservation} \bowtie_{\texttt{guest}=\texttt{id}} \texttt{Guest}\\ \equiv\, &\Pi_{\texttt{id},\texttt{guest},\texttt{room},\texttt{arrival},\texttt{nights},\texttt{name},\texttt{email}}(\\ &\quad \sigma_{\texttt{guest}=\texttt{temp}}(\texttt{Reservation} \times \rho_{\texttt{id}\to\texttt{temp}}(\texttt{Guest})))\end{aligned}$$

- If R and S have for attributes $\mathcal{A}$ and $\mathcal{B}$, we note $R \bowtie S$ the natural join of R and S, where the join formula is $\bigwedge_{A\in\mathcal{A}\cap\mathcal{B}} A = A$.

Bag semantics

In bag semantics (what is actually used by RDBMS):

- All operations return multisets
- In particular, projection and union can introduce multisets even when initial relations are sets

Extension: Aggregation

- Various extensions have been proposed to the relational algebra to add additional features
- In particular, aggregation and grouping [Klug, 1982, Libkin, 2003] of results
- With a syntax inspired from [Libkin, 2003]:

$$\sigma_{\mathtt{avg}>3}(\gamma^{\mathtt{avg}}_{\mathtt{room}}[\lambda x.\mathtt{avg}(x)](\Pi_{\mathtt{room,nights}}(\mathtt{Reservation})))$$

computes the average number of nights per reservation for each room having an average greater than 3

room	avg
302	6
504	3.5

Outline

NoSQL

- No SQL or Not Only SQL
- DBMSs with other trade-offs than those made by classical systems
- Very diversified ecosystem
- Desiderata: different data model, transparent scaling up, extreme performances
- Features abandoned: strong concurrency control and consistency, (possibly) complex queries
- In this lecture: we only care about systems allowing complex queries, yield richest provenance notions

Systems with a different data model

Complex queries, non-relational data model

Type	Organization	Queries	Examples of systems

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XML	Treelike, hierarchical data	XQuery	BASEX existdb

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Object	Complex data, with properties and methods	OQL, VQL	VERSANT

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Object	Complex data, with properties and methods	OQL, VQL	VERSANT
Graph	Graph with vertices, edges, labels	Cypher, Gremlin	Neo4j the graph database
Triples	RDF triples from the Semantic Web	SPARQL	

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]

- $\mathcal{X} = \{x_1, x_2, \dots, x_n\}$ 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
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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
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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
- $(\{\mathit{unclassified}, \mathit{restricted}, \mathit{confidential}, \mathit{secret}, \mathit{top\ secret}\}, \mathit{top\ secret}, \mathit{unclassified}, \min, \max)$: 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
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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
John	Director	New York	unclassified	t_1	0.5
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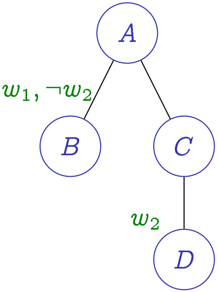
Ellen	Field agent	Berlin	secret	t_4	0.2
Magdalen	Double agent	Paris	top secret	t_5	1.0
Nancy	HR director	Paris	restricted	t_6	0.8
Susan	Analyst	Berlin	secret	t_7	0.2

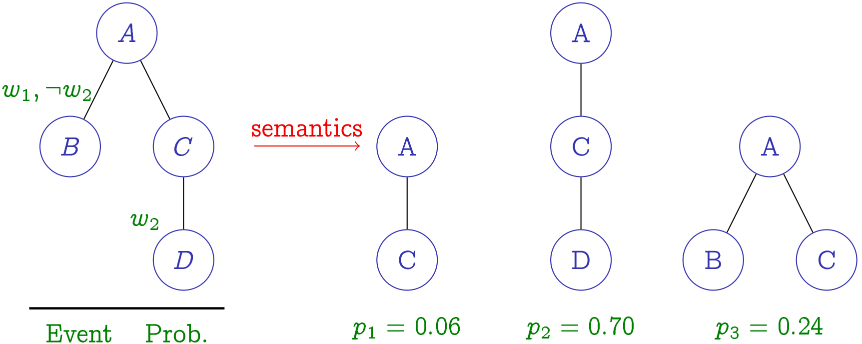
city	prov	prob
New York	$t_1 \vee t_2$	$1-(1-0.5)\times(1-0.7)=0.85$
Paris	$t_3 \vee t_5 \vee t_6$	1.00
Berlin	$t_4 \vee t_7$	$1-(1-0.2)\times(1-0.2)=0.36$

Application: Probabilistic XML



Event	Prob.
w_1	0.8
w_2	0.7

Application: Probabilistic XML



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

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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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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 $\bot$

View maintenance for deletions

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

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]

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- 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

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

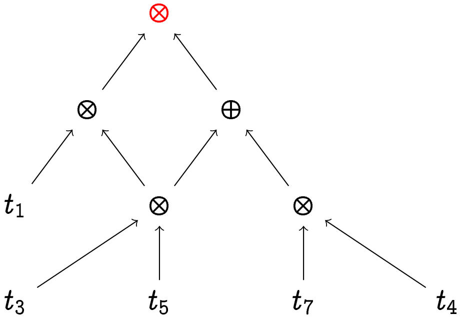
Is there a city with both an analyst and an agent, and if Paris is such a city, is there a director in the agency?

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

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)

Provenance cycluits [Amarilli et al., 2017]

- Cycluit (cyclic circuit): arithmetic circuit with cycles
- Well-defined semantics on some semirings where infinite loops do not matter
- Allows computing provenance in linear-time combined complexity for recursive queries of a certain form (ICG-Datalog of bounded body size [Amarilli et al., 2017], capturing α-acyclic conjunctive queries, 2RPQs, etc.), on bounded tree-width databases
- Related to provenance equation systems and formal series introduced in [Green et al., 2007]

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 ≥ 9.5
- Provenance annotations stored as UUIDs, in an extra attribute of each provenance-aware relation
- A provenance circuit relating UUIDs of elementary provenance annotations and arithmetic gates stored as table
- 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 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-DNNFs)

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 (without aggregation)
  - SELECT DISTINCT queries (i.e., set semantics)
  - UNION's or UNION ALL's of SELECT queries
  - EXCEPT queries
- Longer term project: aggregate computation
- 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), with some extra features; implemented as a middleware

Outline

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; to other data models
  - Compact provenance representation formalisms
- Some theory still missing:
  - Provenance and updates
  - Going beyond the relational algebra for full semiring provenance
- Now is the time to work on concrete implementation
- Need good implementation to convince users they should track provenance!
- How to combine provenance computation and efficient query evaluation, e.g., through tree decompositions?

Preparing for tomorrow's hands-on session

- Bring your own computer
- Make sure you have an Internet connection
- Install a (reasonably recent) PostgreSQL client:

Debian, Ubuntu: `sudo apt-get install postgresql-client`

Fedora: `sudo dnf install postgresql.x86_64`

Mac OS X: `brew install libpq`
`brew link --force libpq`

Windows: Install from `https://www.enterprisedb.com/downloads/postgres-postgresql-downloads` (you can deselect everything but the client)

Merci.

`https://github.com/PierreSenellart/provsql`

`https://youtu.be/iqzSNfGHbEE?vq=hd1080`

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