DATALAB
@Northeastern

A unified and practical approach to Generalized Deletion Propagation

Wolfgang Gatterbauer, joint work with **Neha Makhija**

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

Logic and Algorithms in Database Theory and AI Reunion
Jan 15, 2024

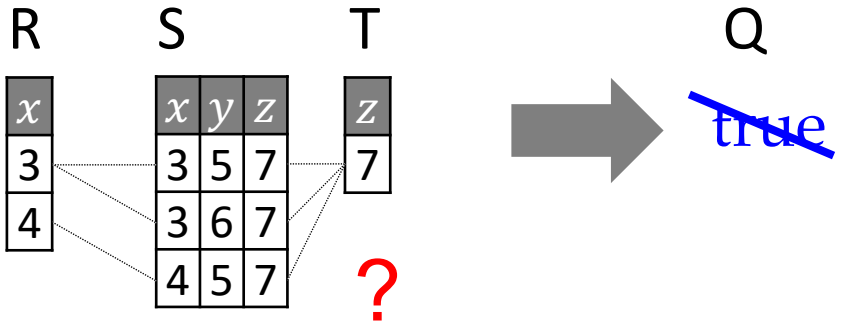
https://simons.berkeley.edu/workshops/logic-algorithms-database-theory-ai-reunion

Example Reverse Data Management Problems

Q:-R(x),S(x,y,z),T(z)

1. Resilience

Delete min number of tuples to make Q false



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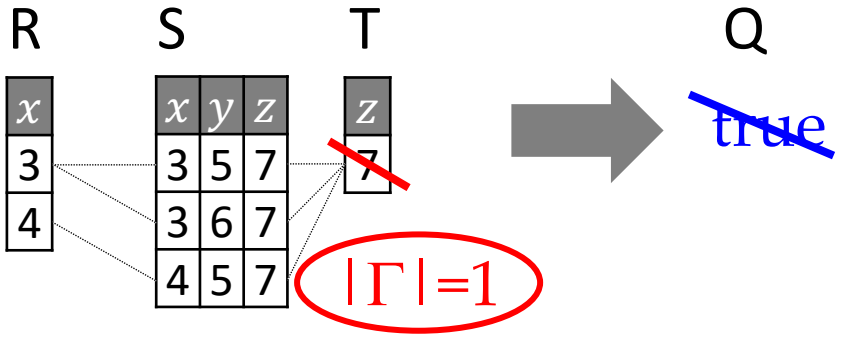

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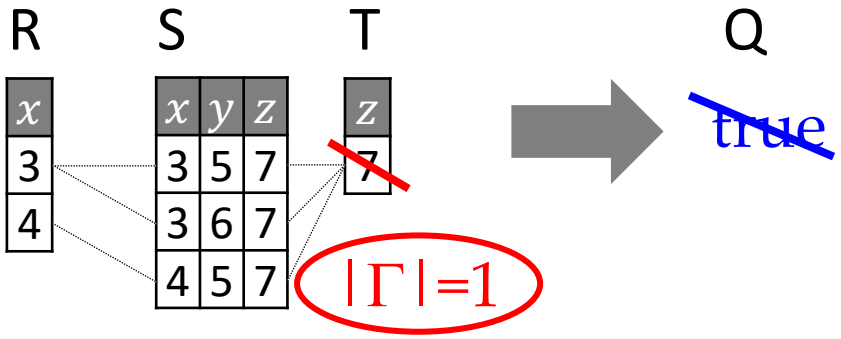

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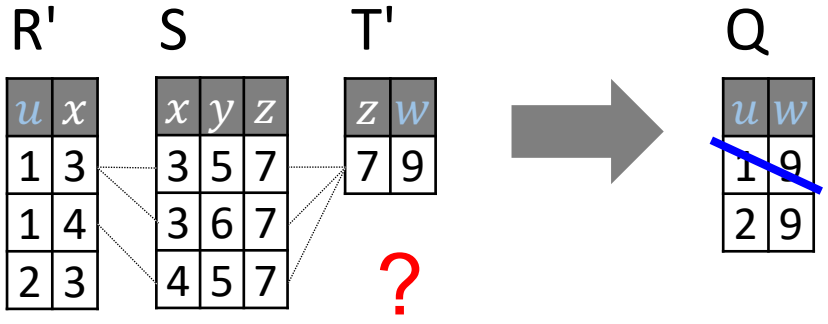

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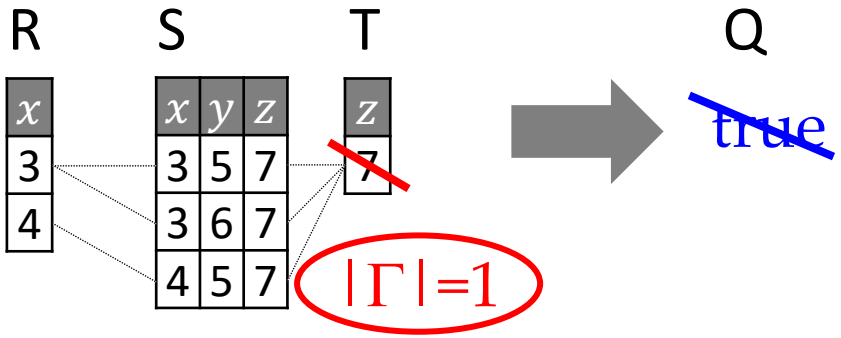

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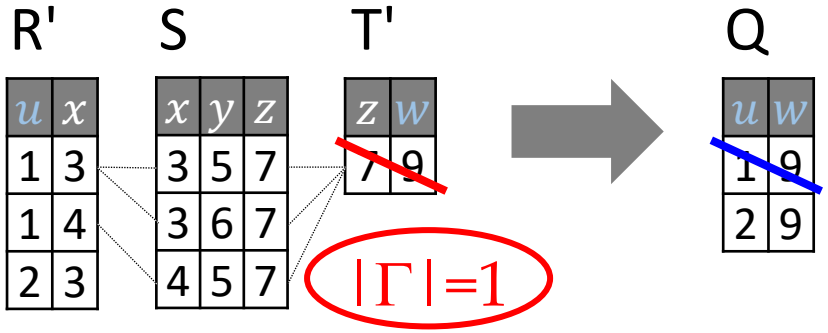

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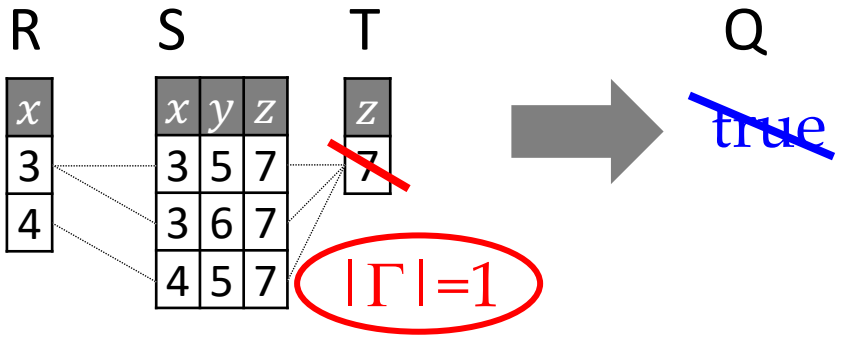

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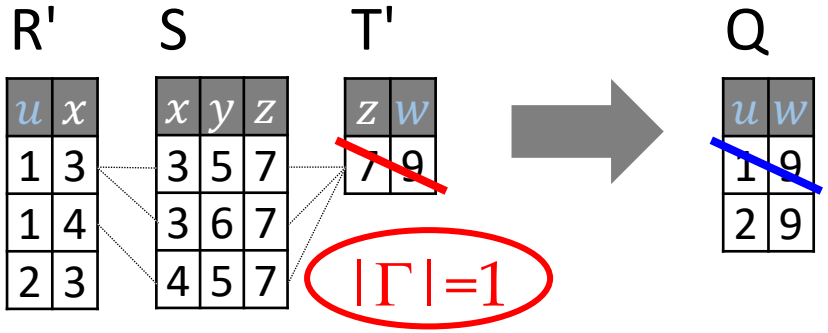

3. Aggregated deletion propagation

Delete min number of tuples to delete $\geq k$ *output tuples*

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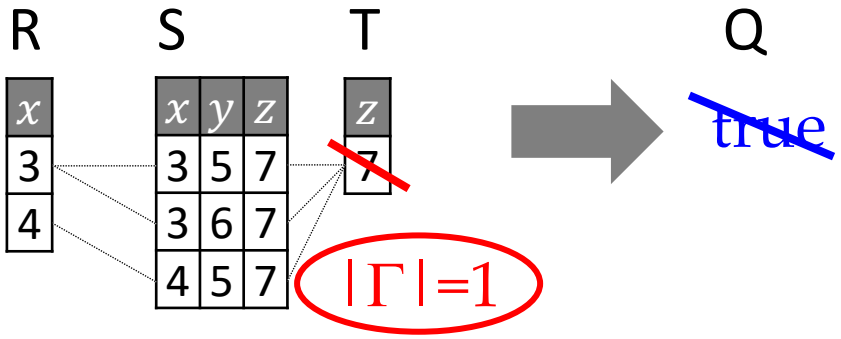

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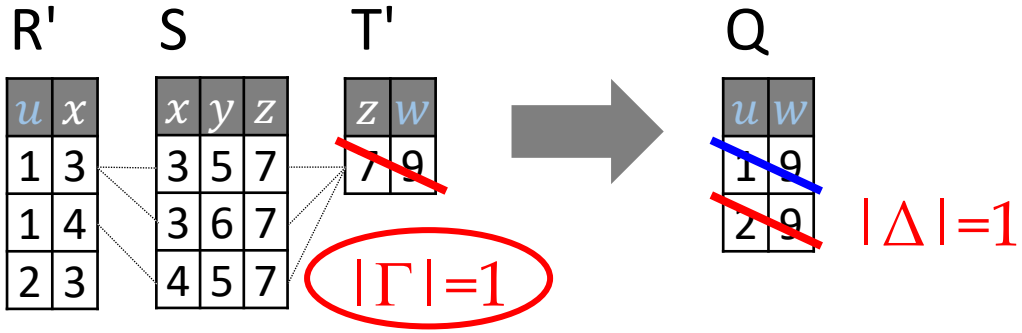

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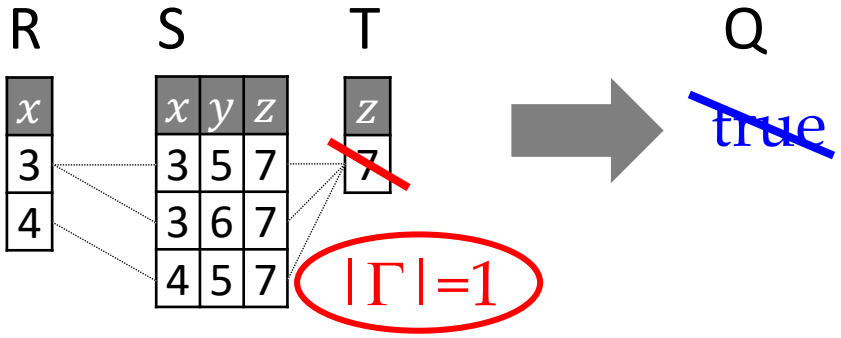

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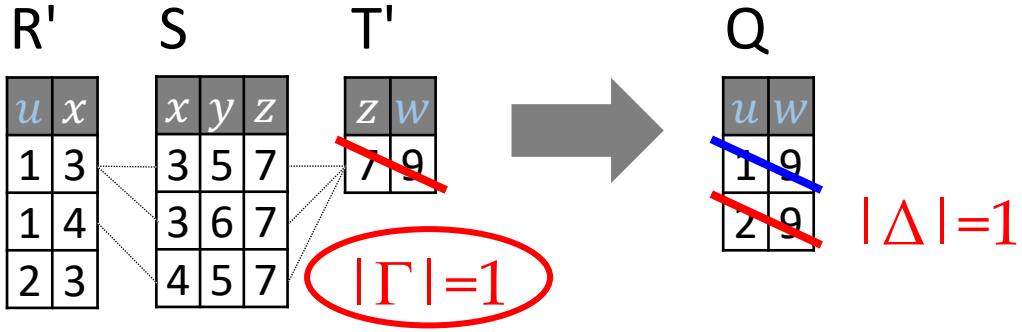

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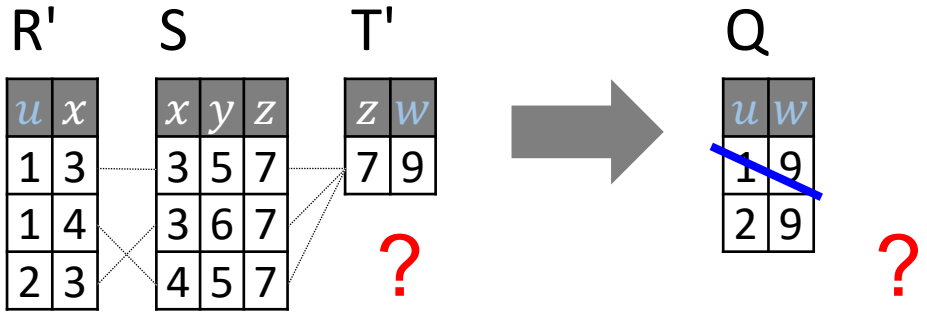
Delete tuples in order to delete an output tuple, while minimizing the other output tuples deleted



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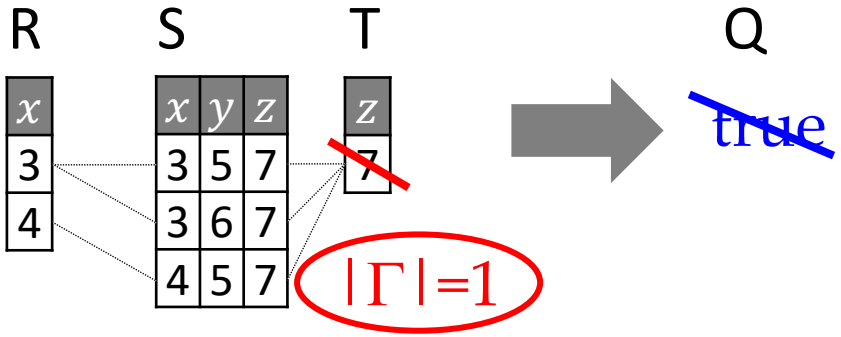

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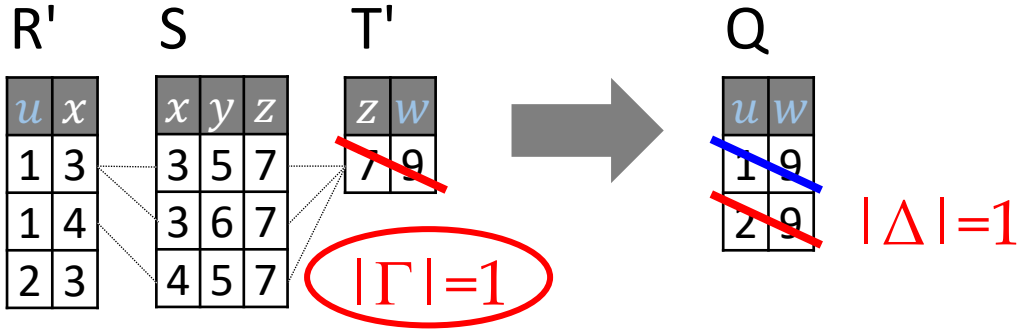

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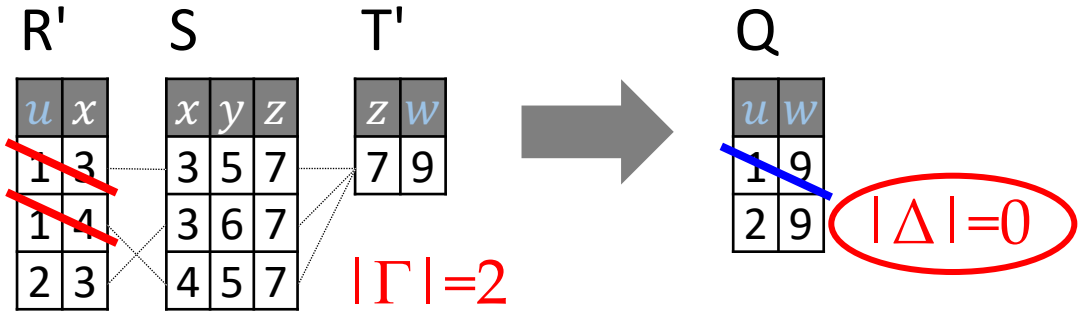

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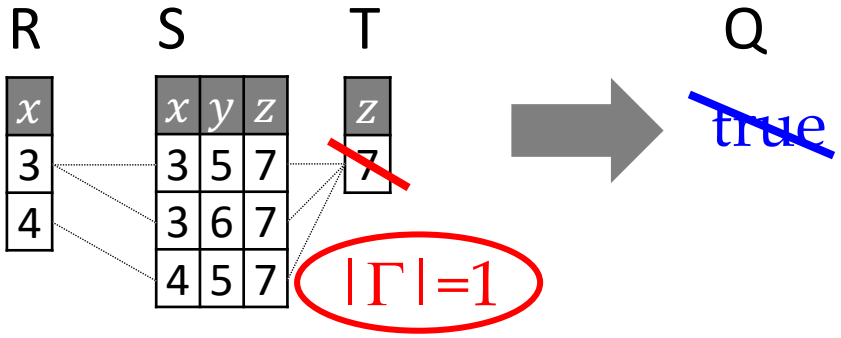

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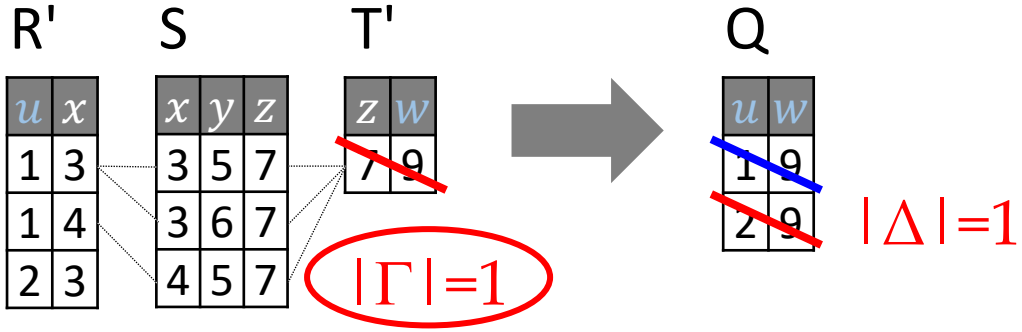

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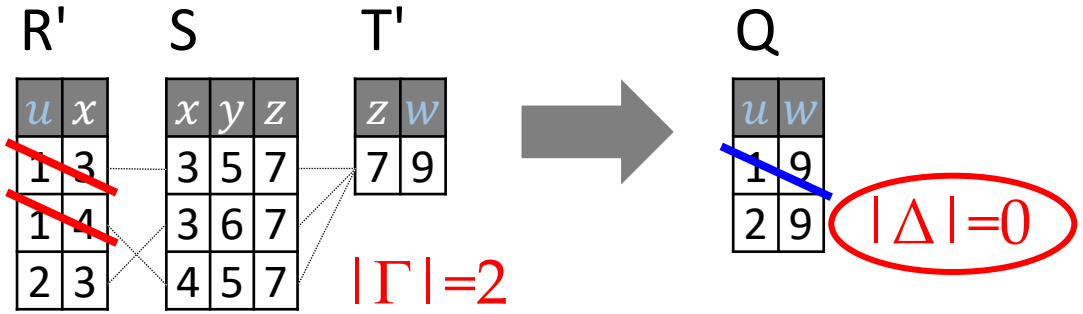

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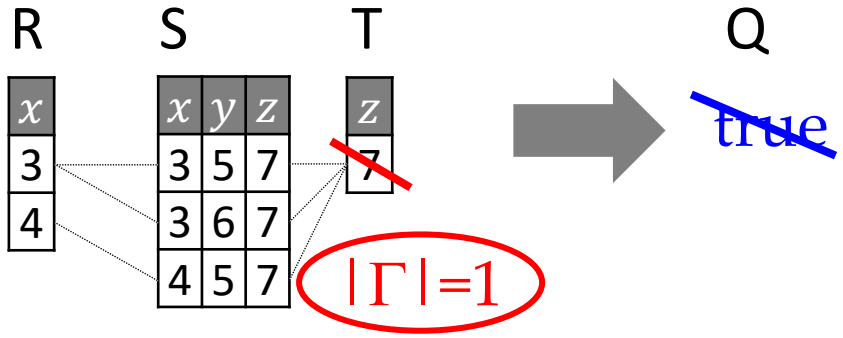

5. Smallest witness problem

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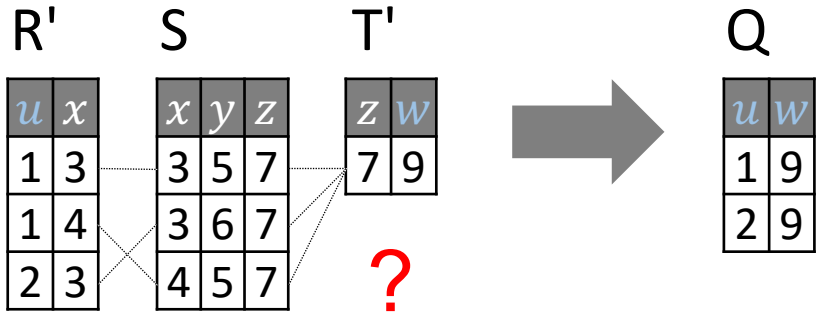

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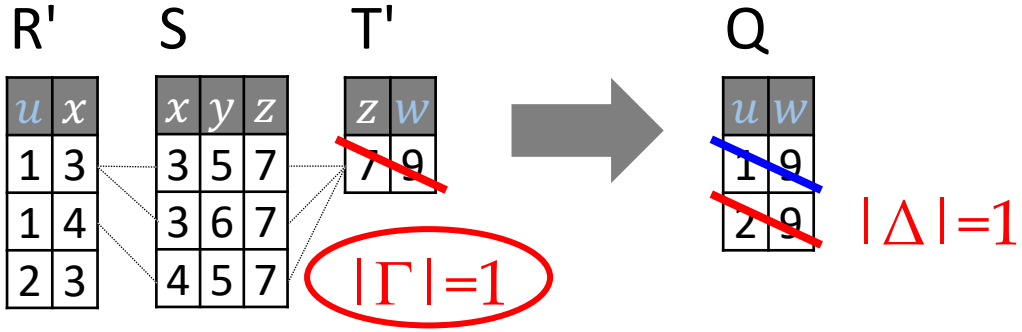

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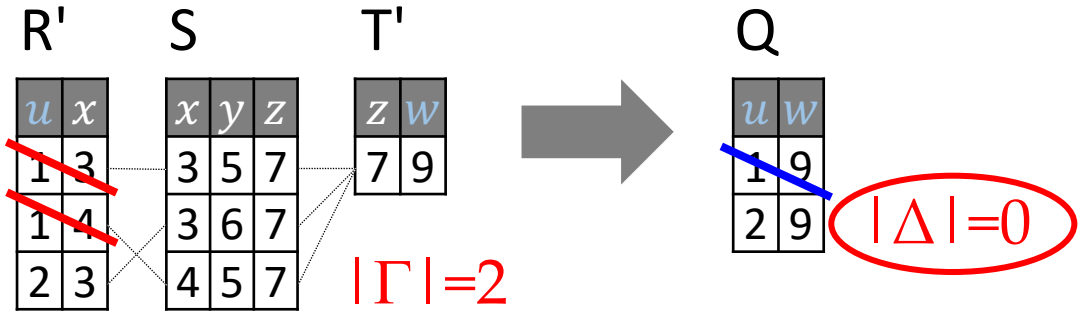

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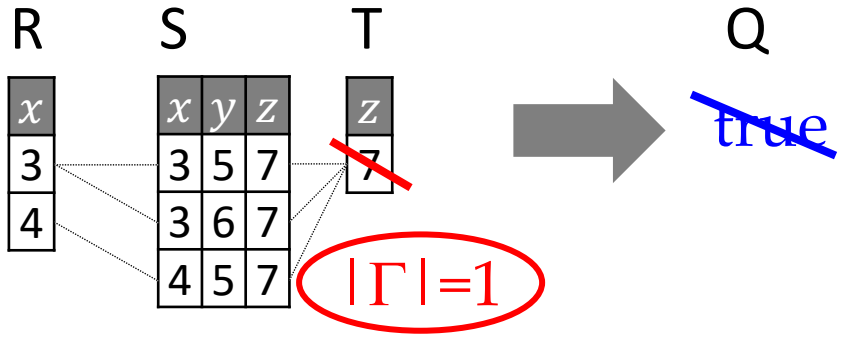

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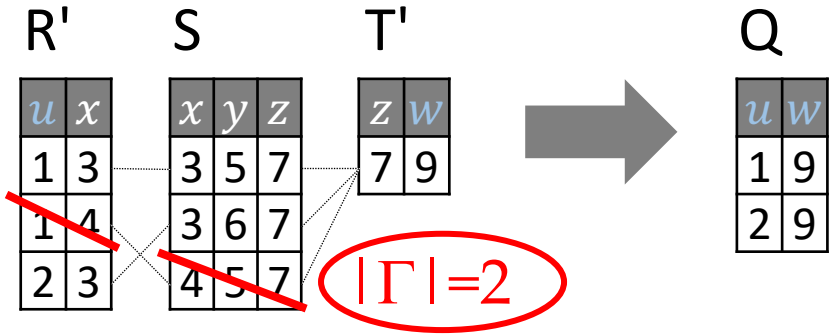

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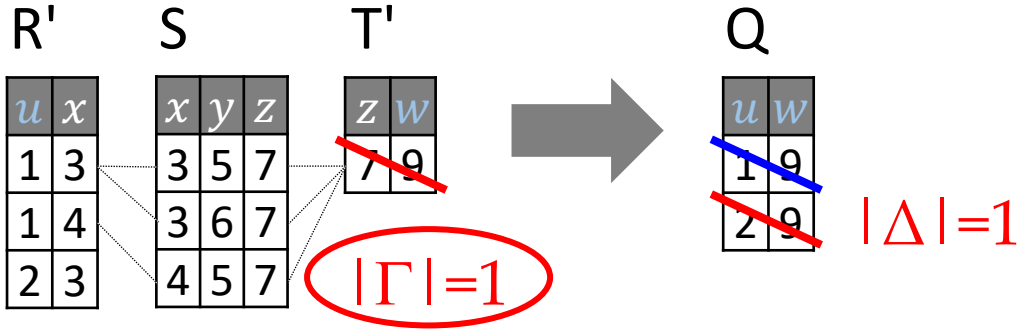

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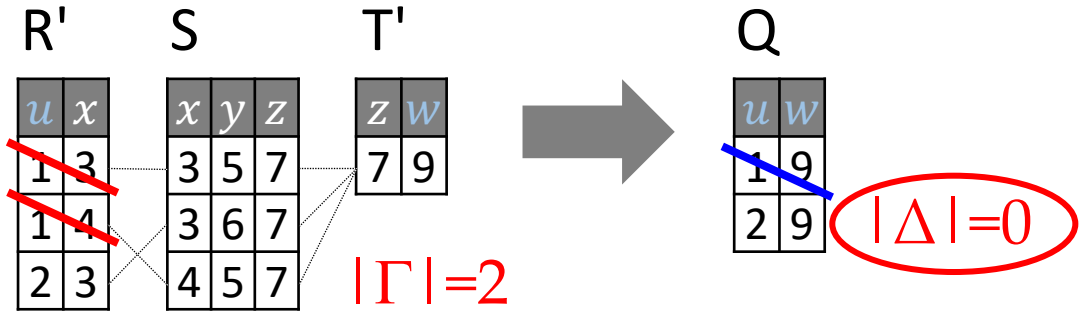

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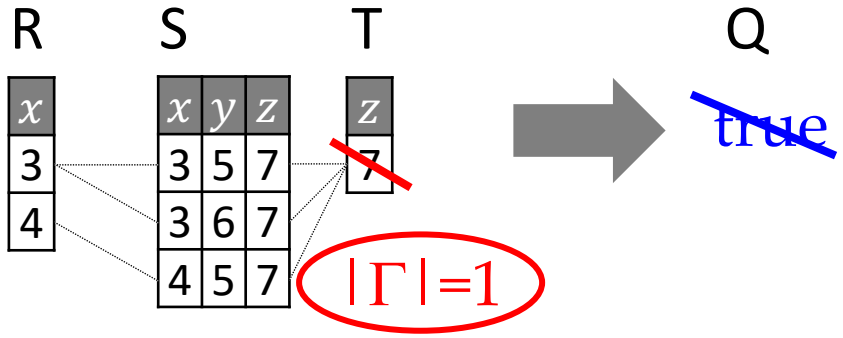

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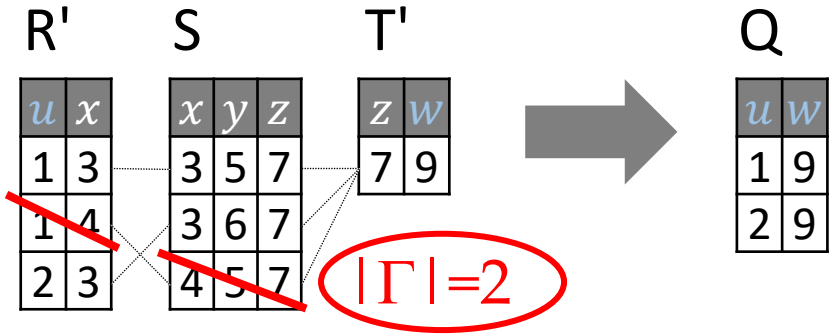

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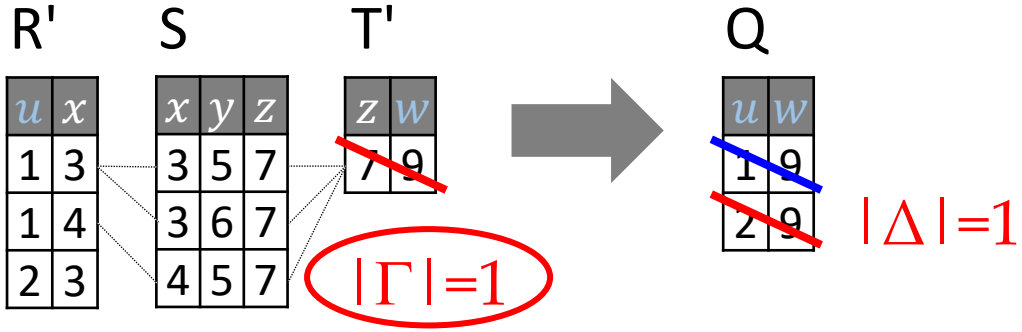

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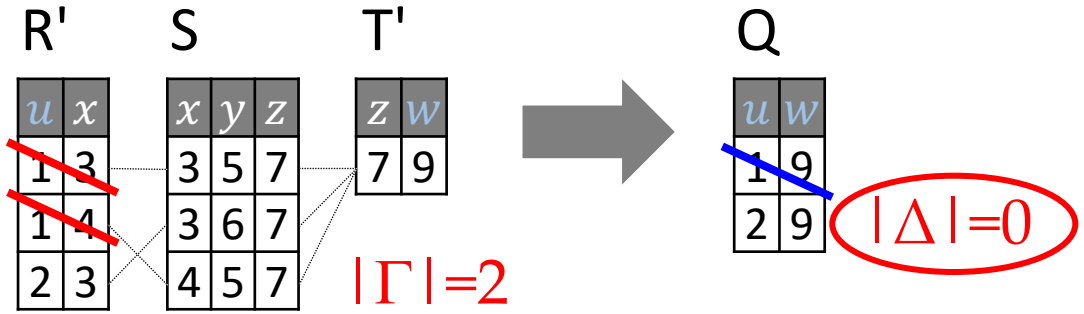

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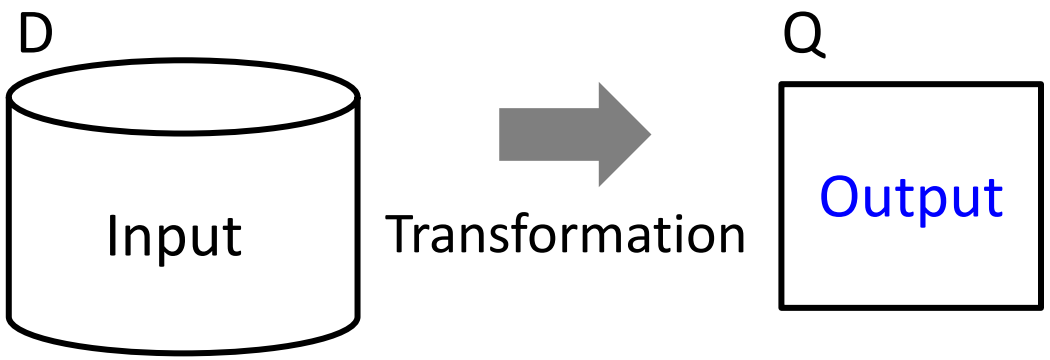
Our topic today: Generalized Deletion Propagation

1. Unify and generalize these problems as instances of "generalized deletion propagation"
   - also allows new problem variants
2. Propose one algorithm to solve all these problems
   - including difficult cases, such as self-joins, or bag semantics
3. The algorithm terminates in PTIME for all known PTIME cases
   - including all known PTIME cases for self-join free queries for the problems of: resilience [VLDB'15], aggregated deletion propagation [VLDB'20], view-side effects [PODS'11], smallest witness problem [ICDT'24]

Reverse Data Management for Conjunctive Queries

QUERY EVALUATION: (Talks today in the morning)

A transformation of the input to the output



Reverse Data Management

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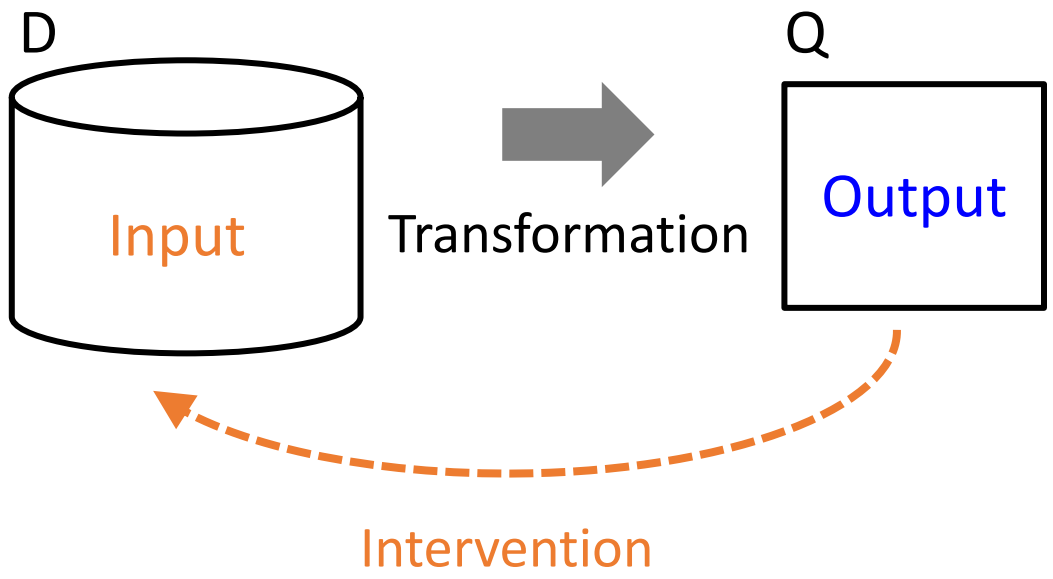

REVERSE DATA MANAGEMENT:

What are the required changes to the input,
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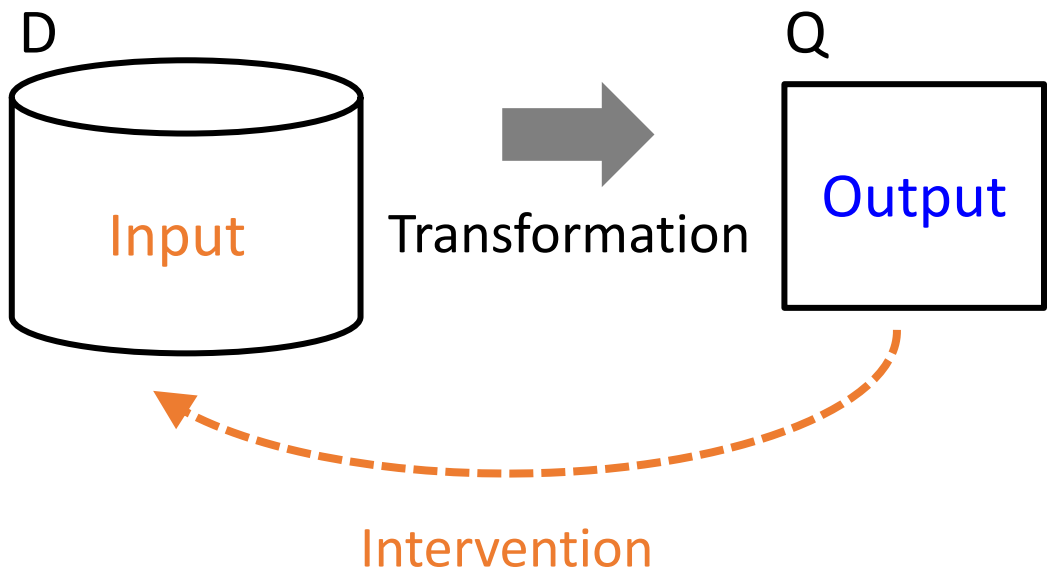

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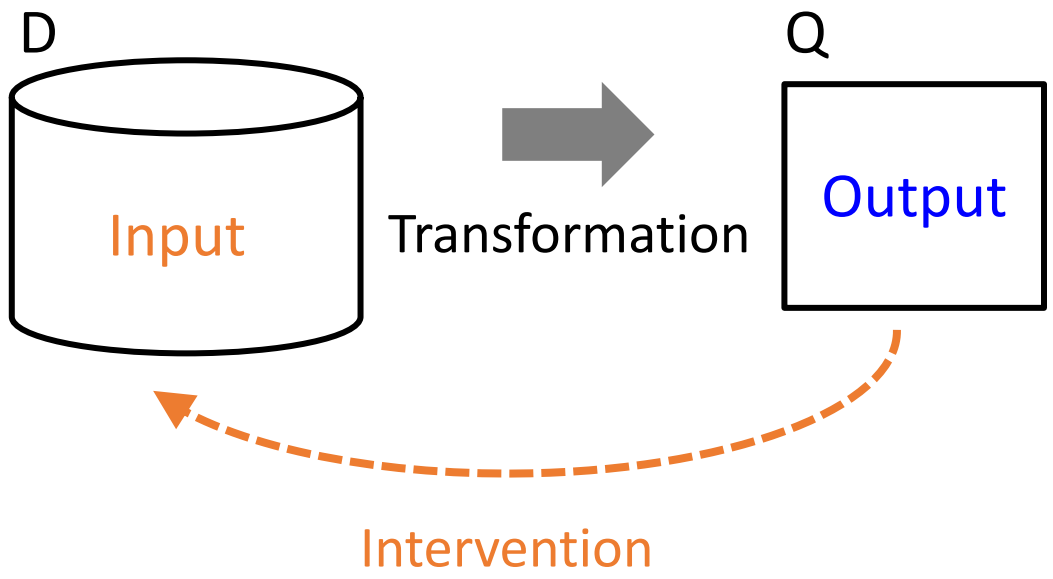

REVERSE DATA MANAGEMENT:

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

2. Abductive (AXp): a subset-minimal set of features (tuples) that are sufficient for ensuring a certain prediction (i.e. fixing these tuples guarantees the output)

= maximum deletions of tuples

1. Contrastive (CXp): subset-minimal set of features (tuples) that are sufficient for changing a prediction (from true to false).

= minimum deletions of tuples

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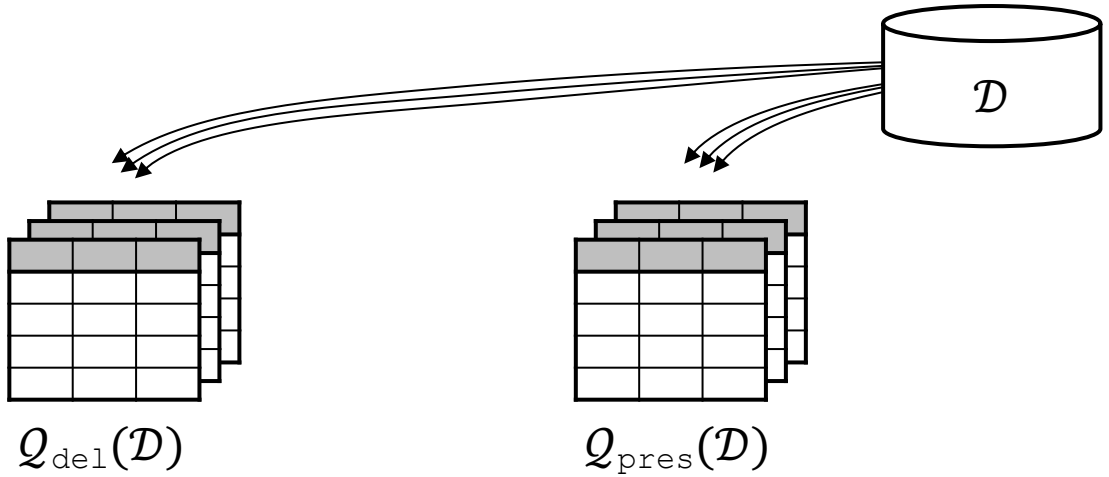
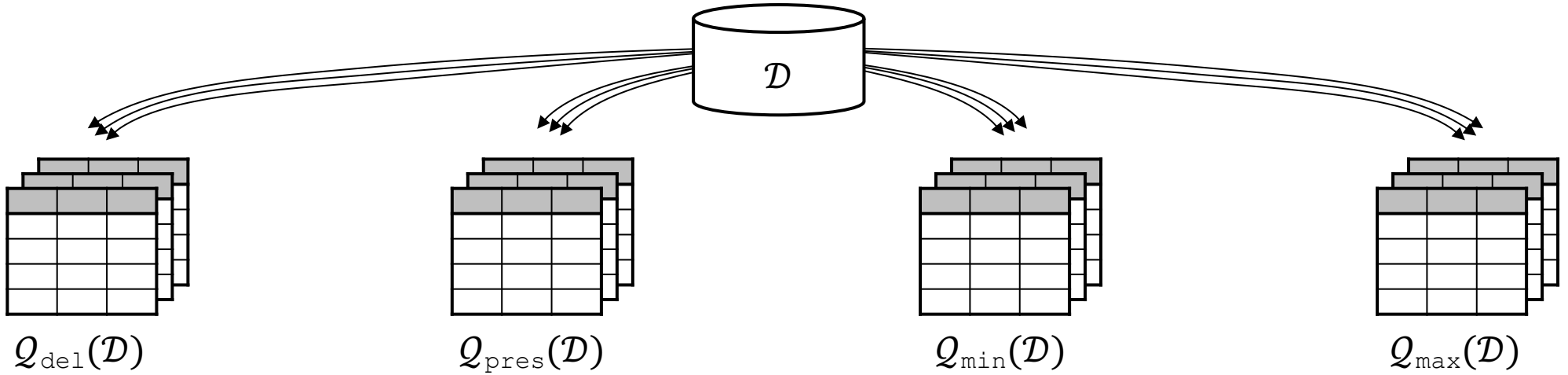
Generalized Deletion Propagation



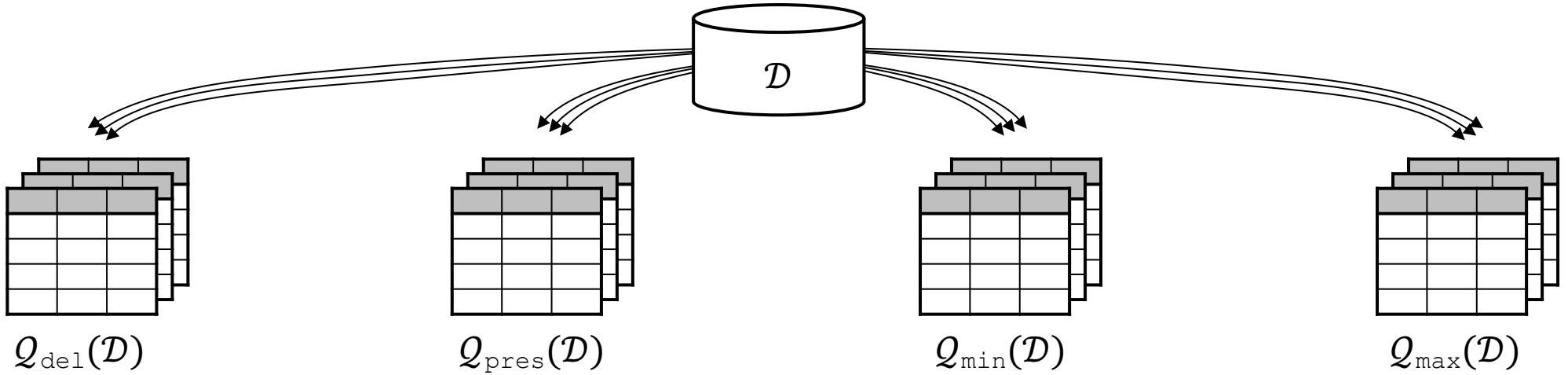
Propagate Requirements (hard constraints)	
Delete	Preserve
$\geq \mathrm{k}^{i}_{\mathbf{del}}$ tuples in $\mathcal{Q}^{i}_{\texttt{del}}(\mathcal{D})$	$\geq \mathrm{k}^{i}_{\mathbf{pres}}$ tuples in $Q^{i}_{\texttt{pres}}(D)$

Generalized Deletion Propagation



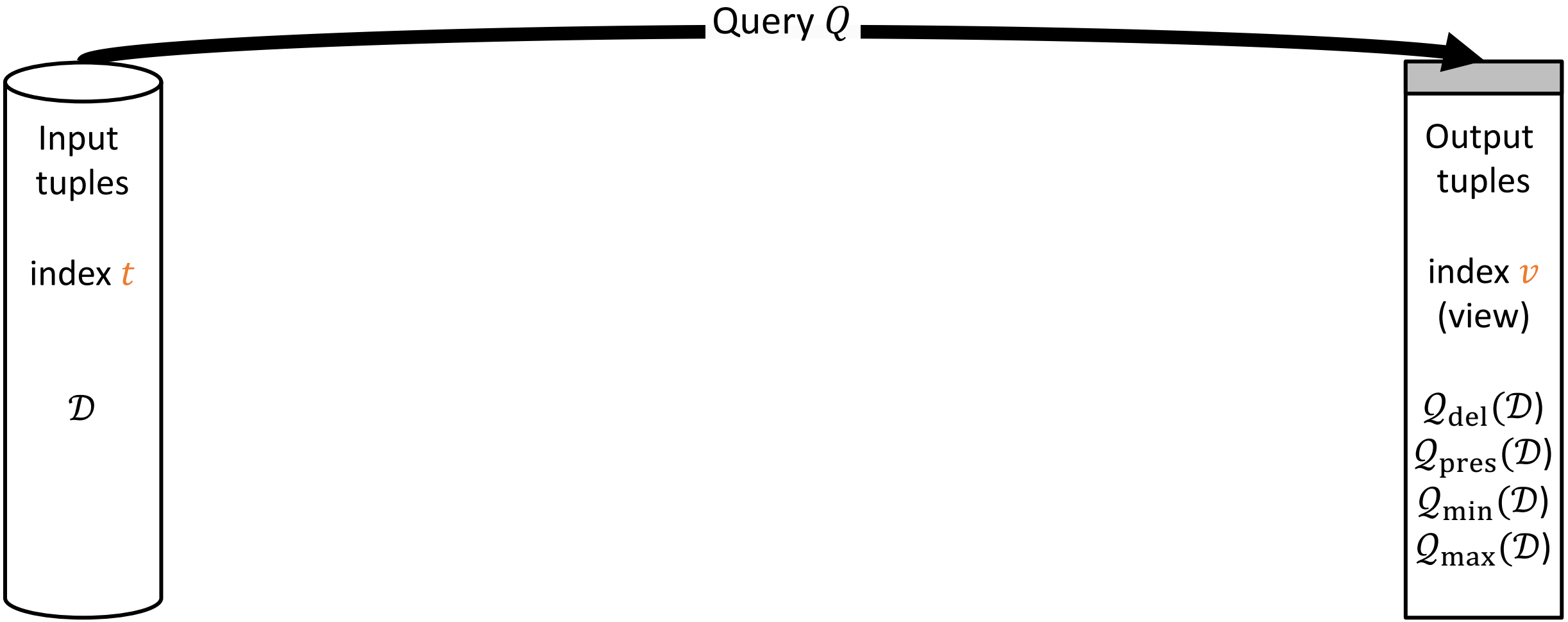
Propagate Requirements (hard constraints)		Optimize Side-Effect (soft constraints)	
Delete	Preserve	Minimize	Maximize
$\geq \mathrm{k}^i_{\mathbf{del}}$ tuples in $\mathcal{Q}^i_{\mathtt{del}}(\mathcal{D})$	$\geq \mathrm{k}^i_{\mathbf{pres}}$ tuples in $Q^i_{\mathtt{pres}}(D)$	Deletions in $\mathcal{Q}_{\mathsf{min}}$	Deletions in $\mathcal{Q}_{\mathsf{max}}$

Generalized Deletion Propagation



	Propagate Requirements (hard constraints)		Optimize Side-Effect (soft constraints)	
	Delete $\geq \mathrm{k}^{i}_{\mathbf{del}}$ tuples in $\mathcal{Q}^{i}_{\mathtt{del}}(\mathcal{D})$	Preserve $\geq \mathrm{k}^{i}_{\mathbf{pres}}$ tuples in $Q^{i}_{\mathtt{pres}}(D)$	Minimize Deletions in $\mathcal{Q}_{\mathtt{min}}$	Maximize Deletions in $\mathcal{Q}_{\mathtt{max}}$
DP-SS	All tuples in $\mathrm{Q}_{\mathtt{del}}(\mathcal{D})$	–	Deletions in $\mathcal{Q}_{\mathtt{min}} = \{R \in \mathcal{D}\}$	–
ADP-SS	$\geq k$ tuples in $\mathrm{Q}_{\mathtt{del}}(\mathcal{D})$	–	Deletions in $\mathcal{Q}_{\mathtt{min}} = \{R \in \mathcal{D}\}$	–
DP-VS	All tuples in $\mathrm{Q}_{\mathtt{del}}(\mathcal{D})$	–	Deletions in $\mathcal{Q}_{\mathtt{min}}(\mathcal{D}) \supseteq \mathcal{Q}_{\mathtt{del}}(\mathcal{D})$	–
SWP	–	All tuples in $\mathcal{Q}_{\mathtt{pres}}(\mathcal{D})$	–	Deletions in $\mathcal{Q}_{\mathtt{max}} = \{R \in \mathcal{D}\}$

Propagation Constraints in the Language of ILPs



$X[t] = 1$ *means that* t *is deleted*

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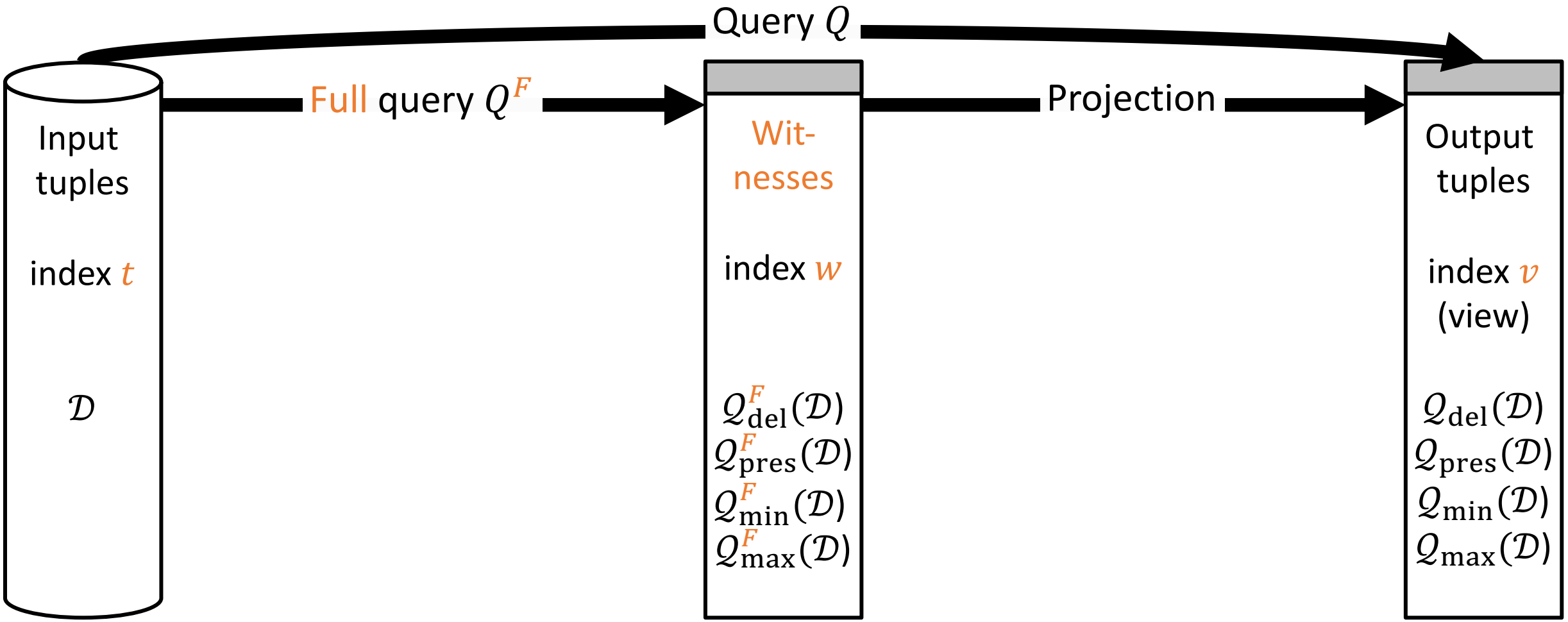

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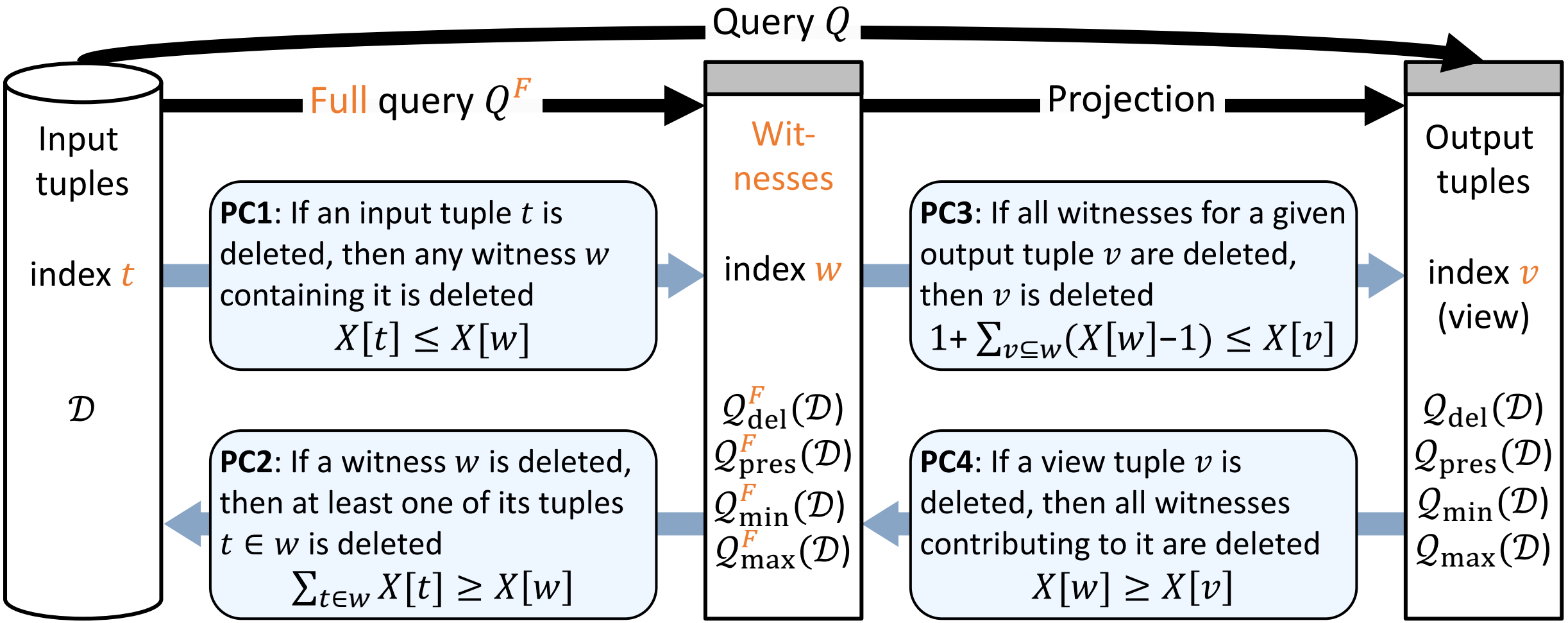

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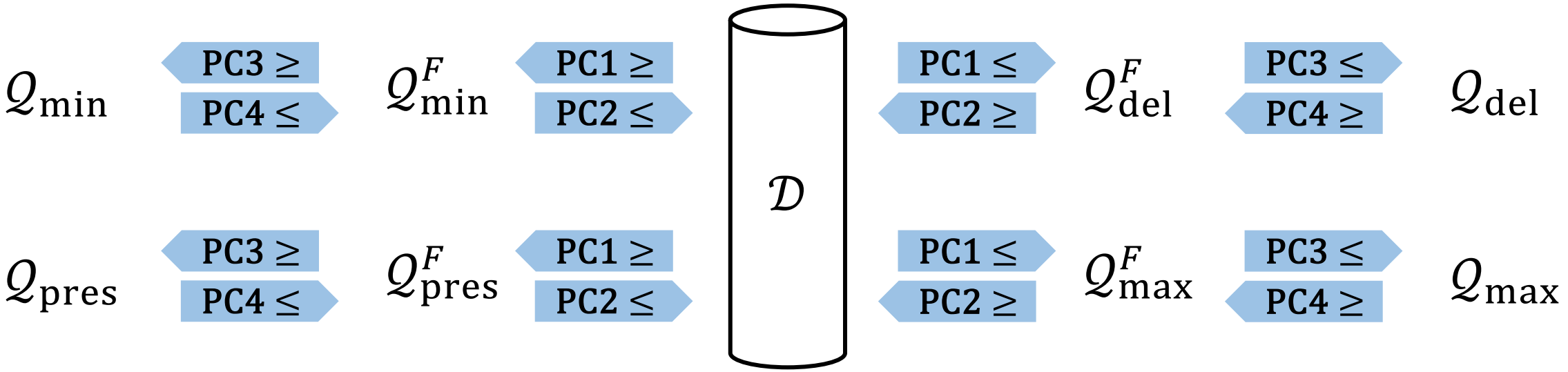
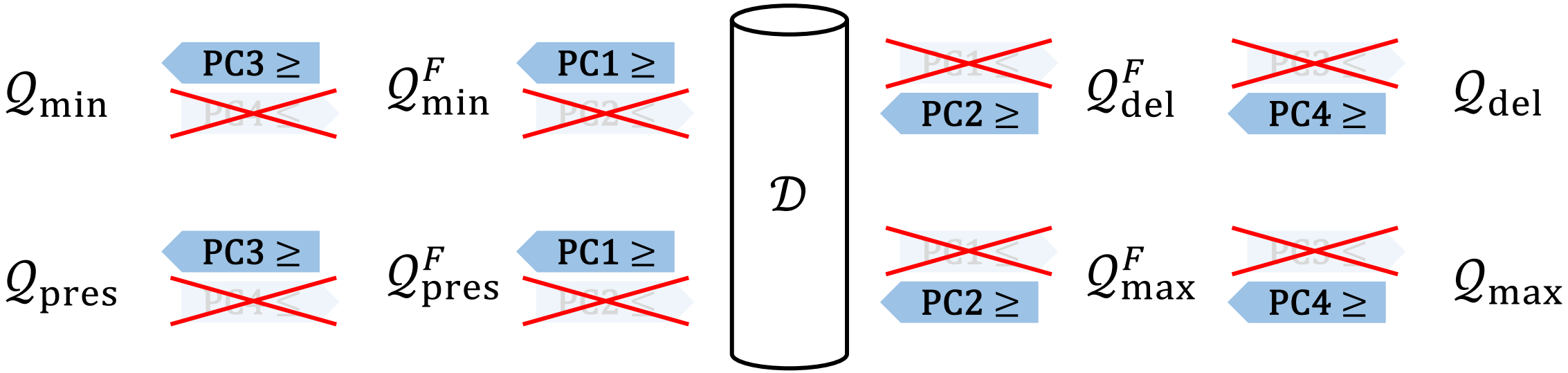
Propagation constraints: Naive ILP (1/3)



Propagation constraints: Wildcard ILP (2/3)

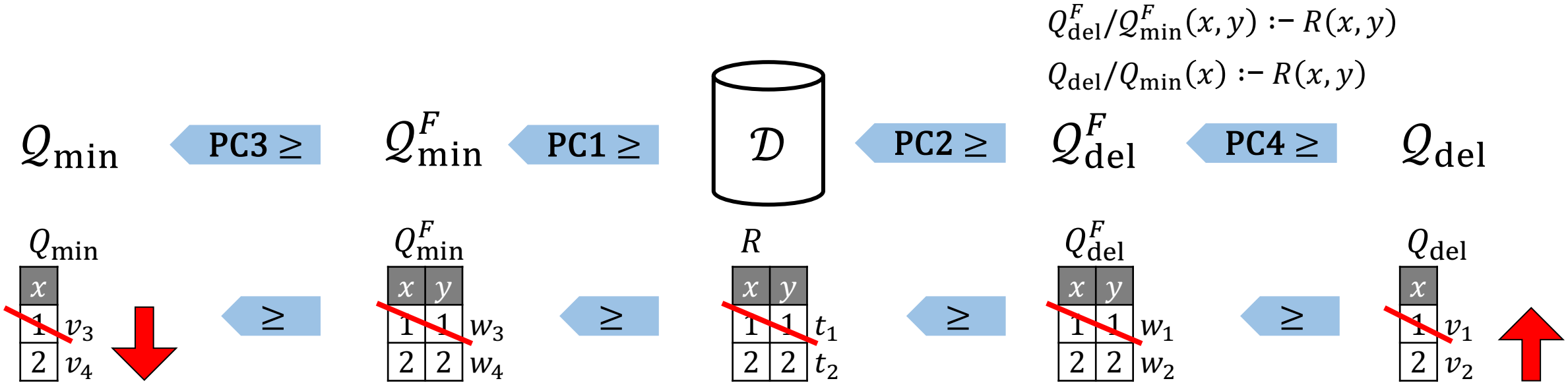


Certain constraints don't need to be explicitly enforced for a given type of view.

Removing the unnecessary constraints *increases* the solution space (from the point of view of the ILP formulation) but keeps all the optimal solutions (projected on the actual interventions on $\mathcal{D}$ that we care about).

Propagation constraints: Wildcard ILP (2/3)

DETAILS

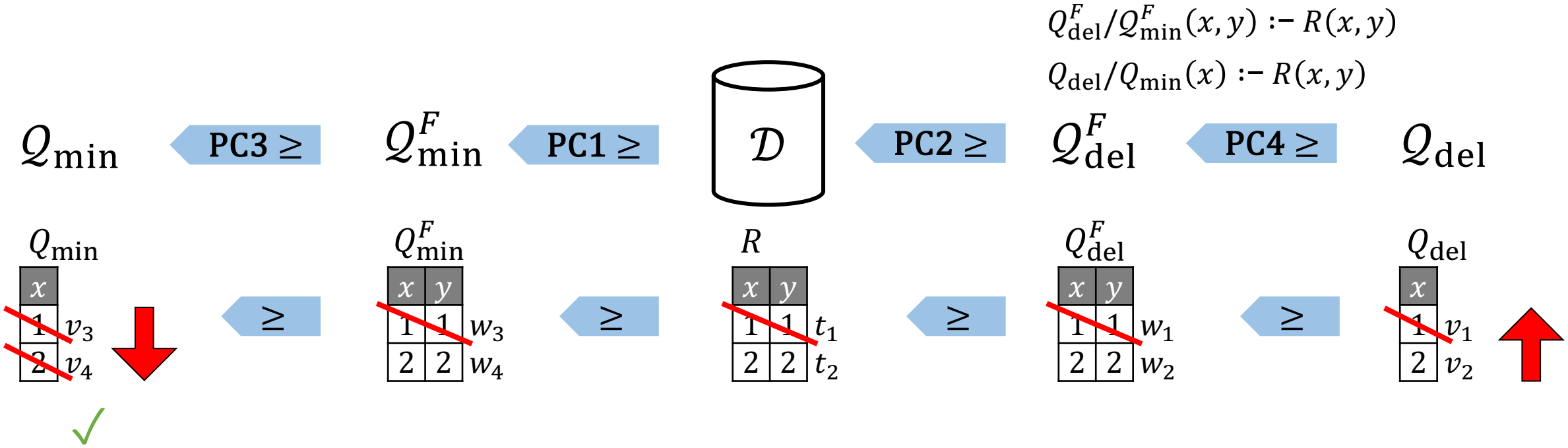


Soft constraint: we want to minimize the number of deletions from Q_{min}

User constraint: we are required to delete a given number of tuples from Q_{del}

Propagation constraints: Wildcard ILP (2/3)

DETAILS



Soft constraint: we want to minimize the number of deletions from Q_{min}

The variables are an upper bound and preservations (X=0) need to get propagated from left to right.

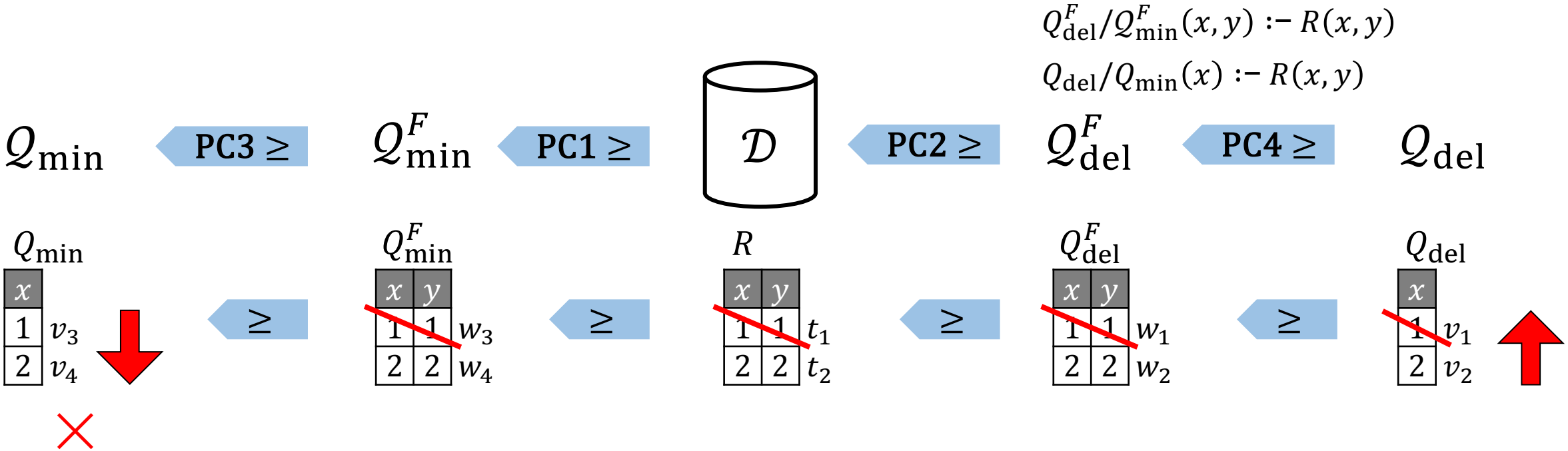
We can set more variables than necessary to 1, but that just penalizes our solution.

User constraint: we are required to delete a given number of tuples from Q_{del}

The variables are a lower bound and deletions (X=1) need to get propagated from right to left.

Propagation constraints: Wildcard ILP (2/3)

DETAILS



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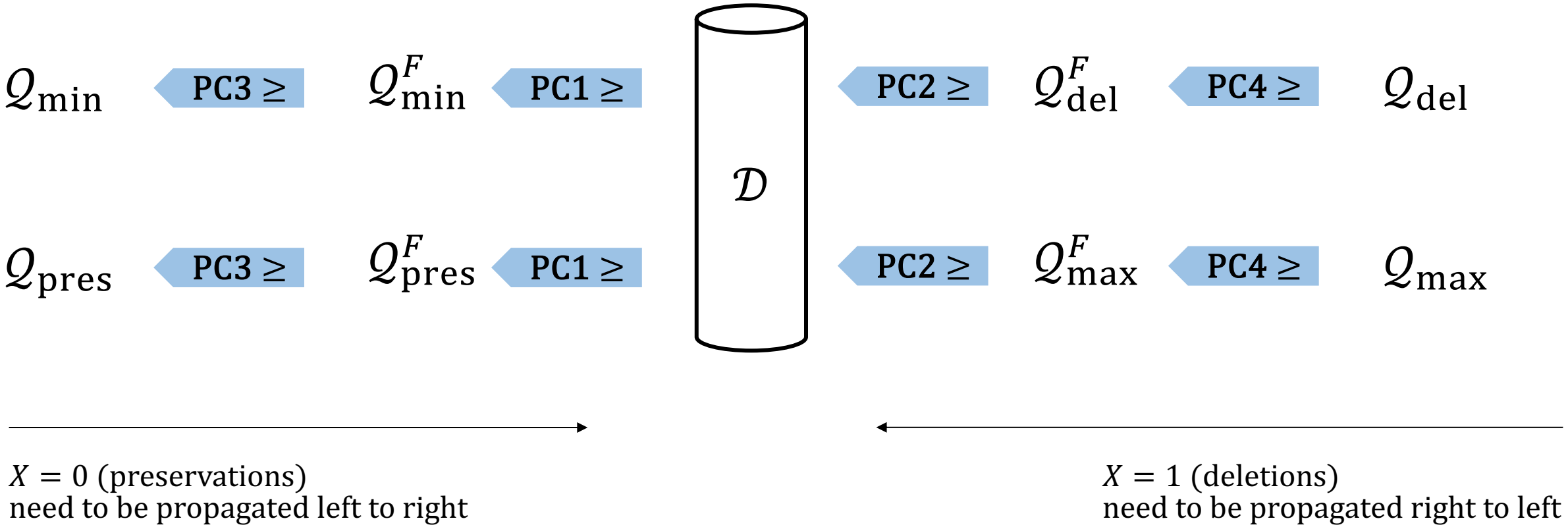
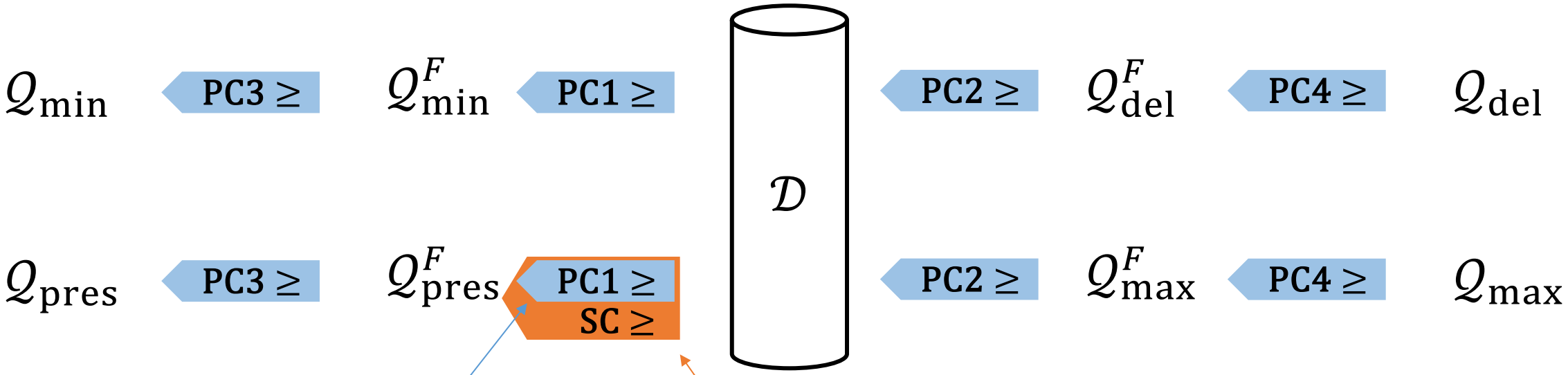


Removing the unnecessary constraints *increases* the solution space (from the point of view of the ILP formulation) but keeps all the optimal solutions (projected on the actual interventions on $\mathcal{D}$ that we care about).

Propagation constraints: Smoothened ILP (3/3)



PC1: If an input tuple t is deleted, then any witness w containing it is deleted

$$X[t] \leq X[w]$$

SC: If an input tuple t is not deleted, then at least one of its witnesses is preserved, for each view tuple v

$$X[t] \leq 1 + \sum_{\substack{w:\, t \in w \\ w \supseteq v}} (X[w]-1)$$

Example: Smoothening for Smallest Witness Problem

DETAILS

$Q_{\text{pres}}(x) :- R(x, y), S(x)$

Q_{pres}

x	
1	v_1

R

x	y	
1	1	t_1
1	2	t_2

S

x	
1	t_3

$Q^F_{\text{pres}}(x, y) :- R(x, y), S(x)$

x	y	
1	1	w_1
1	2	w_2

Optimal integral solution:

$f^* = -1$, $\mathbf{X}^*[t_1, t_2, t_3] = (1,0,0)$ or $(0,1,0)$

*To simplify, ILP formulation is slightly simplified from the actual formulation (PC2, PC3, PC4 are moved into the user constraint). See example 3 in paper for details.

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Naive ILP formulation

$X[t] = 1$ means that t is deleted

Minimization objective

$$f(\mathbf{X}) = -X[t_1] - X[t_2] - X[t_3]$$

Delete as many tuples as possible...

User constraint

$$X[w_1] + X[w_2] \leq 1$$

... but preserve at least one witness.

Propagation Constraints (PCs)*

$$X[t_1] \leq X[w_1]$$
$$X[t_2] \leq X[w_2]$$
$$X[t_3] \leq X[w_1]$$
$$X[t_3] \leq X[w_2]$$

If a tuple is deleted, then so is the corresponding witness

Optimal integral solution:

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$$f(\mathbf{X}) = -X[t_1] - X[t_2] - X[t_3]$$
$$0.5 \qquad 0.5 \qquad 0.5$$

Delete as many tuples as possible...

User constraint

$$X[w_1] + X[w_2] \leq 1$$
$$0.5 \qquad 0.5$$

... but preserve at least one witness.

Propagation Constraints (PCs)*

$$0.5\ X[t_1] \leq X[w_1]\ 0.5$$
$$0.5\ X[t_2] \leq X[w_2]\ 0.5$$
$$0.5\ X[t_3] \leq X[w_1]\ 0.5$$
$$0.5\ X[t_3] \leq X[w_2]\ 0.5$$

If a tuple is deleted, then so is the corresponding witness

Optimal integral solution (ILP)

$f^* = -1, \mathbf{X}^*[t_1,t_2,t_3] = (1,0,0)$ or $(0,1,0)$

Optimal fractional solution (LP relaxation)

$f^* = -1.5, \mathbf{X}^*[t_1,t_2,t_3] = (0.5,0.5,0.5)$ ☹

Example: Smoothening for Smallest Witness Problem

DETAILS

$Q_{\text{pres}}(x) :- R(x,y), S(x)$

Q_{pres}

x	
1	v_1

R

x	y	
1	1	t_1
1	2	t_2

S

x	
1	t_3

$Q^F_{\text{pres}}(x,y) :- R(x,y), S(x)$

x	y	
1	1	w_1
1	2	w_2

Smoothened ILP formulation

$X[t] = 1$ *means that* t *is deleted*

Minimization objective

$$f(\mathbf{X}) = -X[t_1] - X[t_2] - X[t_3]$$ ← *Delete as many tuples as possible...*

User constraint

$$X[w_1] + X[w_2] \leq 1$$ ← *... but preserve at least one witness.*

Propagation Constraints (PCs)*

$$X[t_1] \leq X[w_1]$$
$$X[t_2] \leq X[w_2]$$
$$X[t_3] \leq X[w_1]$$
$$X[t_3] \leq X[w_2]$$

← *If a tuple is deleted, then so is the corresponding witness*

Smoothening constraint (SCs)

$$X[t_3] \leq X[w_1] + X[w_2] - 1$$

← *If a tuple is not deleted, then at least one of its witnesses is preserved*

$$0.5 \not\leq 0.5 + 0.5 - 1$$

← *The smoothening constraint eliminates the fractional solution with* $f^* = -1.5$

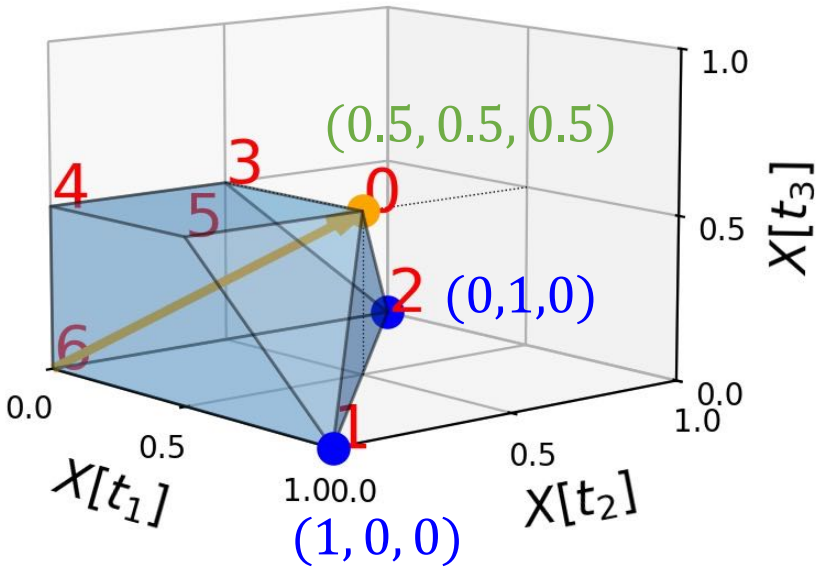
Optimal integral solution (ILP)
= optimal fractional solution (LP relaxation)

$$f^* = -1,\ \mathbf{X}^*[t_1, t_2, t_3] = (1,0,0) \text{ or } (0,1,0)$$ ☺

*ILP formulation is slightly simplified from the actual formulation (PC2, PC3, PC4 are moved into the user constraint). See example 3 in paper for details.

Example: Smoothening for Smallest Witness Problem

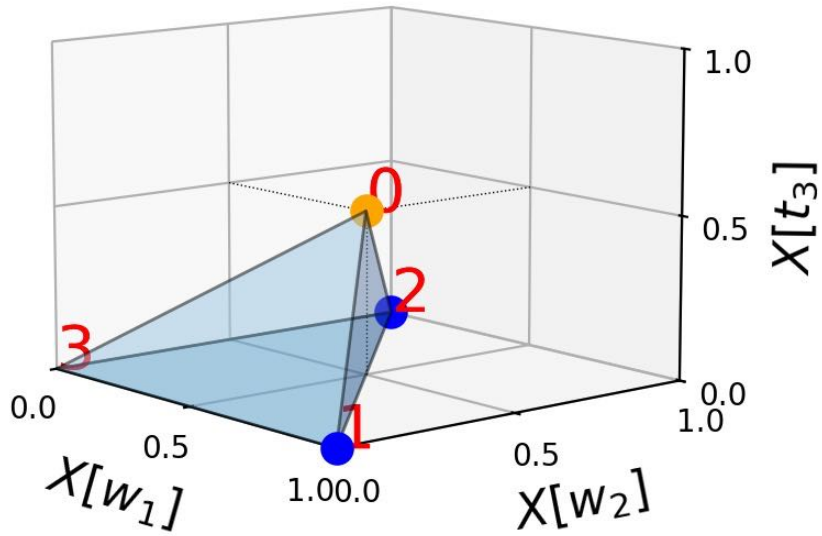
DETAILS



0: $\mathbf{X[t]} = (0.5, 0.5, 0.5)$

1: $\mathbf{X[t]} = (1, 0, 0)$

2: $\mathbf{X[t]} = (0, 1, 0)$



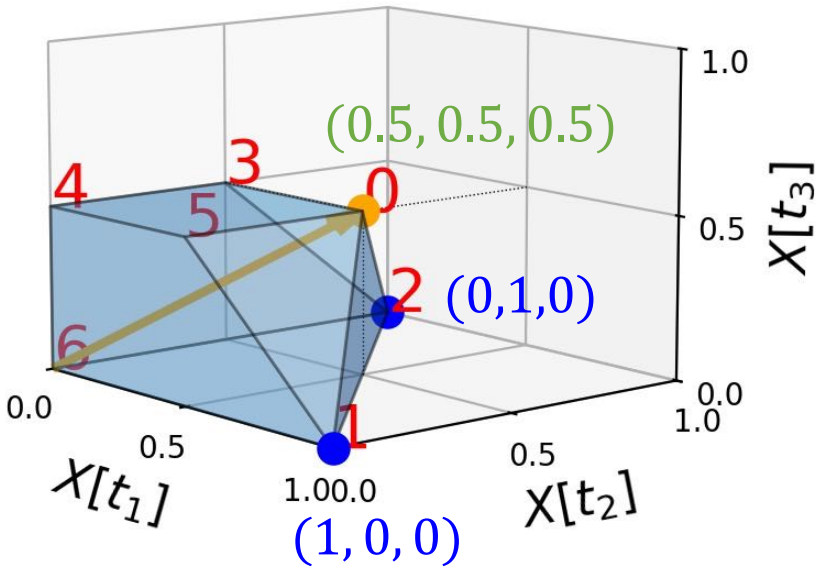
Smoothening constraint (SCs)

$$X[t_3] \leq X[w_1] + X[w_2] - 1$$

$$0.5 \not\leq 0.5 + 0.5 - 1$$

Example: Smoothening for Smallest Witness Problem

DETAILS



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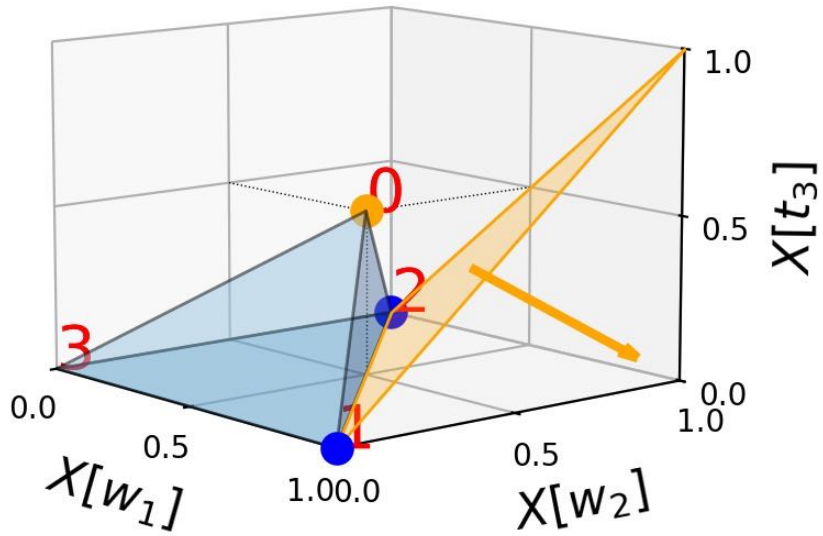

The smoothening constraint eliminates the fractional solution with $f^* = -1.5$

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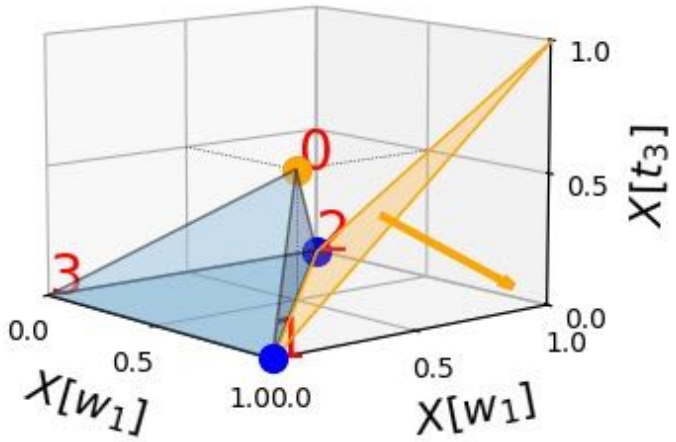
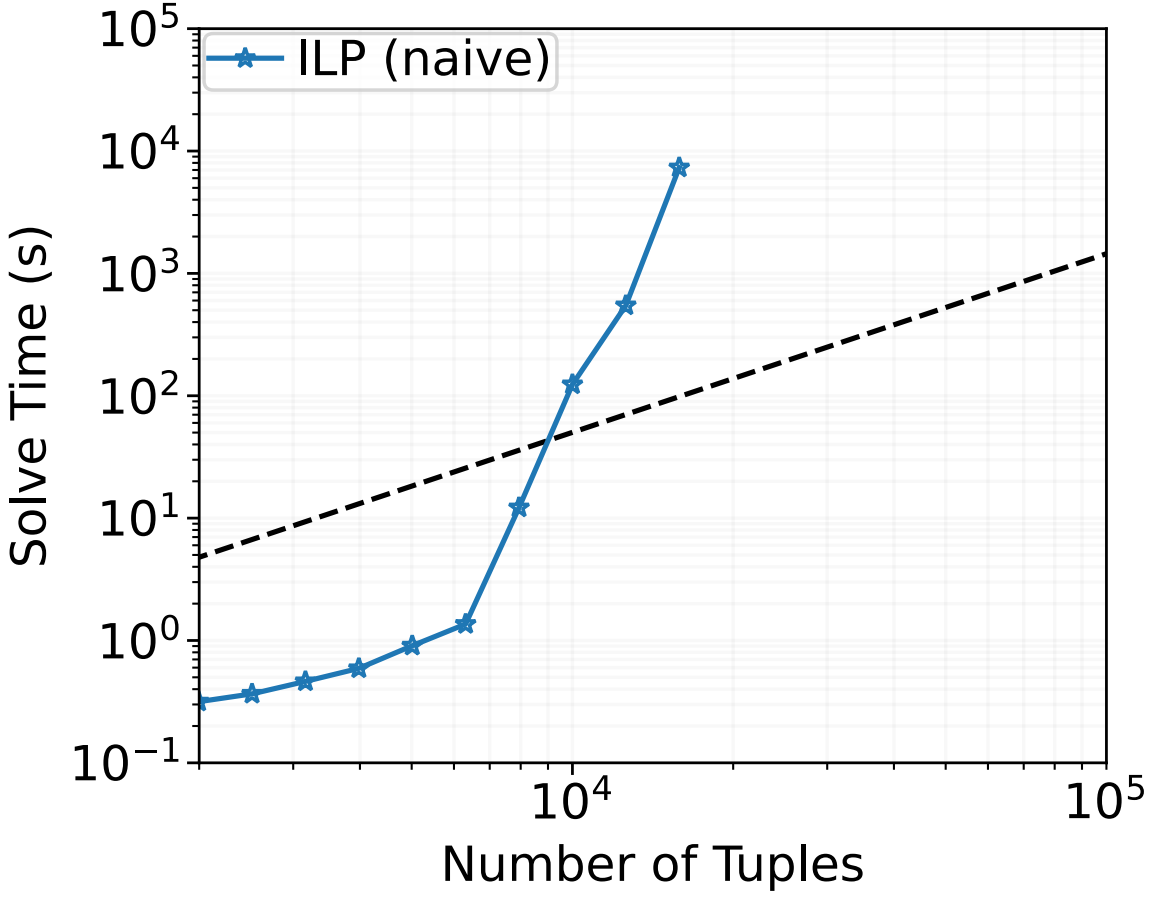


Scalability of Naive vs. Smoothened ILP for PTIME query

Finding an optimal solution for the Smallest Witness Problem

$Q_{5\text{star}}(x)\text{: } -R(x,a), S(x,b), T(x,c), U(x,d), V(x,e), A(x)$



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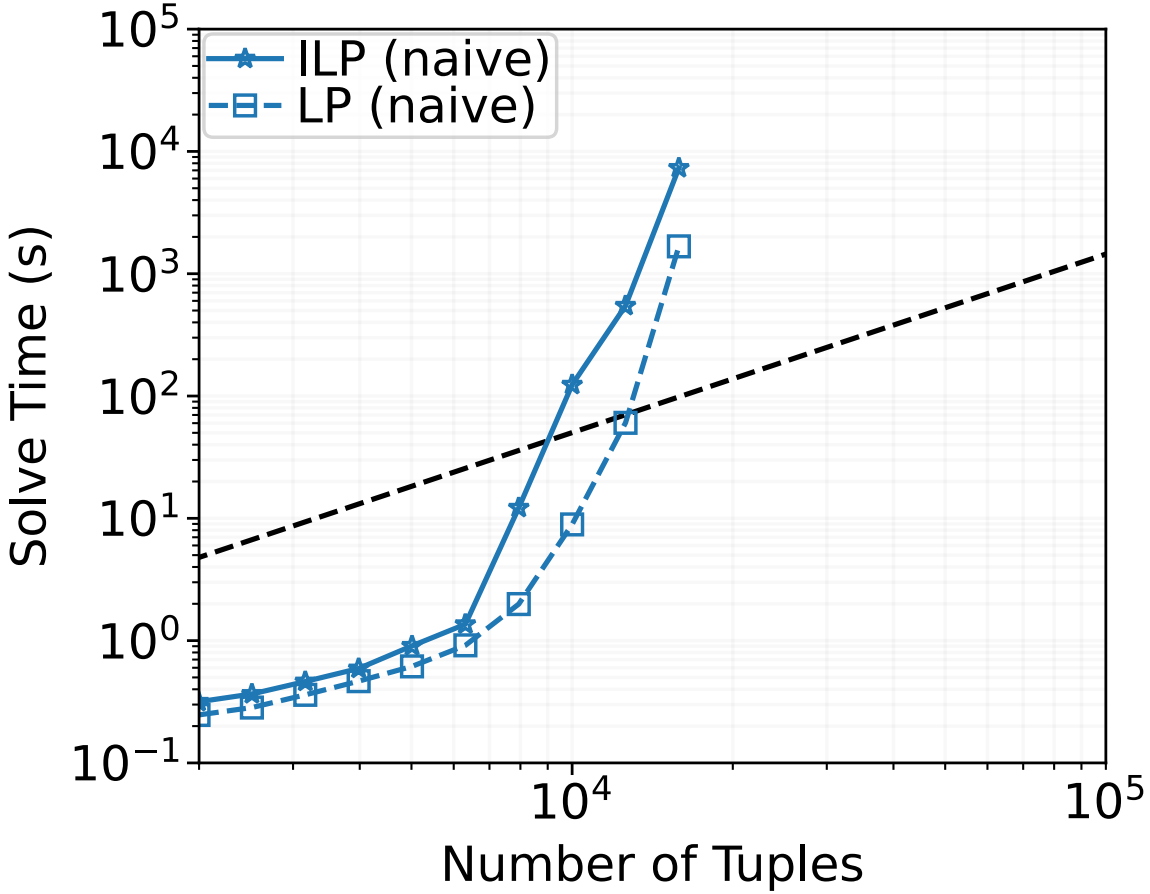

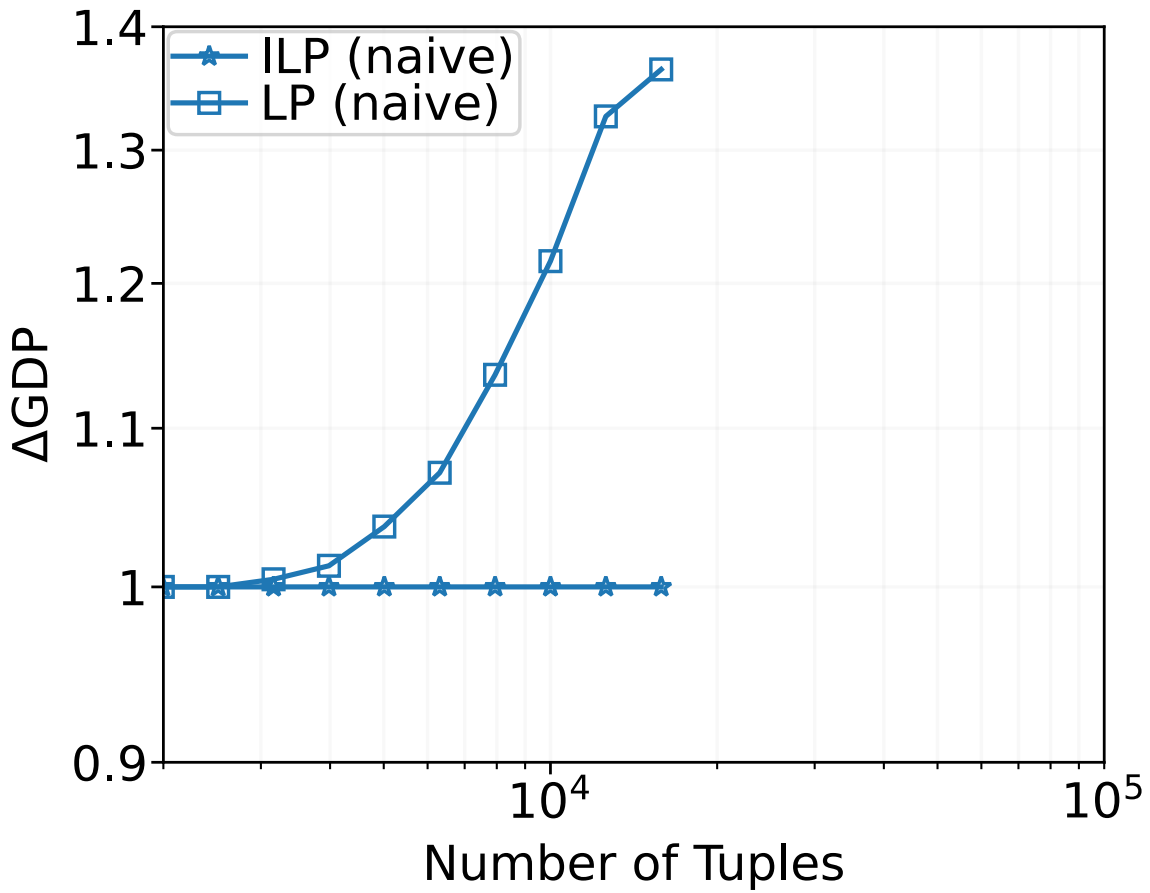

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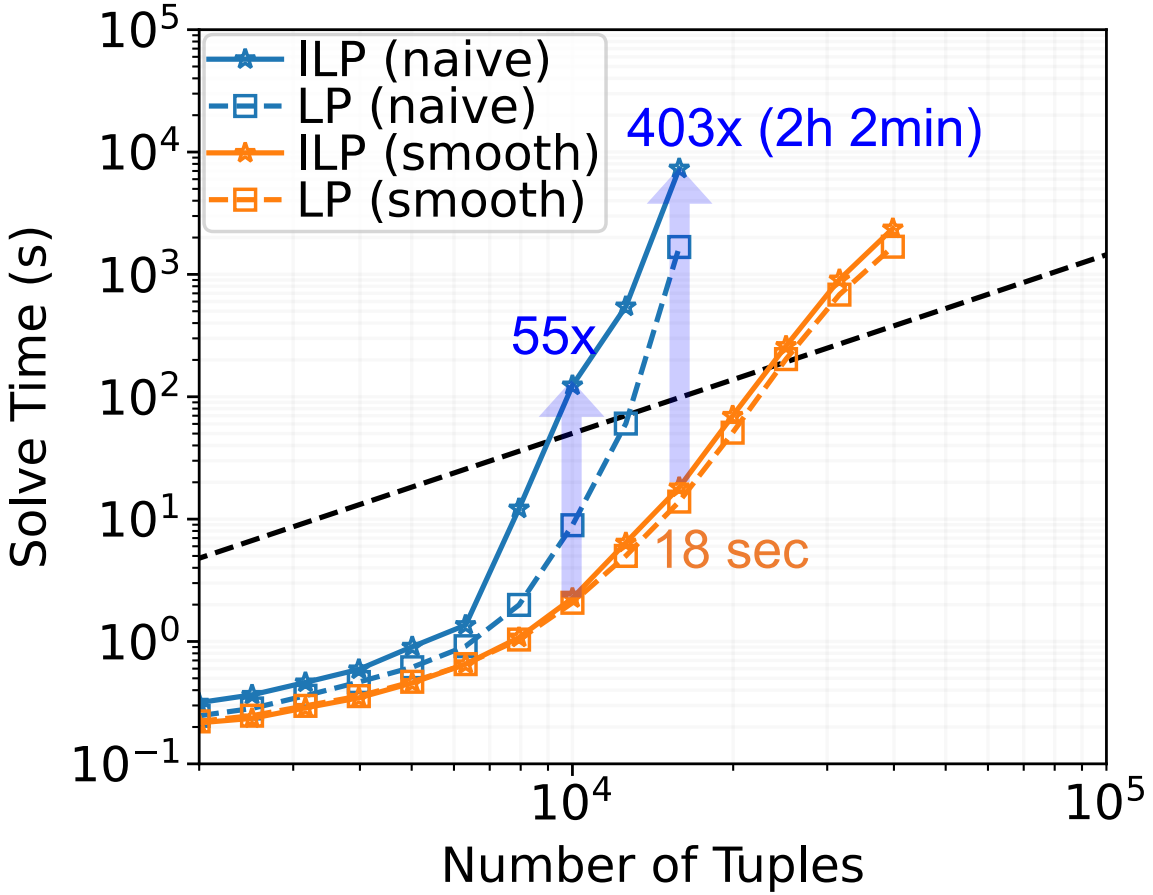
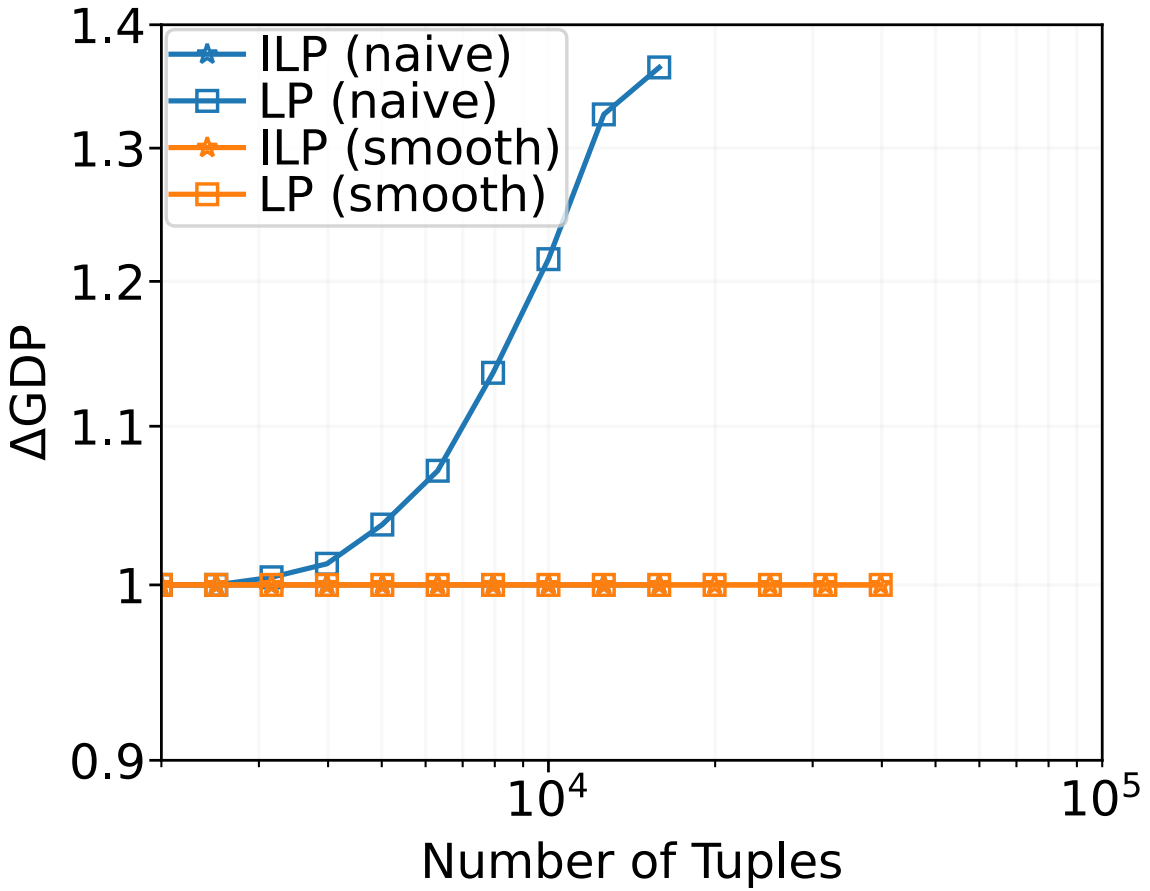
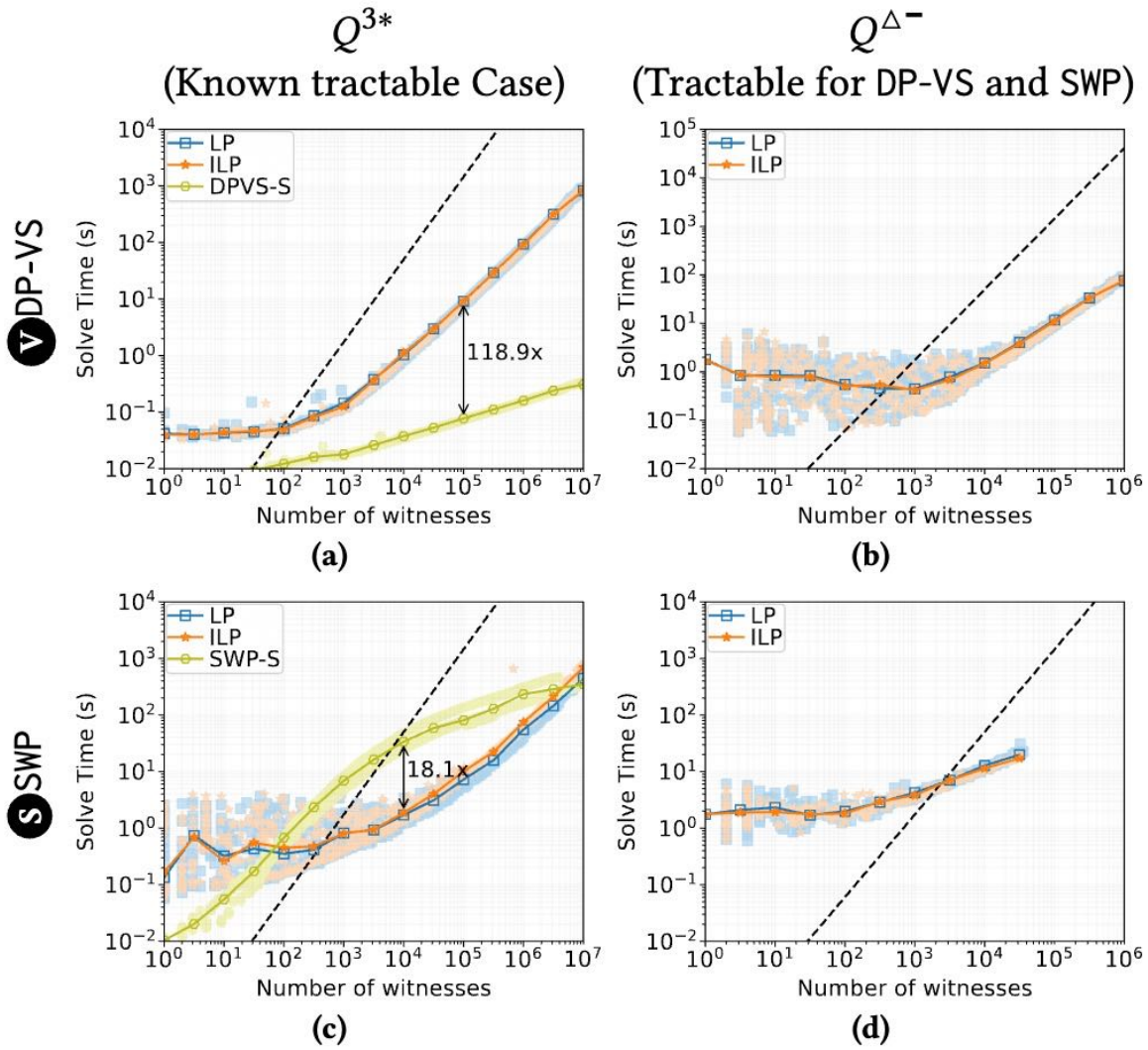




Comparison with specialized algorithms for PTIME cases



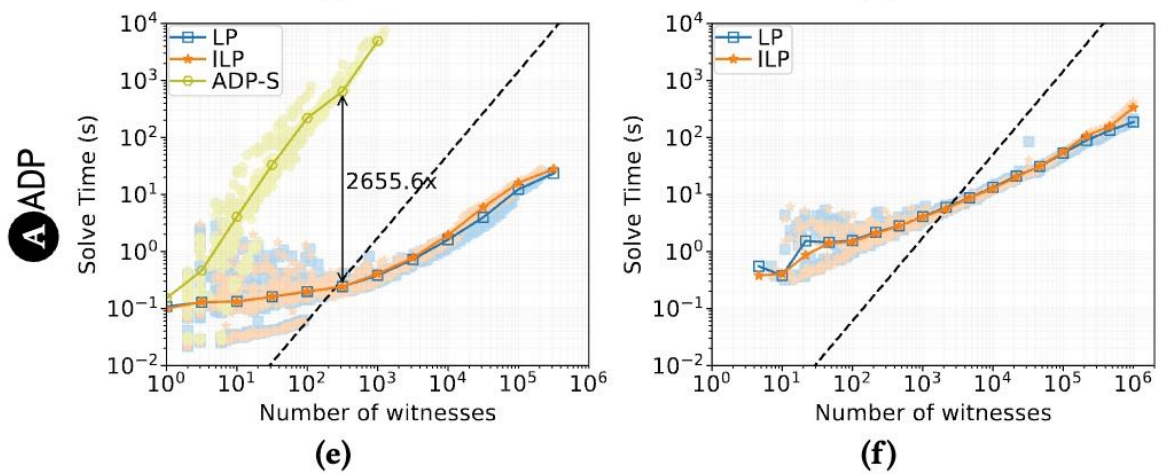


Figure 8: Performance of ILP[GDP] on a previously known (left column compared against prior specialized algorithms) and a newly discovered tractable query (right column with no prior known specialized algorithm) for three prior studied problems (V) DP-VS, (S) SWP, and (A) ADP. In all cases, ILP[GDP] scales well under the theoretical worst case complexity of ILPs and LPs. This is due to the nice algorithmic properties of ILP[GDP], which ensure that the optimal LP solution is integral for all known tractable queries.

A possible shift of focus of algorithm design in database theory?

Current focus: discrete algorithms

Identify tractable cases for a class of problems that can be solved with some dedicated discrete algorithm (like dynamic programming or greedy) or a reduction to flow

For the hard cases:

- prove hardness via some dedicated reduction from some NPC problem.
- optionally design a separate dedicated approximation algorithm

Partial solutions: Often, the algorithm (the dichotomy) does not extend to all types of queries like CQs with self-joins, or problems under bag semantics

Future: polyhedral algorithms

Design one "appropriate" ILP program to solve all problems

- "appropriate" here means that their natural LP relaxation has the same optimal objective for all PTIME cases ("LP=ILP"), which proves the ILP can be solved in PTIME.

All cases are covered (including the hard ones) ✓

- also approximation algorithms, just stop evaluation early, anytime algorithm comes for free ✓

Complete solutions: All problem types are covered ✓ (including self-joins or bag semantics)

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An anonymous concern: "...the ILP constructed is not a simple mathematical object... Since the construction given is .... not a simple mathematical object, it is not clear to me how deep one can push this further by analyzing it."

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Theory

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Partial solutions: Often, the algorithm (the dichotomy) does not extend to all types of queries like CQs with self-joins, or problems under bag semantics

Practical aspects: usually only some problem cases are solved, hard cases often not treated, the practical nature of the algorithms is not always clear

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- also approximation algorithms, just stop evaluation early, anytime algorithm comes for free ✓

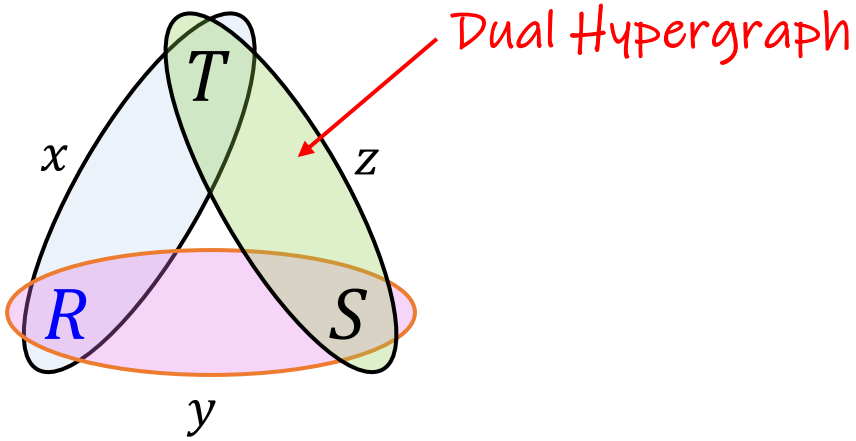
Complete solutions: All problem types are covered ✓ (including self-joins or bag semantics)

Practical aspects: it works from day one ✓

Example complicated landscape for resilience

Triangle query

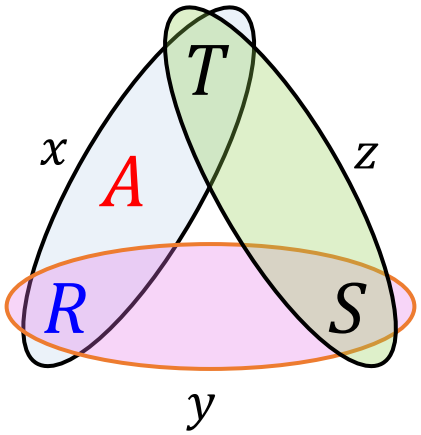
$Q^{\Delta}: -R(x,y), S(y,z), T(x,z)$



NPC

Triangle unary

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



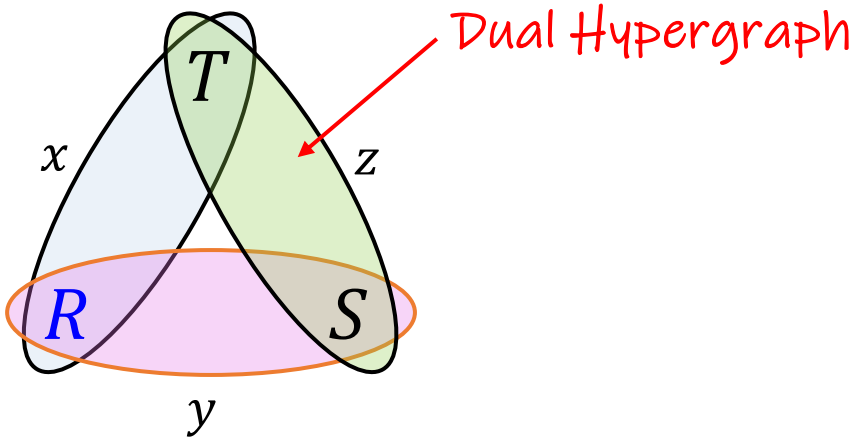
PTIME

Freire, Gatterbauer, Immerman, Meliou. The complexity of resilience and responsibility for self-join-free conjunctive queries, VLDB 2015. https://doi.org/10.14778/2850583.2850592

Example complicated landscape for resilience

Triangle query

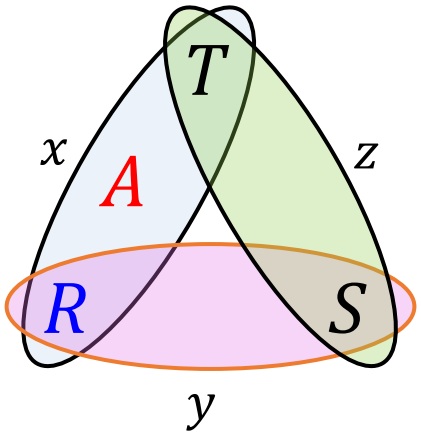
$Q^{\Delta}: -R(x,y), S(y,z), T(x,z)$



NPC

Triangle unary

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



PTIME

PTIME for FD $x \rightarrow y$

NPC under bag semantics

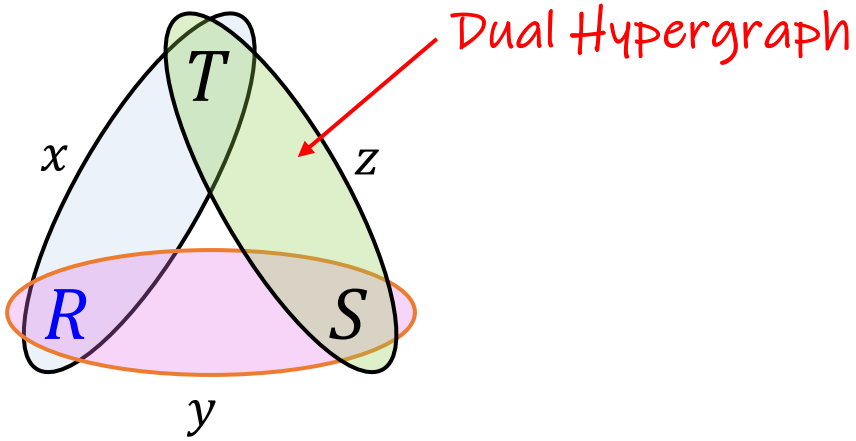
PTIME if provenance happens to be read-once

Freire, Gatterbauer, Immerman, Meliou. The complexity of resilience and responsibility for self-join-free conjunctive queries, VLDB 2015. https://doi.org/10.14778/2850583.2850592
Makhija, Gatterbauer. A Unified Approach for Resilience and Causal Responsibility with Integer Linear Programming (ILP) and LP Relaxations, SIGMOD 2024. https://doi.org/10.1145/3626715

Example complicated landscape for resilience

Triangle query

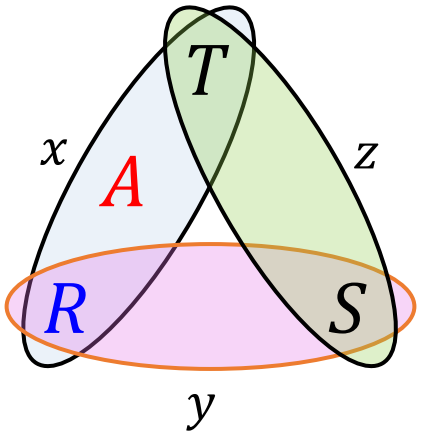
$Q^{\Delta}: -R(x,y), S(y,z), T(x,z)$



NPC

Triangle unary

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



PTIME

PTIME for FD $x \rightarrow y$

NPC under bag semantics

PTIME if provenance happens to be read-once

"Coarse-grained instance-optimal" algorithm

Freire, Gatterbauer, Immerman, Meliou. The complexity of resilience and responsibility for self-join-free conjunctive queries, VLDB 2015. https://doi.org/10.14778/2850583.2850592

Makhija, Gatterbauer. A Unified Approach for Resilience and Causal Responsibility with Integer Linear Programming (ILP) and LP Relaxations, SIGMOD 2024. https://doi.org/10.1145/3626715

Makhija, Gatterbauer: A Unified and Practical Approach for Generalized Deletion Propagation. https://arxiv.org/pdf/2411.17603

Take-aways Generalized Deletion Propagation

- Polyhedral theory solves many database theory problems "out of the box".
  - Shift in focus: instead of trying to find a dedicated PTIME algorithm for PTIME cases, start with a general formulation and prove it finishes in PTIME for PTIME cases.
  - There is some magic in getting the "right" formulation (ILP = LP for PTIME), we don't yet have "the" recipe
  - The proofs for LP=ILP go beyond standard optimization literature. Polyhedral theory alone does not help.
- The overall philosophy is way more general than reverse data management.
  - Makhija, Gatterbauer. *Minimally Factorizing the Provenance of Self-Join Free Conjunctive Queries*, PODS 2024. https://doi.org/10.1145/3651605
  - What about consistent query answering? And even more general logic optimization problems?
- More concretely open: Unifying deletion and insertion propagation ("change propagation"), basically positive and negative provenance / Why or Why not?
  - Meliou, Gatterbauer, Moore, Suciu. *Why so? or Why no? Functional causality for explaining query answers*. MUD 2010. https://arxiv.org/pdf/0912.5340
- Please talk to Neha ☺

Thank you ☺