Updated 3/9/2022

# Topic 2: Complexity of Query Evaluation Unit 3: Provenance Lecture 14

Wolfgang Gatterbauer

CS7240 Principles of scalable data management (sp22)

https://northeastern-datalab.github.io/cs7240/sp22/

3/4/2022

#### Topic 2: Complexity of Query Evaluation & Reverse Data Management

- CONTINUED Lecture 11 (Tue 2/22): 1 Conjunctive Queries
- **Lecture 12 (Fri 2/25):** Conjunctive Queries
- **Lecture 13 (Tue 3/1):** Beyond Conjunctive Queries
- Lecture 14 (Fri 3/4): Provenance
- **Lecture 15 (Tue 3/8):** Provenance, Reverse Data Management

#### Pointers to relevant concepts & supplementary material:

- Unit 1. Conjunctive Queries: Query evaluation of conjunctive queries (CQs), data vs. query complexity, homomorphisms, constraint satisfaction, query containment, query minimization, absorption: [Kolaitis, Vardi'00], [Vardi'00], [Kolaitis'16], [Koutris'19] L1 & L2
- **Unit 2. Beyond Conjunctive Queries**: unions of conjunctive queries, bag semantics, nested queries, tree pattern queries: [Kolaitis'16], [Tan+'14], [G.'11], [Martens'17]
- o Unit 3. Provenance: [Buneman+02], [Green+07], [Cheney+09], [Green, Tannen'17], [Kepner+16], [Buneman, Tan'18]
- Unit 4. Reverse Data Management: update propagation, resilience: [Buneman+02], [Kimelfeld+12], [Freire+15]

# Outline: T2-3/4: Provenance & Reverse Data Management

- T2-3: Provenance
  - Data Provenance
  - The Semiring Framework for Provenance
  - Algebra: Monoids and Semirings
  - Query-rewrite-insensitive provenance
- T2-4: Reverse Data Management
  - View Deletion Problem
  - Resilience & Causality

#### Data provenance.

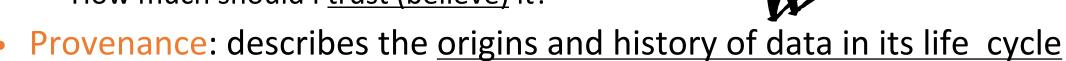
Imagine a computational process that uses a complex input consisting of multiple items. The granularity and nature of "input item" can vary significantly. It can be a single tuple, a database table, or a whole database. It can a spreadsheet describing an experiment, a laboratory notebook entry, or another form of capturing annotation by humans in software. It can also be a file, or a storage system component. It can be a parameter used by a module in a scientific workflow. It can also be a configuration rule used in software-defined routing or in a complex network protocol. Or it can be a configuration decision made by a distributed computation scheduler (think map-reduce). Provenance analysis allows us to understand how these different input items affect the output of the computation. When done appropriately, such

# Near-Term Challenges in II II = Intelligent Infrastructure

- et Error control for multiple decisions
- · Systems that create markets
- Designing systems that can provide meaningful, calibrated notions of their uncertainty
- Achieving real-time performance goals
- Managing cloud-edge interactions
- Designing systems that can find abstractions quickly
  - Provenance in systems that learn and predict
  - Designing systems that can explain their decisions
- Finding causes and performing causal reasoning
- Systems that pursue long-term goals, and actively collect data in service of those goals
- Achieving fairness and diversity
- Robustness in the face of unexpected situations
- Robustness in the face of adversaries
- Sharing data among individuals and organizations
- Protecting privacy and issues of data ownership

### Provenance: "Where Did this Data Come from?"

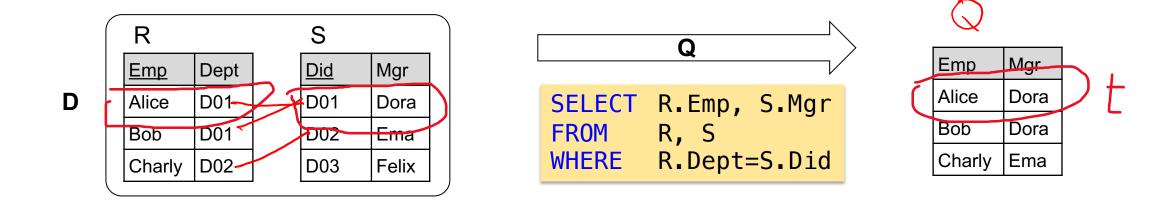
- Whenever data is shared (e.g., science, Web) natural questions appear:
  - How did I get this data?
  - What operations were used to create the data?
  - How much should I trust (believe) it?



- Two types of provenance
  - Provenance inside a database: that's our focus
  - Provenance outside databases: focus of ongoing research esp. in ML (causes, influence, fairness); less well-defined; there is a standard OPM (Open Provenance Model)
- There are also questions for our focus, provenance inside DBMS:
  - What is the "right data model" of provenance?
  - How do we query it? What operations should we support?

# Example of data provenance

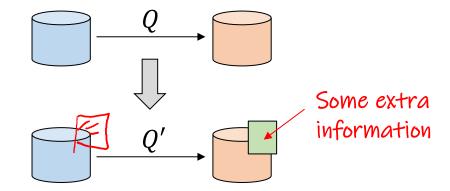
- A typical question:
  - For a given database D, a query Q, and a tuple t in the output of Q(D), which parts of D "contribute" to output tuple t?



- The question can be applied to attribute values, tables, rows, etc.

# Two approaches

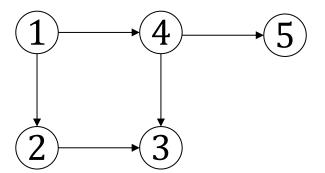
- Eager or annotation-based ("annotation propagation")
  - Changes the transformation from Q to Q' to carry extra information
  - Full source data not needed after transformation



- Lazy or non-annotation based
  - Q is unchanged
  - Recomputation and access to source required.
    - Good when extra storage is an issue.

# Example graph problem, in 5 different variants





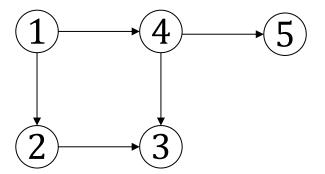
E	. 40
1	2
2	3
1	4
4	3
4	5

Q(z) :-	E(1,y),	E(y,z)
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# Example graph problem, in 5 different variants



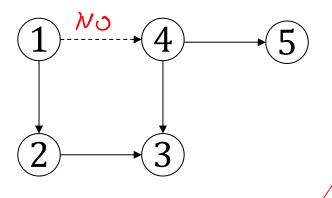


E

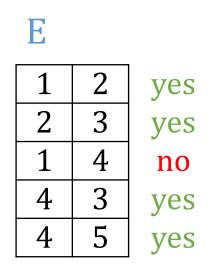
	_
1	2
2	3
1	4
4	3
4	5

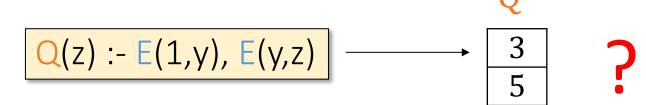
Q(z) := E(1,y), E(y,z)	 3	
	5	



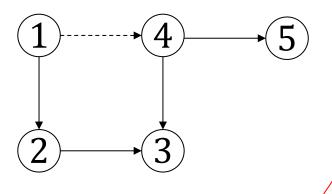


Now assume only certain edges are available (available yes/no or true/false). Which of the points remain reachable?

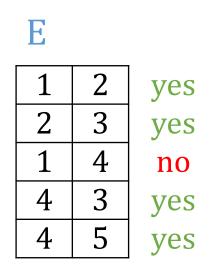


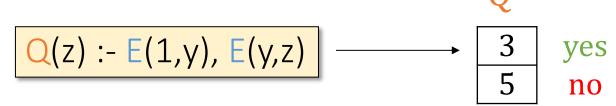




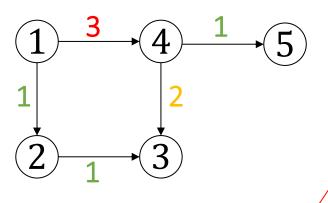


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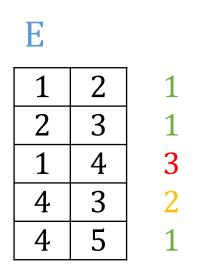


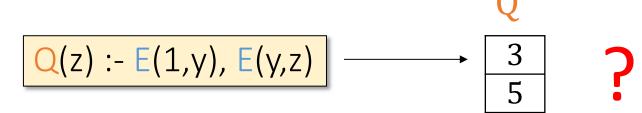




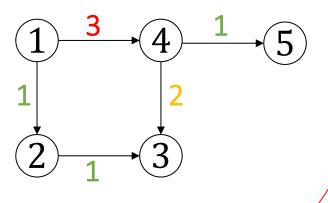


Now assume passing along an edge needs a certain security clearance (1<2<3). What clearance do you need for reaching each point?

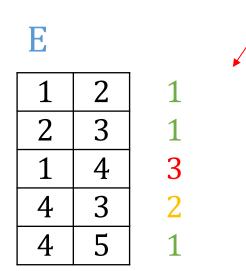






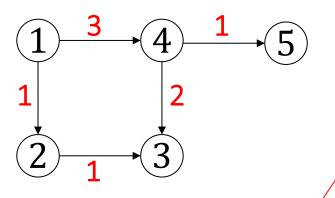


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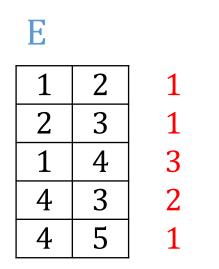


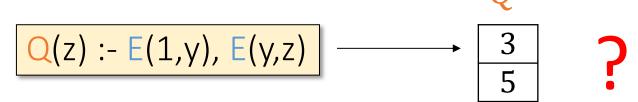
$$Q(z) := E(1,y), E(y,z) \longrightarrow \begin{bmatrix} 3 & 1 \\ 5 & 3 \end{bmatrix}$$



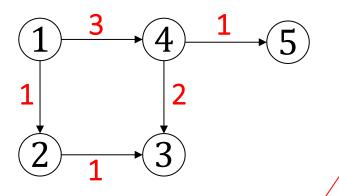


Now assume each edge has a weight. What is the shortest path to reach each point?

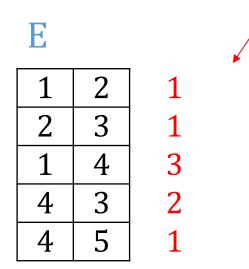


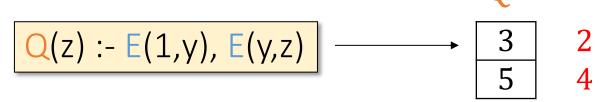




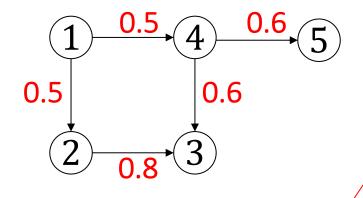


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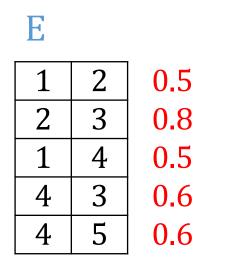


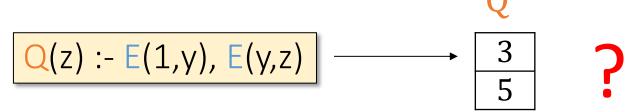




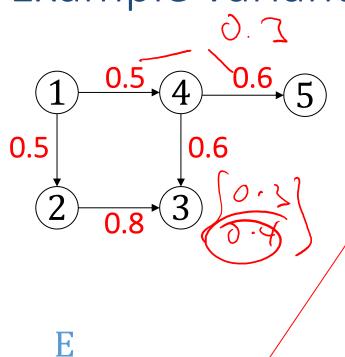


Now assume each edge has a confidence (probability of being available). What is the probability of the most likely path?









3

5

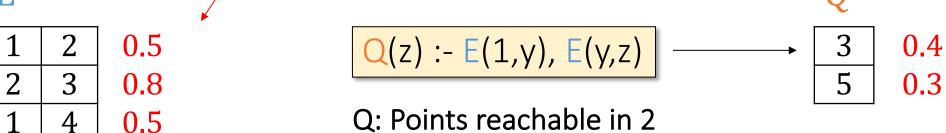
0.6

0.6

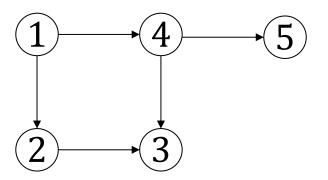
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4

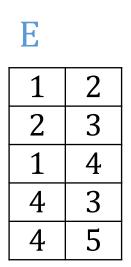
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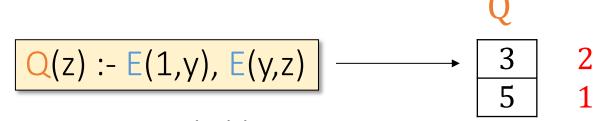






Finally assume we want to calculate the number of paths to a node. How many are there? What is even a reasonable way to calculate that in general?





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POSITIVE RA

#### Do it once and use it repeatedly: provenance

Label (annotate) input items abstractly with provenance tokens.

Provenance tracking: propagate expressions (involving tokens) (to annotate intermediate data and, finally, outputs)

Track two distinct ways of using data items by computation primitives:

- **jointly** (this alone is basically like keeping a log)
- alternatively (doing both is essential, think trust)

Input-output compositional; Modular (in the primitives)

Later, we want to **evaluate** the provenance expressions to obtain binary trust, access control, confidence scores, data prices, etc.

# Algebraic interpretation for RDB \[ \langle \frac{\frac{1}{2}}{2} \\ \tag{2} \\ \tag{2} \\ \tag{3} \\ \tag{3} \\ \tag{4} \\ \tag{2} \\ \tag{2} \\ \tag{3} \\ \tag{4} \\ \tag{4}

Set X of provenance tokens.

Space of annotations, provenance expressions  $\text{Prov}(X) \supset \{x \cdot y \cdot y + z \neq y, \dots\}$ 

#### Prov(X)-relations:

every tuple is annotated with some element from Prov(X).

Binary operations on Prov(X):

- corresponds to joint use (join, cartesian product),
- + corresponds to alternative use (union and projection).

#### Special annotations:

"Absent" tuples are annotated with 0.

1 is a "neutral" annotation (data we do not track).



#### **K**-Relational algebra

```
Algebraic laws of (\text{Prov}(X), +, \cdot, 0, 1)? More generally, for annotations from a structure (K, +, \cdot, 0, 1)?
```

K-relations. Generalize RA+ to (positive) K-relational algebra.

```
Desired optimization equivalences of K- relational algebra iff (K, +, \cdot, 0, 1) is a commutative semiring.
```

```
Generalizes SPJU or UCQ or non-rec. Datalog set semantics (\mathbb{B}, \vee), \wedge, \perp,\top) bag semantics (\mathbb{N}, +), \cdot, 0, 1) c-table-semantics [IL84] (BoolExp(X), \vee, \wedge, \perp,\top) event table semantics [FR97,Z97] (\mathcal{P}(\Omega), \cup, \cap, \emptyset, \Omega)
```



What is a commutative semiring?

An algebraic structure  $(K, +, \cdot, 0, 1)$  where:

- K is the domain
- + is associative, commutative, with 0 identity
- is associative, with 1 identity
- distributes over +
- $a \cdot 0 = 0 \cdot a = 0$
- is also commutative

Unlike ring, no requirement for inverses to +

semiring

#### **Provenance polynomials**

$$\mathbb{N}[\{x,y\}] = \{xy, x + y, 2xy^2 + x, 2xy^2 + xy + x, ...\}$$

 $(\mathbb{N}[X], +, \cdot, 0, 1)$  is the commutative semiring freely generated by X (universality property involving homomorphisms)

Provenance polynomials are **PTIME**-computable (data complexity). (query complexity depends on language and representation)

ORCHESTRA provenance (graph representation) about 30% overhead

Monomials correspond to logical derivations (proof trees in non-rec. Datalog)

#### **Provenance reading of polynomails:**

output tuple has provenance  $2r^2 + rs$ 

three derivations of the tuple - two of them use *r*, twice,

- the third uses *r* and *s*, once each

#### Two kinds of semirings in this framework

#### Provenance semirings, e.g.,

```
(\mathbb{N}[X], +, \cdot, 0, 1) provenance polynomials [GKT07] (Why(X), \cup, \cup, \emptyset, \{\emptyset\}) witness why-provenance [BKT01]
```

#### Application semirings, e.g.,

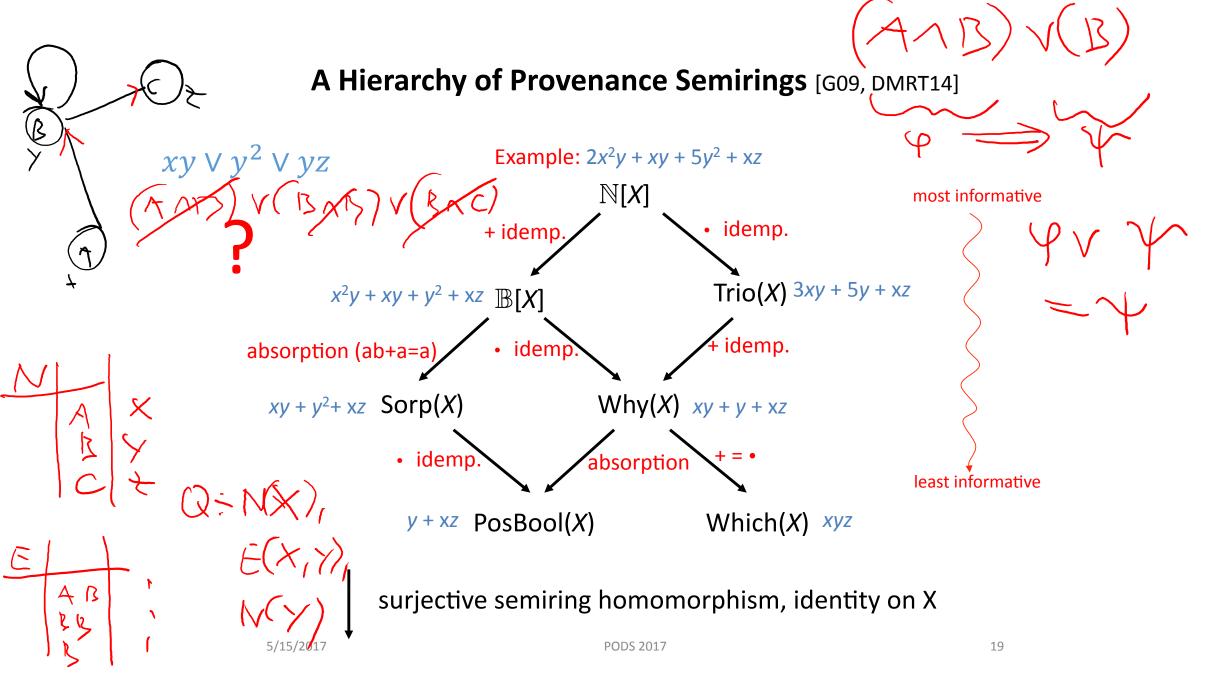
```
(A, min, max, 0, Pub) access control [FGT08] \mathbb{V} = ([0,1], \max, \cdot, 0, 1) Viterbi semiring (MPE) [GKIT07]
```

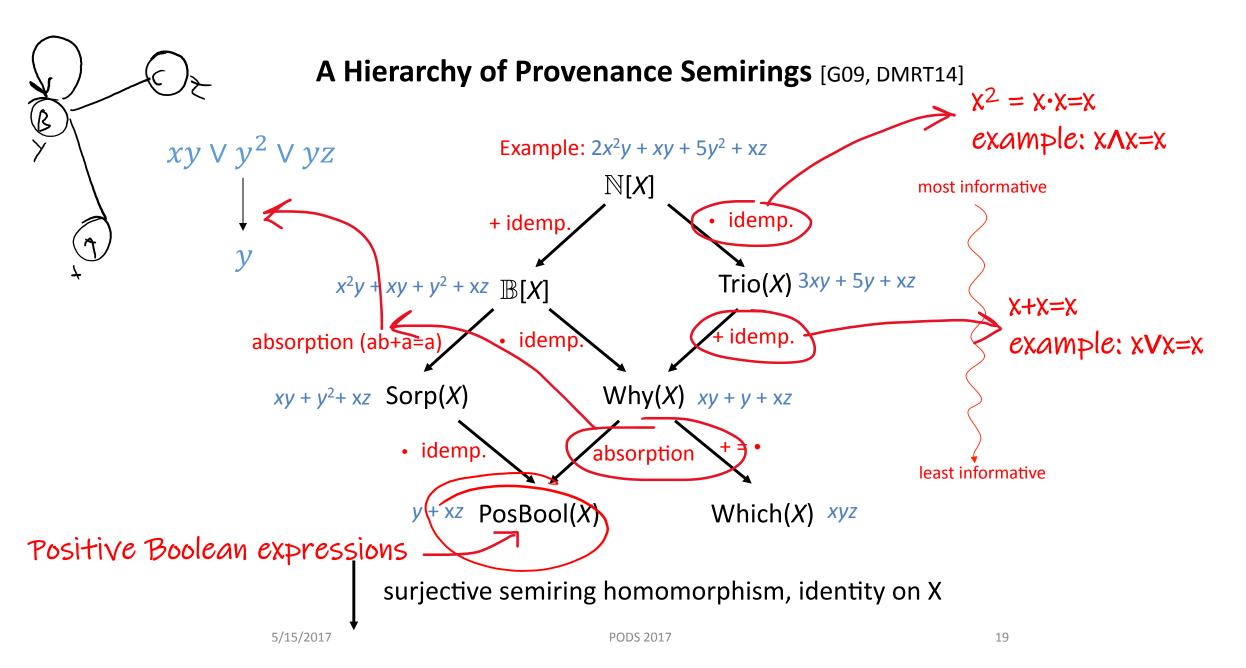
#### **Provenance specialization** relies on

- Provenance semirings are freely generated by provenance tokens
- Query commutation with semiring homomorphisms

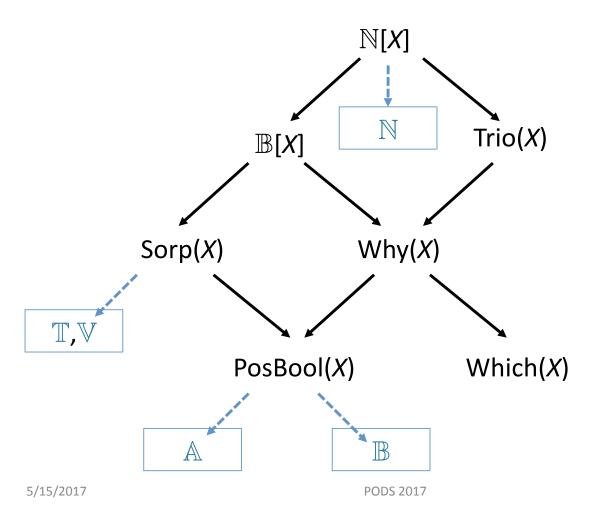
#### Some application semirings

```
(\mathbb{B}, \wedge, \vee, \top, \perp) binary trust
(\mathbb{N}, +, \cdot, 0, 1) multiplicity (number of derivations)
(A, min, max, 0, Pub) access control
\mathbb{V} = ([0,1], \max, \cdot, 0, 1) Viterbi semiring (MPE)
                                                                confidence scores
\mathbb{T} = ([0, \infty], \min, +, \infty, 0)
                  tropical semiring (shortest paths)
                                                                  data pricing
\mathbb{F} = ([0,1], \max, \min, 0, 1) "fuzzy logic" semiring
```





#### A Hierarchy of Provenance Semirings [G09, DMRT14]



Source: Val Tannen. "The Semiring Framework for Database Provenance", PODS 2017 Test of Time Award talk: <a href="https://www.cis.upenn.edu/~val/15MayPODS.pdf">https://www.cis.upenn.edu/~val/15MayPODS.pdf</a>
Wolfgang Gatterbauer. Principles of scalable data management: <a href="https://northeastern-datalab.github.io/cs7240/">https://northeastern-datalab.github.io/cs7240/</a>

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#### A menagerie of provenance semirings

(Which(X),  $\cup$ ,  $\cup^*$ ,  $\emptyset$ ,  $\emptyset^*$ ) sets of contributing tuples "Lineage" (1) [CWW00]

(Why(X),  $\cup$ ,  $\emptyset$ , { $\emptyset$ }) sets of sets of ... Witness why-provenance [BKT01]

(PosBool(X),  $\land$ ,  $\lor$ ,  $\top$ ,  $\bot$ ) minimal sets of sets of... Minimal witness whyprovenance [BKT01] also "Lineage" (2) used in probabilistic dbs [SORK11]

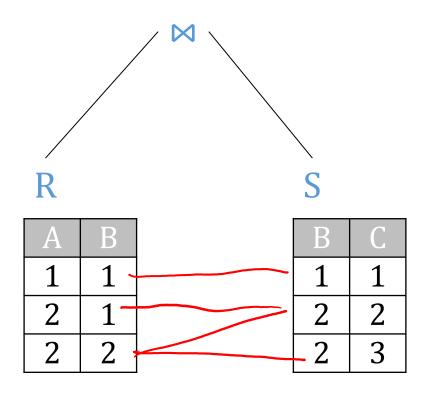
 $(Trio(X), +, \cdot, 0, 1)$  bags of sets of ... "Lineage" (3) [BDHT08,G09]

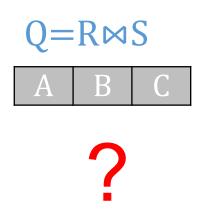
 $(\mathbb{B}[X],+,\cdot,0,1)$  sets of bags of ... Boolean coeff. polynomials [G09]

(Sorp(X),+,  $\cdot$ , 0, 1) minimal sets of bags of ... absorptive polynomials [DMRT14]

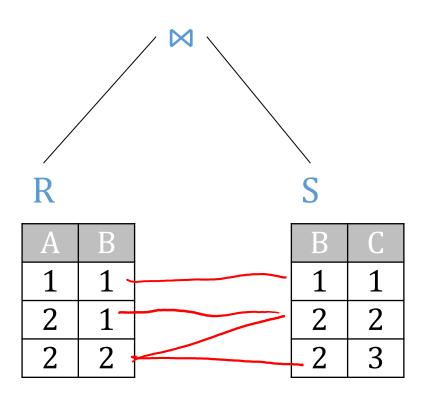
 $(\mathbb{N}[X], +, \cdot, 0, 1)$  bags of bags of... universal provenance polynomials [GKT07]







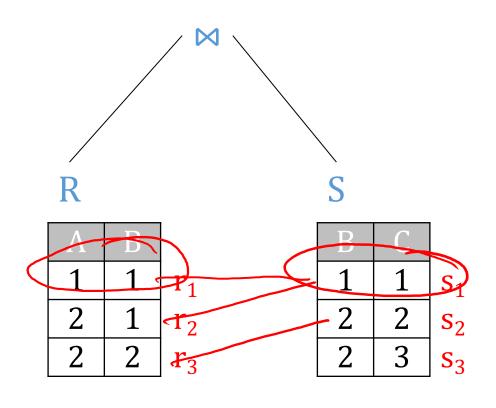


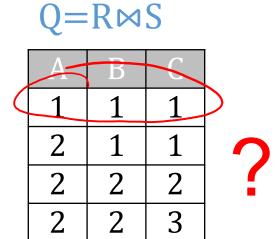


Q	R	M	S
X	1	•	

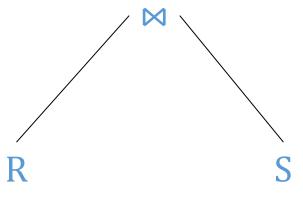
A	В	C
1	1	1
2	1	1
2	2	2
2	2	3











A	В	
1	1	$r_1$
2	1	$r_2$
2	2	$r_3$

В	C	
1	1	$s_1$
2	2	$s_2$
2	3	$S_3$

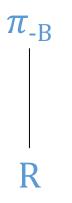
The annotation "r·s" means joint use of data annotated by r and data annotated by s

$$Q=R\bowtie S$$

A	В	С	
1	1	1	$r_1 \cdot s_1$
2	1	1	$r_2 \cdot s_1$
2	2	2	$r_3 \cdot s_2$
2	2	3	$r_3 \cdot s_3$

# Positive relational algebra: Projection $\pi$





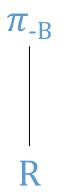
A	В	
1	1	$r_1$
1	2	$r_2$
2	1	$r_3$
2	2	$r_4$
2	3	$r_5$

$$Q = \pi_{-B} R = \pi_A R$$



# Positive relational algebra: Projection $\pi$





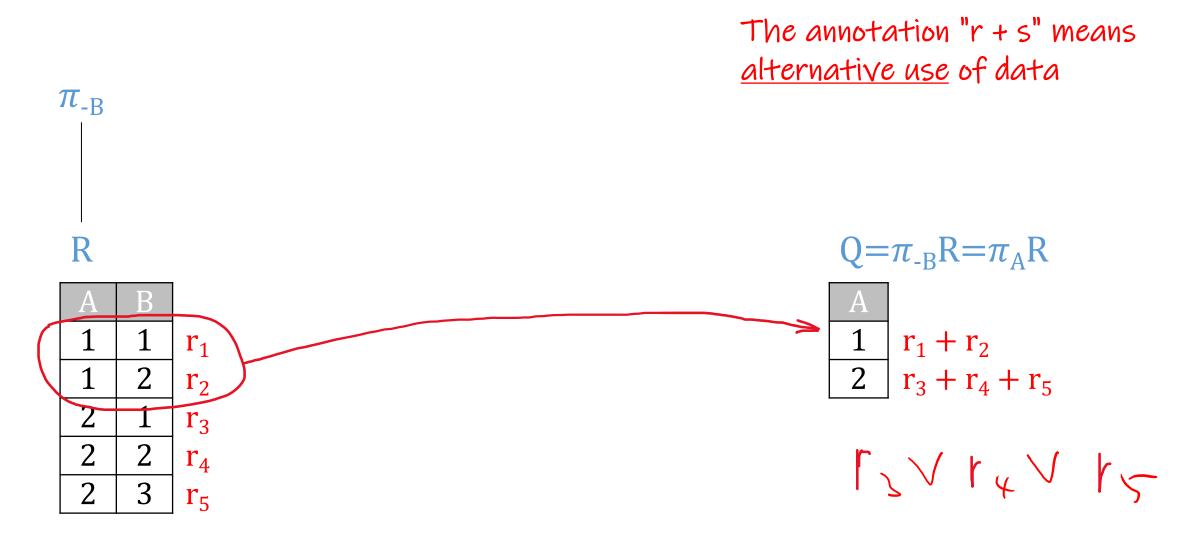
		ı
A	В	
1	1	$r_1$
1	2	$r_2$
2	1	$r_3$
2	2	$r_4$
2	3	$r_5$

0 =	$\pi_{\mathrm{p}}$	R=	$\pi_{\Lambda}R$	
~	- D.		- A	_

A	
1	
2	

# Positive relational algebra: Projection $\pi$

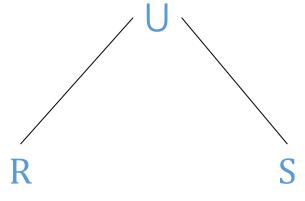






$$\{(21), (2,1)\} = (2,1) \rightarrow 2$$





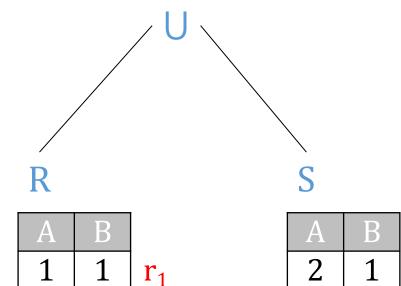
A	В	
1	1	$r_1$
2	1	$r_2$

A	В	
2	1	$s_1$
2	2	$s_2$









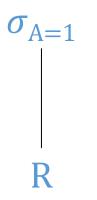
The annotation "r + s" means alternative use of data

A	В	
1	1	$r_1$
2	1	$r_2 + s_1$
2	2	$s_2$

$$k \cup S = \prod_{AB} (R \cup S)$$

# Positive relational algebra: Selection $\sigma$





A	В	
1	1	$r_1$
1	2	$r_2$
2	1	$r_3$
2	2	$r_4$
2	3	$r_5$

$$\begin{array}{c|c}
Q = \sigma_{A=1}R \\
\hline
A & B
\end{array}$$

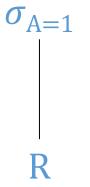


# Positive relational algebra: Selection $\sigma$



Two options for filtering:

1. Remove the tuples filtered out.



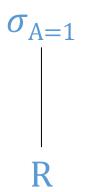
A	В	
1	1	$r_1$
1	2	$r_2$
2	1	$r_3$
2	2	$r_4$
2	3	$r_5$

$$Q = \sigma_{A=1}R$$

A	В	
1	1	$r_1$
1	2	$r_2$

# Positive relational algebra: Selection $\sigma$





A	В	
1	1	$r_1$
1	2	$r_2$
2	1	$r_3$
2	2	$r_4$
2	3	$r_5$

Two options for filtering:

- 1. Remove the tuples filtered out.
- 2. Or keep them around ...

