CS 595 - Hot topics in database systems: Data Provenance

I. Database Provenance I.1 Provenance Models and Systems

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Causality and Responsibility

Outline

1 The Causality and Responsibility Model

- Causality and Responsibility
- Computing Causaility based on Provenance
- Recap



Causality and Responsibility

Causality and Responsibility

Causality

- Models which tuples were necessary to produce output tuple
- Necessary here is context dependent
 - Tuple is necessary assuming that other tuple do not exist

Responsibility

- Model how important a tuple was in deriving an output tuple
- Numeric value
 - 1: Absolutely necessary in deriving the tuple
 - $\rightarrow 1/\infty$: Very marginal necessity

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Causality and Responsibility

Counterfactual Cause

- A tuple t' ∈ I is counterfactual cause for a tuple t in result of query q
 - If removing it from the database causes *t* to disappear from the result of *q*
 - $\Rightarrow t'$ is strictly necessary to derive t

Definition (Counterfactual Cause)

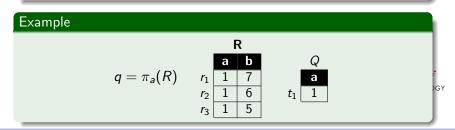
 $t' \in I$ is counterfactual cause for $t \in Q(I)$ iff

•
$$t \notin Q(I - \{t'\})$$

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Actual Cause

- Tuples influence result without being strictly necessary
 - E.g., three tuples are projected on one result tuple t
 - None of these tuples is a counterfactual cause
 - However, these tuples clearly caused t to be in result

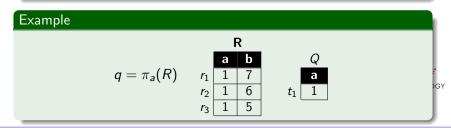


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Causality and Responsibility

Actual Cause

- Tuples influence result without being strictly necessary
 - E.g., three tuples are projected on one result tuple t
 - None of these tuples is a counterfactual cause
 - However, these tuples clearly caused t to be in result
- ⇒Model that tuples are only necessary under certain conditions
 - E.g., removing two tuples from the example before ⇒the remaining tuple to be a cause



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Causality and Responsibility

Actual Cause

Definition (Actual Cause)

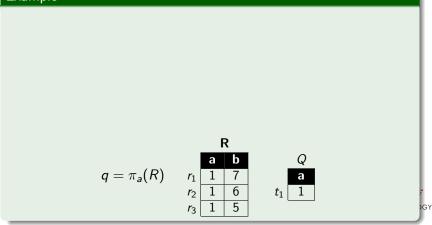
- $t' \in I$ is actual cause for $t \in Q(I)$ iff
 - exists $\Gamma \subset (I \{t'\})$ (call contingency)
 - $t \in Q(I \Gamma)$ and $t \notin Q(I \Gamma \{t'\})$



Causality and Responsibility

Actual Cause Example

Example



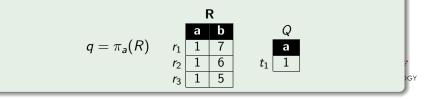
Causality and Responsibility

Actual Cause Example

Example

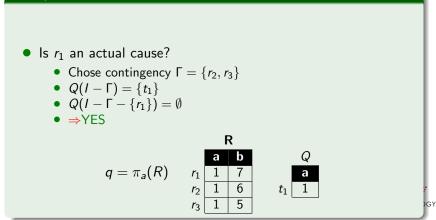
• Is r_1 a counterfactual cause?

•
$$Q(I - \{r_1\}) = \{t_1\} \Rightarrow \mathsf{NO}$$



Causality and Responsibility

Actual Cause Example



Causality and Responsibility

Exogenous vs. Endogenous Tuple

Rationale

• Let user choose which tuples are considered as causes

- Exclude trusted relation from reasoning
- User divides instance into
 - Potential causes Iⁿ (endogenous)
 - Tuples which are not considered as causes I^x (exogenous)

Adapted Definitions

• Counterfactual Cause t' for t: $t' \in D^n \land t \notin Q(I - \{t'\})$

• Actual Cause t' for t: $t' \in D^n \land \exists \Gamma \subset D^n : t' \in Q(I - \Gamma) \land t' \notin Q(I - \Gamma - \{t'\})$

Causality and Responsibility

Responsibility

Rationale

- Not all causes are equal
- Some causes are more important than others
- ⇒Create model that quantifies the importance of causes
- Tuples with large contingency are less important



Causality and Responsibility

Responsibility

Rationale

- Not all causes are equal
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Definition (Responsibility)

The responsibility ρ_t of a cause t is computed as

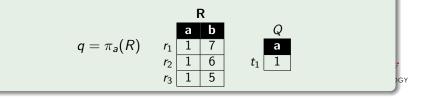
•
$$\rho_t = \frac{1}{1 + \min_{\Gamma} \|\Gamma\|}$$

Γ ranges over all contingencies for t

Causality and Responsibility

Responsibility Example

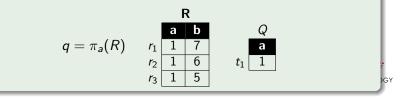
- Compute responsibility ρ_{r_1} for t_1
- Find smalles contingency, test subsets of $I \{r_1\}$



Causality and Responsibility

Responsibility Example

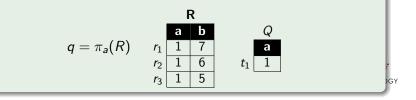
- Compute responsibility ρ_{r_1} for t_1
- Find smalles contingency, test subsets of $I \{r_1\}$
 - {*r*₂} **NO**



Causality and Responsibility

Responsibility Example

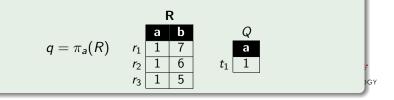
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 - {*r*₂} **NO**
 - {*r*₃} NO



Causality and Responsibility

Responsibility Example

- Compute responsibility ρ_{r_1} for t_1
- Find smalles contingency, test subsets of $I \{r_1\}$
 - {*r*₂} **NO**
 - {*r*₃} NO
 - $\{r_2, r_3\}$ YES



Causality and Responsibility

Responsibility Example

Example

- Compute responsibility ρ_{r_1} for t_1
- Find smalles contingency, test subsets of $I \{r_1\}$
 - {*r*₂} **NO**
 - {*r*₃} NO

$$\rho_{r_1} = \frac{1}{1 + \|\{r_2, r_3\}\|} = \frac{1}{3}$$

$$H = \pi_a(R) \qquad \begin{array}{ccc} R \\ a & b \\ r_1 & 1 & 7 \\ r_2 & 1 & 6 \\ r_3 & 1 & 5 \end{array} \qquad \begin{array}{c} Q \\ a \\ t_1 & 1 \\ t_1 \end{array}$$

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Causality and Responsibility

Insensitivity to Query Rewrite

Causality is insensitive!

- The definition is purely declarative
- ⇒has to be insensitive

• E.g,
$$q \equiv q'$$
 and $t \in Q/Q'(I)$

• If t' is cause for t in q then $\exists \Gamma$ so that

•
$$t \in Q(I - \Gamma) = Q'(I - \Gamma)$$

•
$$t \notin Q(I - \Gamma - \{t'\}) = Q'(I - \Gamma - \{t'\})$$

• $\Rightarrow t'$ is cause for t in q'



Causality and Responsibility

Notation

Causality

- Cau(q, t) is set of all actual causes for t
 - $Cau(q, t) = \{t' \mid t' \text{ is actual cause for } t\}$

Responsibility

 ρ_{q,t}(t') is function mapping each cause t' its responsibility value



Causality and Responsibility

Computing Causes and Responsibility - Brute Force

Causes
• For each tuple t' in I
• Enumerate all subsets Г
• For each such subset test
• $Q(I - \Gamma)$ and $Q(I - \Gamma - \{t'\})$
 If test is successful then t' is actual cause



Causality and Responsibility

Computing Causes and Responsibility - Brute Force

Causes

- For each tuple t' in I
 - Enumerate all subsets Γ
 - For each such subset test

•
$$Q(I - \Gamma)$$
 and $Q(I - \Gamma - \{t'\})$

• If test is successful then t' is actual cause

Complexity

- ||*I*|| number of iterations
- In each iteration in worst case we have $2^{\|I\|-1}$ subsets to consider
- For each subset we have to execute two queries
- $O(||I|| \times 2^{||I||} \times 2 \times cost(Q(I))) = O(2^{||I||})$

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Causality and Responsibility

Computing Causes and Responsibility - Brute Force

Responsibility

- For each tuple t' in I init $minCont = \infty$
 - Enumerate all subsets Γ
 - For each such subset test
 - $Q(I \Gamma)$ and $Q(I \Gamma \{t'\})$
 - If test is successful then
 - minCont = min(||Γ||, minCont)



Causality and Responsibility

Computing Causes and Responsibility - Brute Force

Responsibility

- For each tuple t' in I init $minCont = \infty$
 - Enumerate all subsets Γ
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•
$$Q(I - \Gamma)$$
 and $Q(I - \Gamma - \{t'\})$

- If test is successful then
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Complexity

- ||1|| number of iterations
- In each iteration in worst case we have 2^{||||-1} subsets to consider
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•
$$O(||I|| \times 2^{||I||} \times 2 \times cost(Q(I))) = O(2^{||I||})$$

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Computing Causaility based on Provenance

Outline

1 The Causality and Responsibility Model

- Causality and Responsibility
- Computing Causaility based on Provenance
- Recap



Computing Causaility based on Provenance

Using Provenance for Cause Computation

Rationale

- Provenance contains all tuples that effect a tuple
- ⇒Limit search for contingency to provenance
- Relationship with view update (delete tuple t from view)
 - View Update: Find set of tuples from the input that cause *t* to disappear
 - \neq Find set of tuples so that after removal additional tuples cause t
 - Exogenous tuples!
 - Queries are assumed to be CQ's

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Computing Causaility based on Provenance

Excursion: Datalog

Datalog

- Relational query language (set-semantics)
- Similar to Prolog: Queries are expressed as logical implications
- Declarative:
 - Query specifies what result is rather than how to compute it

• Expressive Power:

- Supports recursion
- Without recursion + with negation it is equivalent to relational algebra (no aggregation)
- Without negation and recursion is equivalent to SPJ queries (using equality predicates only) - called Conjunctive Queries (CQ)

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Computing Causaility based on Provenance

Excursion: Datalog rules

Queries

Set of datalog rules

Datalog rule

•
$$q(\vec{X}):-R_1(\vec{X_1}),\ldots,R_n(\vec{X_n})$$

- R_i's are relations
- \vec{X} and $\vec{X_i}$ are lists of variables and/or constants
- The variables in \vec{X} have to appear in at least one $\vec{X_i}$
- Head: $q(\vec{X})$ is called the head
- Body: $R_1(\vec{X_1}), \ldots, R_n(\vec{X_n})$ is called the body of the rule
- Single rule (conjunctive query) = SPJ query

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Excursion: Evaluating CQ's

Valuation θ

- a replacement of variables in body (⇒also in head) with constants
- such that every atom $R_i(\theta(\vec{X_i}))$ is a tuple in the instance I

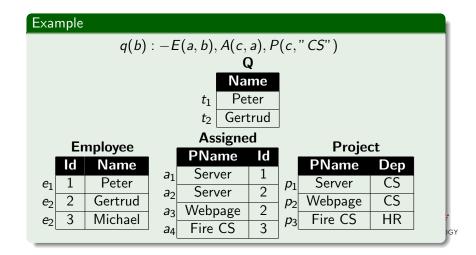
Result of Conjunctive Query

- For each valuation θ
- add $\theta(\vec{X})$ to the result of query



Computing Causaility based on Provenance

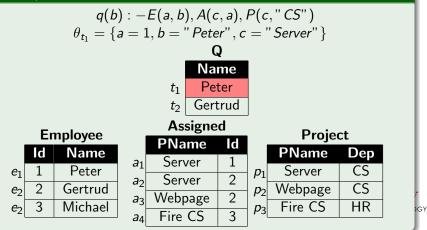
Excursion: Example CQ



Computing Causaility based on Provenance

Excursion: Example CQ

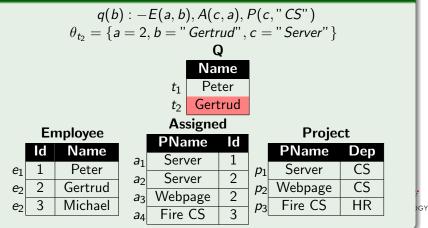
Example



Computing Causaility based on Provenance

Excursion: Example CQ

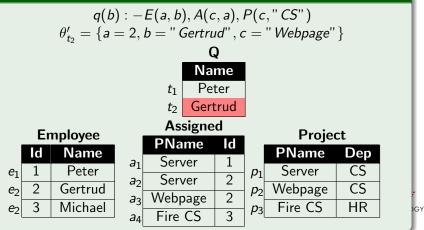
Example



Computing Causaility based on Provenance

Excursion: Example CQ

Example



Computing Causaility based on Provenance

Excursion: Boolean queries

Boolean query

- Conjunctive query with empty head
- Evaluates to {*true*, *false*}

Example

Department(Name, Headcount, Budget)

• Evaluates to true if there is an "CS" department



Computing Causaility based on Provenance

Excursion: Union of Conjunctive Queries

Union of Conjunctive Queries

- Set of datalog rules with same name and arity in head
- Evaluation: union the evaluation results for all rules

Example

$$q(a)$$
: $-R(a)$
 $q(b)$: $-R(b), S(b)$

is the same as $R \cup (R \bowtie S)$ (natural join)

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Computing Causaility based on Provenance

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Computing Causaility based on Provenance

Excursion: Recursive Datalog and Negation

Recursive Datalog

- Set of datalog rules with same name and arity in head
- + rules can reference themselves or other rules in the body
- Evaluation:
 - *I*′ = *I*
 - Evaluate one rule and add result to I'
 - Repeat until no more new data can be added

Example

Computing Causaility based on Provenance

Excursion: Recursive Datalog and Negation

Datalog with Negation

- Allow negated atoms in the body
- Evaluation:
 - Find valuations so that for every negated atom $\neg R_i(\vec{X_i})$
 - $R_i(\theta(\vec{X}_i))$ is not in the instance

Example

$$Civil(a) : -Person(a), \neg WorksInArmy(a)$$

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Computing Causaility based on Provenance

The $\mathbb{B}[I]$ Semiring for conjunctive queries

Recall

- $\mathbb{B}[I]$ is boolean expressions over variables presenting the tuples in I
- E.g., $(t_1 \wedge t_2) \vee t_3$
- Here always formulas in DNF (disjunctive normal form)

Provenance for conjunctive queries

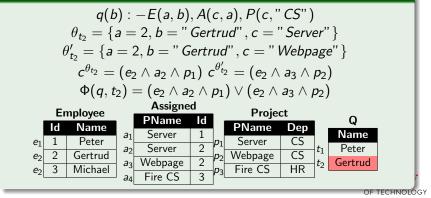
- CQ: $q: -a_1, ..., a_m$
- Valuation θ with $\theta(a_i) = t_i$
- X_t is boolean variable for tuple t
- Formula $c^{\theta} = X_1 \wedge \ldots \wedge X_m$

• Provenance
$$\Phi(q, t) = \bigvee_{\theta:q \to I} c^{\theta}$$

Computing Causaility based on Provenance

Example Provenance for CQ

Example



Computing Causaility based on Provenance

Determine Causes based on Provenance

• Testing whether t is in the result of removing some tuples

Computing Causaility based on Provenance

Determine Causes based on Provenance

- Testing whether t is in the result of removing some tuples
- ⇒Deletion propagation

Computing Causaility based on Provenance

Determine Causes based on Provenance

- Testing whether t is in the result of removing some tuples
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- \Rightarrow Set variables for deleted tuples *S* to *false*

Computing Causaility based on Provenance

Determine Causes based on Provenance

- Testing whether t is in the result of removing some tuples
- ⇒Deletion propagation
- \Rightarrow Set variables for deleted tuples *S* to *false*
- For set S of tuples: Φ[S = false] sets all variables corresponding to tuples in S to false
 - If $\Phi(q, t)[S = false] = true$: tuple t in result of Q(I S)
 - If $\Phi(q, t)[S = false] = false$: tuple t not in result of Q(I S)

Computing Causaility based on Provenance

Determine Causes based on Provenance

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 - If $\Phi(q, t)[S = false] = false$: tuple t not in result of Q(I S)
- \Rightarrow We can test whether t' is cause by
 - Testing for every subset Γ of the provenance whether Φ(q, t)[Γ = false] = true
 - ... and $\Phi(q, t)[(\Gamma \cup \{t'\}) = false]$

Computing Causaility based on Provenance

Determine Causes based on Provenance

- Testing whether t is in the result of removing some tuples
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 - Testing for every subset Γ of the provenance whether Φ(q, t)[Γ = false] = true
 - ... and $\Phi(q, t)[(\Gamma \cup \{t'\}) = false]$

⇒still exponential, but in size of provenance

Computing Causaility based on Provenance

Determine Causes based on Provenance cont.

- Exploit structure of the formula for more efficient computation
- $\Phi(Q, t)$ evaluates to false, if every conjunct evaluates to false
- A conjunct evaluates to false if any of its variables it set to false
- \Rightarrow To make t' a cause
 - Let $\mathcal{C}(t')$ be the set of conjuncts that contain t'
 - Set one variable form every conjunct not in C(t') to false (contingency)
 - Use variable that is not in a conjunct in C(t')!
 - ⇒the resulting formula is true
 - Setting $X_{t'}$ to false will make all conjuncts in $\mathcal{C}(t')$ false
 - $\Rightarrow t'$ is cause

Computing Causaility based on Provenance

Determine Causes based on Provenance cont.

Caveat

- There may not be variables that are only in conjuncts not in C(t')!
 - Example: $X_{t_2} \vee X_{t_2} X_{t_1}$.
- This is the case for redundant conjuncts
- \Rightarrow apply absorption $a \land b \lor a = a$
- ⇒All tuples corresponding to variables in this formula are actual causes
- \Rightarrow Polynomial complexity!

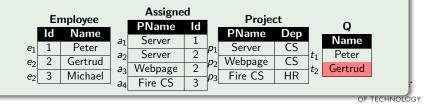
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Computing Causaility based on Provenance

Determine Causes based on Provenance cont.

Example

- q(b): -E(a, b), A(c, a), P(c, "CS")
- $\Phi(q, t_2) = (e_2 \wedge a_2 \wedge p_1) \vee (e_2 \wedge a_3 \wedge p_2)$
- No redundant conjuncts
- \Rightarrow Cau $(q, t_2) = \{e_2, a_2, a_3, p_1, p_2\}$



Computing Causaility based on Provenance

Endogenous Provenance

- Exogenous tuples cannot be used
- Set all exogenous tuple variables to true $\Rightarrow \Phi^n(q, t)$
- \Rightarrow Compute non-redundant conjuncts based on $\Phi^n(q, t)$



Computing Causaility based on Provenance

Endogenous Provenance

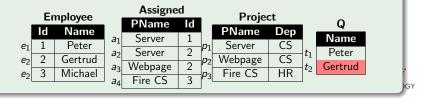
Example

•
$$q(b) : -E(a, b), A(c, a), P(c, "CS")$$

•
$$\Phi(q, t_2) = (e_2 \wedge a_2 \wedge p_1) \vee (e_2 \wedge a_3 \wedge p_2)$$

•
$$I^x = \{p_1\} \cup A$$

•
$$\Rightarrow \Phi^n(q, t_2) = (e_2 \land true \land true) \lor (e_2 \land true \land p_2) = e_2 \lor (e_2 \land p_2) = e_2$$



Recap

Outline

1 The Causality and Responsibility Model

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- Recap



Recap

Recap

Causality based Provenance

- Rationale: Models necessity negatively
 - Cause not there \Rightarrow Tuple not there
- **Representation**: Set of tuples (Cause) / numeric value (Responsibility)
 - Contingency Γ
- Declarative Definition:
 - For any queries
- Provenance Based Definition:
 - SPJ queries

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Recap

Recap

Responsibility

- Quantifies responsibility of cause
- Defined over size of smallest contingency



Provenance Model Comparison

Property	Why	Lin	PI-CS	Where	How	Causality
Representation	Set of Set of Tuples	List of Set of Tuples	Set/Bag of List of Tuples	Sets of At- tribute Value Positions	Values of provenance semiring	Set of causes + numeric responsibility value
Granularity	Tuple	Tuple	Tuple	Attribute Value	Tuple	Tuple
Language Support	USPJ	ASPJ-Set	ASPJ-Set + Nested subqueries	U-SPJ	A*SPJ-UD*	SPJ
Semantics	Set	$Set + Bag^*$	Bag	Set	Set + Bag	Set
Variants	Wit, Why, IWhy	Set/Bag	Influence + Copy	SPJ + In- sensitive + Insensitive Union	semirings	For multiple tuples
Definition	Decl Synt. - Decl./Synt.	Decl. + Synt.	Decl. + Synt.	Synt.	Synt.	Decl.
Design Principles	Sufficiency - No false pos- itives	Sufficiency + No false neg- atives + no false positives	Sufficiency + No false neg- atives + No false positives	Copying	Equivalent to query evalua- tion	Contextual Necessity
Systems	-	WHIPS	Perm	DBNotes	ORCHESTRA	Thesias*
Insensitivity	Yes - No - Yes	No	No	No - Yes - Yes	Yes	Yes

Recap

Literature I



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Recap

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