

Topic 2: Complexity of Query Evaluation

Unit 4: Reverse Data Management (RDM)

Lecture 18

Wolfgang Gatterbauer

CS7240 Principles of scalable data management (sp24)

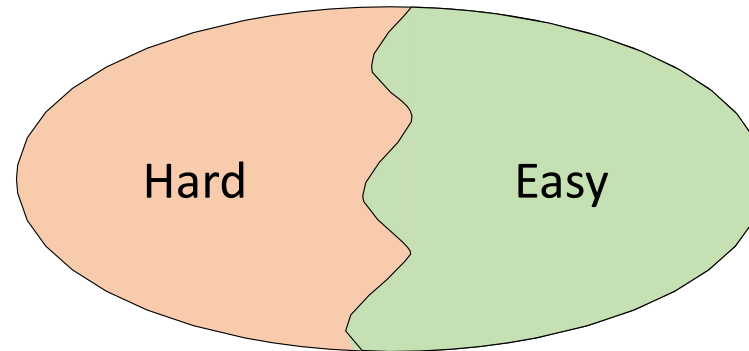
<https://northeastern-datalab.github.io/cs7240/sp24/>

3/22/2024

Dichotomy theorems

Dichotomy theorem

classifying every member of a family of problems as easy or hard.



In database context

Given a certain problem and a query. Solving this problem for a query is either easy or hard.

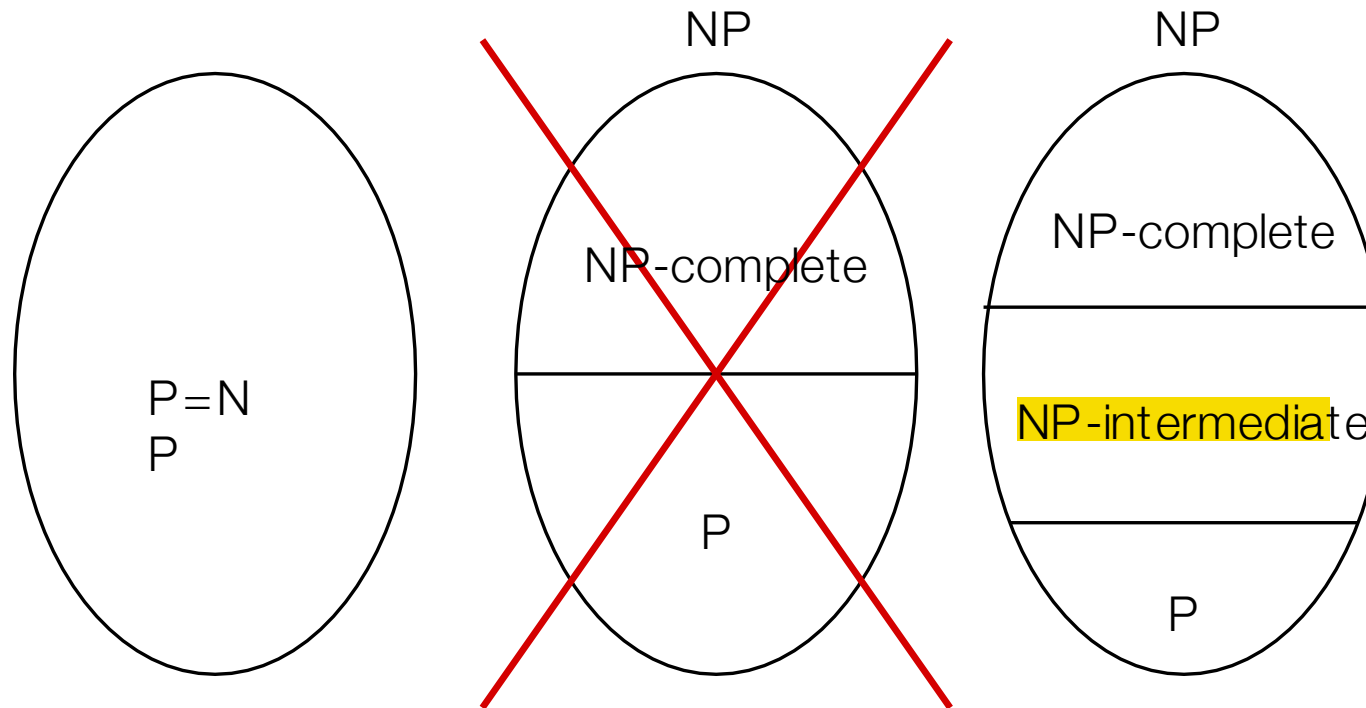
Dichotomy theorems

Every problem is either in P or NP -complete.

Why are such theorems surprising?

Theorem [Ladner, 1973]

If $P \neq NP$, then there is a language $L \in NP \setminus P$ that is not NP -complete.



Dichotomy theorems

- Dichotomy theorems give goods research programs: easy to formulate, but can be hard to complete.
- The search for dichotomy theorems may uncover algorithmic results that no one has thought of.
- Proving dichotomy theorems requires attacking the problem both from the algorithmic and the complexity side. Requires good command of both algorithmic and hardness proof techniques.
- Possible outcomes:
 - Everything is hard, except some trivial cases.
 - Everything is hard, except the famous known nontrivial positive cases.
 - **Some unexpected easy cases are found.**

Example dichotomy theorems in DB theory

- Probabilistic databases
 - Self-join (SJ) free: [Dalvi, Suciu, VLDB 2004]
 - SJ: [Dalvi, Suciu, JACM 2012]
- Resilience
 - SJ-free: [Freire+, VLDB 2015]
 - SJ: open (some progress in [Freire+, PODS'20], [Makhija+, SIGMOD'24])
- View-side effect problem
 - SJ free with FDs [Kimelfeld, PODS 2012]
- Consistent query answering
 - SJ-free: [Koutris, Wijsen, PODS 2015]

Source: Dalvi, Suciu. "Efficient query evaluation on probabilistic databases", VLDB 2004. <https://dl.acm.org/doi/abs/10.5555/1316689.1316764>, Dalvi, Suciu. "The dichotomy of probabilistic inference for unions of conjunctive queries", JACM 2012. <https://doi.org/10.1145/2395116.2395119>, Freire, Gatterbauer, Immerman, Meliou, The complexity of resilience and responsibility for self-join-free conjunctive queries. PVLDB 2015. <https://doi.org/10.14778/2850583.2850592>, Freire, Gatterbauer, Immerman, Meliou. New Results for the Complexity of Resilience for Binary Conjunctive Queries with Self-Joins. PODS 2020. <https://doi.org/10.1145/3375395.3387647>, Kimelfeld. "A dichotomy in the complexity of deletion propagation with functional dependencies". PODS 2012. <https://doi.org/10.1145/2213556.2213584>, Koutris, Wijsen, "The Data Complexity of Consistent Query Answering for Self-Join-Free Conjunctive Queries Under Primary Key Constraints", PODS 2015, <https://doi.org/10.1145/2745754.2745769>

Wolfgang Gatterbauer. Principles of scalable data management: <https://northeastern-datalab.github.io/cs7240/>

The view deletion problem

- ◆ D a database instance and $V=Q(D)$ a view defined over D .
 - ◆ Find a set of tuples ΔD to remove from D so that a specific tuple t is removed from the view
 - ◆ Minimize the number of side-effects in the view VIEW
 - ◆ View side-effect problem
 - ◆ Hard: queries with joins and projection or union
 - ◆ PTIME: the rest
 - ◆ Minimize the number of tuples deleted from D SOURCE
 - ◆ Source side-effect problem
 - ◆ Same dichotomy

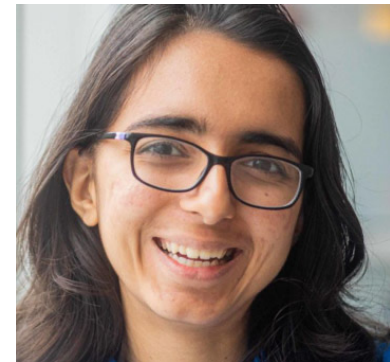
Solving **Reverse DM Problems** with **ILPs** and **LP relaxations**

Wolfgang Gatterbauer

Based on joint work with **Neha Makhija**

Dagstuhl seminar 24032

Jan 15, 2024



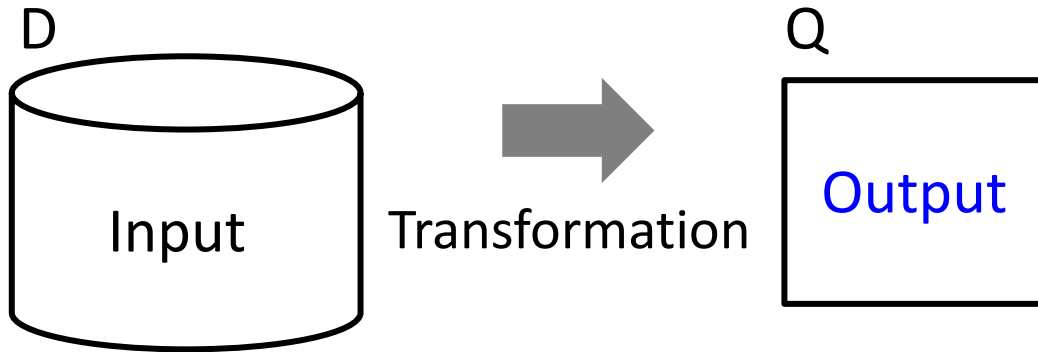
<https://northeastern-datalab.github.io/unified-reverse-data-management/>

<https://www.dagstuhl.de/en/seminars/seminar-calendar/seminar-details/24032>

Reverse Data Management

QUERY EVALUATION:

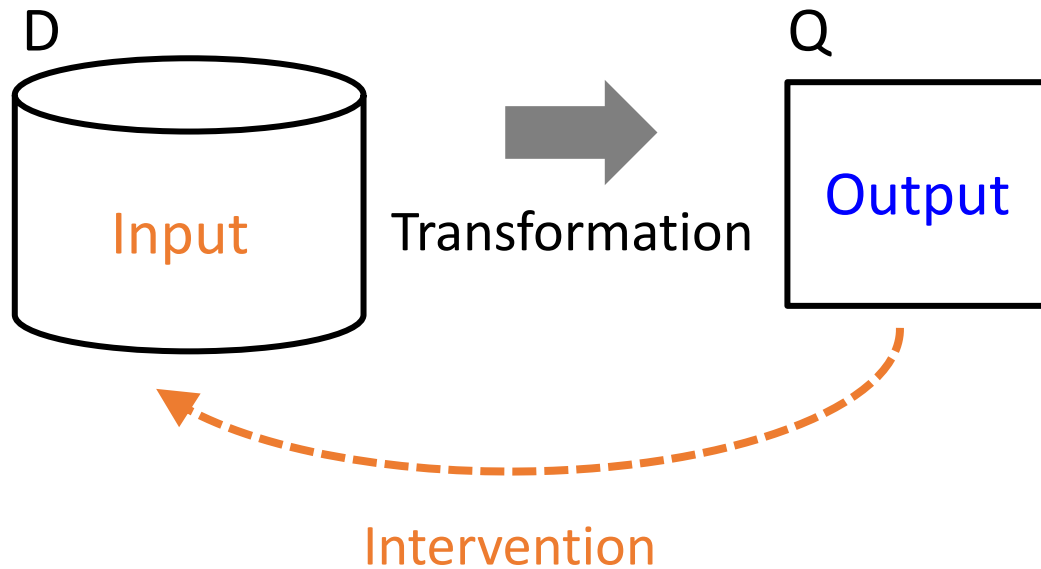
A transformation of the input to the output



Reverse Data Management

QUERY EVALUATION:

A transformation of the input to the output



REVERSE DATA MANAGEMENT:

What are the required changes to the input, in order to achieve a desired output?

uses some notion of minimality

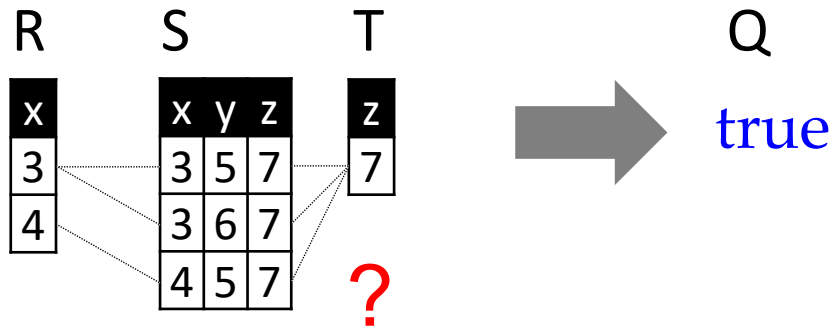
Cp. to "explanation by intervention" (Sudeepa's earlier talk today), and "minimum change required" (Pablo's earlier talk today)

Example Reverse Data Management Problems

Q: $\neg R(x), S(x,y,z), T(z)$

Resilience

Delete min number of tuples to make Q false

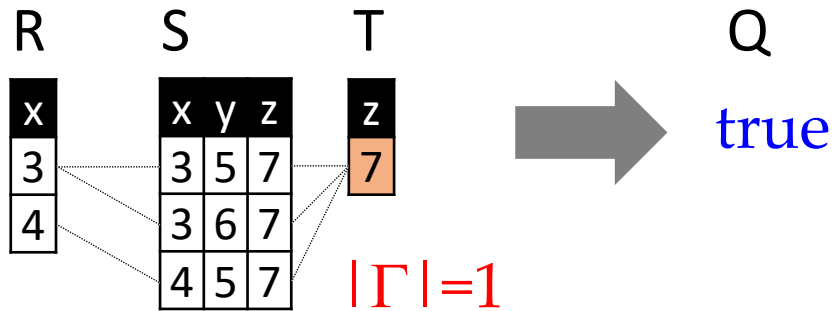


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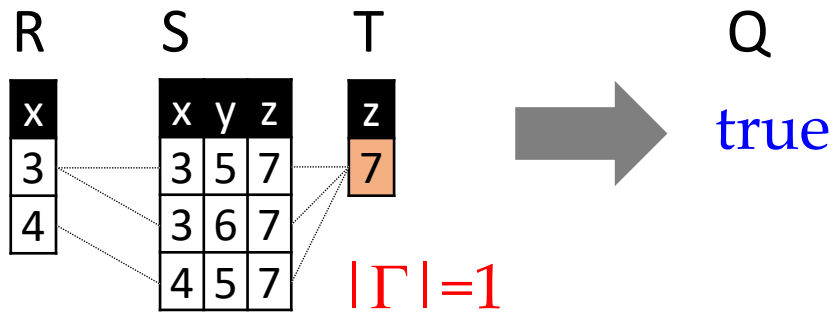


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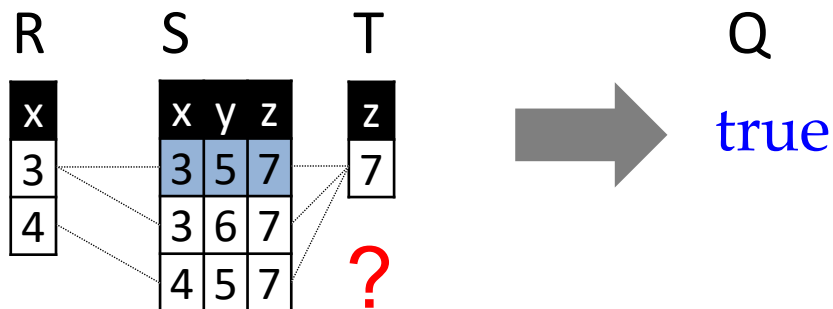
Resilience

Delete min number of tuples to make Q false



Causal responsibility

Delete min number of tuples to make an input tuple counterfactual

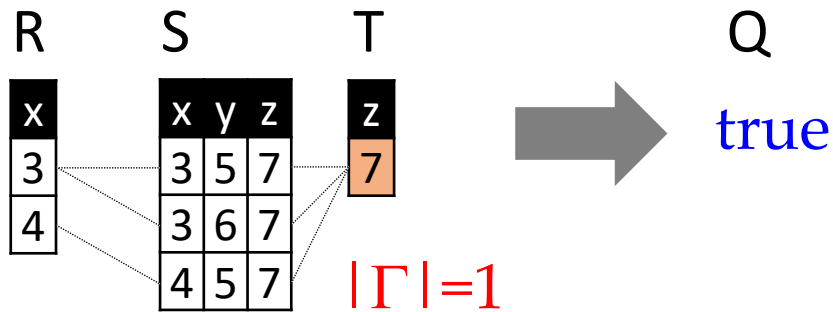


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Resilience

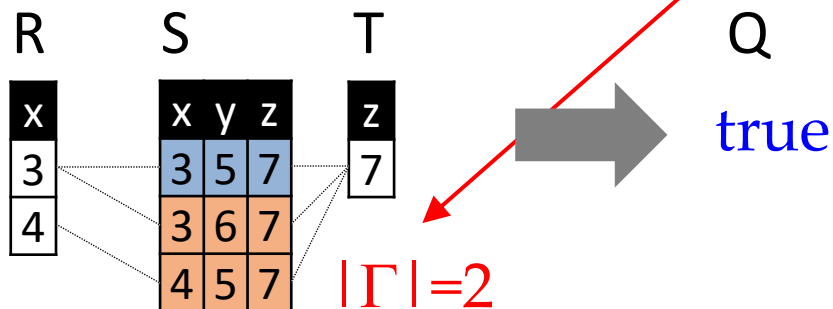
Delete min number of tuples to make Q false



recall Pablo's discussion on "interactions" for actual causes in disjunctions

Causal responsibility

Delete min number of tuples to make an input tuple counterfactual

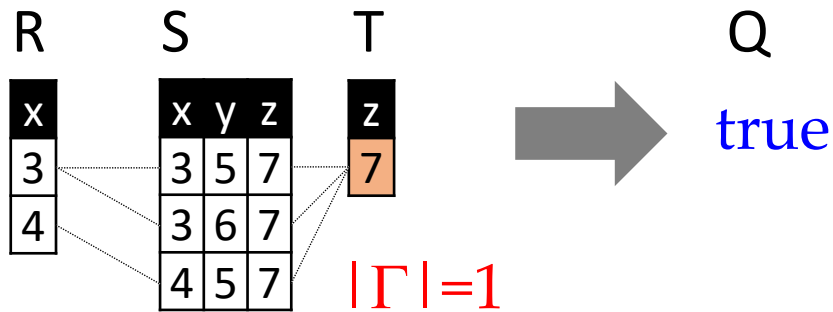


Example Reverse Data Management Problems

$Q: \neg R(x), S(x,y,z), T(z)$

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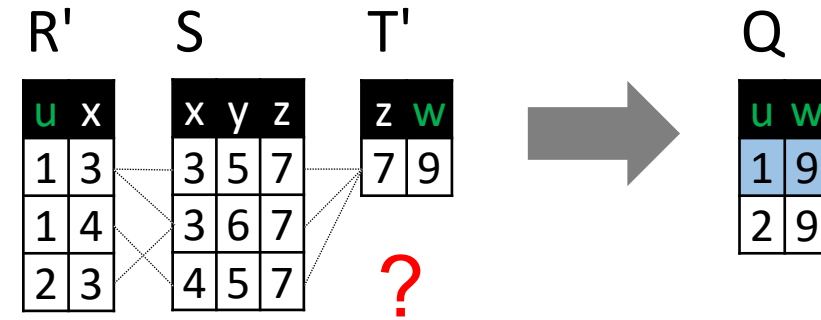
Delete min number of tuples to make Q false



$Q(u,w): \neg R'(u,x), S(x,y,z), T'(z,w)$

Source side-effects (in deletion prop.)

Delete min number of tuples to delete an output tuple



Dayal, Bernstein. On the correct translation of update operations on relational views, TODS 1982, <https://doi.org/10.1145/319732.319740>

Buneman, Khanna, Tan. On propagation of deletions and annotations through views, PODS 2002, <https://doi.org/10.1145/543613.543633>

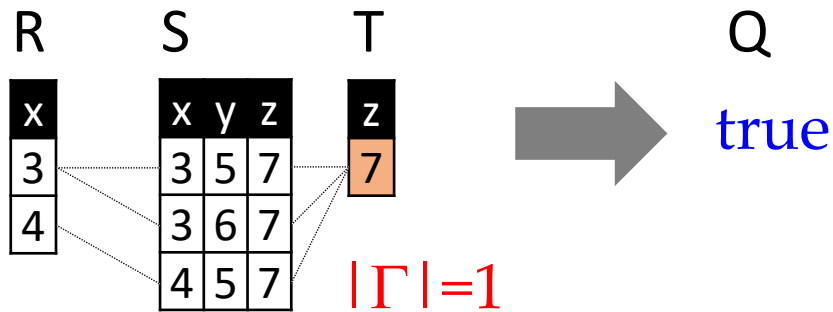
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Example Reverse Data Management Problems

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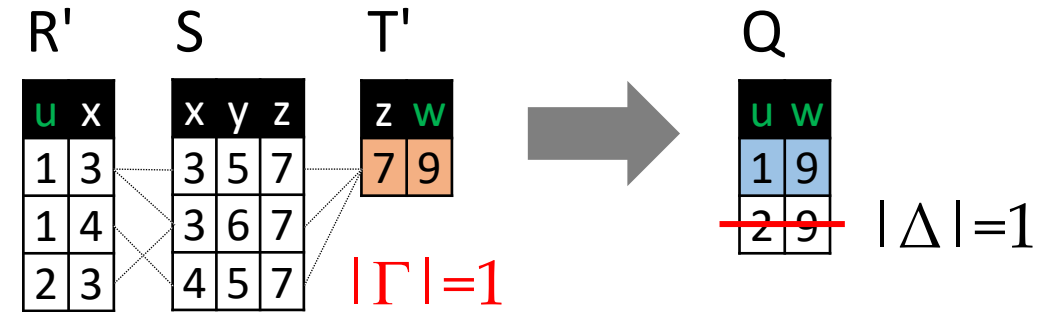
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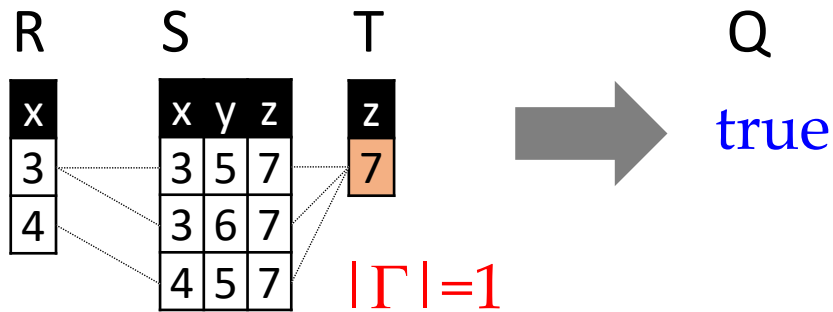


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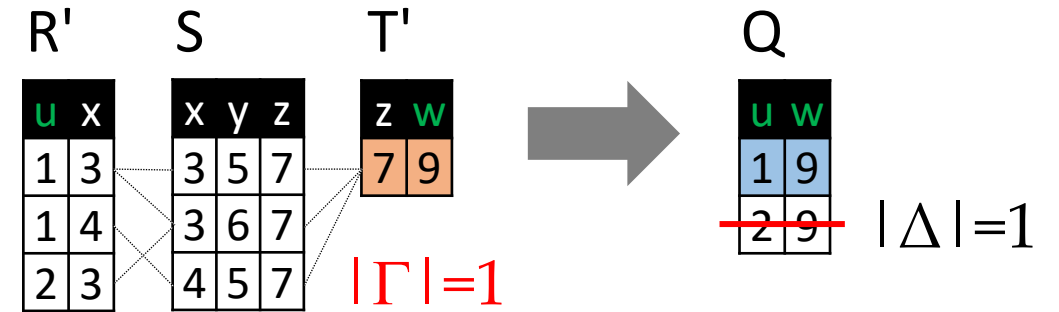
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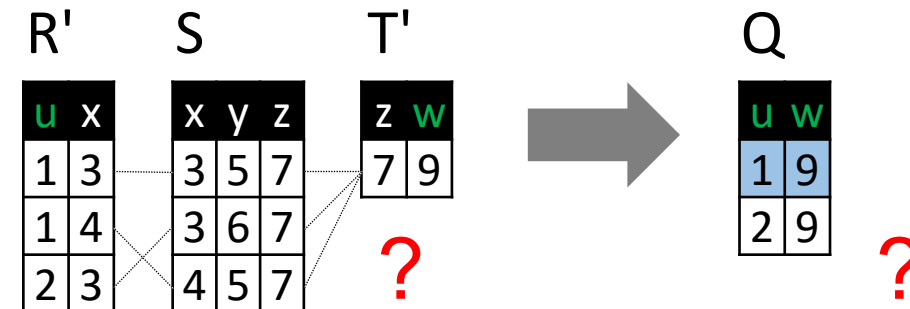
Source side-effects (in deletion prop.)

Delete min number of tuples to delete an output tuple



View side-effects (in deletion propagation)

Delete tuples in order to delete an output tuple, while minimizing the other output tuples deleted

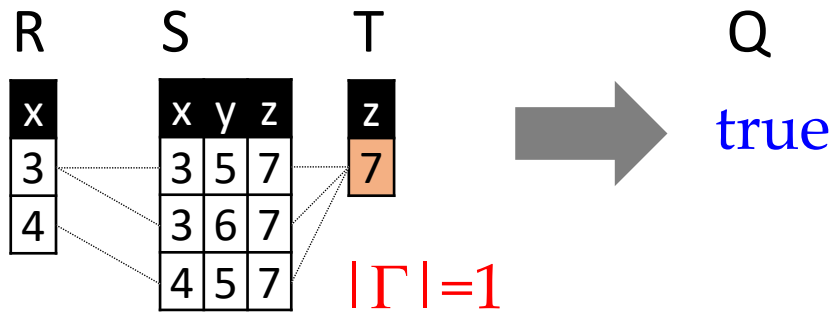


Example Reverse Data Management Problems

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Resilience

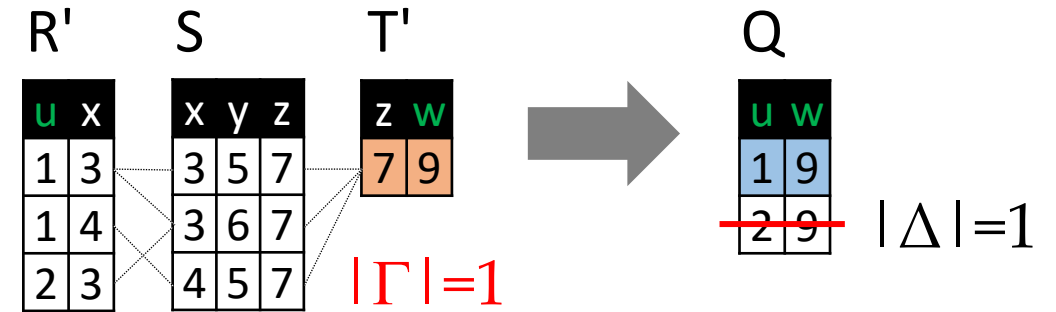
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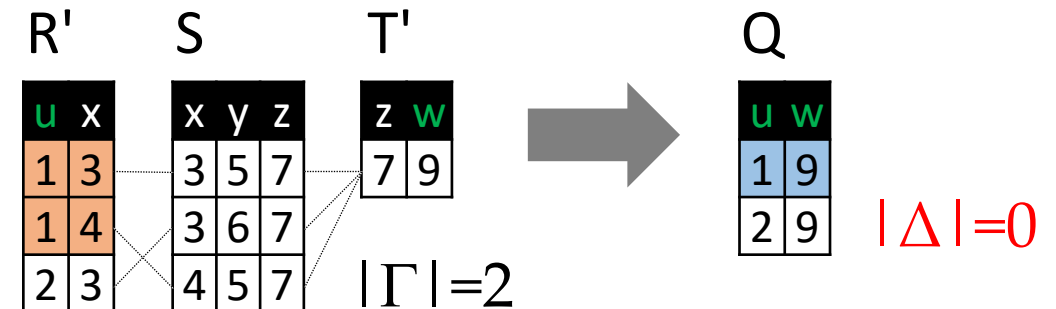
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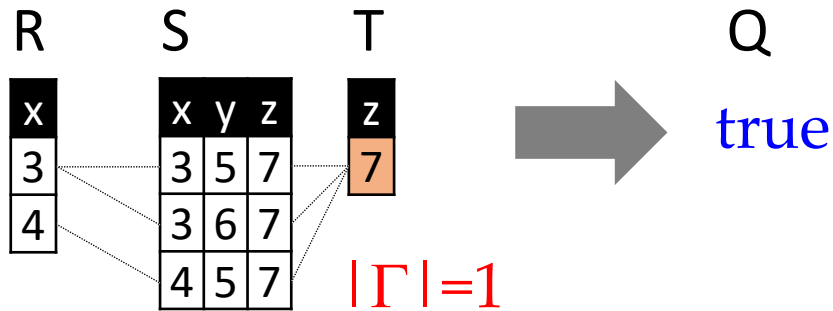


Example Reverse Data Management Problems

Q: $\neg R(x), S(x,y,z), T(z)$

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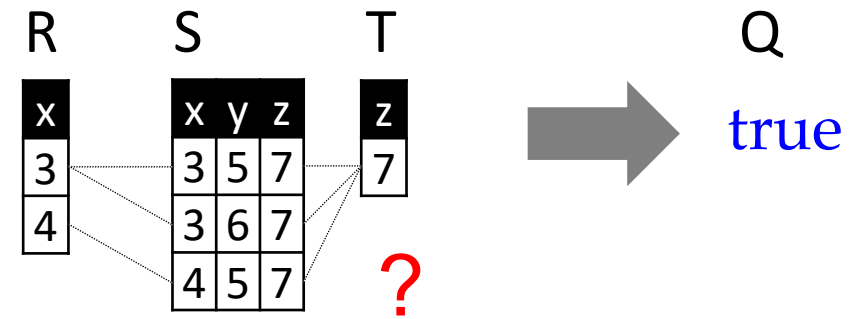
Delete min number of tuples to make Q false



Q: $\neg R(x), S(x,y,z), T(z)$

Smallest witness problem

Delete max number of tuples while keeping Q true

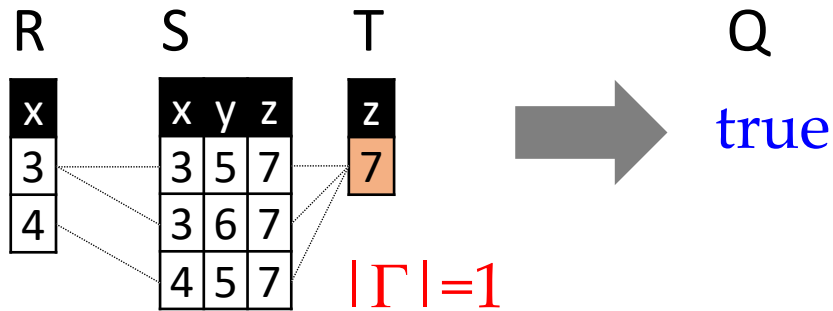


Example Reverse Data Management Problems

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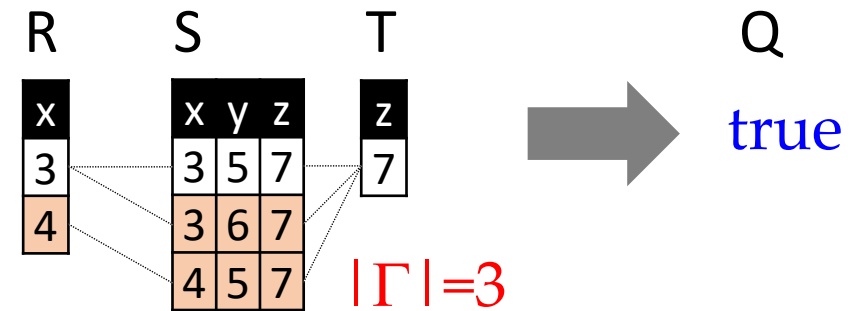
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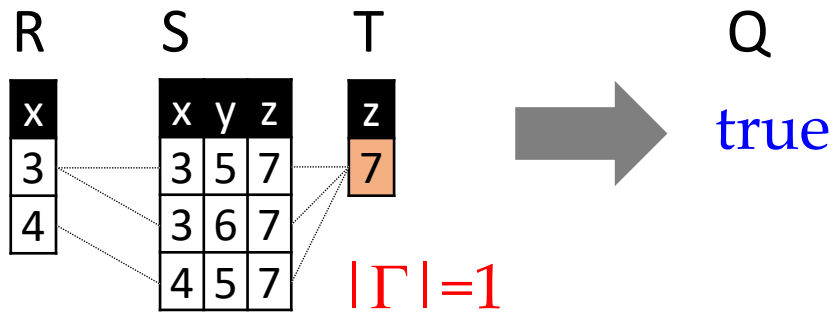
becomes more interesting
once you add projections

Example Reverse Data Management Problems

Q: $\neg R(x), S(x,y,z), T(z)$

Resilience

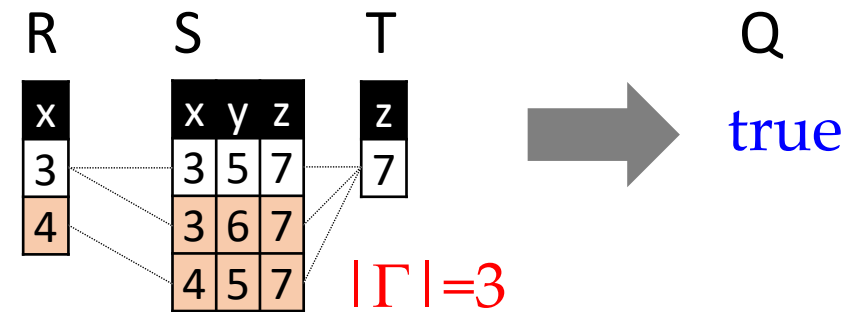
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Q: $\neg R(x), S(x,y,z), T(z)$

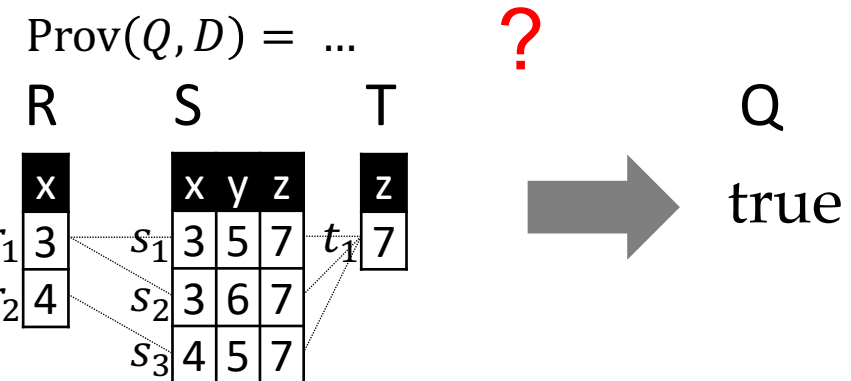
Smallest witness problem

Delete max number of tuples while keeping Q true



Minimal size factorization

Find a provenance factorization of minimum length



Miao, Roy, Yang. Explaining Wrong Queries Using Small Examples. SIGMOD 2019. <https://doi.org/10.1145/3299869.3319866>

Hu, Sintos. Finding Smallest Witnesses for Conjunctive Queries, ICDT 2024. <https://cs.uwaterloo.ca/~xiaohu/icdt2024.pdf>

Makhija, Gatterbauer: Towards a Dichotomy for Minimally Factorizing the Provenance of Self-Join Free Conjunctive Queries. <https://arxiv.org/pdf/2105.14307>

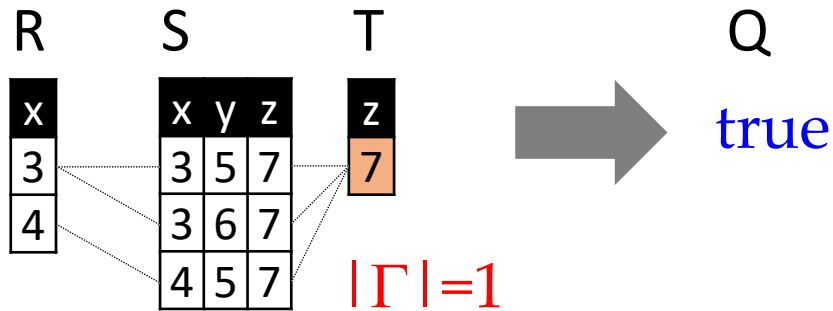
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Example Reverse Data Management Problems

Q: $\neg R(x), S(x,y,z), T(z)$

Resilience

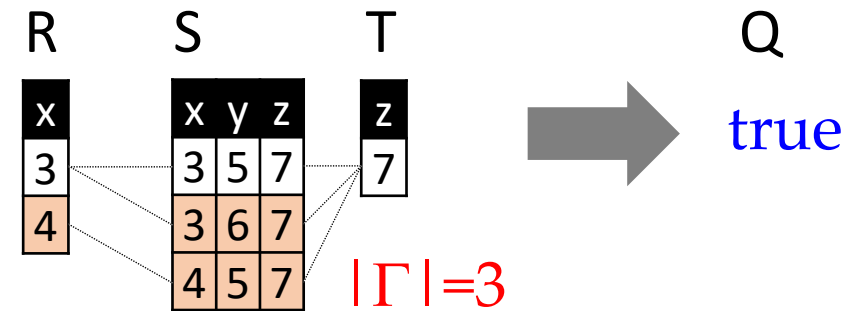
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Q: $\neg R(x), S(x,y,z), T(z)$

Smallest witness problem

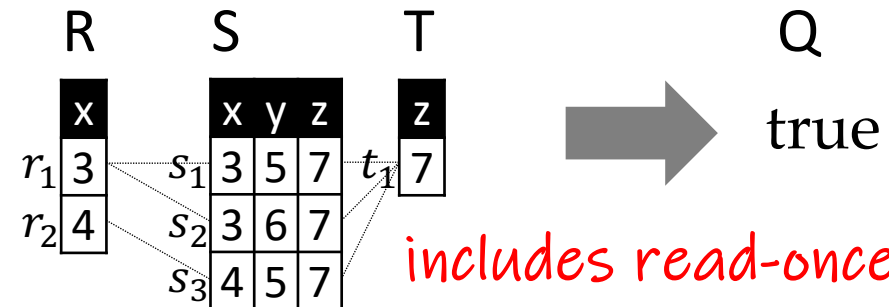
Delete max number of tuples while keeping Q true



Minimal size factorization

Find a provenance factorization of minimum length

$\text{Prov}(Q, D) = t_1(r_1(s_1 + s_2) + r_2s_3)$ $|\Gamma|=6$



includes read-once provenance as special case

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A recipe for solving RDM problems that goes a long way

1. Model problem as "appropriate" Integer Linear Program (ILP)
2. For what queries does the LP relaxation always return the same optimal objective ("ILP = LP")?
 - 3. For queries with $ILP \neq LP$: prove hardness
 - 4. For queries with $ILP = LP$: find a MFMC (Max-Flow Min-Cut) encoding

Interesting: hardness proofs can be automated! (with ASP Answer Set Programming)

Interesting: the encoding can be quite different, e.g. the original constraint matrix is usually not Totally Unimodular

This is the difficult part!

ILP for triangle query $Q^\Delta: -R(x, y), S(y, z), T(z, x)$

R	
x	y
1	1
2	1
2	3
5	3
5	1

S	
y	z
1	1
3	1
3	4
1	4

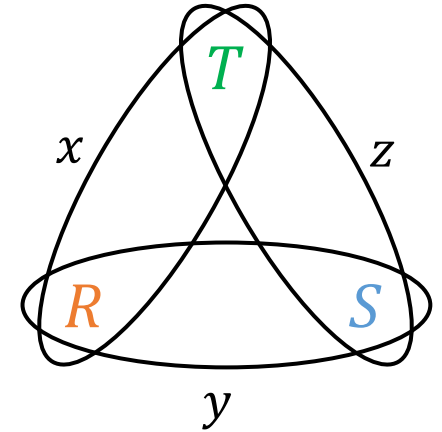
T	
z	x
1	1
1	2
4	2
4	5
4	1

$Q^\Delta: -R(x, y), S(y, z), T(z, x)$

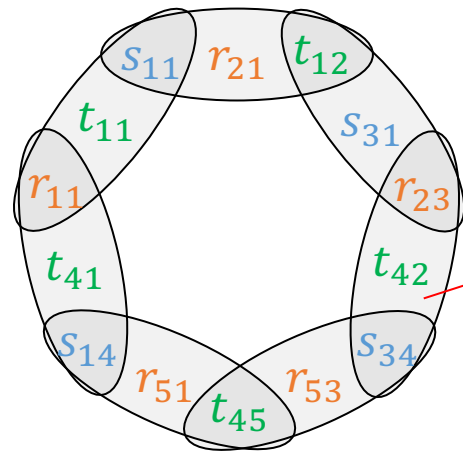
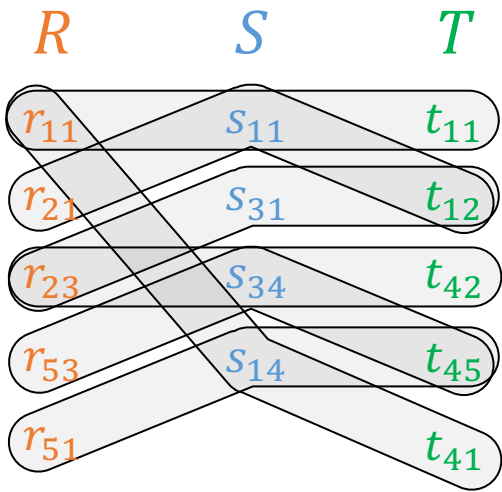
Boolean query

$Q_f^\Delta(x, y, z): -R(x, y), S(y, z), T(z, x)$

Full query



Data instance hypergraph
(tuples as vertices, "witnesses" as edges)



Q_f^Δ

	x	y	z	
w ₁	1	1	1	r ₁₁ s ₁₁ t ₁₁
w ₂	2	1	1	r ₂₁ s ₁₁ t ₁₂
w ₃	2	3	1	r ₂₃ s ₃₁ t ₁₂
w ₄	2	3	4	r ₂₃ s ₃₄ t ₄₂
w ₅	5	3	4	r ₅₃ s ₃₄ t ₄₅
w ₆	5	1	4	r ₅₁ s ₁₄ t ₄₅
w ₇	1	1	4	r ₁₁ s ₁₄ t ₄₁

Query dual hypergraph

- atoms as vertices
- variables as edges

ILP for triangle query $Q^\Delta: -R(x, y), S(y, z), T(z, x)$

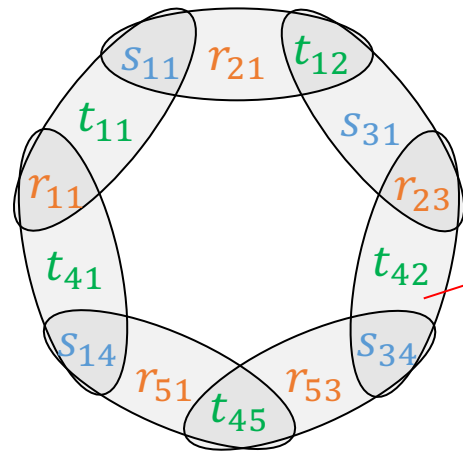
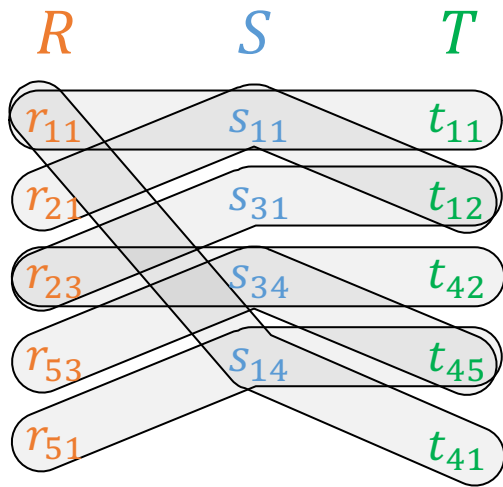
$$\begin{aligned} \min_{\mathbf{x}} \quad & \mathbf{c}^T \mathbf{x} \\ & \mathbf{A} \mathbf{x} \geq \mathbf{b} \\ & \mathbf{x} \in \{0, 1\}^n \end{aligned}$$

\mathbf{c} objective vector
 \mathbf{A} constraint matrix
 \mathbf{b} constraint vector
 \mathbf{x} decision variables

\mathbf{A} is 0,1
 $\mathbf{b} = \mathbf{1}_m$
 $\mathbf{c}^T = \mathbf{1}_n$

} set covering problems
 unweighted: $\min \sum \mathbf{x}$

Data instance hypergraph
 (tuples as vertices, "witnesses" as edges)



Q_f^Δ

	x	y	z	
w_1	1	1	1	$r_{11} s_{11} t_{11}$
w_2	2	1	1	$r_{21} s_{11} t_{12}$
w_3	2	3	1	$r_{23} s_{31} t_{12}$
w_4	2	3	4	$r_{23} s_{34} t_{42}$
w_5	5	3	4	$r_{53} s_{34} t_{45}$
w_6	5	1	4	$r_{51} s_{14} t_{45}$
w_7	1	1	4	$r_{11} s_{14} t_{41}$

ILP for triangle query $Q^\Delta: -R(x, y), S(y, z), T(z, x)$

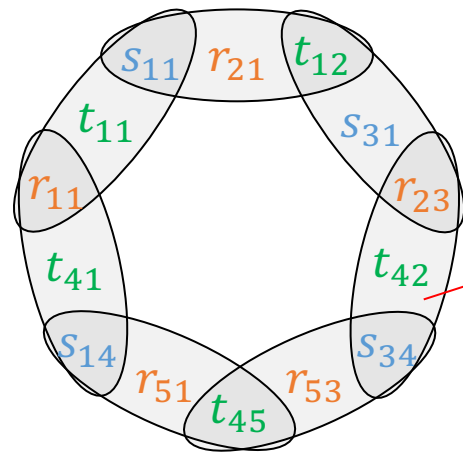
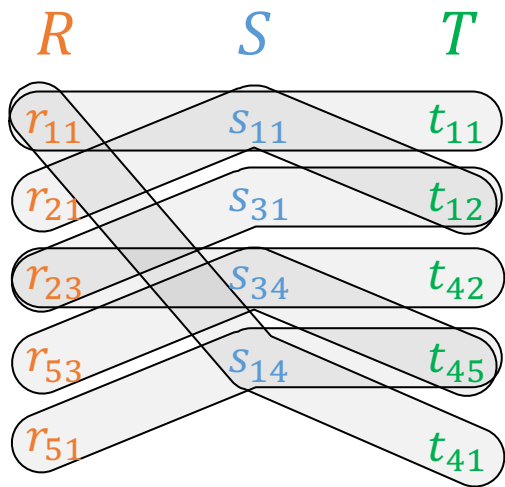
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} set covering problems
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Data instance hypergraph
 (tuples as vertices, "witnesses" as edges)



Objective

$$\begin{aligned} \min \quad & x[r_{11}] + x[r_{21}] + x[r_{23}] + x[r_{53}] + x[r_{51}] + \\ & x[s_{11}] + x[s_{31}] + x[s_{34}] + x[s_{14}] + \\ & x[t_{11}] + x[t_{12}] + x[t_{42}] + x[t_{45}] + x[t_{41}] \end{aligned}$$

optimal value: ?

Constraints (one per witness)

$$\begin{aligned} x[r_{11}] + x[s_{11}] + x[t_{11}] &\geq 1 \\ x[r_{21}] + x[s_{31}] + x[t_{12}] &\geq 1 \\ x[r_{23}] + x[s_{31}] + x[t_{12}] &\geq 1 \\ x[r_{23}] + x[s_{34}] + x[t_{42}] &\geq 1 \\ x[r_{53}] + x[s_{34}] + x[t_{45}] &\geq 1 \\ x[r_{51}] + x[s_{14}] + x[t_{45}] &\geq 1 \\ x[r_{11}] + x[s_{14}] + x[t_{42}] &\geq 1 \end{aligned}$$

$$\mathbf{x} \in \{0,1\}^{11}$$

Q_f^Δ

	x	y	z	
w_1	1	1	1	$r_{11} s_{11} t_{11}$
w_2	2	1	1	$r_{21} s_{11} t_{12}$
w_3	2	3	1	$r_{23} s_{31} t_{12}$
w_4	2	3	4	$r_{23} s_{34} t_{42}$
w_5	5	3	4	$r_{53} s_{34} t_{45}$
w_6	5	1	4	$r_{51} s_{14} t_{45}$
w_7	1	1	4	$r_{11} s_{14} t_{41}$

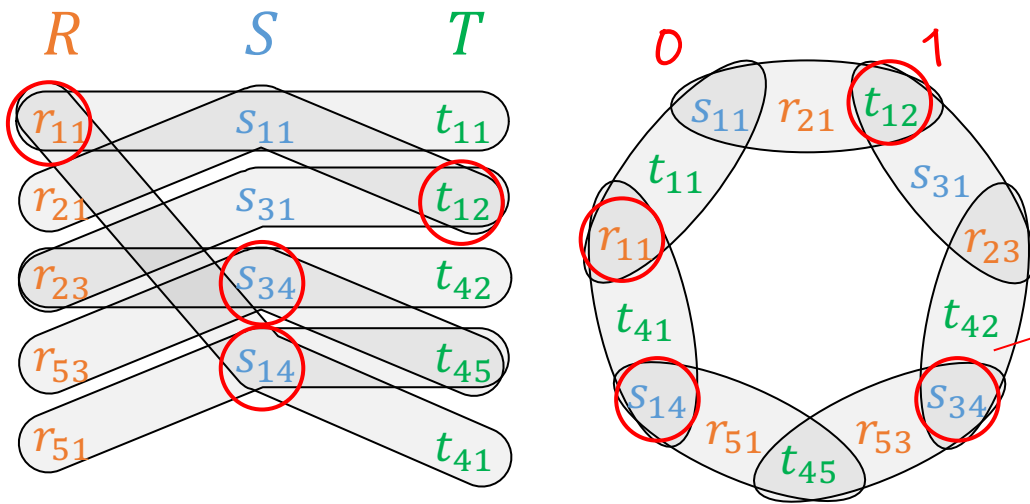
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Data instance hypergraph
(tuples as vertices, "witnesses" as edges)



Objective

$$\begin{aligned} \min \quad & x[r_{11}] + x[r_{21}] + x[r_{23}] + x[r_{53}] + x[r_{51}] + \\ & x[s_{11}] + x[s_{31}] + x[s_{34}] + x[s_{14}] + \\ & x[t_{11}] + x[t_{12}] + x[t_{42}] + x[t_{45}] + x[t_{42}] \\ & \qquad \qquad \qquad =1 \qquad \qquad =0 \end{aligned}$$

optimal value: 4

Constraints (one per witness)

$$\begin{aligned} x[r_{11}] + x[s_{11}] + x[t_{11}] &\geq 1 \\ x[r_{21}] + x[s_{11}] + x[t_{12}] &\geq 1 \\ x[r_{23}] + x[s_{31}] + x[t_{12}] &\geq 1 \\ x[r_{23}] + x[s_{34}] + x[t_{42}] &\geq 1 \\ x[r_{53}] + x[s_{34}] + x[t_{45}] &\geq 1 \\ x[r_{51}] + x[s_{14}] + x[t_{45}] &\geq 1 \\ x[r_{11}] + x[s_{14}] + x[t_{42}] &\geq 1 \end{aligned}$$

$$\mathbf{x} \in \{0,1\}^{11}$$

Q_f^Δ

	x	y	z	
w_1	1	1	1	$r_{11} s_{11} t_{11}$
w_2	2	1	1	$r_{21} s_{11} t_{12}$
w_3	2	3	1	$r_{23} s_{31} t_{12}$
w_4	2	3	4	$r_{23} s_{34} t_{42}$
w_5	5	3	4	$r_{53} s_{34} t_{45}$
w_6	5	1	4	$r_{51} s_{14} t_{45}$
w_7	1	1	4	$r_{11} s_{14} t_{41}$

ILP for triangle query $Q^\Delta: -R(x, y), S(y, z), T(z, x)$

$$\begin{aligned} \min_{\mathbf{x}} \quad & \mathbf{c}^T \mathbf{x} && \mathbf{c} \text{ objective vector} \\ & \mathbf{A} \mathbf{x} \geq \mathbf{b} && \mathbf{A} \text{ constraint matrix} \\ & \mathbf{x} \in \{0,1\}^n && \mathbf{b} \text{ constraint vector} \\ & && \mathbf{x} \text{ decision variables} \end{aligned}$$

\mathbf{A} is 0,1 } set covering problems
 $\mathbf{b} = \mathbf{1}_m$ }
 $\mathbf{c}^T = \mathbf{1}_n$ unweighted: $\min \sum \mathbf{x}$

Objective

$$\begin{aligned} \min \quad & x[r_{11}] + x[r_{21}] + x[r_{23}] + x[r_{53}] + x[r_{51}] + \\ & x[s_{11}] + x[s_{31}] + x[s_{34}] + x[s_{14}] + \\ & x[t_{11}] + x[t_{12}] + x[t_{42}] + x[t_{45}] + x[t_{42}] \\ & \qquad \qquad \qquad =1 \qquad \qquad =0 \end{aligned}$$

optimal value: 4

Constraints (one per witness)

$$\begin{aligned} & x[r_{11}] + x[s_{11}] + x[t_{11}] \geq 1 \\ & x[r_{21}] + x[s_{11}] + x[t_{12}] \geq 1 \\ & x[r_{23}] + x[s_{31}] + x[t_{12}] \geq 1 \\ & x[r_{23}] + x[s_{34}] + x[t_{42}] \geq 1 \\ & x[r_{53}] + x[s_{34}] + x[t_{45}] \geq 1 \\ & x[r_{51}] + x[s_{14}] + x[t_{45}] \geq 1 \\ & x[r_{11}] + x[s_{14}] + x[t_{42}] \geq 1 \end{aligned}$$

$$\mathbf{x} \in \{0,1\}^{11}$$

	r_{11}	r_{21}	r_{23}	r_{53}	r_{51}	s_{11}	s_{31}	s_{34}	s_{14}	t_{11}	t_{12}	t_{42}	t_{45}	t_{42}
w_1	1					1				1				
w_2		1				1					1			
w_3			1				1				1			
w_4			1					1				1		
w_5				1				1					1	
w_6					1				1				1	
w_7	1								1				1	1

$$\begin{matrix} \mathbf{x} \\ x[r_{11}] \\ x[r_{21}] \\ \dots \\ x[s_{11}] \\ x[s_{31}] \\ \dots \\ x[t_{45}] \\ x[t_{42}] \end{matrix} \geq \mathbf{1}_7$$

LP relaxation for triangle query $Q^\Delta: -R(x, y), S(y, z), T(z, x)$

$$\begin{aligned} \min_{\mathbf{x}} \quad & \mathbf{c}^T \mathbf{x} \\ & \mathbf{A} \mathbf{x} \geq \mathbf{b} \\ & \mathbf{x} \in [0, 1]^n \\ & \mathbf{x} \in \{0, 1\}^n \end{aligned}$$

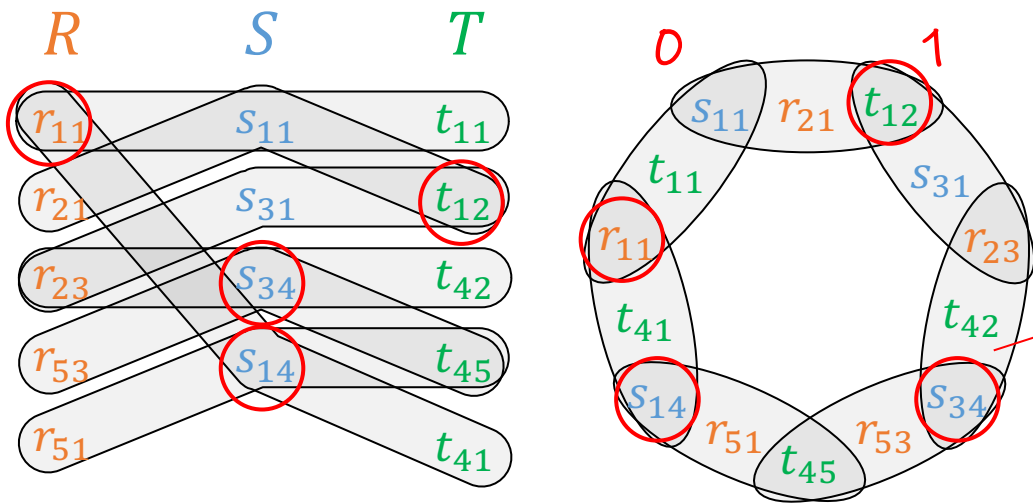
\mathbf{c} objective vector
 \mathbf{A} constraint matrix
 \mathbf{b} constraint vector
 \mathbf{x} decision variables

\mathbf{A} is 0,1
 $\mathbf{b} = \mathbf{1}_m$
 $\mathbf{c}^T = \mathbf{1}_n$

fractional set covering problems

unweighted: $\min \sum \mathbf{x}$

Data instance hypergraph
(tuples as vertices, "witnesses" as edges)



Objective

$$\begin{aligned} \min \quad & x[r_{11}] + x[r_{21}] + x[r_{23}] + x[r_{53}] + x[r_{51}] + \\ & x[s_{11}] + x[s_{31}] + x[s_{34}] + x[s_{14}] + \\ & x[t_{11}] + x[t_{12}] + x[t_{42}] + x[t_{45}] + x[t_{42}] \\ & \qquad \qquad \qquad =1 \qquad \qquad =0 \end{aligned}$$

optimal value: ?

Constraints (one per witness)

$$\begin{aligned} & x[r_{11}] + x[s_{11}] + x[t_{11}] \geq 1 \\ & x[r_{21}] + x[s_{11}] + x[t_{12}] \geq 1 \\ & x[r_{23}] + x[s_{31}] + x[t_{12}] \geq 1 \\ & x[r_{23}] + x[s_{34}] + x[t_{42}] \geq 1 \\ & x[r_{53}] + x[s_{34}] + x[t_{45}] \geq 1 \\ & x[r_{51}] + x[s_{14}] + x[t_{45}] \geq 1 \\ & x[r_{11}] + x[s_{14}] + x[t_{42}] \geq 1 \end{aligned}$$

Q_f^Δ

	x	y	z	
w_1	1	1	1	$r_{11} s_{11} t_{11}$
w_2	2	1	1	$r_{21} s_{11} t_{12}$
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w_6	5	1	4	$r_{51} s_{14} t_{45}$
w_7	1	1	4	$r_{11} s_{14} t_{41}$

~~$\mathbf{x} \in \{0, 1\}^{11}$~~
 $\mathbf{x} \in [0, 1]^{11}$

LP relaxation for triangle query $Q^\Delta: -R(x, y), S(y, z), T(z, x)$

$$\begin{aligned} \min_{\mathbf{x}} \quad & \mathbf{c}^T \mathbf{x} \\ & \mathbf{A} \mathbf{x} \geq \mathbf{b} \\ & \mathbf{x} \in [0, 1]^n \\ & \mathbf{x} \in \{0, 1\}^n \end{aligned}$$

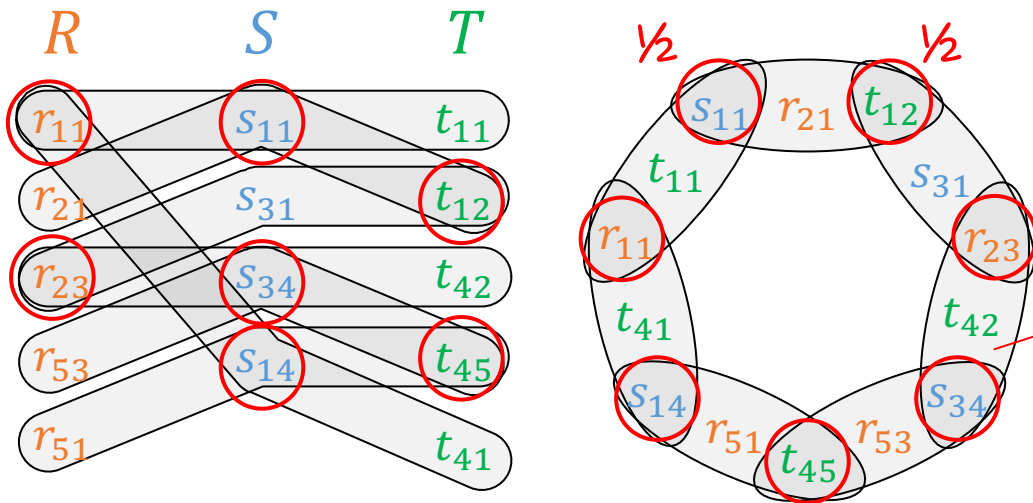
\mathbf{c} objective vector
 \mathbf{A} constraint matrix
 \mathbf{b} constraint vector
 \mathbf{x} decision variables

\mathbf{A} is 0,1
 $\mathbf{b} = \mathbf{1}_m$
 $\mathbf{c}^T = \mathbf{1}_n$

fractional set covering problems

unweighted: $\min \sum \mathbf{x}$

Data instance hypergraph
(tuples as vertices, "witnesses" as edges)



Objective

$$\begin{aligned} \min \quad & x[r_{11}] + x[r_{21}] + x[r_{23}] + x[r_{53}] + x[r_{51}] + \\ & x[s_{11}] + x[s_{31}] + x[s_{34}] + x[s_{14}] + \\ & x[t_{11}] + x[t_{12}] + x[t_{42}] + x[t_{45}] + x[t_{42}] \\ & \qquad \qquad \qquad = \frac{1}{2} \qquad \qquad = 0 \end{aligned}$$

optimal value: 3.5

Constraints (one per witness)

$$\begin{aligned} & x[r_{11}] + x[s_{11}] + x[t_{11}] \geq 1 \\ & x[r_{21}] + x[s_{11}] + x[t_{12}] \geq 1 \\ & x[r_{23}] + x[s_{31}] + x[t_{12}] \geq 1 \\ & x[r_{23}] + x[s_{34}] + x[t_{42}] \geq 1 \\ & x[r_{53}] + x[s_{34}] + x[t_{45}] \geq 1 \\ & x[r_{51}] + x[s_{14}] + x[t_{45}] \geq 1 \\ & x[r_{11}] + x[s_{14}] + x[t_{42}] \geq 1 \end{aligned}$$

Q_f^Δ

	x	y	z	
w_1	1	1	1	$r_{11} s_{11} t_{11}$
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~~$\mathbf{x} \in \{0, 1\}^{11}$~~
 $\mathbf{x} \in [0, 1]^{11}$

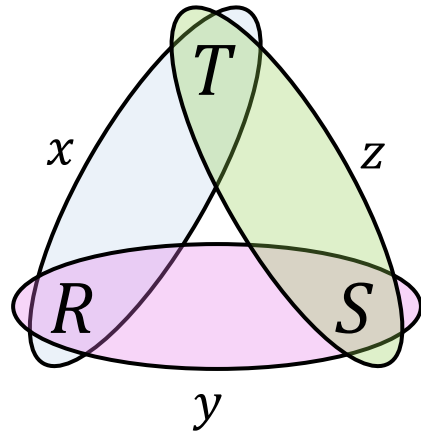
Outline

- Resilience for self-join free CQs
 - hard & easy cases
- Resilience for general CQs
 - hard & easy cases

"Active triads" as hardness criterion for SJ-free CQs

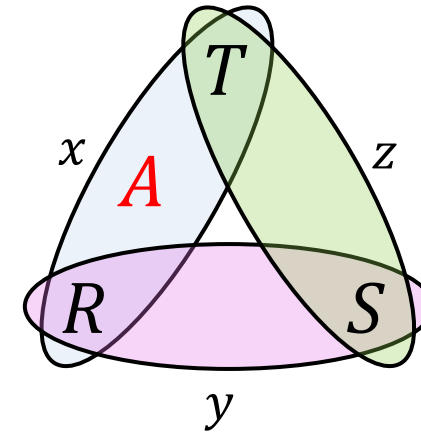
Triangle query

$$Q^\Delta: \neg R(x, y), S(y, z), T(x, z)$$



Triangle unary

$$Q_A^\Delta: \neg R(x, y), S(y, z), T(x, z), A(x)$$



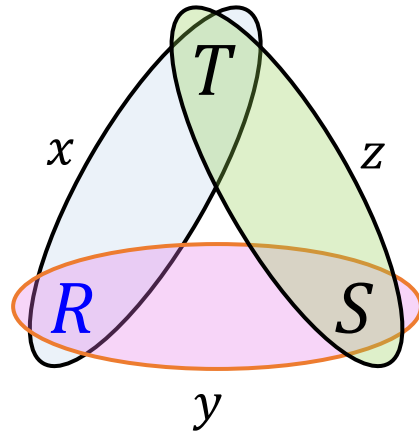
Query dual hypergraph

- atoms as vertices
- variables as edges

"Active triads" as hardness criterion for SJ-free CQs

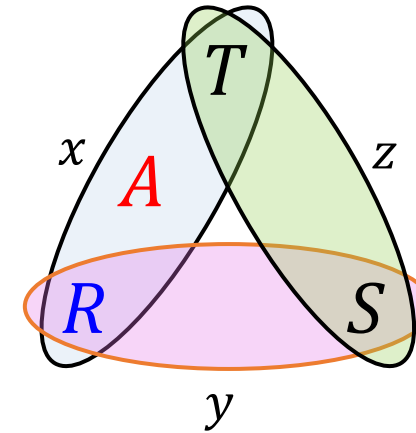
Triangle query

$$Q^\Delta: \neg R(x, y), S(y, z), T(x, z)$$



Triangle unary

$$Q_A^\Delta: \neg R(x, y), S(y, z), T(x, z), A(x)$$



The path $R - y - S$ from R to S is **INDEPENDENT** of $T(x, z)$, as it uses no variable from $T\{x, z\}$

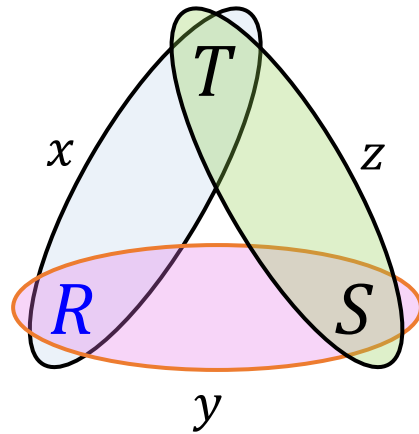
Atom $R(x, y)$ is **UNDOMINATED** since there is no other atom S s.t. $\text{var}(S) \subset \text{var}(R)$

Atom R is **DOMINATED** since $\text{var}(A) = \{x\} \subset \{x, y\} = \text{var}(R)$

"Active triads" as hardness criterion for SJ-free CQs

Triangle query

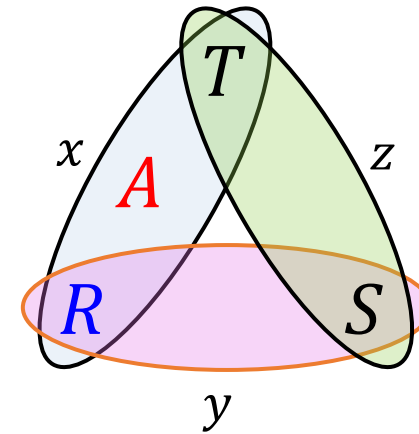
$$Q^\Delta: \neg R(x, y), S(y, z), T(x, z)$$



NPC

Triangle unary

$$Q_A^\Delta: \neg R(x, y), S(y, z), T(x, z), A(x)$$



PTIME

The path $R - y - S$ from R to S is **INDEPENDENT** of $T(x, z)$, as it uses no variable from $T\{x, z\}$

Atom $R(x, y)$ is **UNDOMINATED** since there is no other atom S s.t. $\text{var}(S) \subset \text{var}(R)$

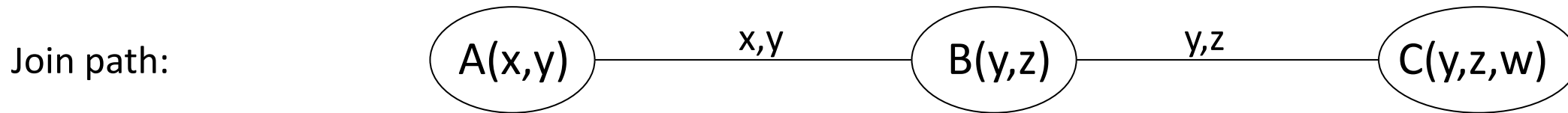
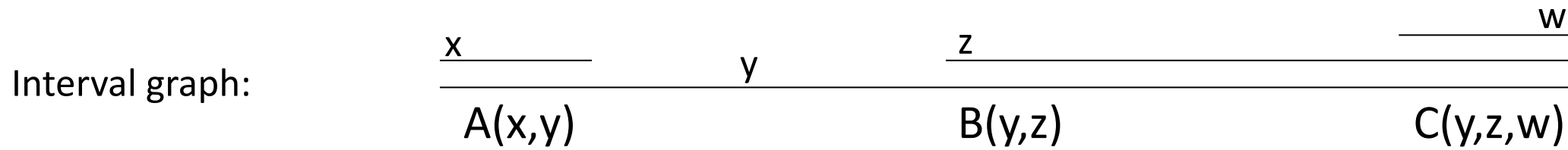
Atom R is **DOMINATED** since $\text{var}(A) = \{x\} \subset \{x, y\} = \text{var}(R)$

ACTIVE TRIAD: 3 undominated atoms R, S, T that have independent paths among each other

TRIAD: 3 atoms R, S, T that have independent paths among each other

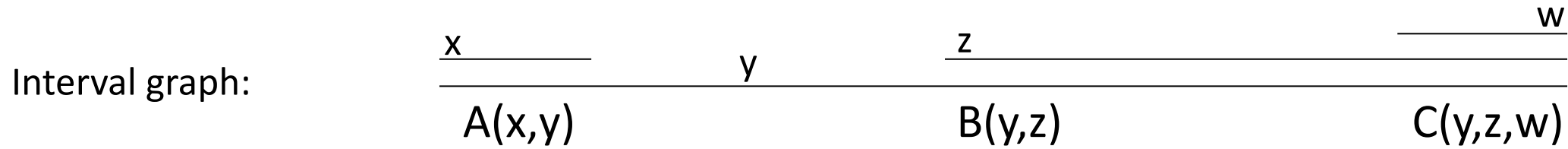
does not yet make a query hard (under set semantics)

Example linear query $Q: -A(x, y), B(y, z), C(y, z, w)$

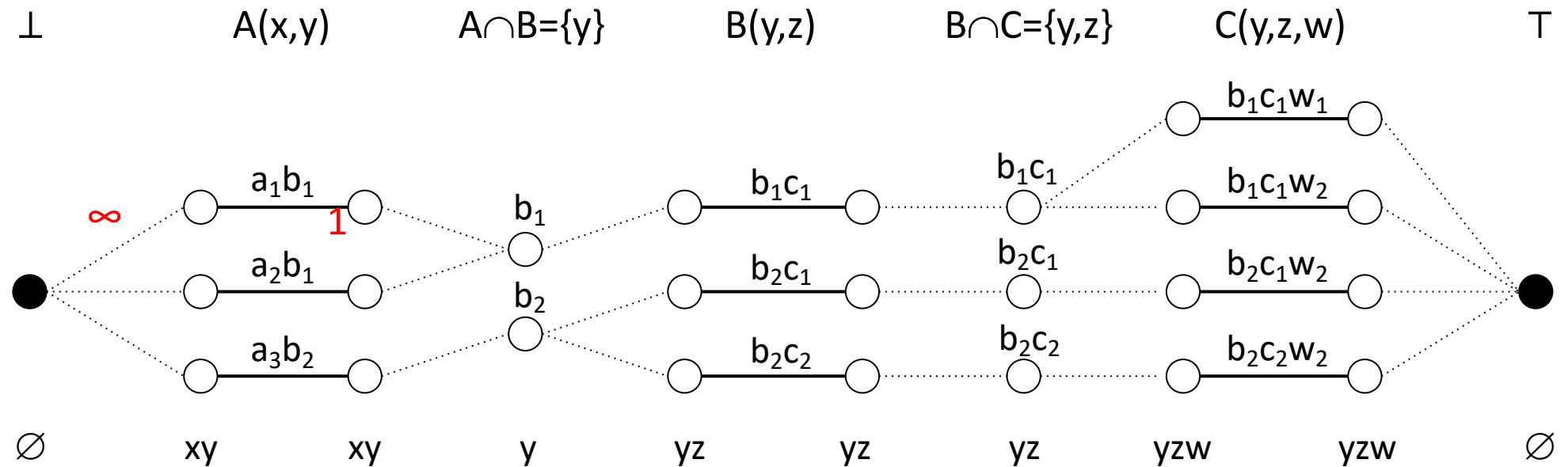


DEFINITION: A query q is **LINEAR** if it has a **join path** (i.e. a **join tree that forms a path**)

Example linear query $Q: -A(x, y), B(y, z), C(y, z, w)$



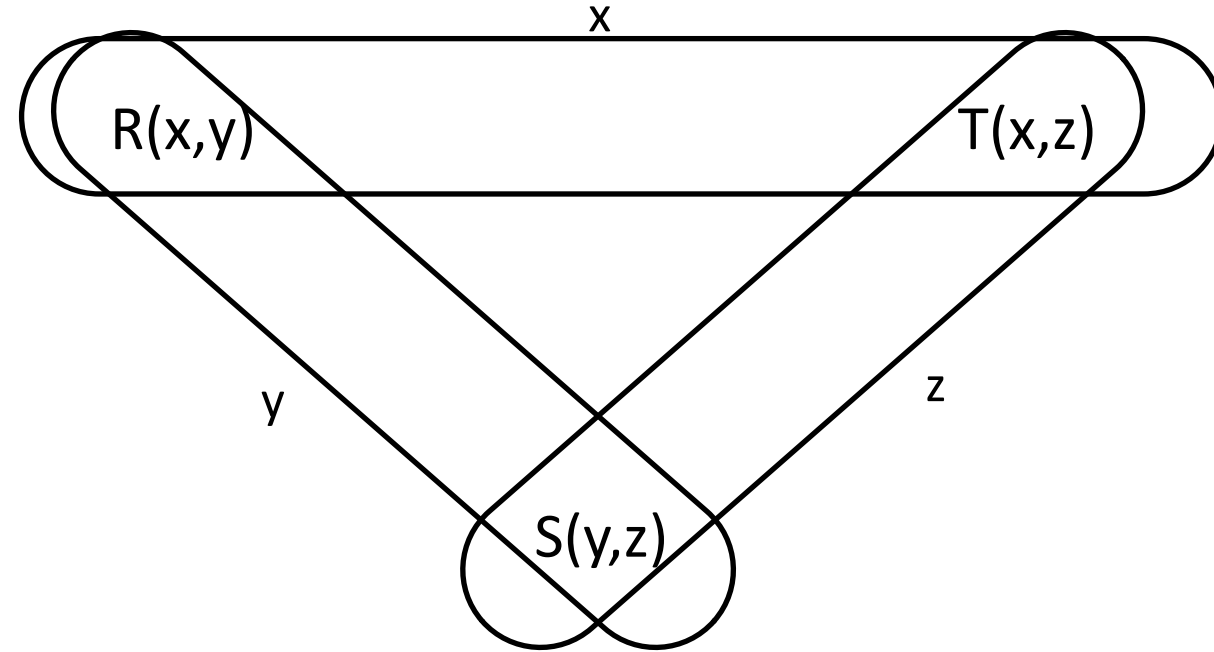
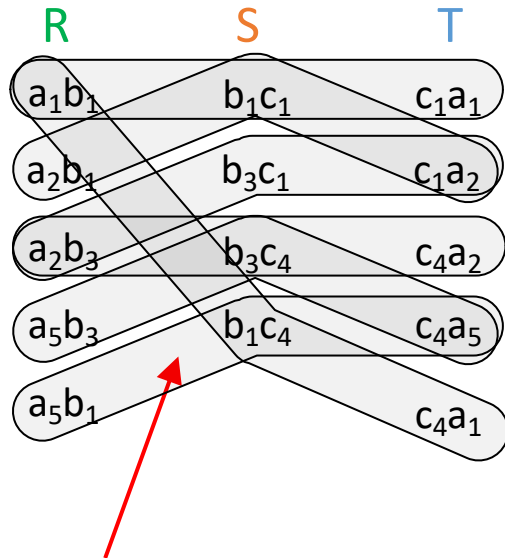
Source-Target flow graph encoding (MFMC)



Non-Linearizable Queries: those with active triads

$Q^\Delta: -R(x, y), S(y, z), T(x, z)$

Triangle query



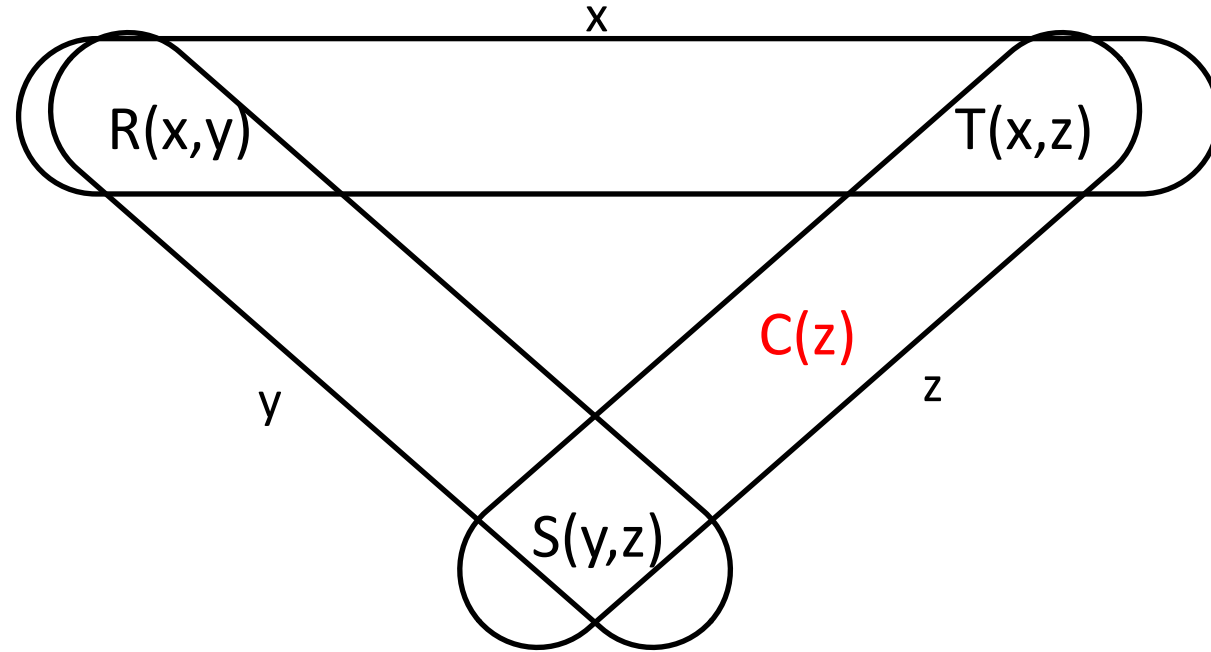
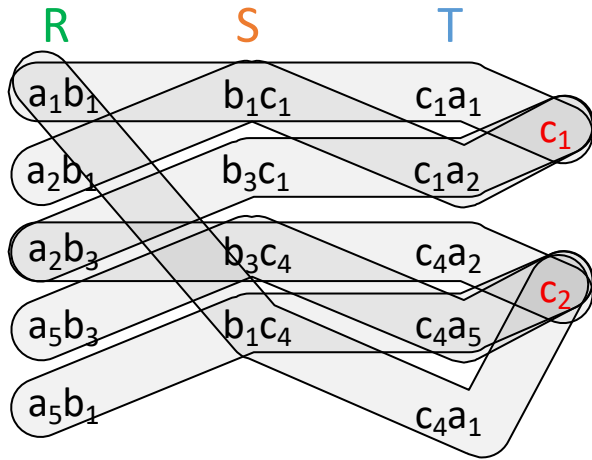
each hyperedge corresponds to one witness,
each tuple of domain values to one database tuple,
if Q is evaluated over the database over all shown tuples

"Hard instance" (more complicated than it needs to be). A ϕ -hole in the constraint matrix of the associated ILP. We can also make a 3-hole

Linearizable Queries: "domination" to the rescue

$Q_C^\Delta: -R(x, y), S(y, z), T(x, z), C(z)$

Triangle unary

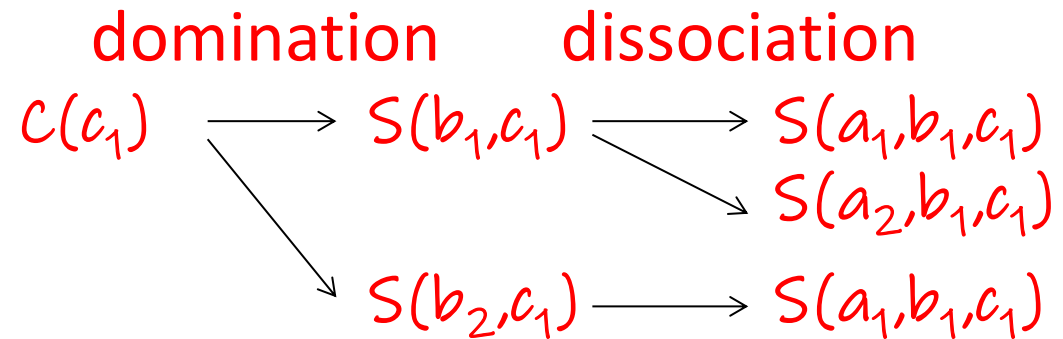
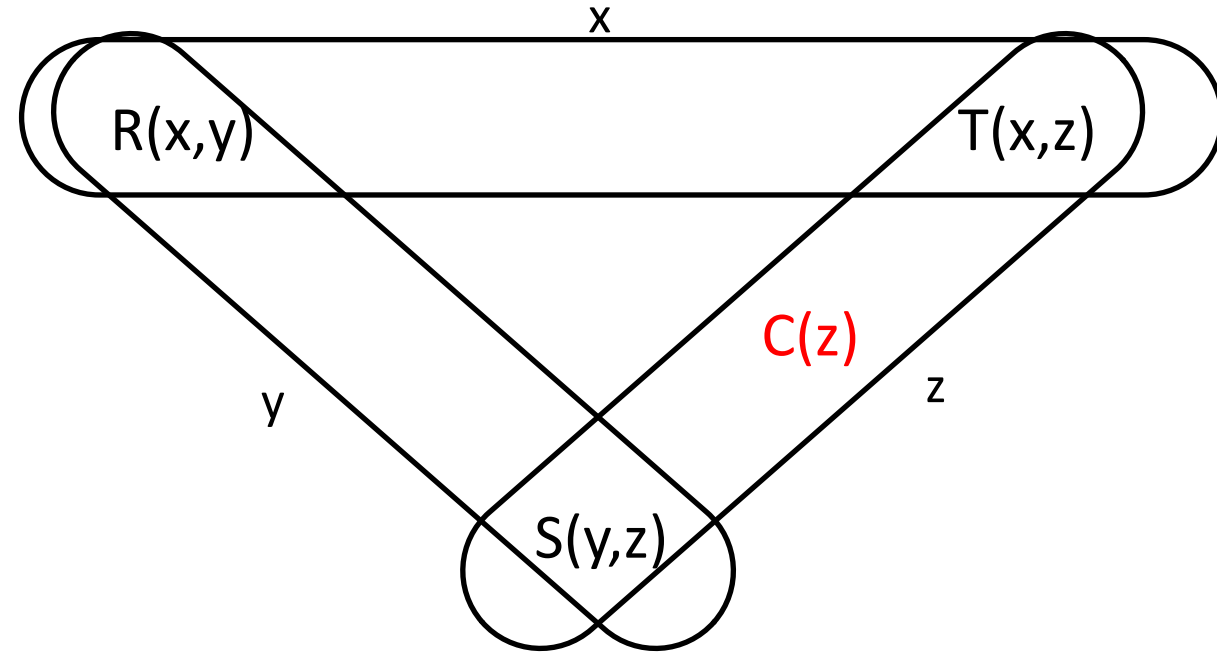
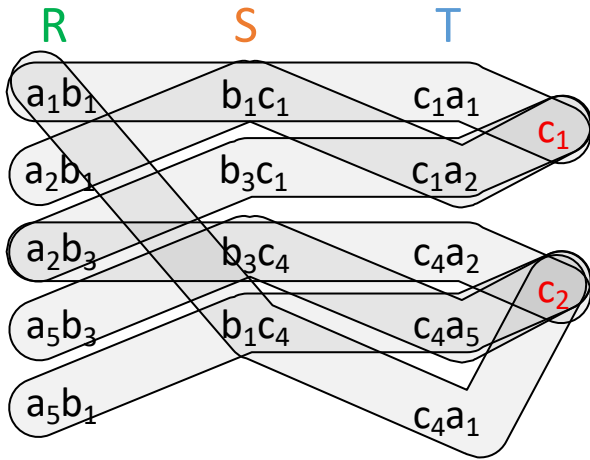


This instance (similar for smaller 3-hole) can be solved with flow. Key insight: The resulting flow graph does not "correspond exactly" to the original instance, but a *minimal* cut of the resulting implementation still corresponds to a *minimal* VC of the original problem

Linearizable Queries: "domination" to the rescue

$Q_C^\Delta: \neg R(x, y), S(y, z), T(x, z), C(z)$

Triangle unary

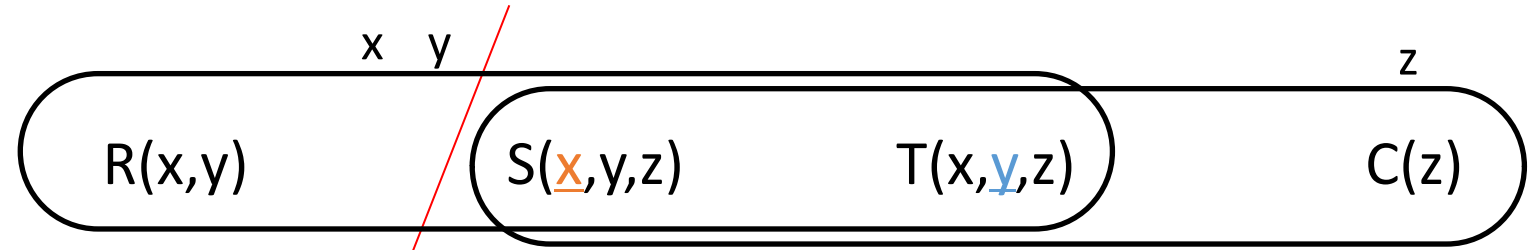
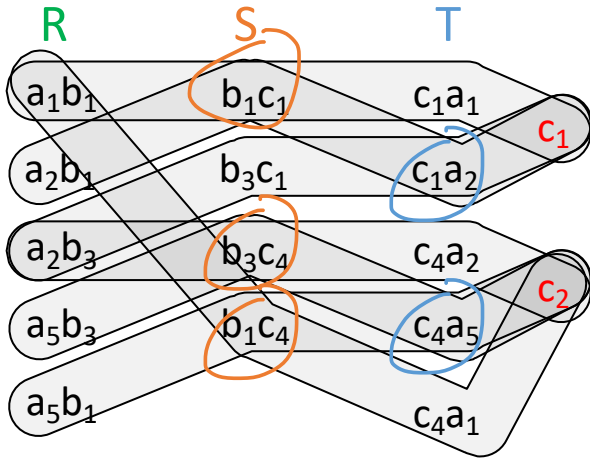


Linearizable Queries

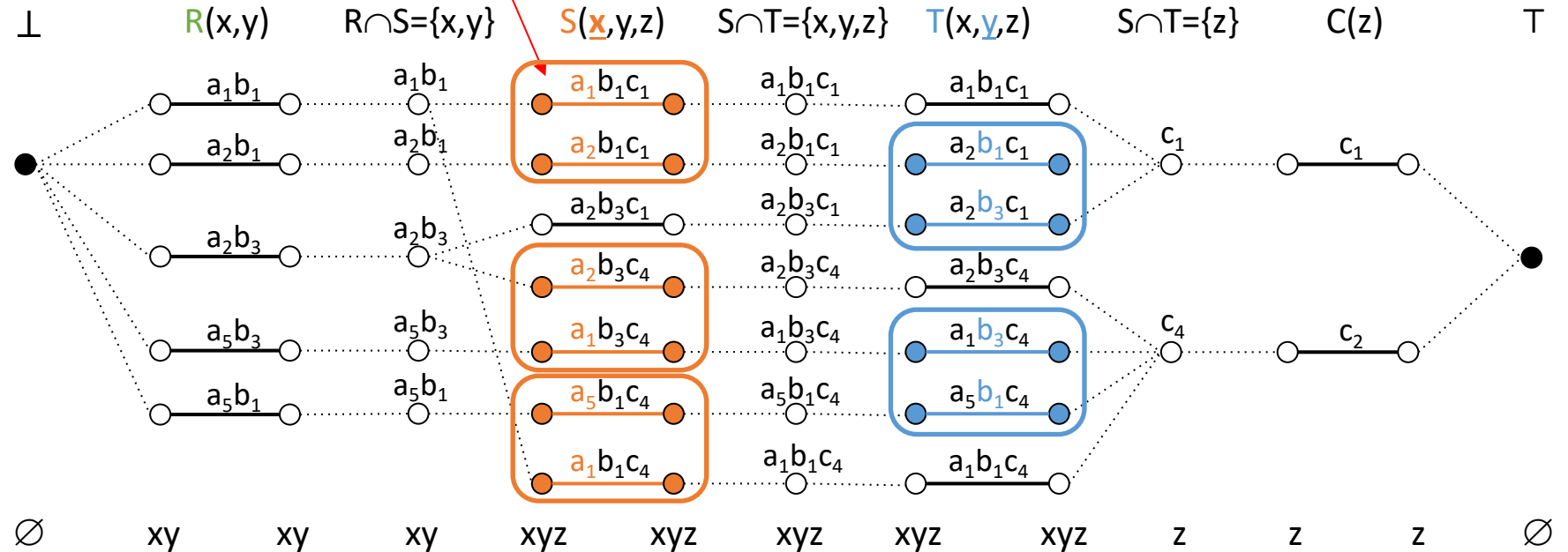
$$Q_C^{\Delta'}: -R(x, y), S(x, y, z), T(x, y, z), C(z)$$

Query first has to be linearized

Notice that these are now "dissociated" tuples, they don't correspond anymore to real tuples. But we would never need to pick them anyway 😊



$S(b_1, c_1) \rightarrow S(a_1, b_1, c_1)$
 $S(b_1, c_1) \rightarrow S(a_2, b_1, c_1)$

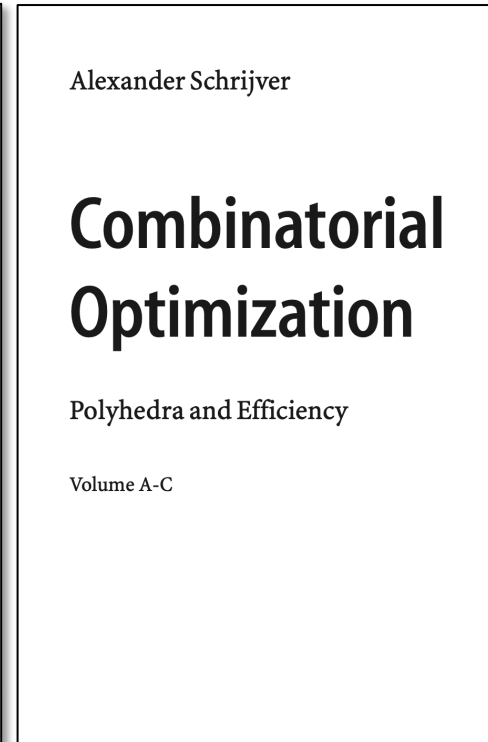
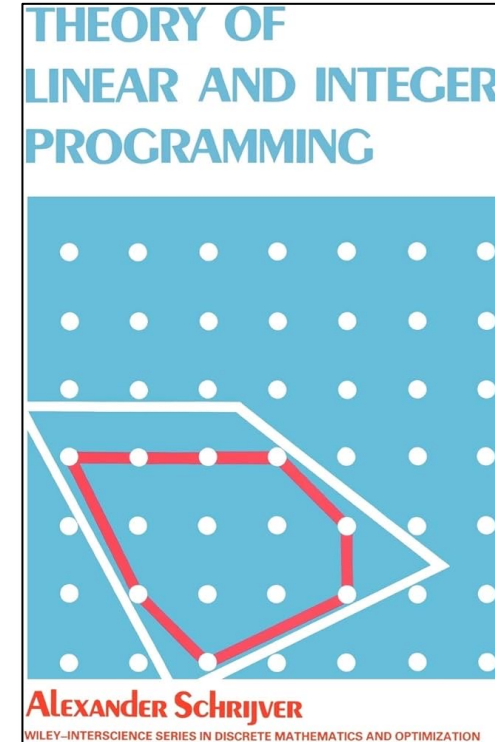


Polyhedral theory on ILP for triangle unary query

$$\begin{aligned} \min \quad & \mathbf{c}^T \mathbf{x} \\ \text{subject to} \quad & \mathbf{A} \mathbf{x} \geq \mathbf{b} \\ & \mathbf{x} \in \{0,1\}^n \end{aligned}$$

objective vector (red arrow pointing to \mathbf{c})
constraint matrix (orange arrow pointing to \mathbf{A})
constraint vector (blue arrow pointing to \mathbf{b})

83	Balanced and unimodular hypergraphs	1439
83.1	Balanced hypergraphs	1439
83.2	Characterizations of balanced hypergraphs	1440
83.2a	Totally balanced matrices	1444
83.2b	Examples of balanced hypergraphs	1447
83.2c	Balanced $0, \pm 1$ matrices	1447
83.3	Unimodular hypergraphs	1448
83.3a	Further notes	1450

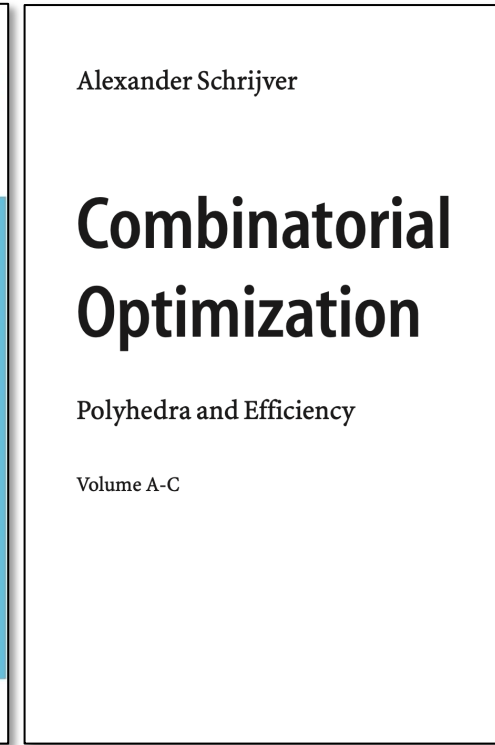
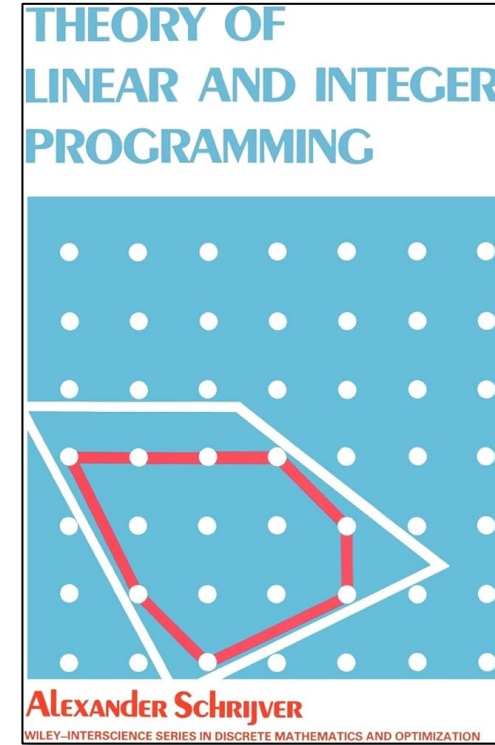


Polyhedral theory on ILP for triangle unary query: not useful ☹️

$$\begin{aligned} \min \quad & \mathbf{c}^T \mathbf{x} \\ \text{subject to} \quad & \mathbf{A} \mathbf{x} \geq \mathbf{b} \\ & \mathbf{x} \in \{0,1\}^n \end{aligned}$$

objective vector → \mathbf{c}^T
constraint matrix → \mathbf{A}
constraint vector → \mathbf{b}

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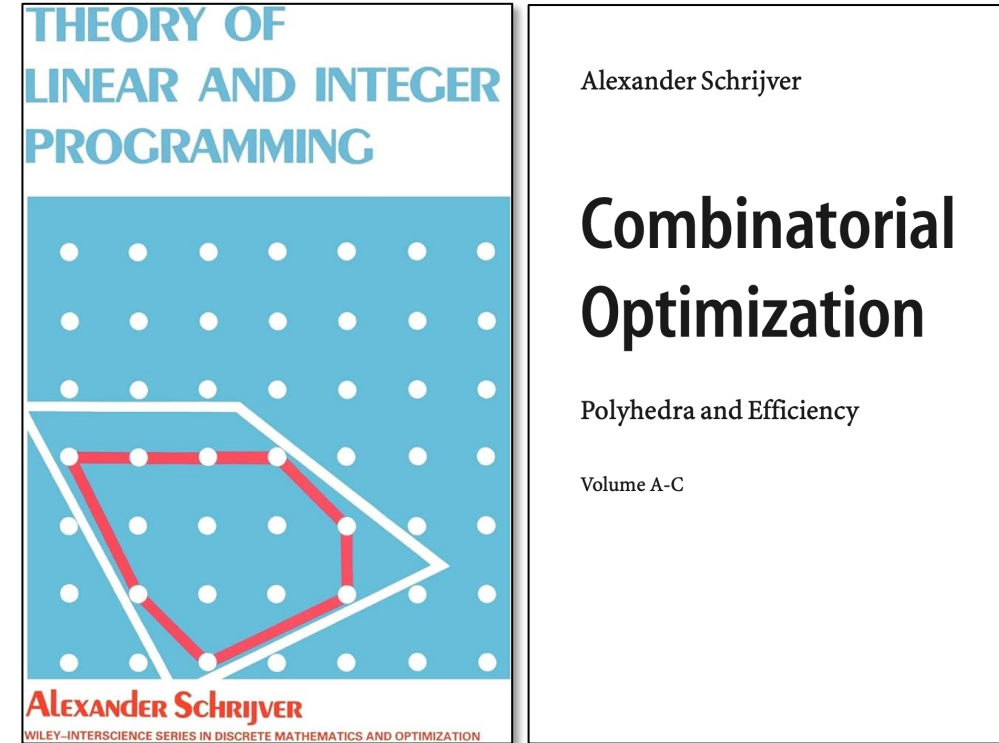
- Focus of polyhedral theory mainly on **constraint matrix \mathbf{A}** . But our PTIME constraint matrixes need not be balanced, nor Totally Unimodular, etc.

Polyhedral theory on ILP for triangle unary query: not useful 😞

$$\begin{aligned} \min \quad & \mathbf{c}^T \mathbf{x} \\ \text{subject to} \quad & \mathbf{A} \mathbf{x} \geq \mathbf{b} \\ & \mathbf{x} \in \{0,1\}^n \end{aligned}$$

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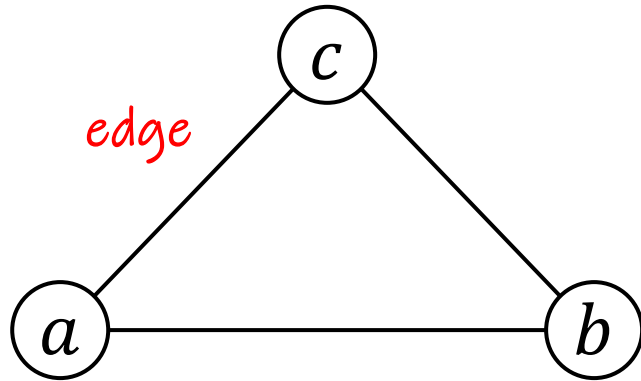
- Focus of polyhedral theory mainly on **constraint matrix \mathbf{A}** . But our PTIME constraint matrixes need not be balanced, nor Totally Unimodular, etc.

1. Our complexity results take into account the **objective vector \mathbf{c}** !
2. This gives us a separation between the problem under set vs. bag semantics!
3. We use an indirect proof via the earlier-described MFMC encoding 😊

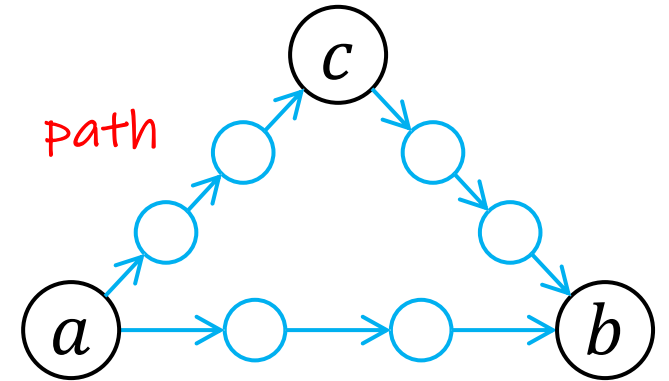
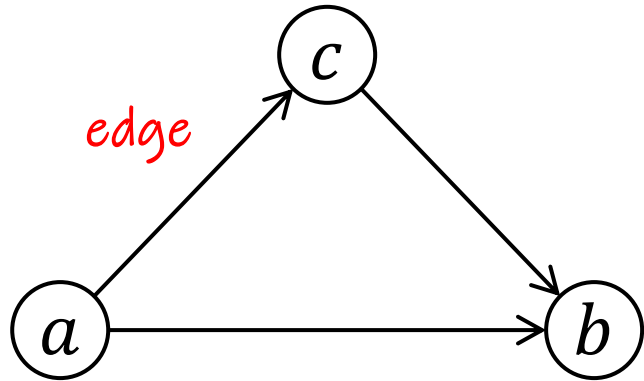
Outline

- Resilience for self-join free CQs
 - hard & easy cases
- Resilience for general CQs
 - hard & easy cases

A template of hardness reduction from minimal VC

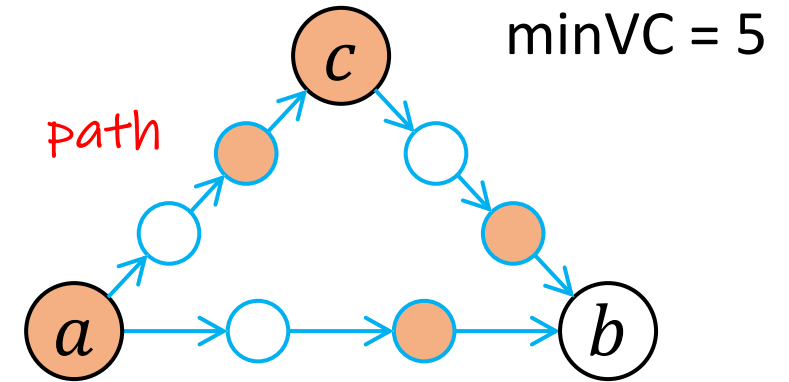
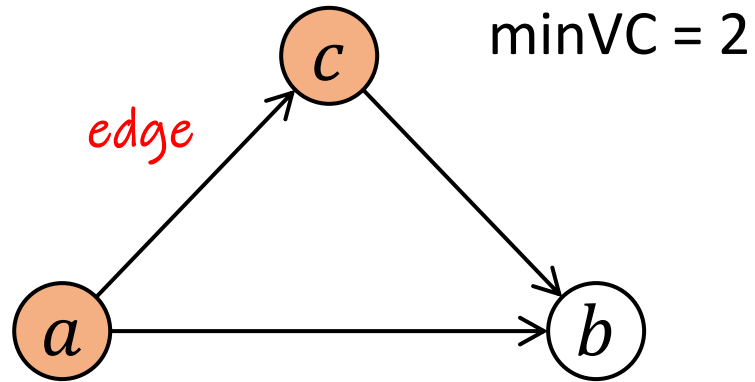


A template of hardness reduction from minimal VC



What is the minimum VC for either graph ?

A template of hardness reduction from minimal VC

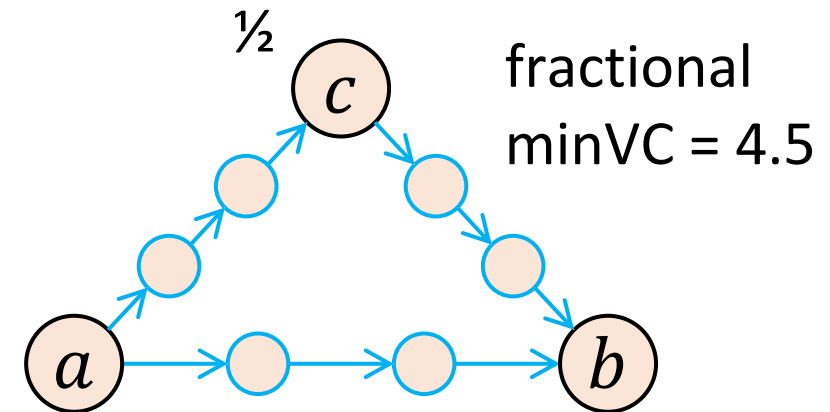
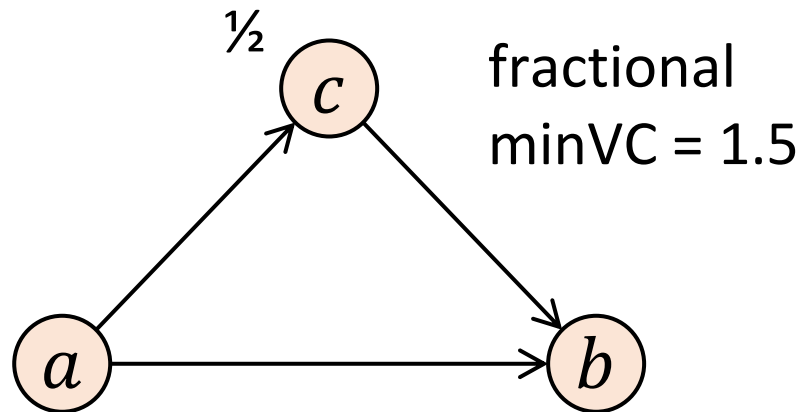
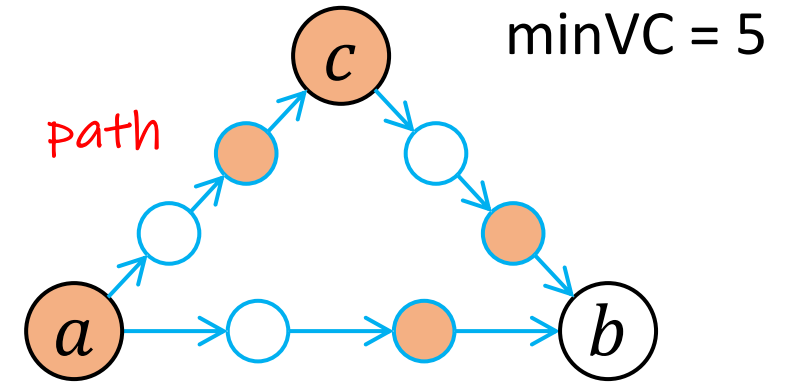
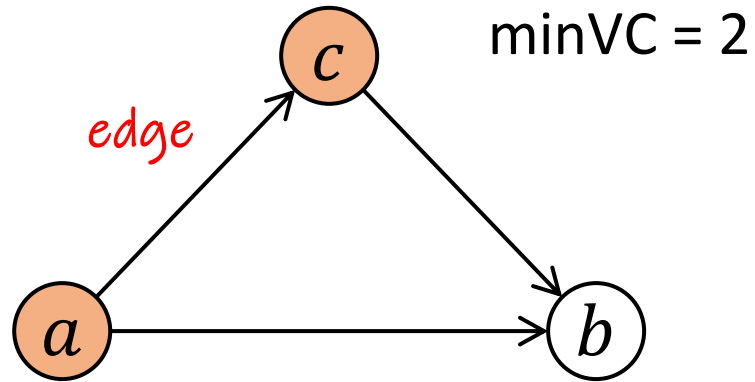


Side-topic:

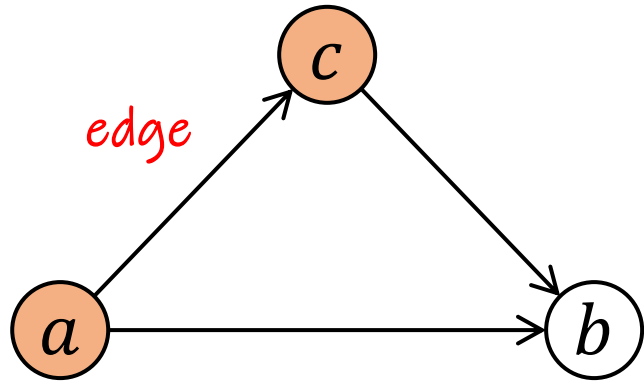
What is the minimum fractional VC for either graph ?

(Assign weights in $[0,1]$ to vertices s.t. the sum of weights of endpoints for each edge is ≥ 1)

A template of hardness reduction from minimal VC

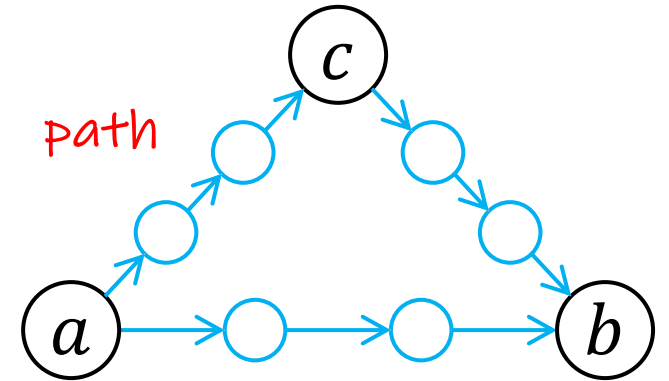


A template of hardness reduction from minimal VC



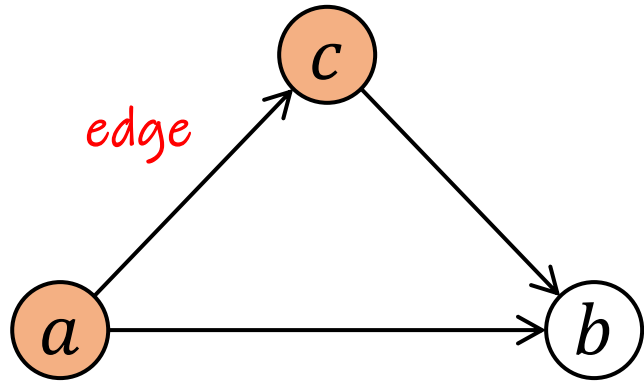
VC of size k

\Rightarrow



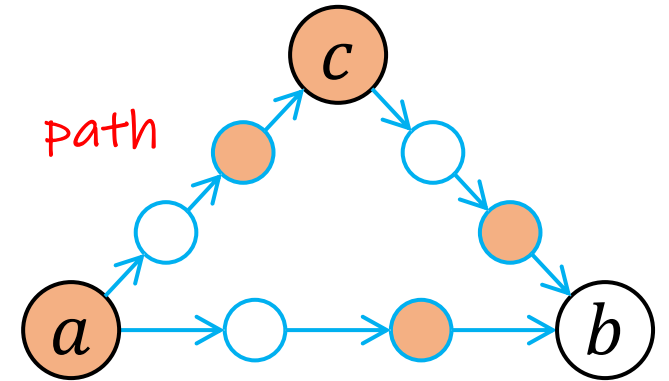
VC of size ?

A template of hardness reduction from minimal VC



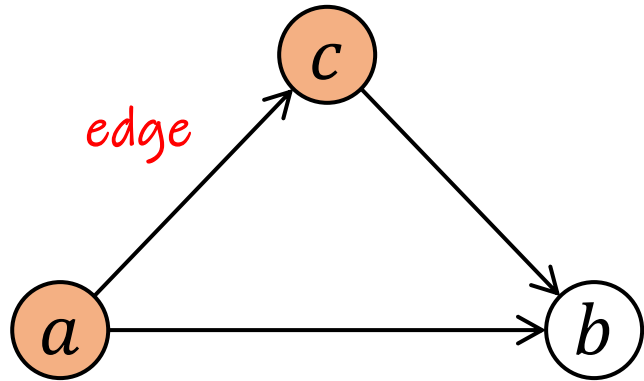
VC of size k

\Rightarrow



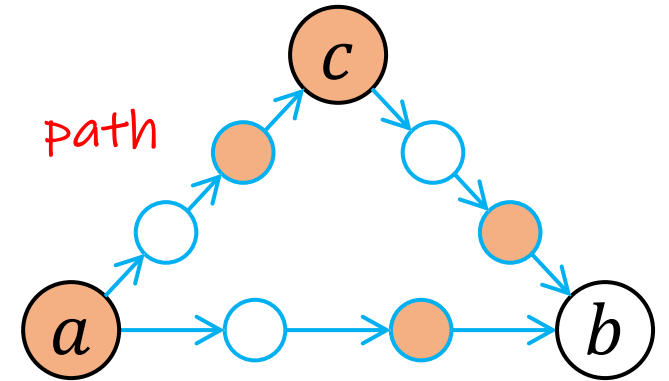
VC of size $k + \# \text{ edges}$

A template of hardness reduction from minimal VC



VC of size k

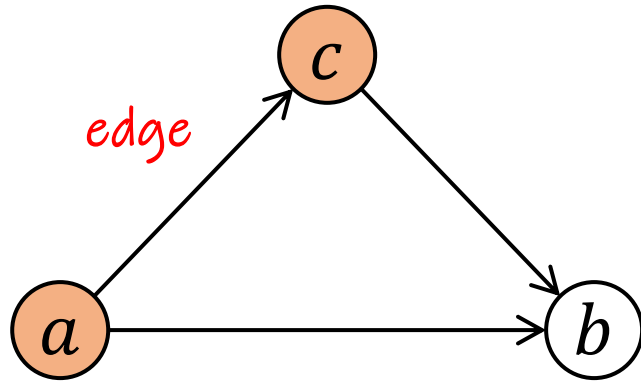
←



VC of size $k + \# \text{ edges}$

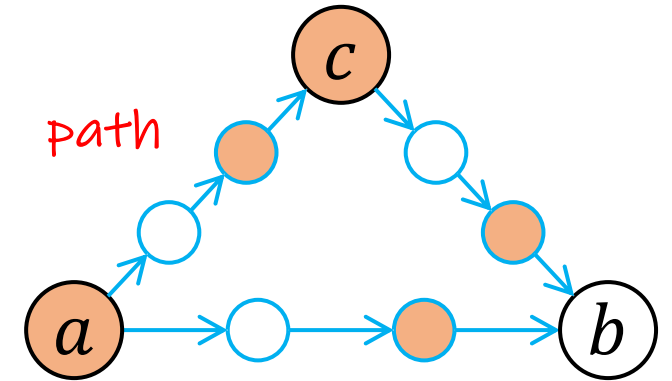
?

A template of hardness reduction from minimal VC



VC of size k

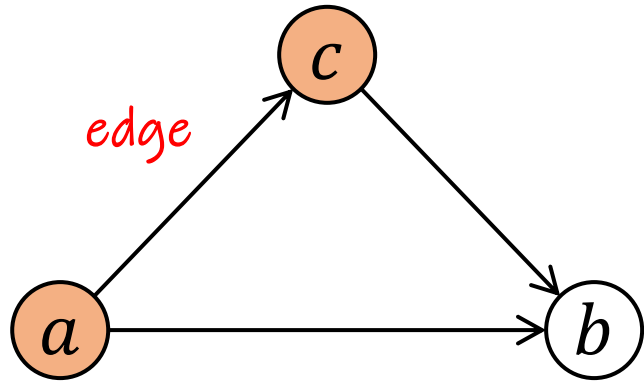
\Leftrightarrow



VC of size $k + \# \text{ edges}$

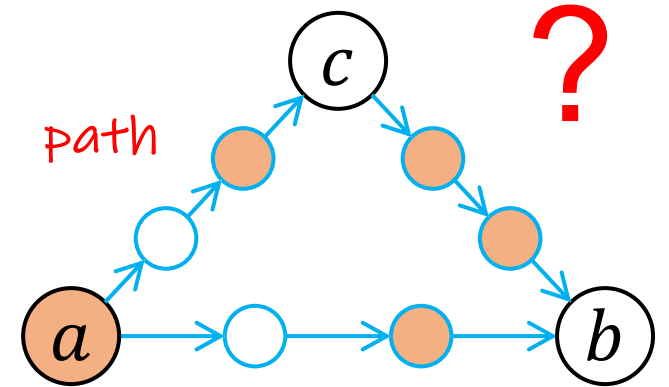
(as long as $k \leq \# \text{ vertices}$)

A template of hardness reduction from minimal VC



VC of size k

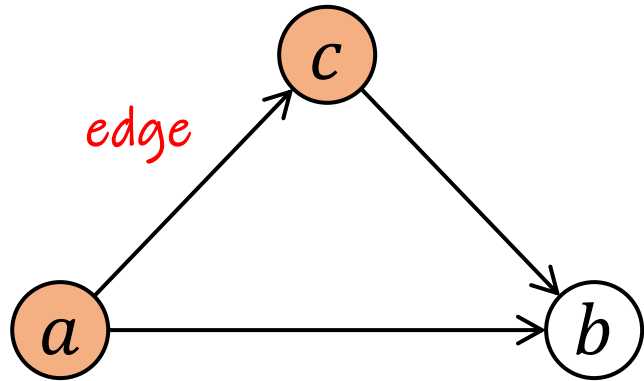
\Leftrightarrow



VC of size $k + \# \text{ edges}$

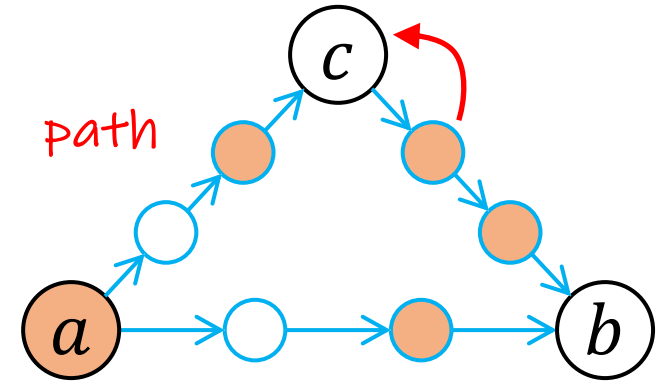
(as long as $k \leq \# \text{ vertices}$)

A template of hardness reduction from minimal VC



VC of size k

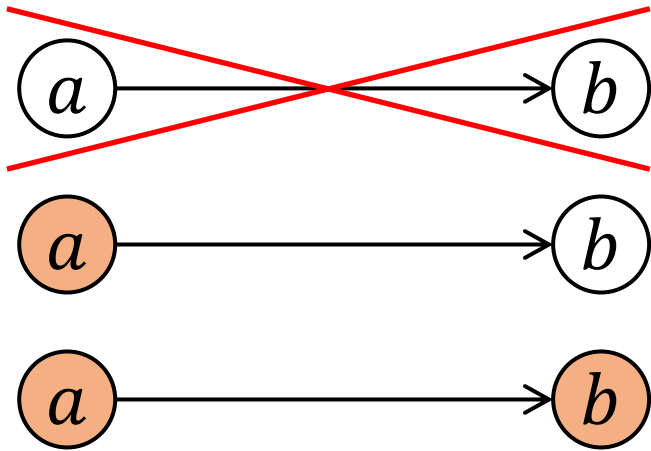
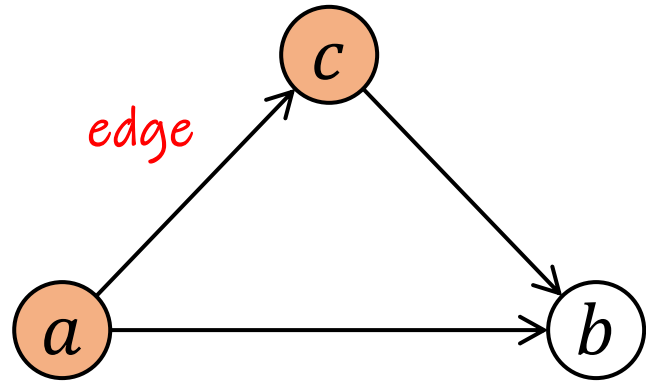
\Leftrightarrow



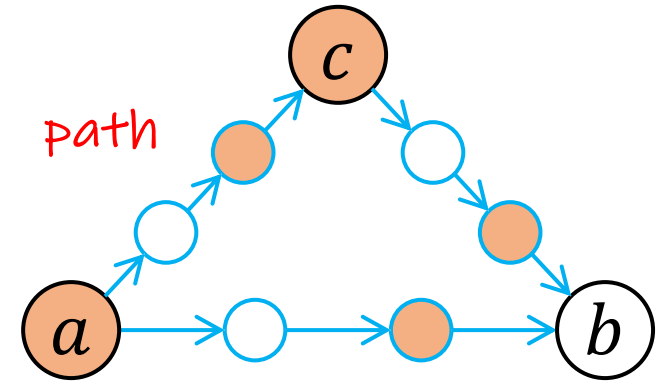
VC of size $k + \# \text{ edges}$

(as long as $k \leq \# \text{ vertices}$)

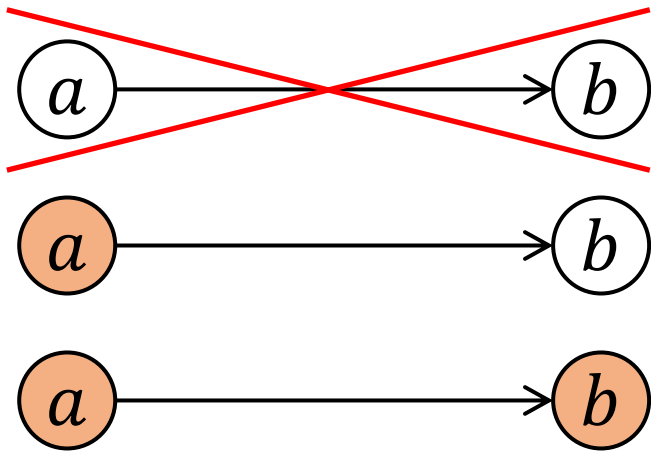
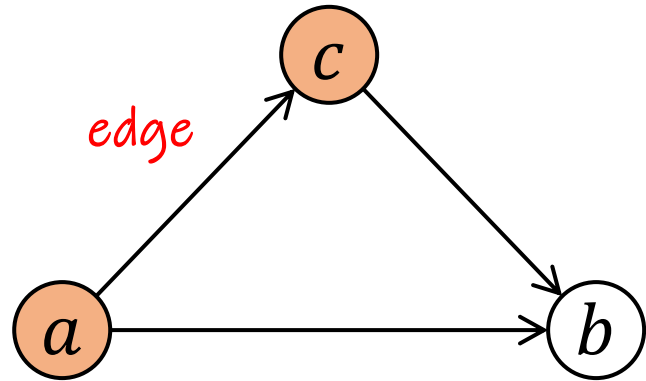
A template of hardness reduction from minimal VC



OR-property of an edge: we need to choose one (or both) of the end points

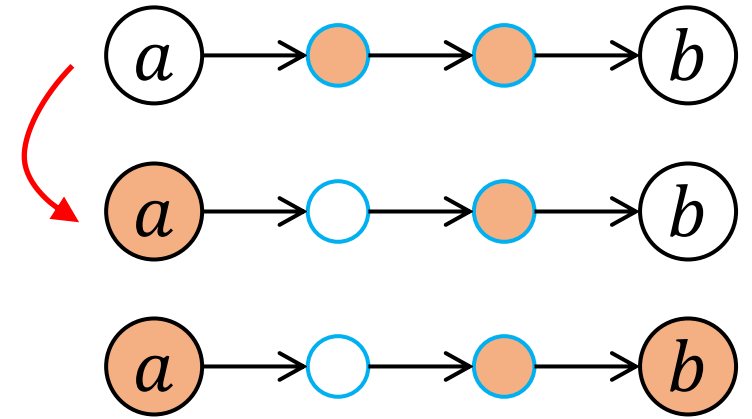
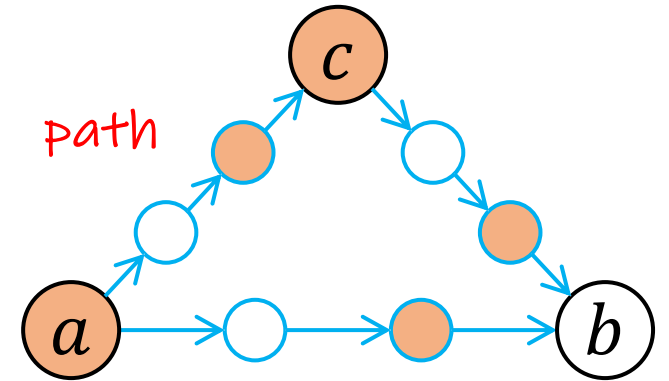


A template of hardness reduction from minimal VC



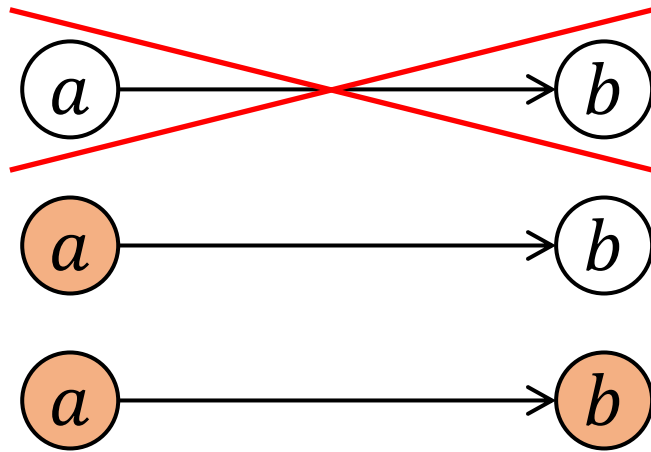
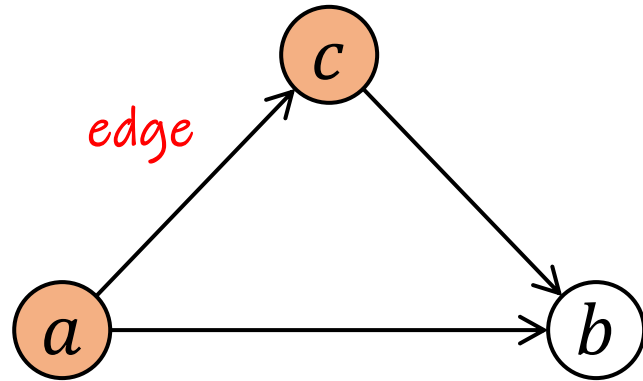
OR-property of an edge: we need to choose one (or both) of the end points

It is not immediately obvious why this is the "right" way to think about "edge gadgets", but we found it is 😊

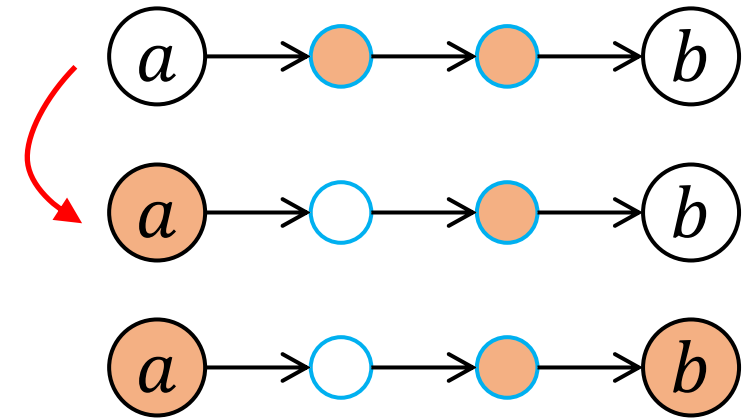
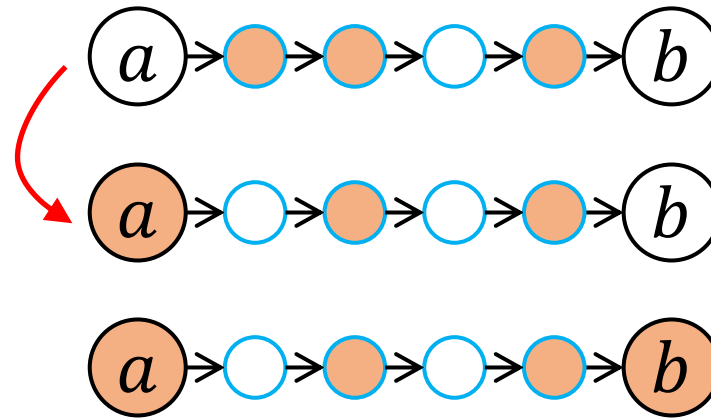
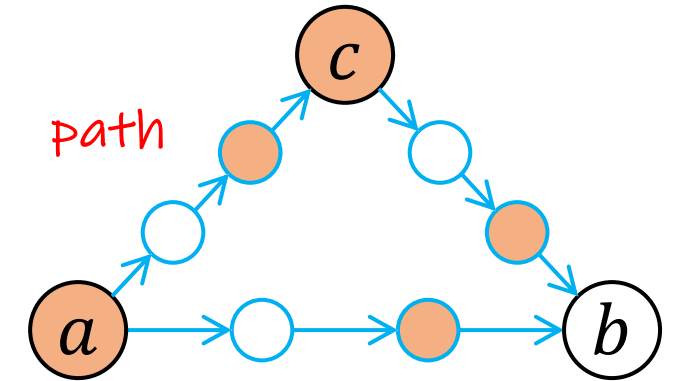


OR-property of a path gadget: choosing one (or both) of the end points of a path reduces the Minimum VC of the remaining path gadget by 1 (we need to pick ≥ 2 vertices per path anyway)

A template of hardness reduction from minimal VC

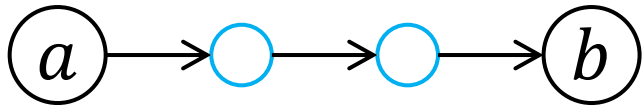


OR-property of an edge: we need to choose one (or both) of the end points



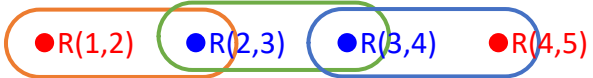
OR-property of a path gadget: choosing one (or both) of the end points of a path reduces the Minimum VC of the remaining path gadget by 1 (we need to pick ≥ 2 vertices per path anyway)

A template of hardness reduction from minimal VC

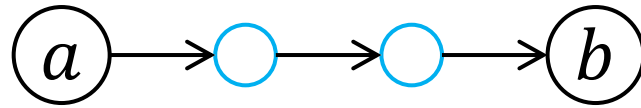
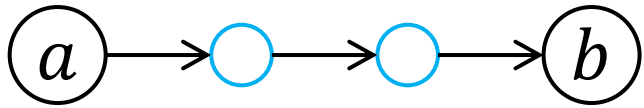


$$x \xrightarrow{R} y \xrightarrow{R} z$$

$$q_{2chain} := \neg R(x,y), R(y,z)$$



A template of hardness reduction from minimal VC

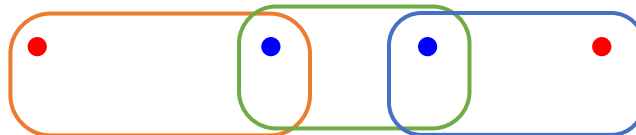
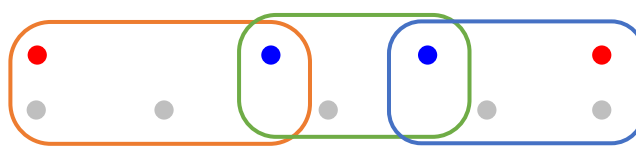
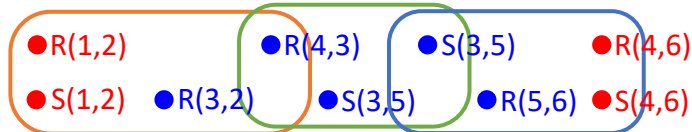
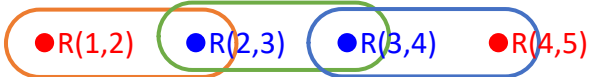


$$x \xrightarrow{R} y \xrightarrow{R} z$$

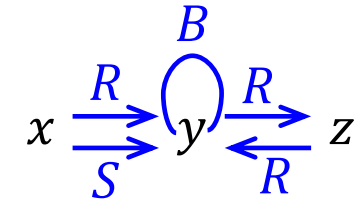
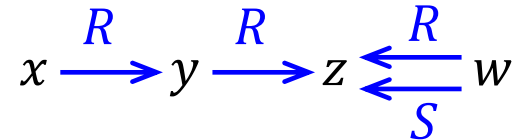
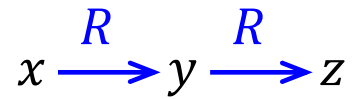
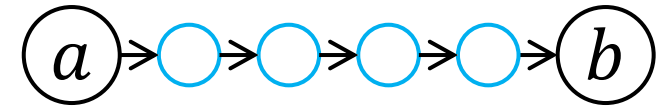
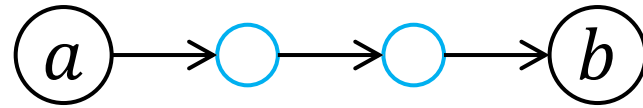
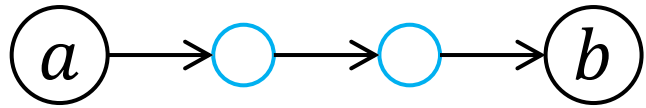
$$x \xrightarrow{R} y \xrightarrow{R} z \begin{matrix} \xleftarrow{R} w \\ \xleftarrow{S} w \end{matrix}$$

$$q_{2chain} := \neg R(x,y), R(y,z)$$

$$q_{3cc}^S := \neg R(x,y), R(y,z), R(w,z), S(w,z)$$



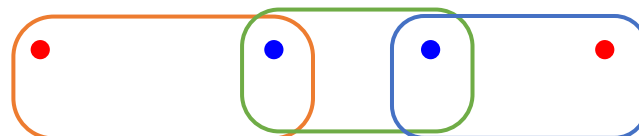
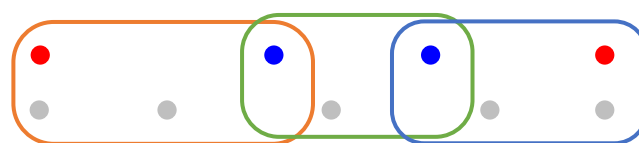
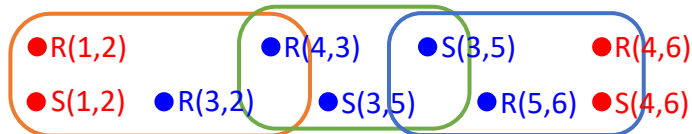
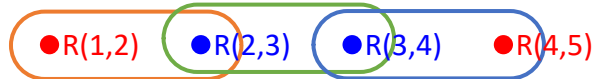
A template of hardness reduction from minimal VC



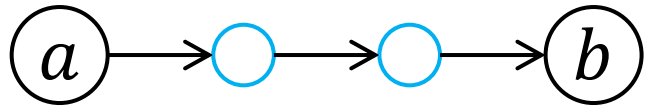
$$q_{2chain} := \neg R(x,y), R(y,z)$$

$$q_{3cc}^S := \neg R(x,y), R(y,z), R(w,z), S(w,z)$$

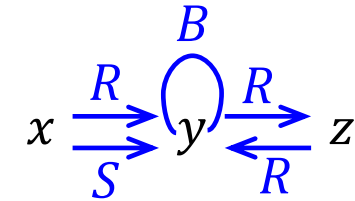
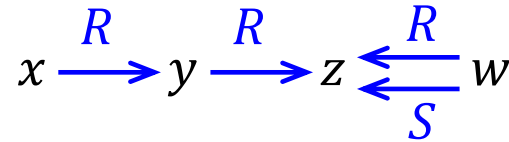
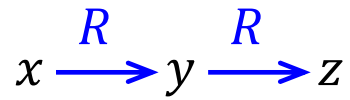
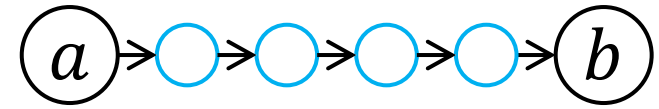
$$q_{3perm-R}^{SxyB} := \neg S(x,y), R(x,y), B(y), R(y,z), R(z,y)$$



A template of hardness reduction from minimal VC



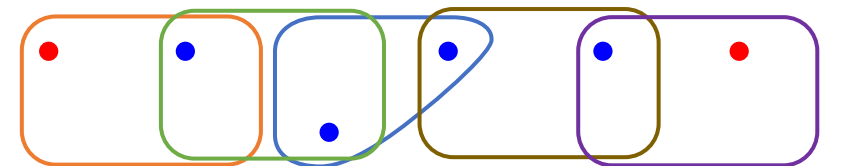
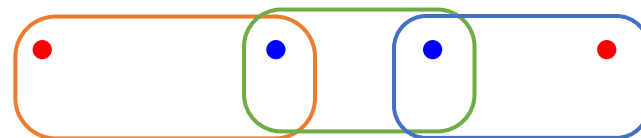
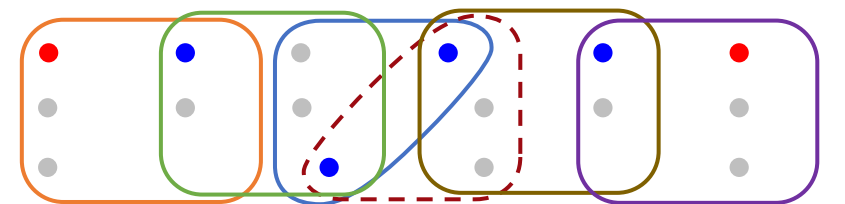
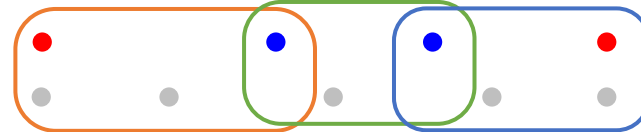
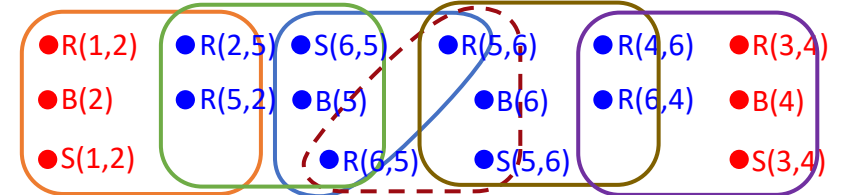
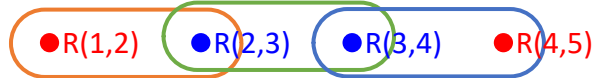
computer-generated "IJP"
with disjunctive logic program
(answer set programming ASP)



$$q_{2chain} :- R(x,y), R(y,z)$$

$$q_{3cc}^S :- R(x,y), R(y,z), R(w,z), S(w,z)$$

$$q_{3perm-R}^{SxyB} :- S(x,y), R(x,y), B(y), R(y,z), R(z,y)$$



Formal definitions of IJPs

1. Join paths with end points
(possible set of tuples)

Definition 7.1 (Join Path (JP)). A database D (under set or bag semantics) forms a Join Path from a set of tuples \mathcal{S} (start) to a set of tuples \mathcal{T} (terminal), for query Q if

- (1) Each tuple in D participates in some witness (i.e. D is reduced).
- (2) The witness hypergraph is connected.
- (3) \mathcal{S} and \mathcal{T} form a *valid endpoint pair*, i.e.:
 - (i) \mathcal{S} and \mathcal{T} are isomorphic and non-identical.
 - (ii) There is no endogenous tuple $t \in D, t \notin \mathcal{S} \cup \mathcal{T}$ whose constants are a subset of the constants of tuples in $\mathcal{S} \cup \mathcal{T}$.

We also call two join paths *isomorphic* if there is a bijective mapping between the shared constants across the witnesses. Given a fixed query, we usually leave away the implied qualifier “isomorphic” when discussing join paths. We talk about the “*composition*” of two join paths if one endpoint of the first is identical to an endpoint of the second, and all other constants are different. We call a composition of join paths “non-leaking” if the composition adds no additional witnesses that were not already present in any of the non-composed join paths.

3. Composability defined semantically: composition cannot create additional witnesses = does not “leak”

Definition 7.3 (Independent Join Path). A Join Path D forms an *Independent Join Path (IJP)* if it fulfills two additional conditions:

- (4) “OR-property”: Let c be the resilience of Q on D . Then resilience is $c - 1$ in all 3 cases of removing either \mathcal{S} or \mathcal{T} or both.
- (5) Any composition of two or more isomorphic JPs is non-leaking.

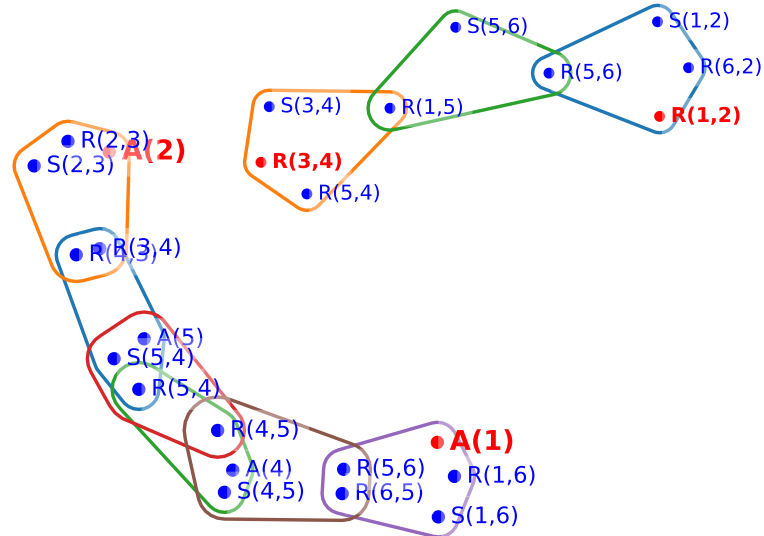
2. OR-property

Finding IJPs with ASP: 5 New Hardness Gadgets

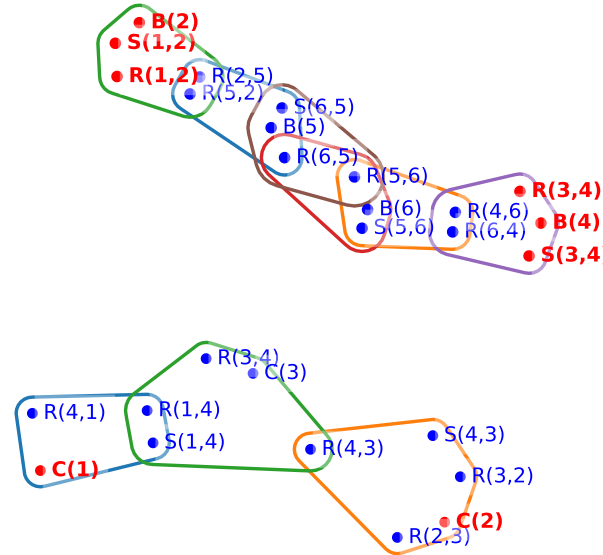
- Using the **Automatic IJP Generator**, able to prove 5 queries hard (out of 7 previously **open** from [Freire+ PODS'20])

$$q_{3cc}^S :- R(x,y), R(y,z), R(w,z), S(w,z)$$

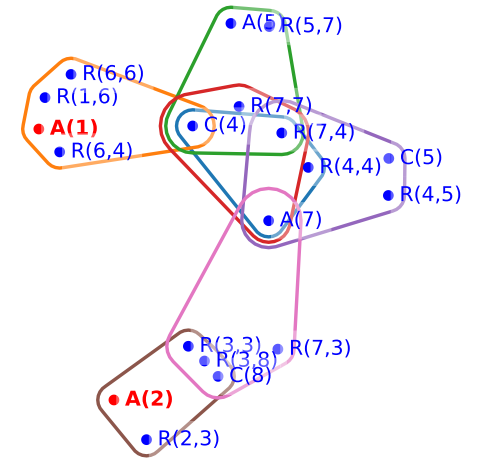
$$q_{3perm-R}^{S_{xy}B} :- S(x,y), R(x,y), B(y), R(y,z), R(z,y)$$



$$q_{3perm-R}^{AS_{xy}} :- A(x), S(x,y), R(x,y), R(y,z), R(z,y)$$



$$q_{3perm-R}^{S_{xy}C} :- S(x,y), R(x,y), R(y,z), R(z,y), C(z)$$



$$z_6 :- A(x), R(x,y), R(y,y), R(y,z), C(z)$$

- Can recover all previous hardness results + find new ones!

Dichotomy Conjectures for Resilience

Theorem.

$IJP \rightarrow NPC$

Conjecture. [Hardness]

$IJP \leftrightarrow NPC$

Conjecture. [Hardness]

$IJP \rightarrow IJP$ of domain size $\leq 7 * var(Q)$

Conjecture. [PTIME]

$\nexists IJP \rightarrow LP = ILP$

Theorem.

$IJP \leftrightarrow NPC$ for SJ-Free Queries

Conjecture. [Hardness] Corollary

$NPC \rightarrow$ DLP finds a hardness proof

Conjecture. [PTIME]

$\nexists IJP \rightarrow$ There is a flow graph that encodes resilience

Outlook

- Flow becomes complicated. Goal: can we automate as well?
- Resilience Binary CQs: is the ASP really "all we need"?
- Resilience Union of Binary CQs: the current ASP abstraction is not enough (but can likely be fixed)
- Resilience Non-binary CQs: gets more hairy
- Minimum size factorization of provenance
 - constraint matrices contain $\{-1,0,1\}$; minimal vertex cover analogy breaks
 - flow encodings still possible but become factored in nontrivial ways
 - leverages a connection between factorizations, query plans, and VEOs

Thank you 😊

BACKUP

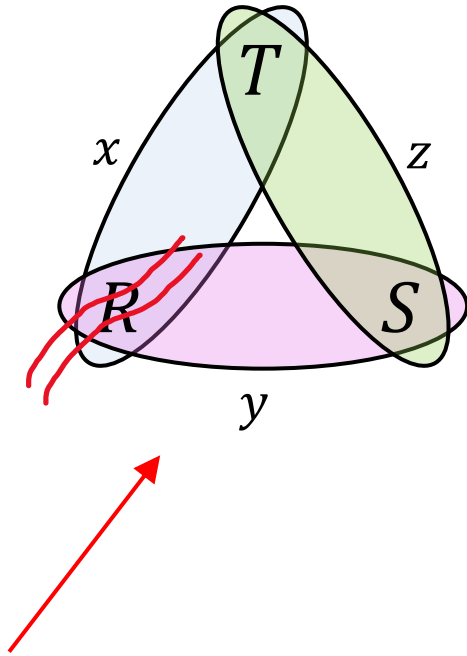
IJPs
generalize
triads

"IJPs" generalize "active triads"

Triangle query

$$Q^\Delta: \neg R(x, y), S(y, z), T(x, z)$$

Triad in the Triangle query



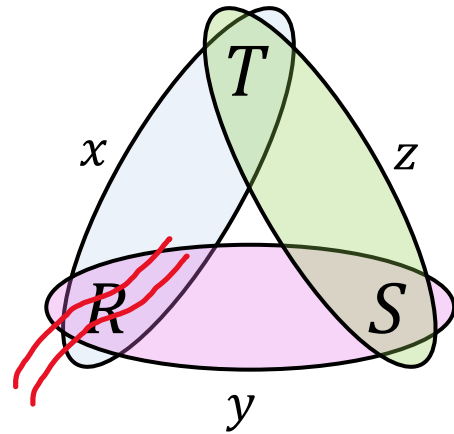
This is the query dual hypergraph.
Each node corresponds to one tuple, each
hyperedge to one variable in the query

"IJPs" generalize "active triads"

Triangle query

$$Q^\Delta: \neg R(x, y), S(y, z), T(x, z)$$

Triad in the Triangle query

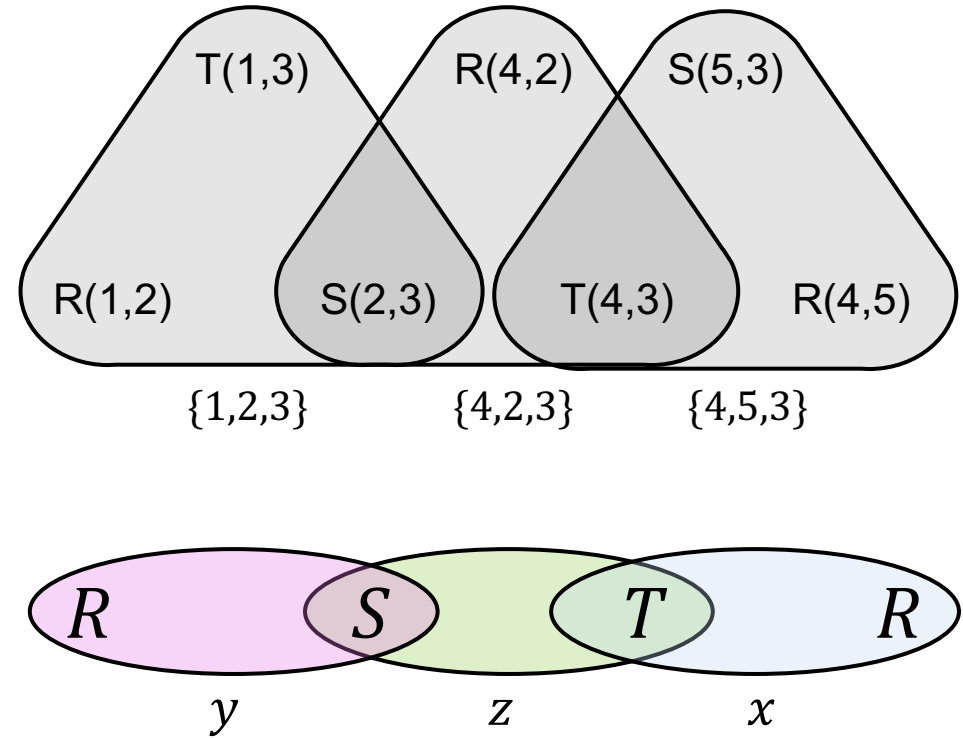


This this the query dual hypergraph.
Each node corresponds to one tuple, each hyperedge to one variable in the query

This this the data instance hypergraph.
Each node corresponds to one tuple, each hyperedge to one witness

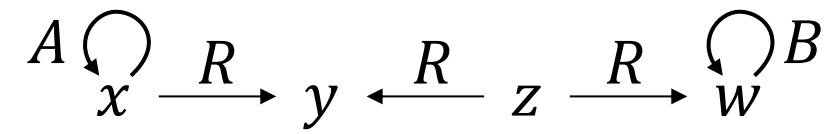


Implied IJP



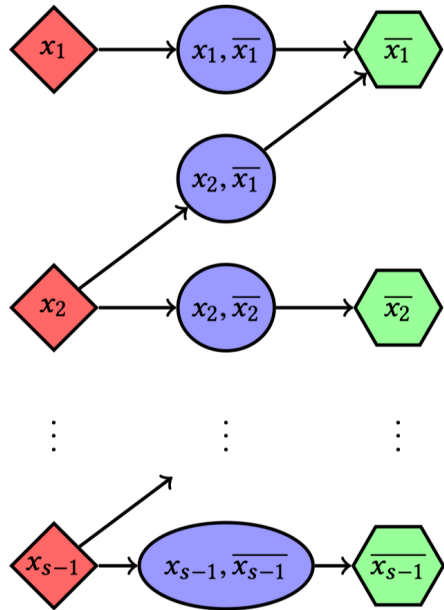
IJPs unify
past proofs for SJs

Evidence for IJPs as unifying criterion

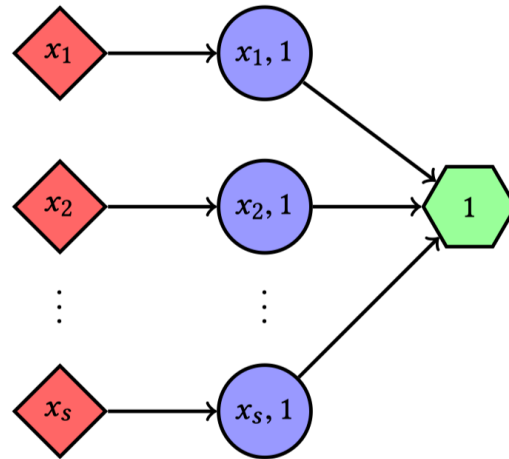


Original hardness proof for via reduction from Max 2SAT

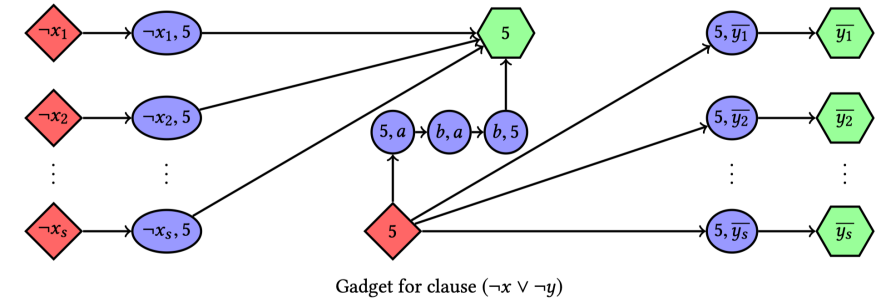
$$Q_{3\text{conf}}^{AC}: -A(x), R(x, y), R(z, y), R(z, w), C(w)$$



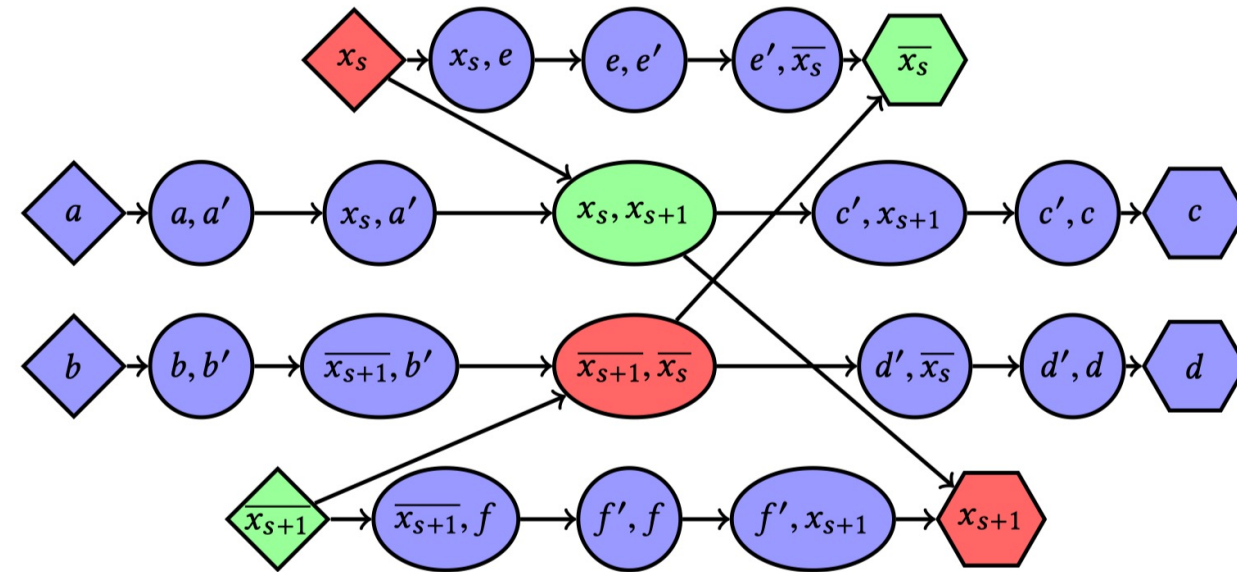
Top half of Variable Gadget



Gadget for clause (x)



Gadget for clause $(\neg x \vee \neg y)$



Middle Crossover Part of Variable Gadget

Figure 15: Reduction Gadgets for proof of Proposition 39: diamonds represent A , ellipses, R , and hexagons, C . In the variable gadgets, the minimum contingency sets choose all red vertices and no green, or all green vertices and no red.

Source: Freire, New Results for the Complexity of Resilience for Binary Conjunctive Queries with Self-Joins, PODS 2020. <https://arxiv.org/pdf/1907.01129>

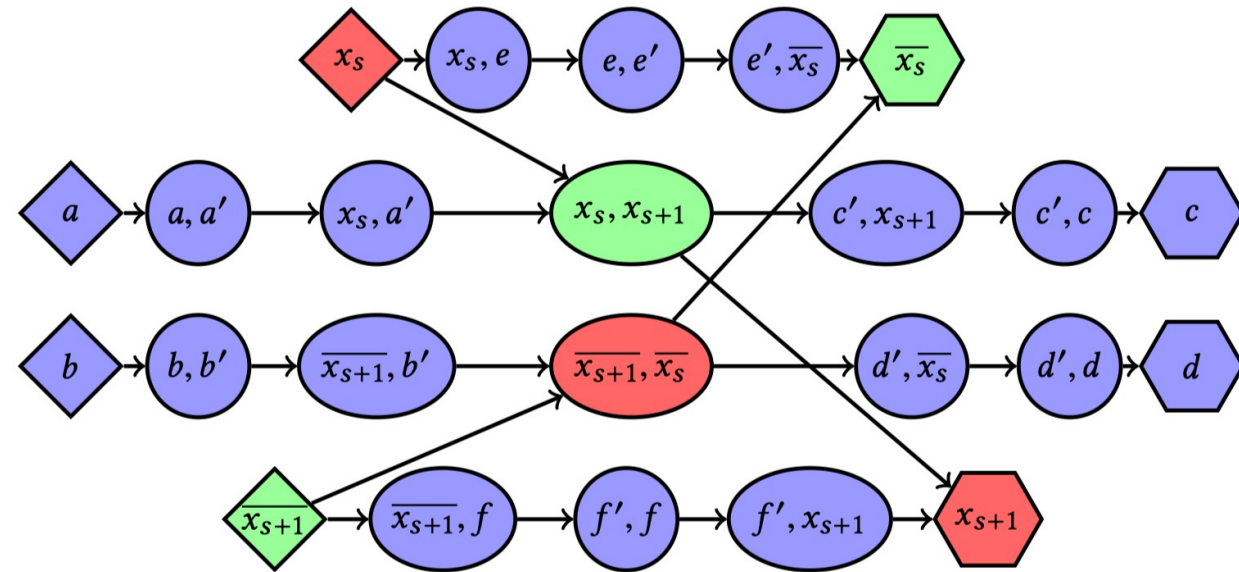
Wolfgang Gatterbauer, Principles of Scalable Data Management. <https://northeastern-datafab.github.io/cs7240/>

Evidence for IJPs as unifying criterion

$$A \overset{\curvearrowright}{x} \xrightarrow{R} y \xleftarrow{R} z \xrightarrow{R} \overset{\curvearrowright}{w} B$$

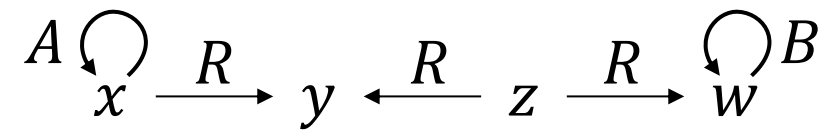
Original hardness proof for via reduction from Max 2SAT

$$Q_{3\text{conf}}^{AC}: \neg A(x), R(x, y), R(z, y), R(z, w), C(w)$$



Middle Crossover Part of Variable Gadget

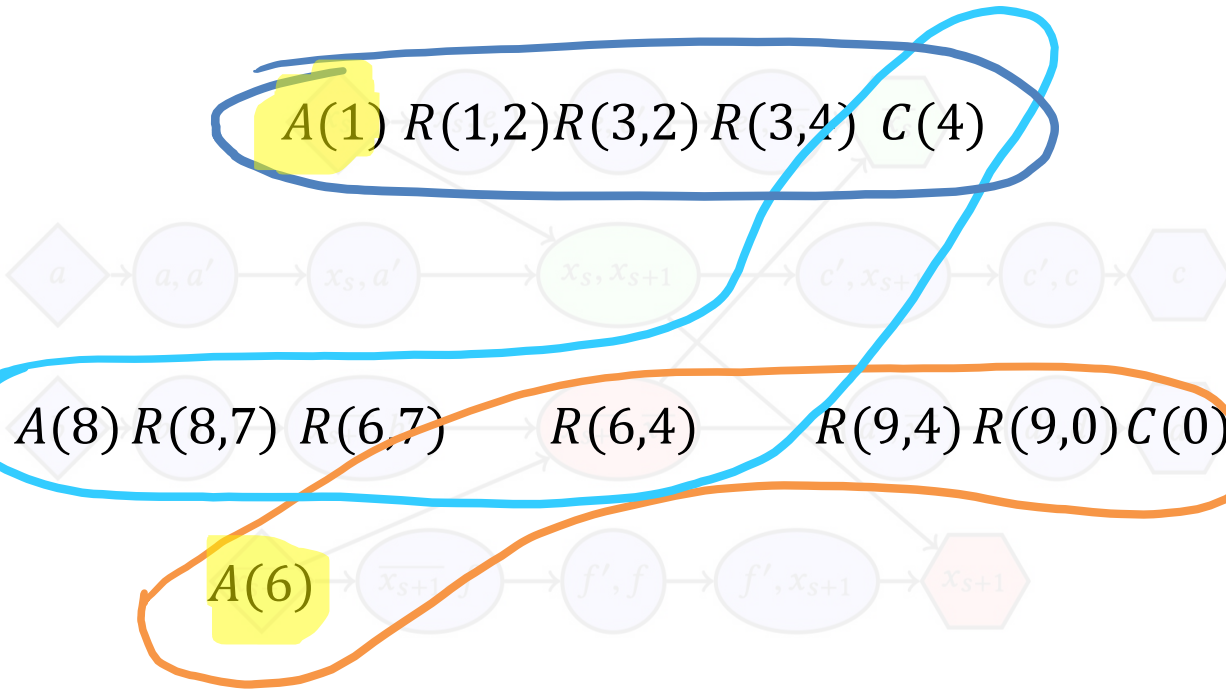
Evidence for IJPs as unifying criterion



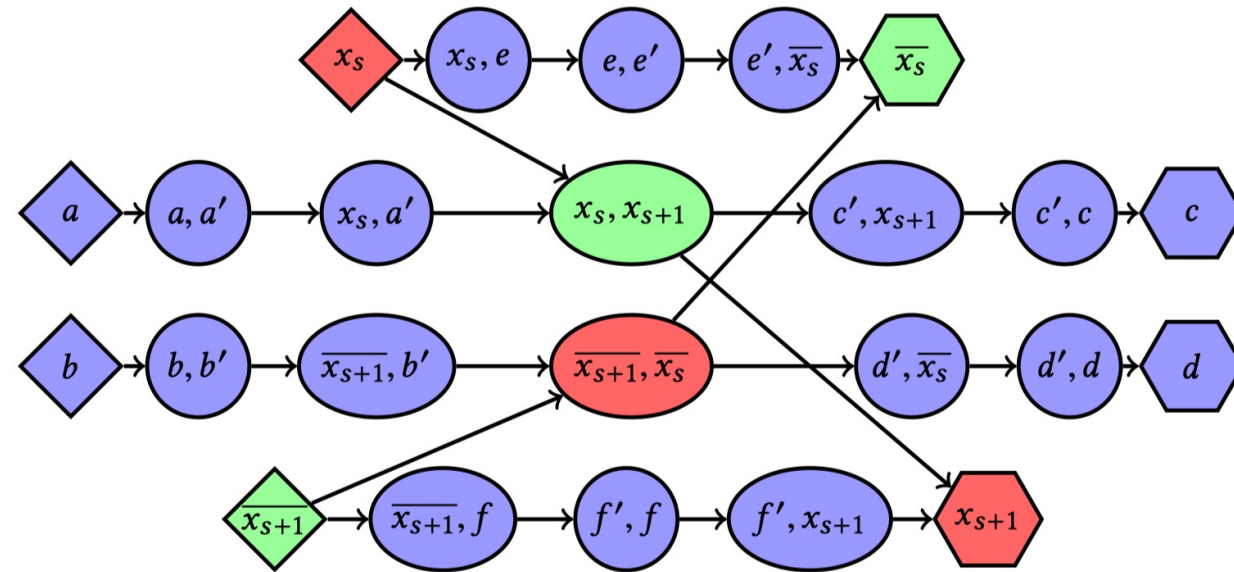
Original hardness proof for via reduction from Max 2SAT

$$Q_{3\text{conf}}^{AC}: \neg A(x), R(x, y), R(z, y), R(z, w), C(w)$$

IJP with pivots $A(1), A(6)$ was already hiding in the original gadgets
 [not shown are "extensions" one still needs to add to the end points]

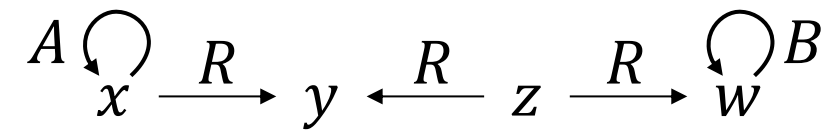


Middle Crossover Part of Variable Gadget



Middle Crossover Part of Variable Gadget

Evidence for IJPs as unifying criterion



Original hardness proof for via reduction from Max 2SAT

$$Q_{3\text{conf}}^{AC}: \neg A(x), R(x, y), R(z, y), R(z, w), C(w)$$

IJP with pivots $A(1), A(6)$ was already hiding in the original gadgets
 [not shown are "extensions" one still needs to add to the end points]

$A(1) R(1,2) R(3,2) R(3,4) C(4)$

$A(8) R(8,7) R(6,7) R(6,4) R(9,4) R(9,0) C(0)$

$A(6)$

Additional dominated witnesses (in gray):

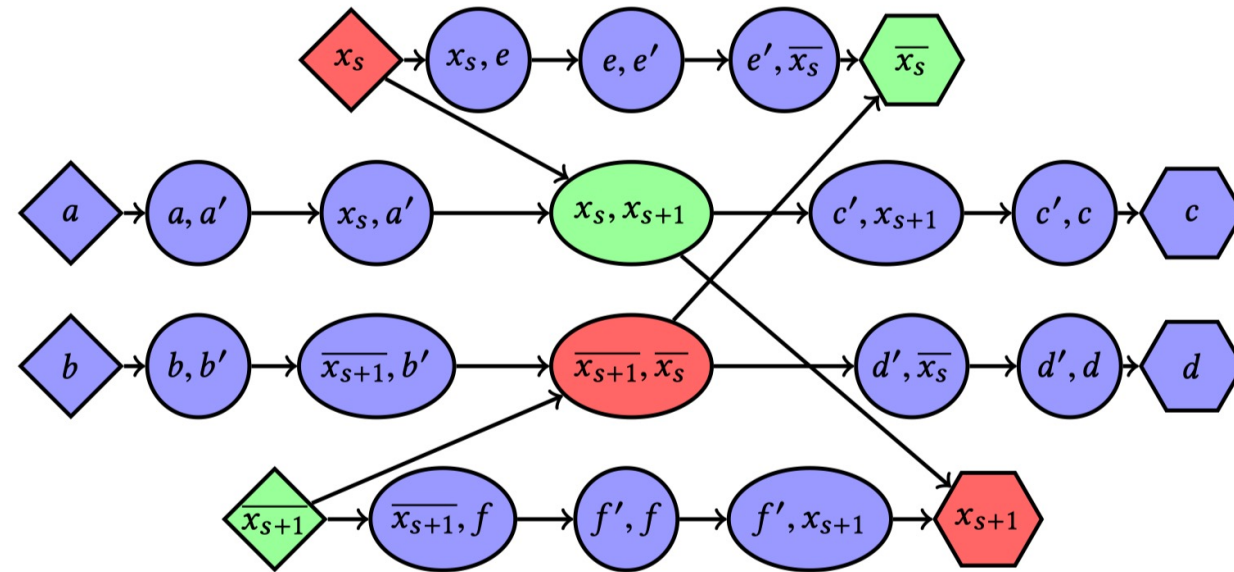
$\{A(6), R(6,4), R(3,4), C(4)\}$

$\{A(6), R(6,4), R(9,4), C(4)\}$

$\{A(6), R(6,7), R(6,4), C(4)\}$

$\{A(6), R(6,7), R(6,4), R(3,4), C(4)\}$

$\{A(6), R(6,7), R(6,4), R(9,4), C(4)\}$



Middle Crossover Part of Variable Gadget