Tutorial:
Causality and Explanations in Databases

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VLDB 2014
Hangzhou, China

We need to understand unexpected or interesting behavior of systems, experiments, or query answers to gain knowledge or troubleshoot

Unexpected results

```
select     distinct g.genre
from       Director d, Movie_Directors md,
           Movie m, Genre g
where      d.lastName like 'Burton'
           and g. mid=m.mid
           and m. mid=md.mid
           and md. did=d.did
order by   g.genre
```

genre
...
Fantasy
History
Horror
Music
Musical
Mystery
Romance
...

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genre
. . .
Fantasy
History
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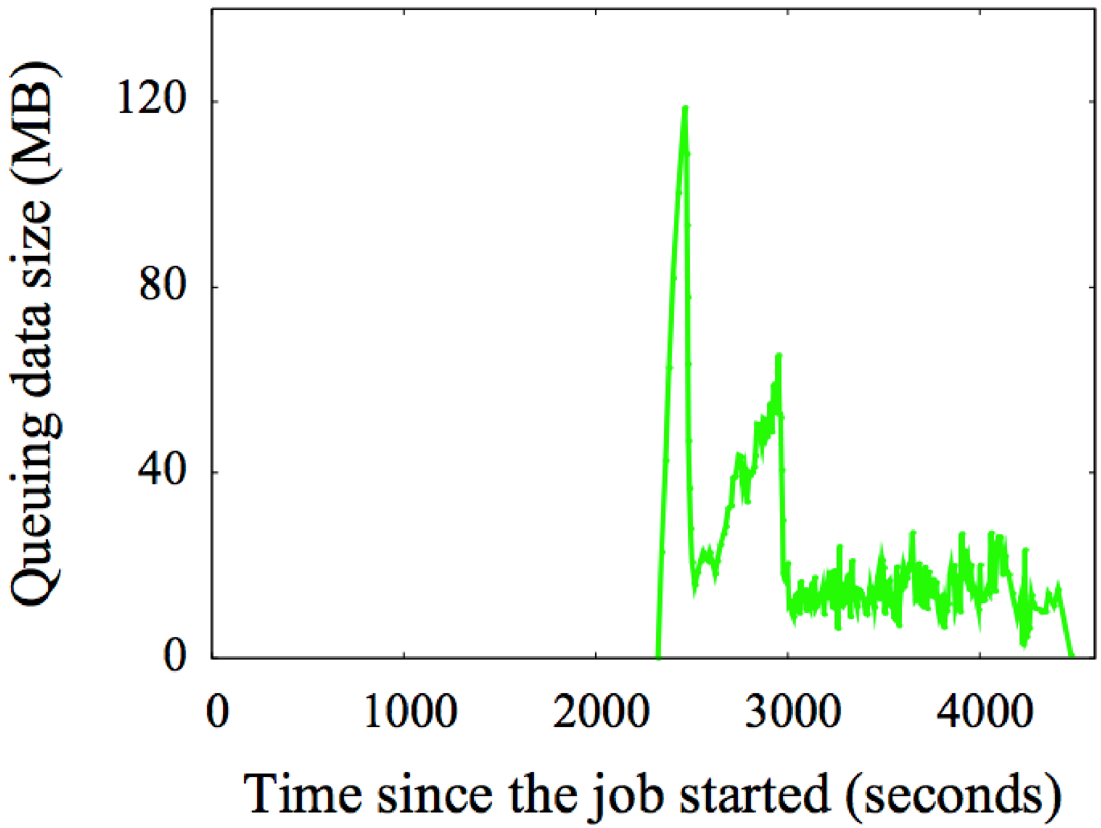
R nce

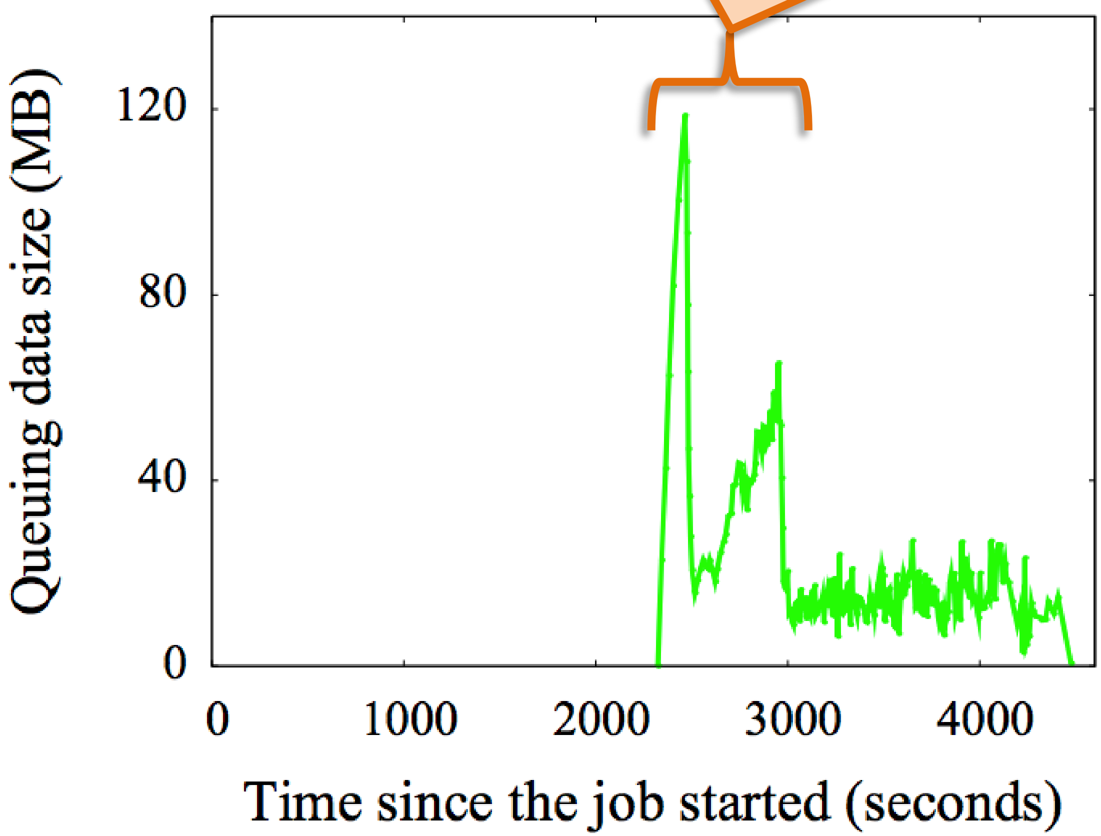
I didn’t know that Tim Burton directs Musicals!
Why are these items in the result of my query?

Inconsistent performance

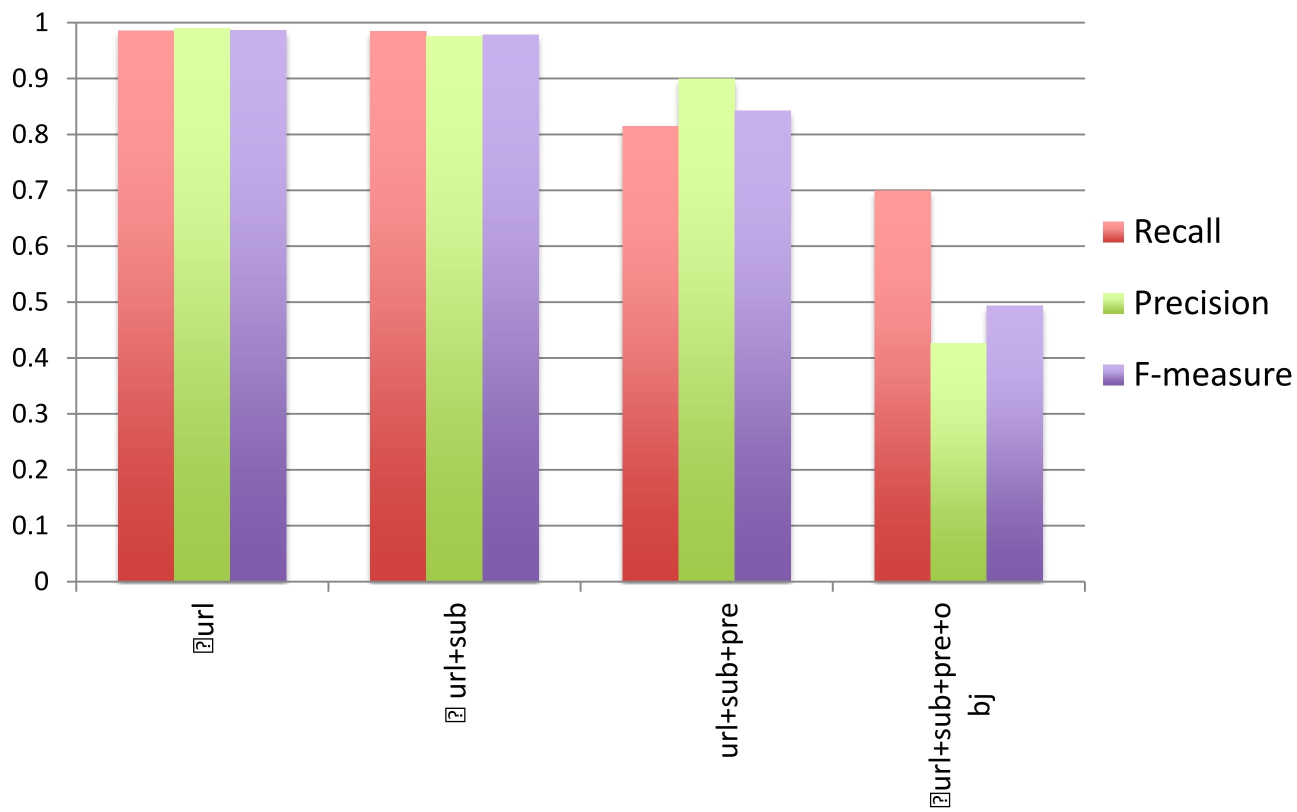


Inconsistent performance

Why is there such variability during this time interval?

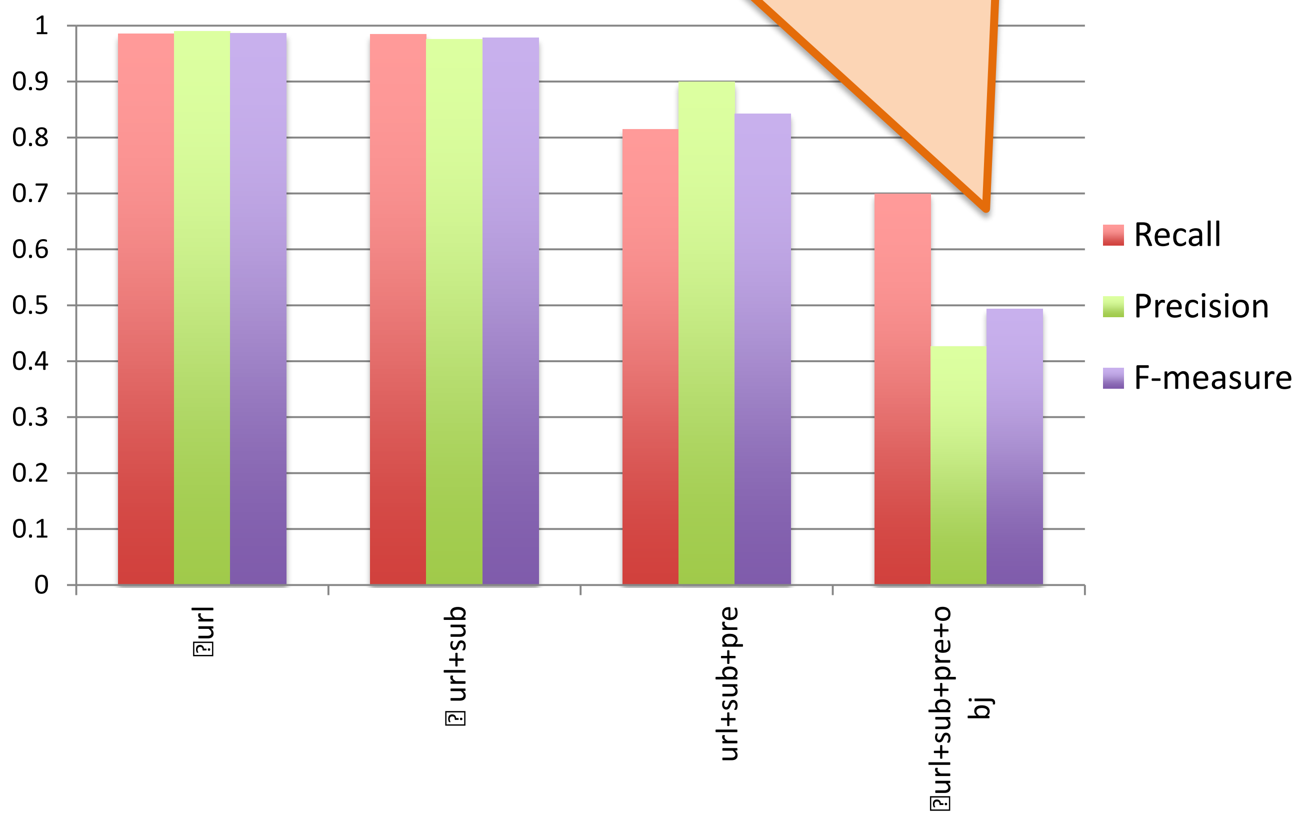


Understanding results



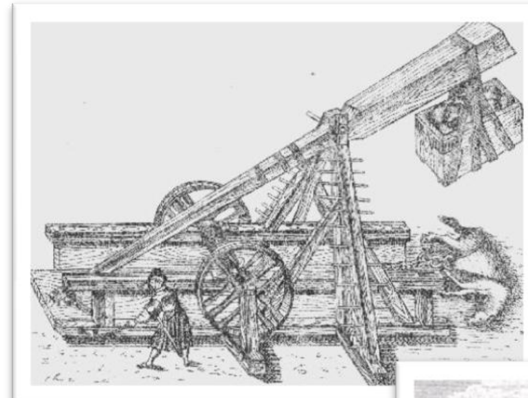
Understanding results

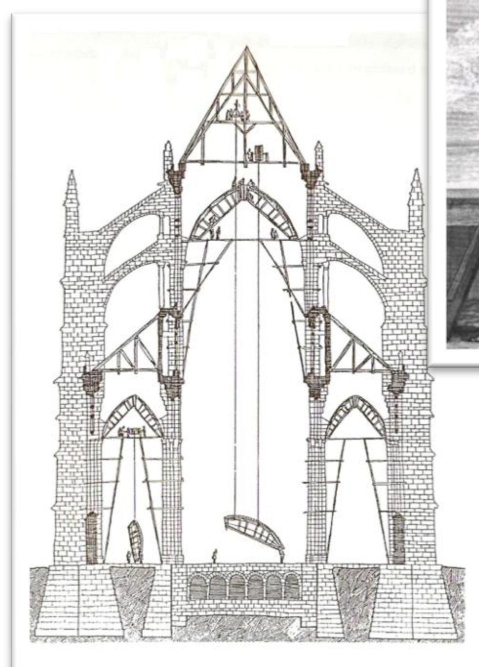
Why does the performance of my algorithm drop when I consider additional dimensions?

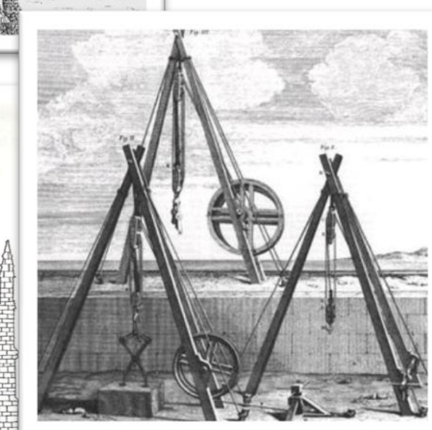


Causality in science

- Science seeks to understand and explain physical observations
  - *Why* doesn't the wheel turn?
  - *What if* I make the beam half as thick, will it carry the load?
  - *How* do I shape the beam so it will carry the load?







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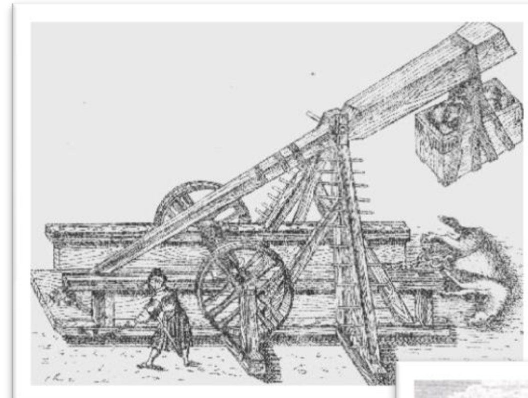
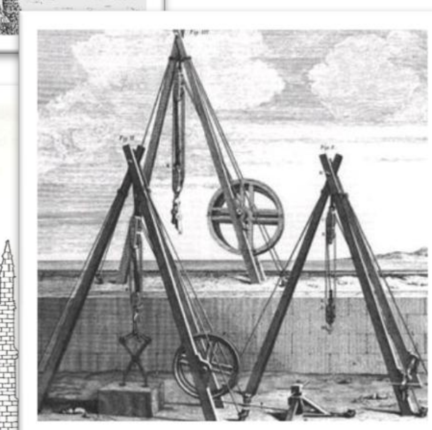
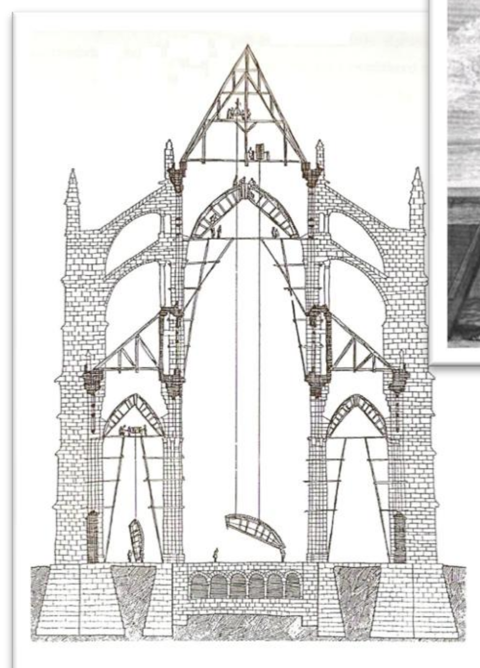
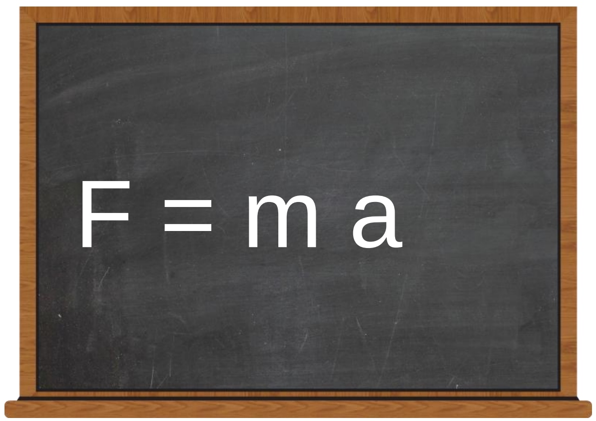
- We now have similar questions in databases!

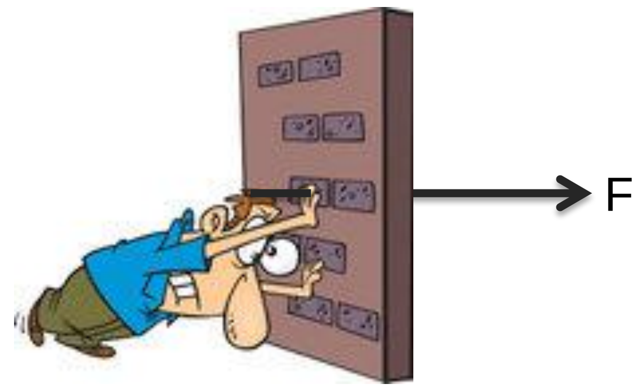






What is causality?





- Does acceleration cause the force?
- Does the force cause the acceleration?
- Does the force cause the mass?

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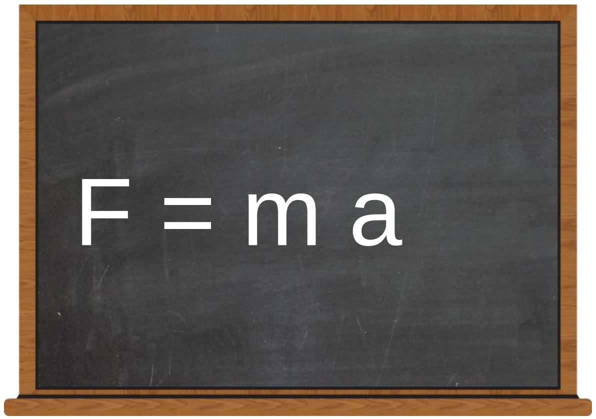

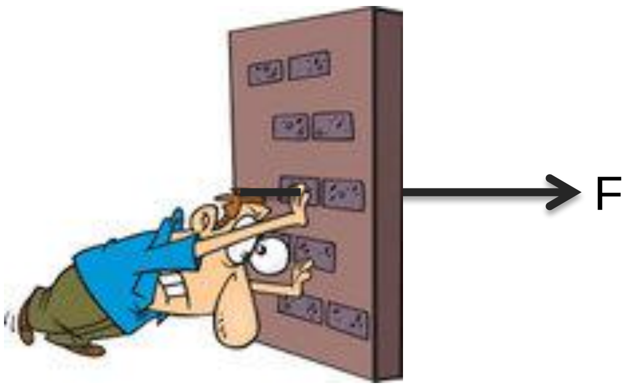

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- Does the force cause the acceleration?
- Does the force cause the mass?

We cannot derive causality from data, yet we have developed a perception of what constitutes a cause.

Some history

David Hume (1711-1776)

Causation is a matter of perception

We remember seeing the <u>flame</u>, and feeling a sensation called <u>heat</u>; without further ceremony, we call the one <u>cause</u> and the other <u>effect</u>

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Statistical ML

Forget causation! Correlation is all you should ask for.

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Judea Pearl (1936-)

A mathematical definition of causality

Forget empirical observations! Define causality based on a network of known, physical, causal relationships

Tutorial overview

Part 1: Causality

- Basic definitions
- Causality in AI
- Causality in DB

Part 2: Explanations

- Explanations for DB query answers
- Application-specific approaches

Part 3: Related topics and Future directions

- Connections to lineage/provenance, deletion propagation, and missing answers
- Future directions

Part 1: Causality

a. Basic Definitions
b. Causality in AI
c. Causality in DB

Part 1.a

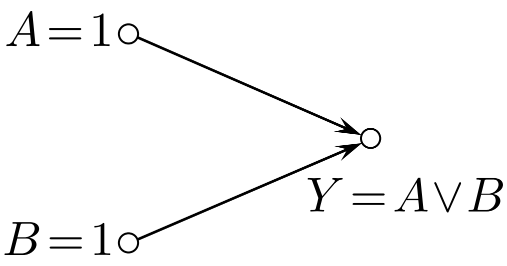
- **BASIC DEFINITIONS**

Basic definitions: overview

- Modeling causality
  - Causal networks
- Reasoning about causality
  - Counterfactual causes
  - Actual causes (Halpern & Pearl)
- Measuring causality
  - Responsibility

Causal networks

- Causal structural models:
  - Variables: A, B, Y
  - Structural equations: Y = A v B



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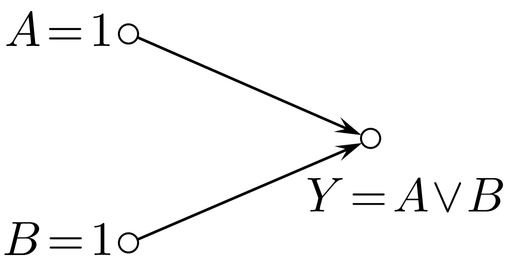

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  - *E.g., A bottle breaks if either Alice or Bob throw a rock at it.*

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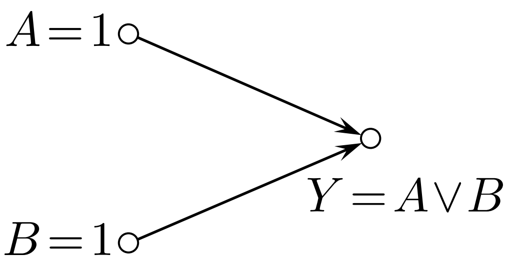

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    - Alice throws a rock (A)
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[Pearl, 2000]

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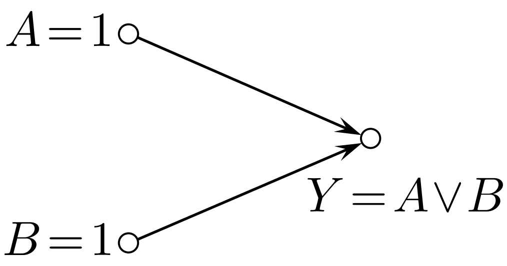
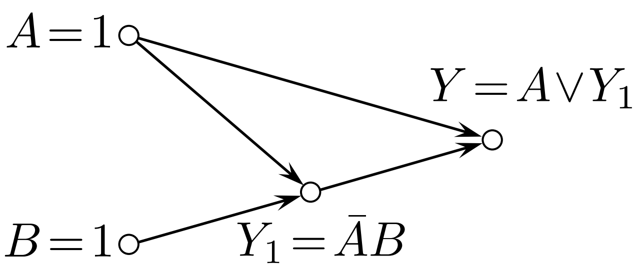


- Modeling problems:
  - *E.g., A bottle breaks if either Alice or Bob throw a rock at it.*
  - Endogenous variables:
    - Alice throws a rock (A)
    - Bob throws a rock (B)
    - The bottle breaks (Y)
  - Exogenous variables:
    - Alice’s aim, speed of the wind, bottle material etc.

[Woodward, 2003] [Hagmeyer, 2007]

Intervention / contingency

- External interventions modify the structural equations or values of the variables.



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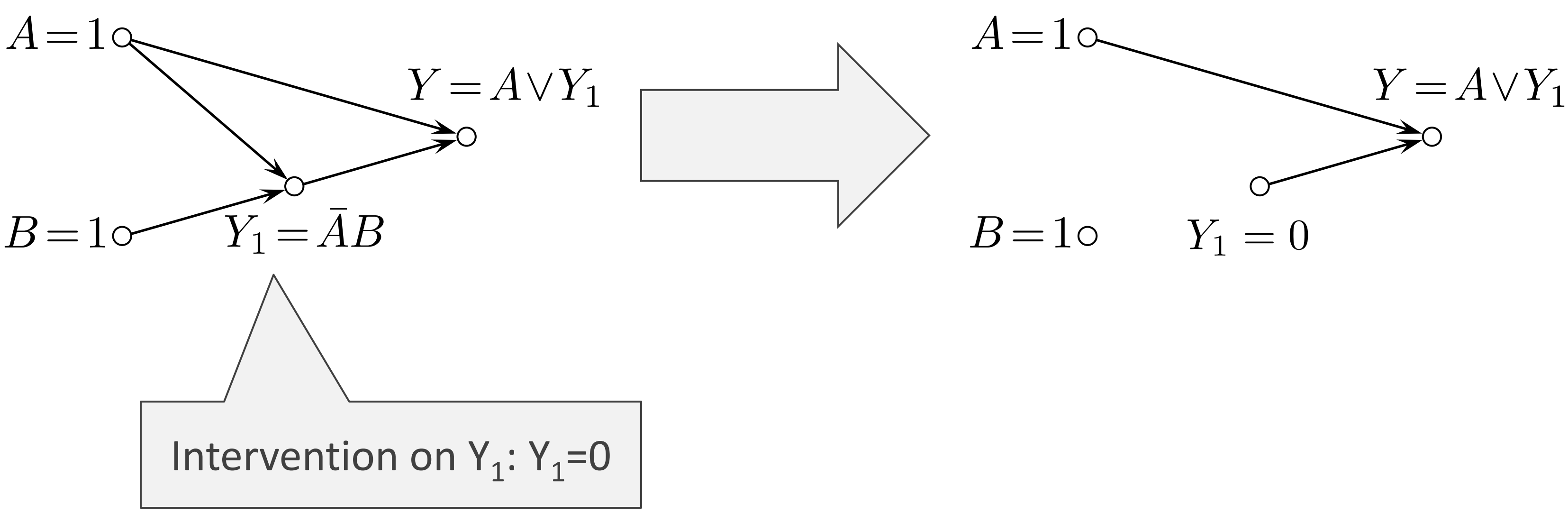

[Hume, 1748] [Menzies, 2008] [Lewis, 1973]

Counterfactuals

- If *not A* then *not φ*
  - In the absence of a cause, the effect doesn't occur

$$C = A \wedge B, \quad A = 1 \wedge B = 1 \longleftarrow \text{Both counterfactual}$$

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  - If Alice doesn't throw a rock, the bottle still breaks (because of Bob)
  - Neither Alice nor Bob are counterfactual causes

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$$C = A \lor B, \quad A = 1 \land B = 1 \longleftarrow \text{No counterfactual causes}$$

[Halpern-Pearl, 2001] [Halpern-Pearl, 2005]

Actual causes

[simplification]

A variable X is an <u>actual cause</u> of an effect Y if there exists a contingency that makes X counterfactual for Y.

$$C = A \vee B, \quad A = 1 \wedge B = 1 \longleftarrow$$ A is a cause under the contingency B=0

Example 1

$$Y = X_1 \wedge X_2 \qquad X_1 = X_2 = 1 \Rightarrow Y = 1$$

X_1=1 is counterfactual for Y=1

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Example 2

$$Y = X_1 \vee X_2 \qquad X_1 = X_2 = 1 \Rightarrow Y = 1$$

X_1=1 is not counterfactual for Y=1

X_1=1 is an <u>actual</u> cause for Y=1, with contingency X_2=0

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Example 3

$$Y = (\neg X_1 \wedge X_2) \vee X_3 \qquad X_1 = X_2 = X_3 = 1 \Rightarrow Y = 1$$

X_1=1 is not counterfactual for Y=1

X_1=1 is not an actual cause for Y=1

[Chockler-Halpern, 2004]

Responsibility

A measure of the degree of causality

$$\rho = \frac{1}{1 + \min_{\Gamma} |\Gamma|}$$

size of the contingency set

[Chockler-Halpern, 2004]

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A measure of the degree of causality

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Example

$Y = A \wedge (B \vee C)$ $\quad A = B = C = 1 \Rightarrow Y = 1$

A=1 is counterfactual for Y=1 (ρ=1)

B=1 is an actual cause for Y=1, with contingency C=0 (ρ=0.5)

Basic definitions: summary

- Causal networks model the known variables and causal relationships
- Counterfactual causes have direct effect to an outcome
- Actual causes extend counterfactual causes and express causal influence in more settings
- Responsibility measures the contribution of a cause to an outcome

Part 1.b

• CAUSALITY IN AI

Causality in AI: overview

- Actual causes: going deeper into the Halpern-Pearl definition
- Complications of actual causality and solutions
- Complexity of inferring actual causes

Dealing with complex settings

- The definition of actual causes was designed to capture complex scenarios

Permissible contingencies

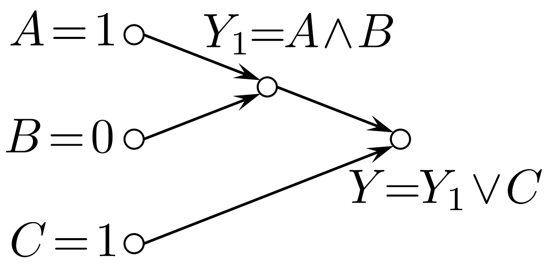
Not all contingencies are valid => Restrictions in the Halpern-Pearl definition of actual causes.

Preemption

Model priorities of events => one event may *preempt* another

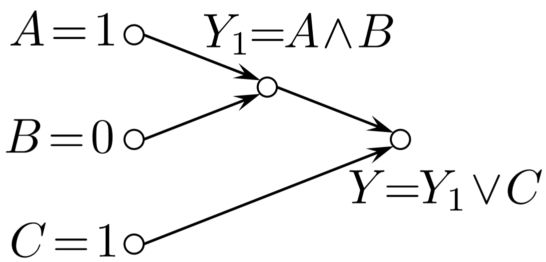
[Halpern-Pearl, 2001] [Halpern-Pearl, 2005]

Permissible contingencies



A: Alice loads Bob's gun
B: Bob shoots
C: Charlie loads and shoots his own gun
Y: the prisoner dies

Permissible contingencies



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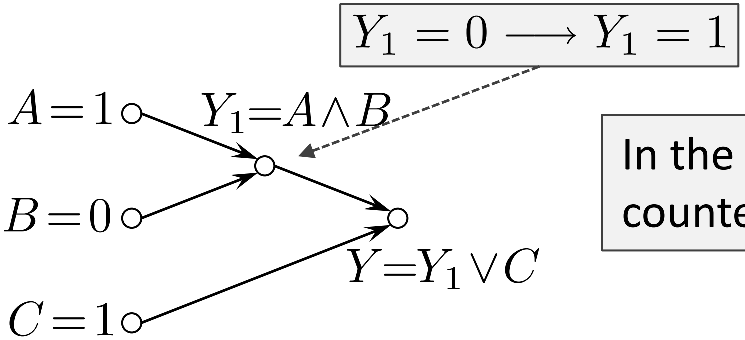

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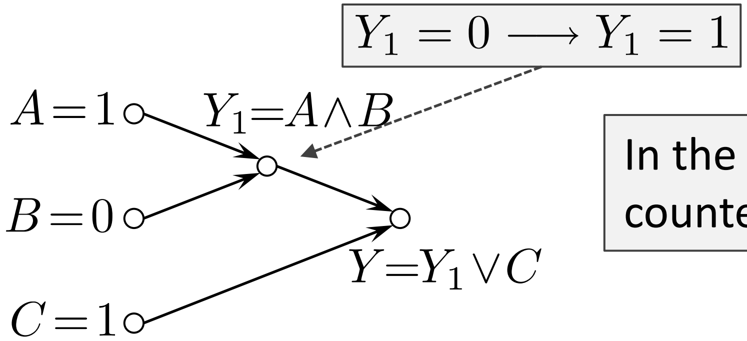

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A: Alice loads Bob's gun

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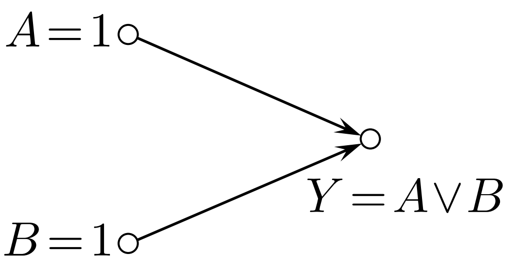
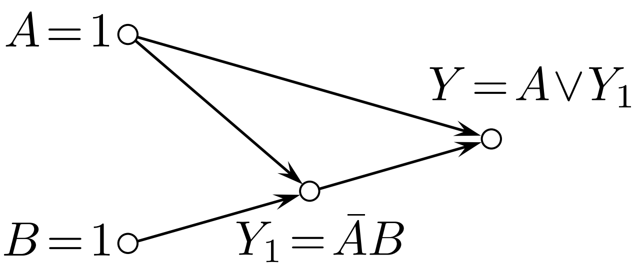
Additional restriction in the HP definition:
Nodes in the causal path should not change value.

[Schaffer, 2000] [Halpern-Pearl, 2001] [Halpern-Pearl, 2005]

Causal priority: preemption





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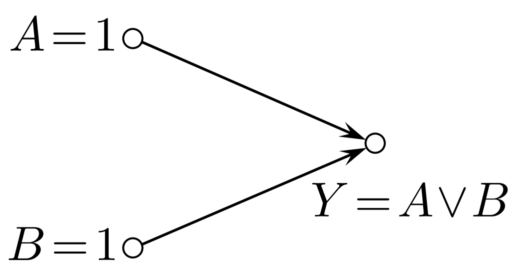
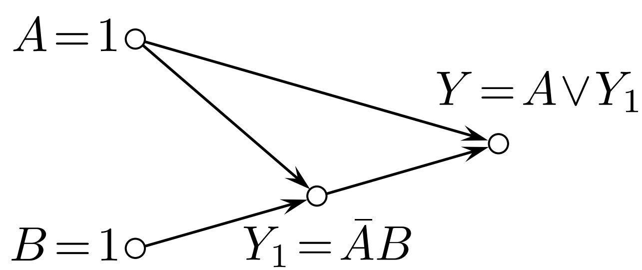
Causal priority: preemption

$$\boxed{A \vee B = A \vee \bar{A}B}$$





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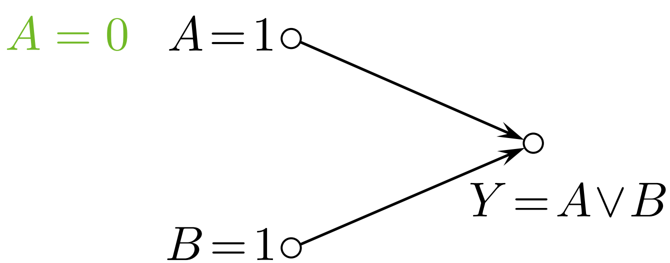
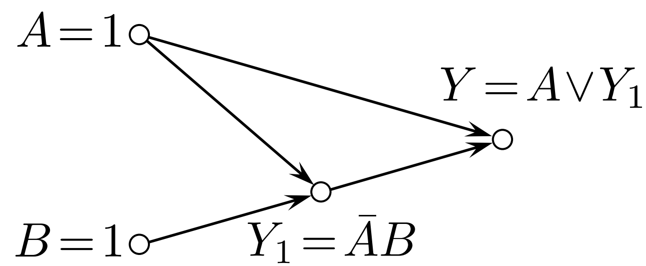
$$A \lor B = A \lor \bar{A}B$$





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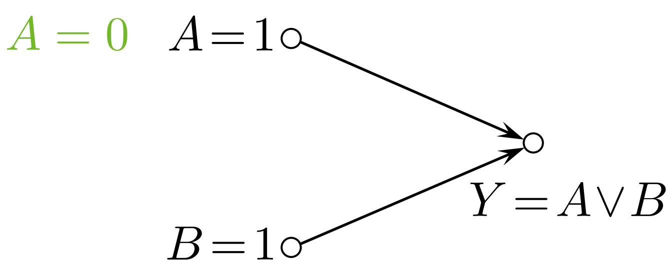

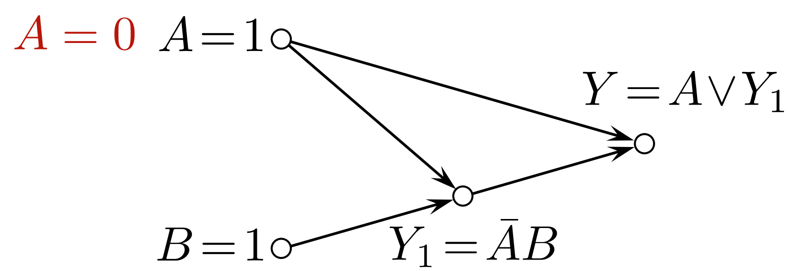

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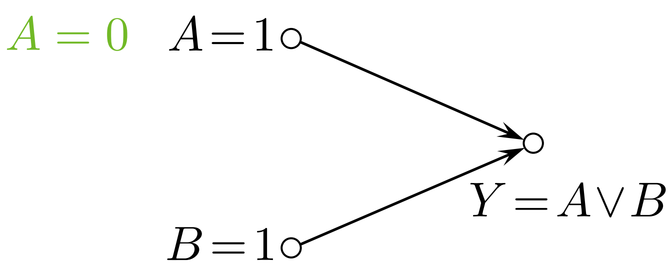

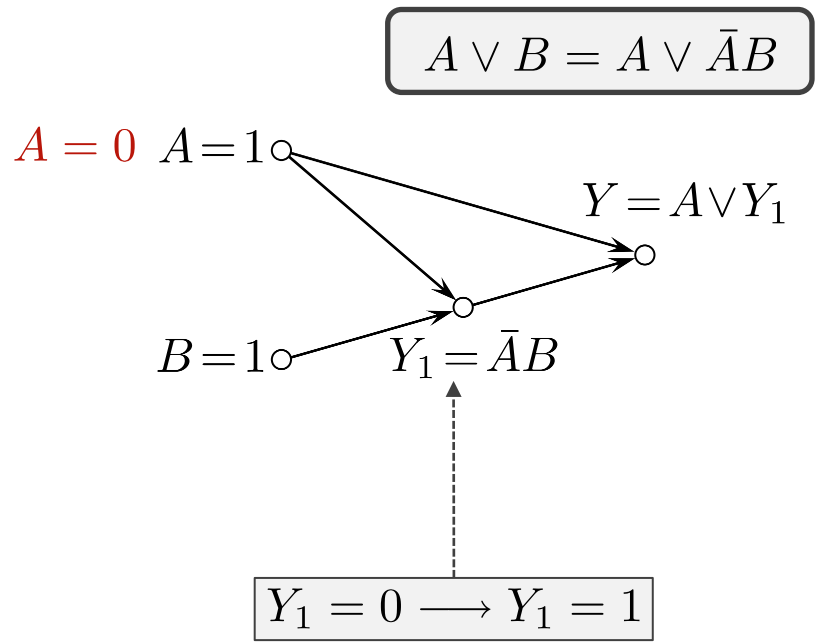

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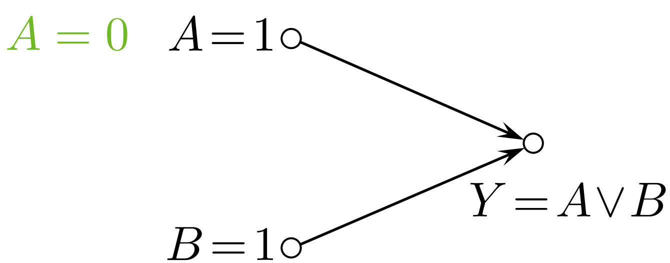

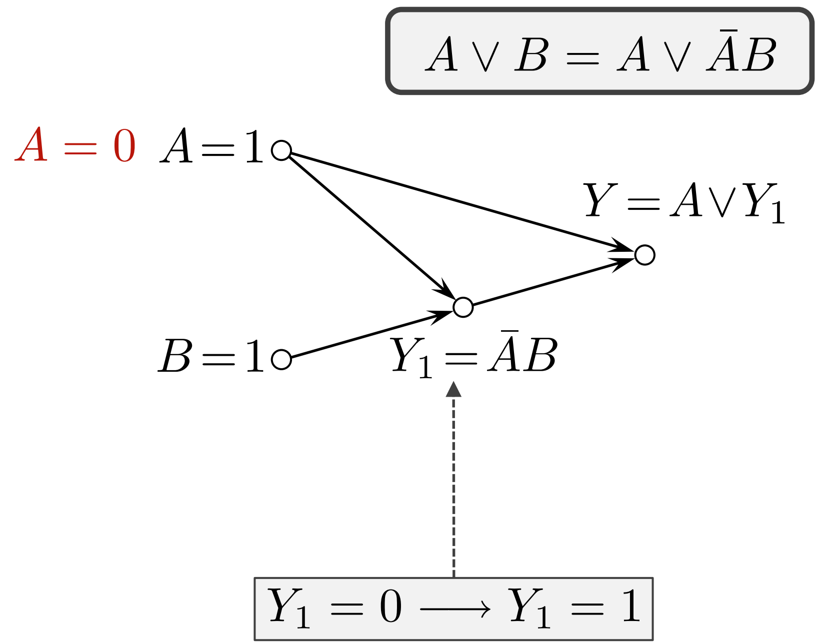

A: Alice throws a rock

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Even though the structural equations for Y are equivalent, the two causal networks result in different interpretations of causality

[Meliou et al., 2010a]

Complications

- Intricacy
  - The definition has been used incorrectly in literature: [Chockler, 2008]

[Meliou et al., 2010a]

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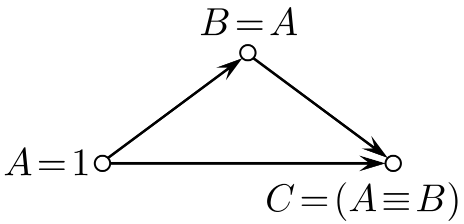
Shock C



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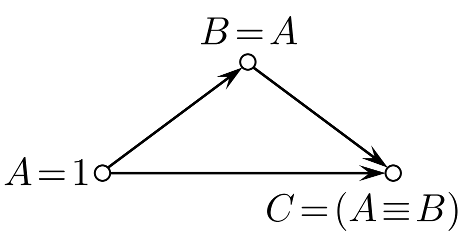
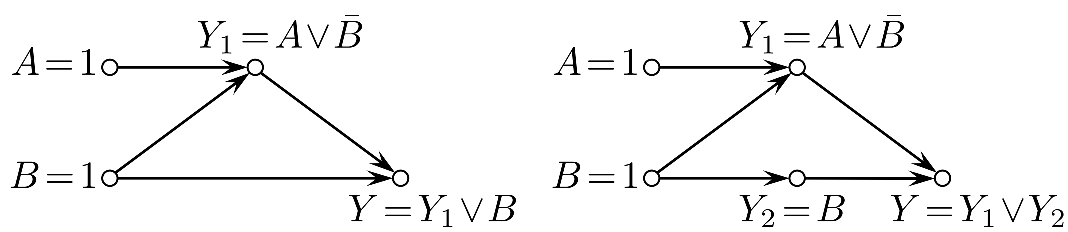


Network expansion



Defaults and normality

- **World**: a set of values for all the variables
- **Rank:** each world has a rank; the higher the rank, the less likely the world
- **Normality:** can only pick contingencies of lower rank (more likely worlds)

[Halpern, 2008]

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Addresses some of the complications, but requires ordering of possible worlds.

[Eiter- Lukasiewicz 2002]

Complexity of causality

Counterfactual cause	Actual cause
PTIME	NP-complete

Proof: Reduction from SAT.

Given F, F is satisfiable iff X is an actual cause for $X \wedge F$

[Eiter- Lukasiewicz 2002]

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PTIME	NP-complete

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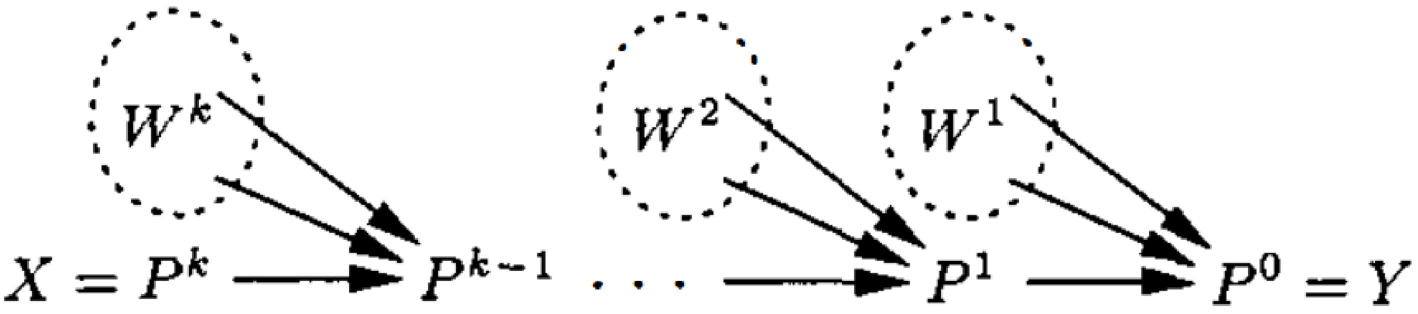
For non-binary models: Σ_2^P-complete

[Eiter- Lukasiewicz 2002]

Tractable cases

1. Causal trees



[Eiter- Lukasiewicz 2002]

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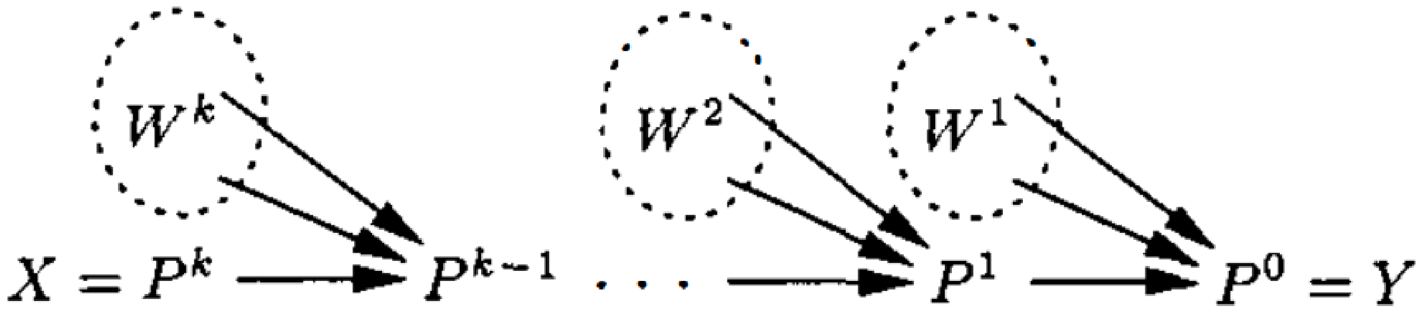
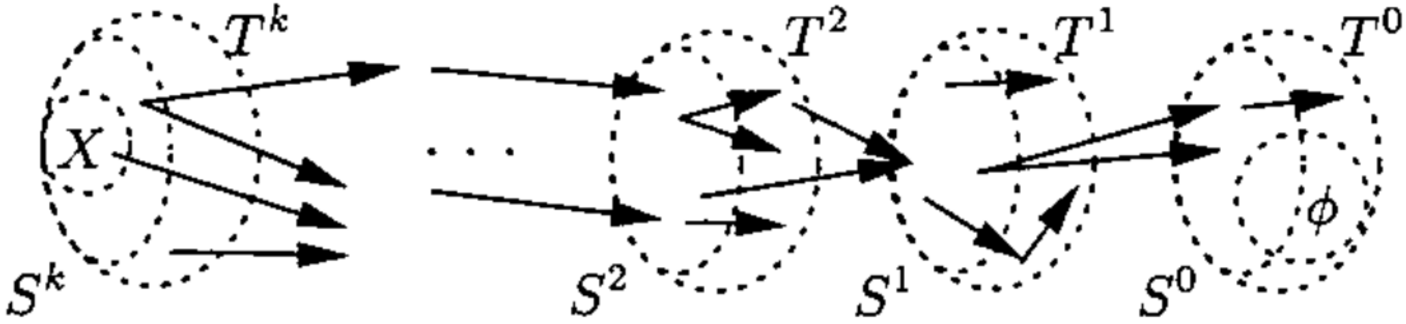


Actual causality can be determined in linear time

[Eiter- Lukasiewicz 2002]

Tractable cases

2. Width-bounded decomposable causal graphs



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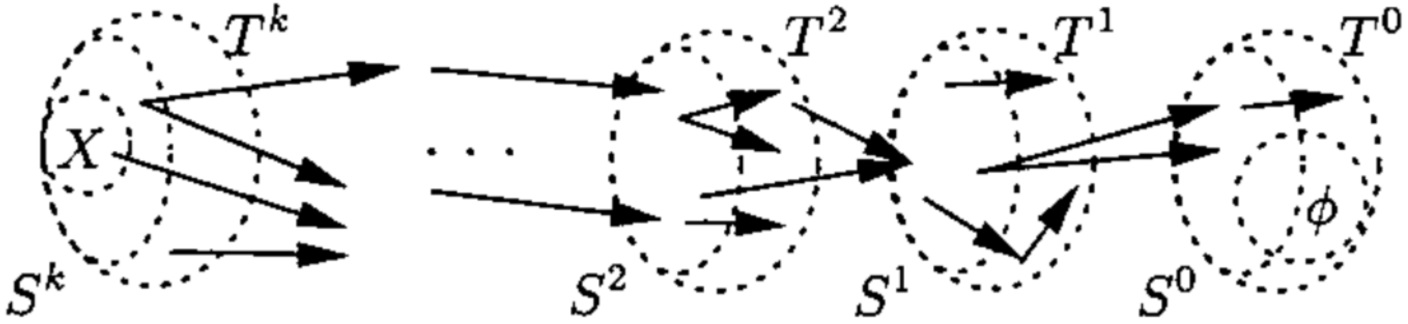
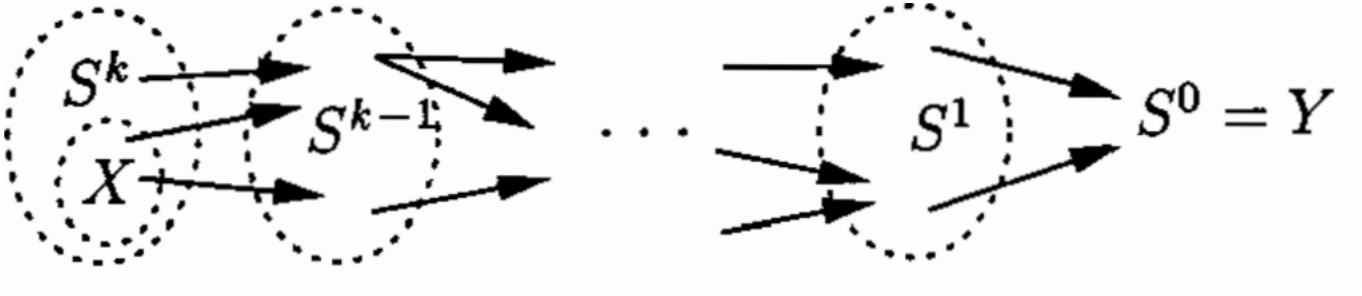


It is unclear whether decompositions can be efficiently computed

Tractable cases

3. Layered causal graphs



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Tractable cases

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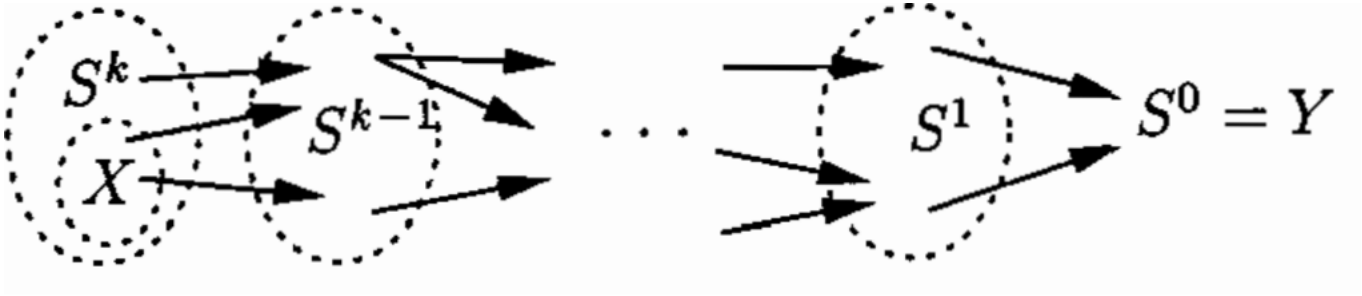


Layered graphs are decompositions that can be computed in linear time.

Causality in AI: summary

- Actual causes:
  - permissible contingencies and preemption
  - Weaknesses of the HP definition: normality

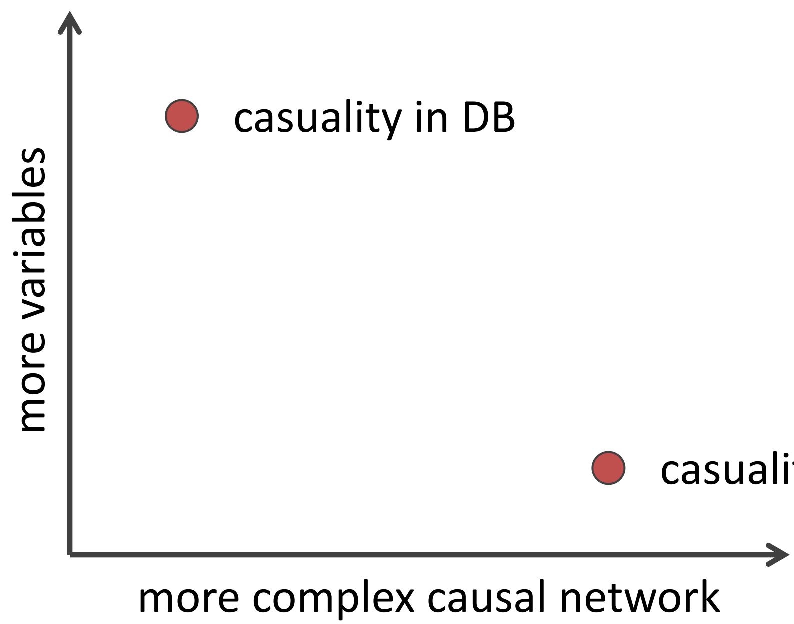
- Complexity:
  - Based on a given causal network
  - Tractable cases

Part 1.c

• CAUSALITY IN DATABASES

Causality in databases: overview

- What is the causal network, a cause, and responsibility in a DB setting?



Motivating example: IMDB dataset

IMDB Database Schema

Actor

<u>*aid*</u>	*firstName*	*lastName*

Director

<u>*did*</u>	*firstName*	*lastName*

Movie

<u>*mid*</u>	*name*	*year*	*rank*

Genre

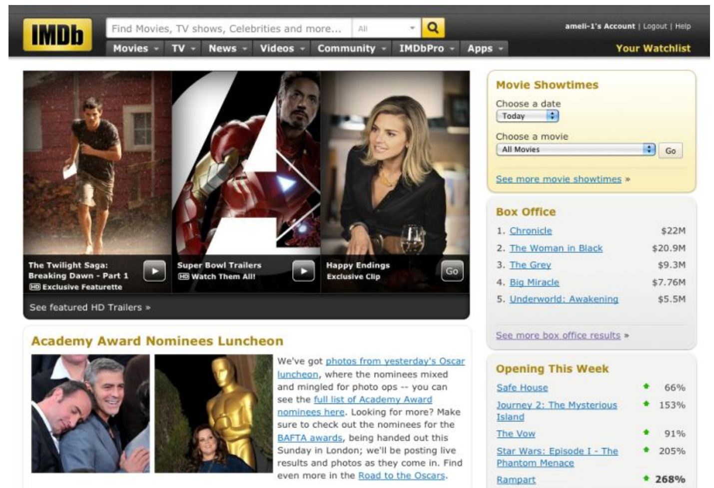
mid	*genre*

Movie_Directors

did	*mid*

Casts

aid	*mid*	*role*



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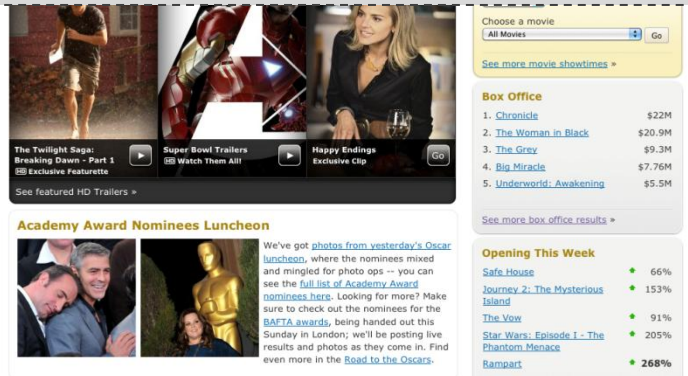
Query

"What genres does Tim Burton direct?"



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"What genres does Tim Burton direct?"


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select     distinct g.genre
from       Director d, Movie_Directors md,
           Movie m, Genre g
where      d.lastName like 'Burton'
           and g. mid=m.mid
           and m. mid=md.mid
           and md. did=d.did
order by   g.genre
```

genre
...
Fantasy
History
Horror
Music
Musical
Mystery
Romance
...

[Meliou et al., 2010]

Motivating example: IMDB dataset

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What can databases do

Provenance / Lineage:
The set of all tuples that contributed to a given output tuple

[Cheney et al. FTDB 2009], [Buneman et al. ICDT 2001], …

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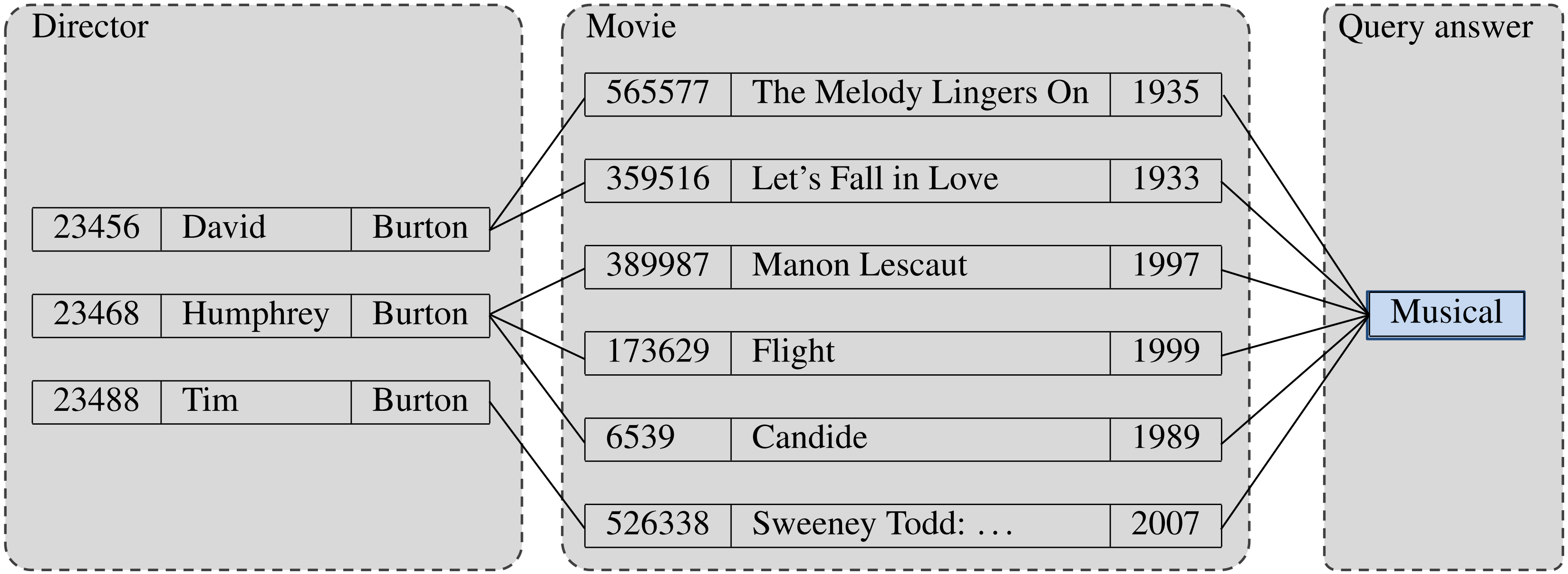
[Cheney et al. FTDB 2009], [Buneman et al. ICDT 2001], …

But

In this example, the lineage includes **137 tuples** !!

[Meliou et al., 2010]

From provenance to causality



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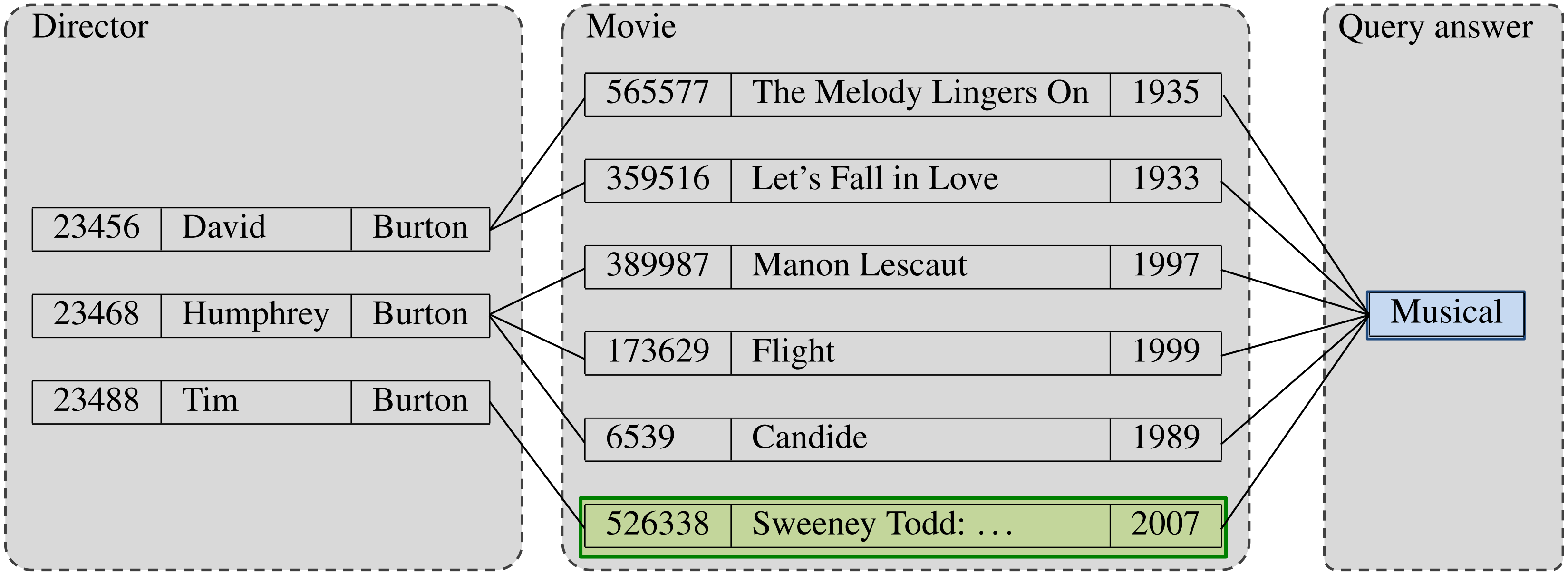

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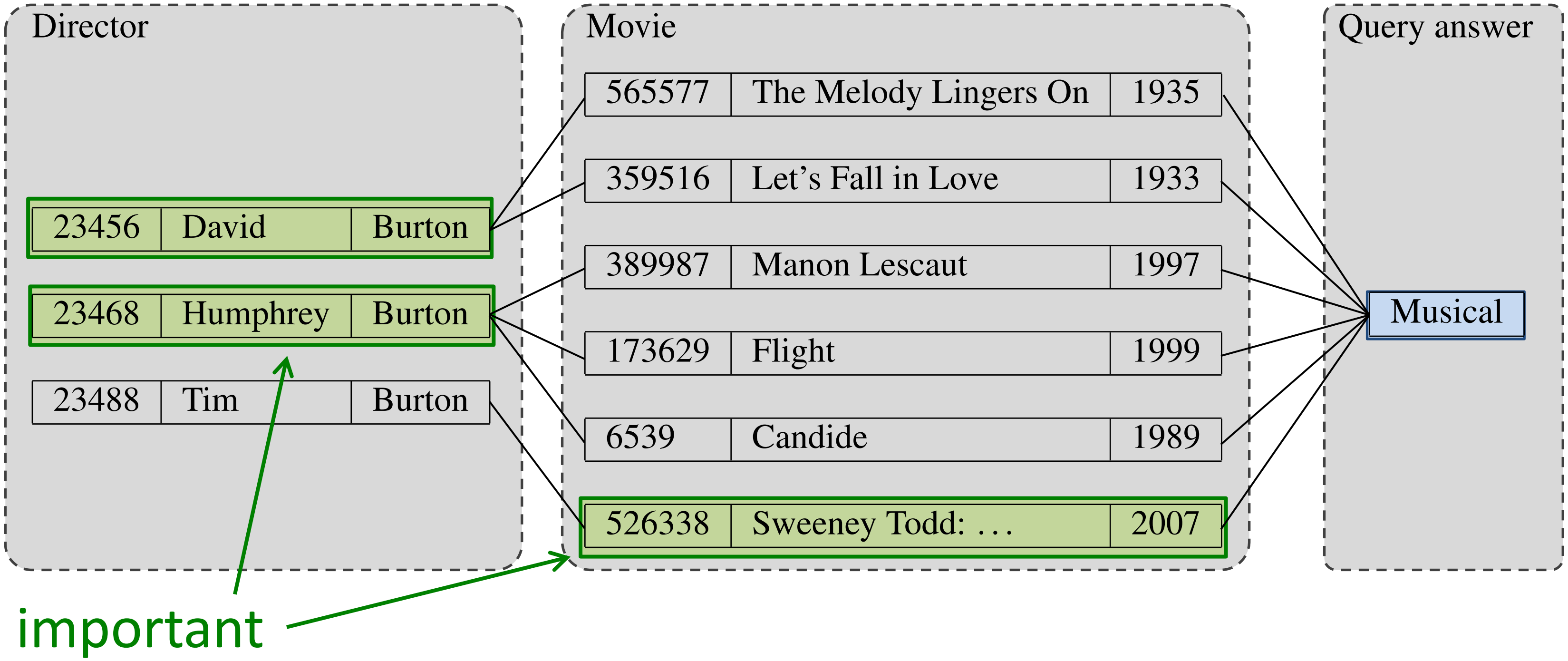

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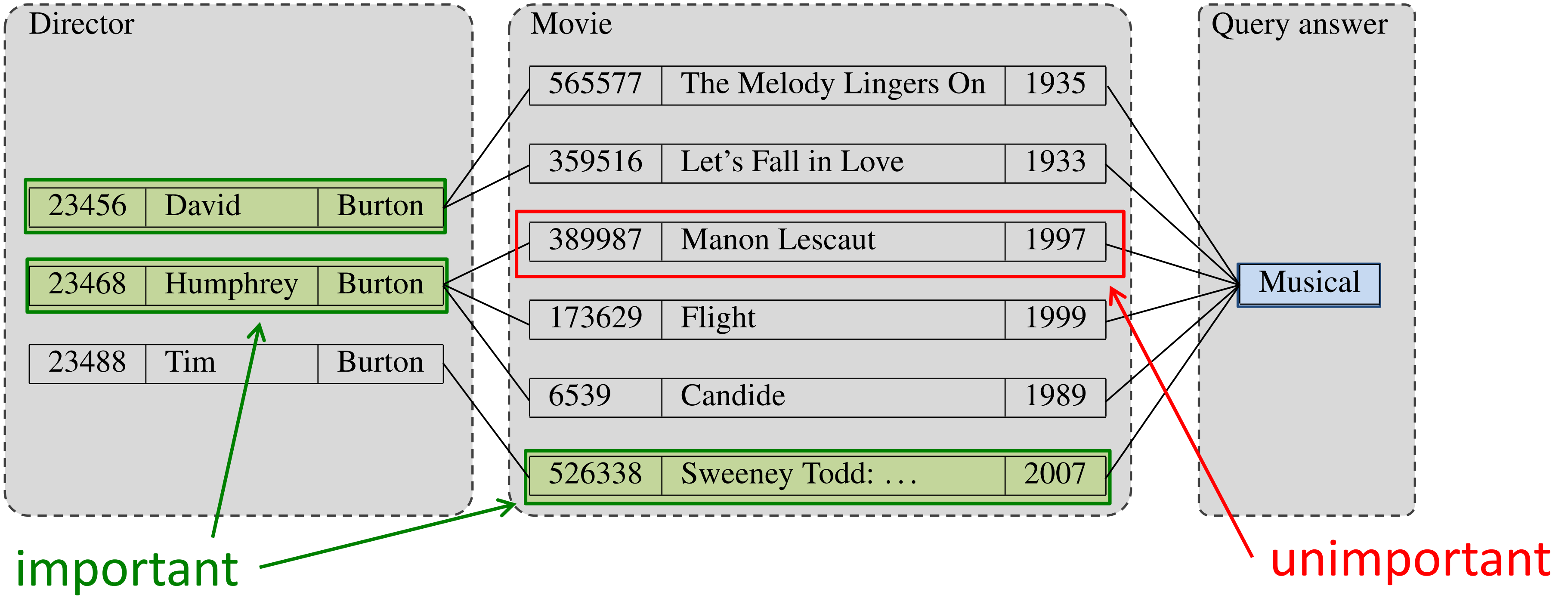

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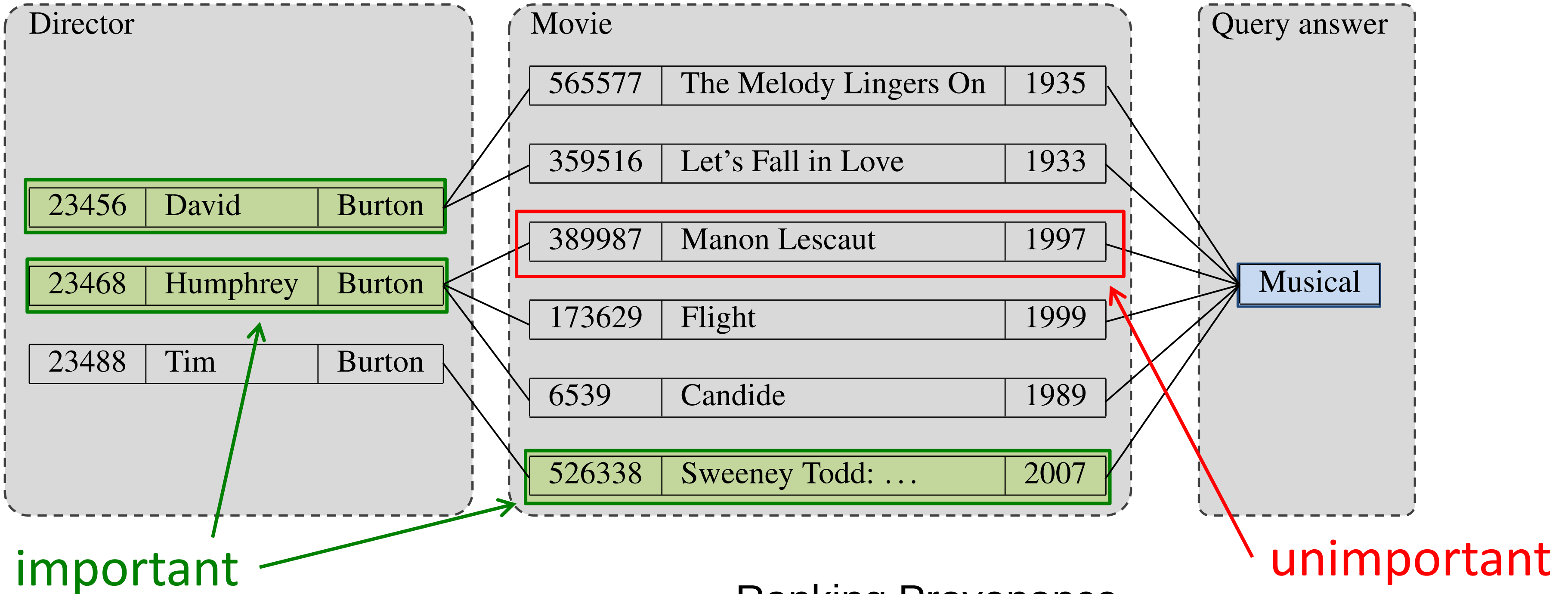


Goal:

Rank tuples in order of importance

Ranking Provenance

Answer tuple
Movie(526338, "Sweeney Todd", 2007)
Director(23456, David, Burton)
Director(23468, Humphrey, Burton)
Director(23488, Tim, Burton)
Movie(359516, "Let's Fall in Love", 1933)
Movie(565577, "The Melody Lingers On", 1935)
Movie(6539, "Candide", 1989)
Movie(173629, "Flight", 1999)
Movie(389987, "Manon Lescaut", 1997)

Causality for database queries

Input: database D and query Q. Output: D’=Q(D)

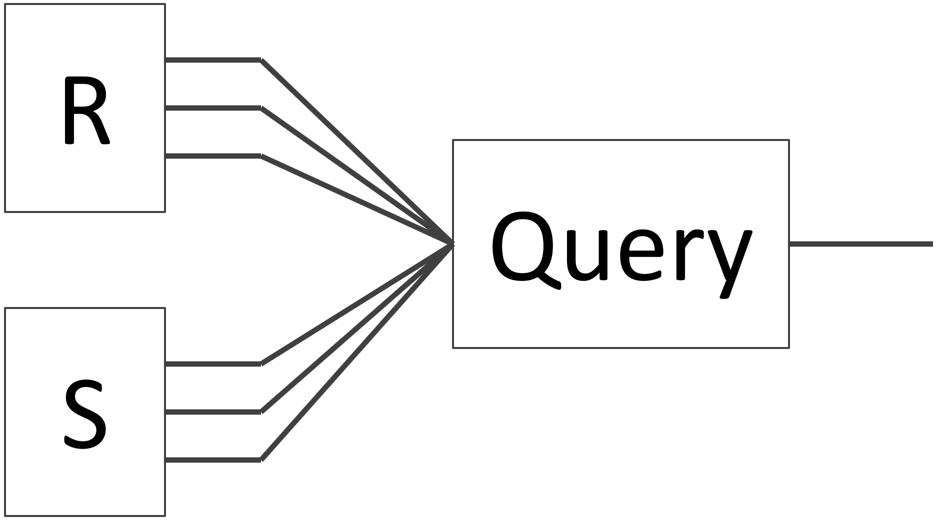
- Exogenous tuples: D^x
  - Not considered for causality: external sources, trusted sources, certain data
- Endogenous tuples: D^n
  - Potential causes: untrusted sources or tuples

[Meliou et al., 2010]

Causality for database queries

Input: database D and query Q. Output: D’=Q(D)

- Causal network:
  - Lineage of the query



$r_1 s_1 \vee r_2 s_1$

[Meliou et al., 2010]

Causality of a query answer

Input: database D and query Q. Output: D'=Q(D)

- $t \in D^n$ is a counterfactual cause for answer α
  - If $\alpha \in Q(D)$ and $\alpha \notin Q(D-t)$
- $t \in D^n$ is an actual cause for answer α
  - If $\exists \Gamma \subset D^n$ such that t is counterfactual in $D - \Gamma$

contingency set

Relationship with Halpern-Pearl causality

- Simplified definition:
  - No preemption
  - More permissible contingencies

- Open problems:
  - More complex query pipelines and reuse of views may require preemption
  - Integrity and other constraints may restrict permissible contingencies

Complexity

- Do the results of Eiter and Lukasiewicz apply?

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- What is the complexity for a given query?
  - A given query produces a family of possible lineage expressions (for different data instances)
  - Data complexity:

    the query is fixed, the complexity is a function of the data

[Meliou et al., 2010]

Complexity

- For every conjunctive query, causality is: Polynomial, expressible in FO

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- Responsibility is a harder problem

[Meliou et al., 2010]

Responsibility: example

Directors

did	firstName	lastName
28736	Steven	Spielberg
67584	Quentin	Tarantino
23488	Tim	Burton
72648	Luc	Besson

Movie_Directors

did	mid
28736	82754
67584	17653
72648	17534
23488	27645
23488	81736
67584	18764

Query: (Datalog notation)

```
q :- Directors(did,'Tim','Burton'),Movie_Directors(did,mid)
```

[Meliou et al., 2010]

Responsibility: example

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$$\rho_{r_1} = \frac{1}{2} \qquad \Gamma = \{r_2\}$$

[Meliou et al., 2010]

Responsibility dichotomy

PTIME	NP-hard
$q_1 :- \quad R(x,y), S(y,z)$	$h_1^* :- \quad A(x), B(y), C(z), W(x,y,z)$
$q_2 :- \quad A(x) S_1(x,v), S_2(v,y), B(y,u), S_3(y,z), D(z,w), C(z)$	$h_2^* :- \quad R(x,y), S(y,z), T(z,x)$
	$h_3^* :- \quad A(x), B(y), C(z), R(x,y), S(y,z), T(z,x)$

[Meliou et al., 2010]

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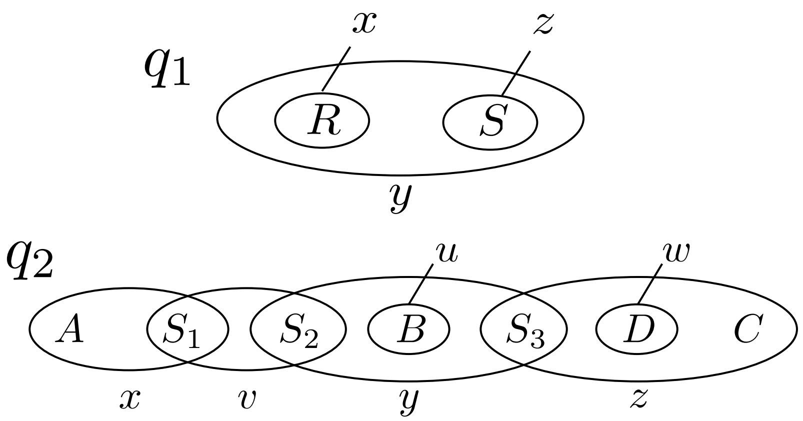

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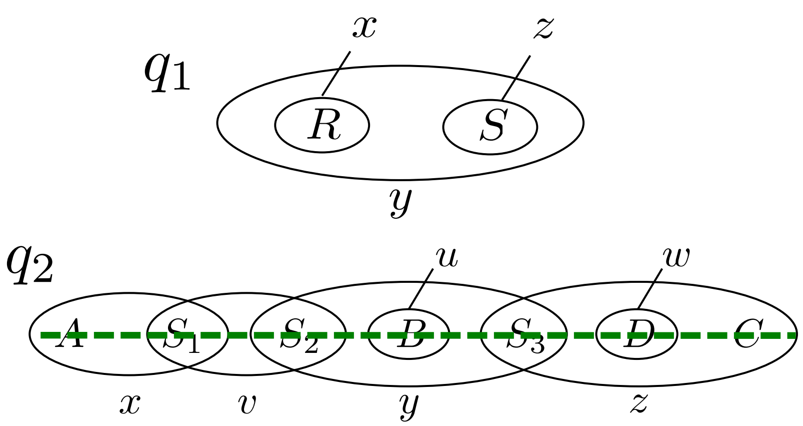

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Responsibility dichotomy

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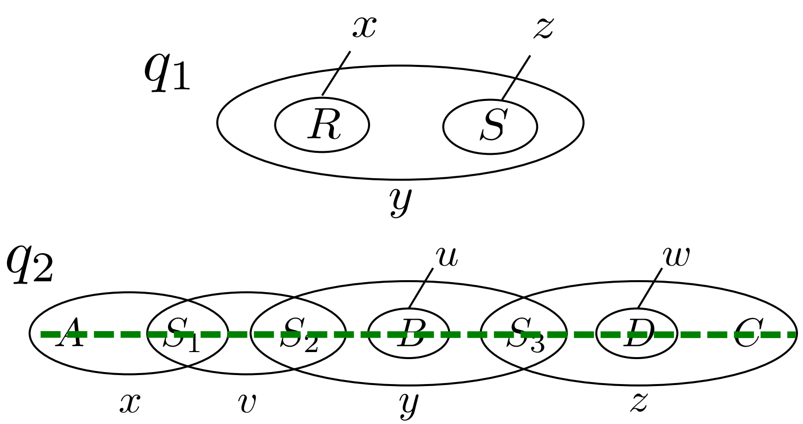
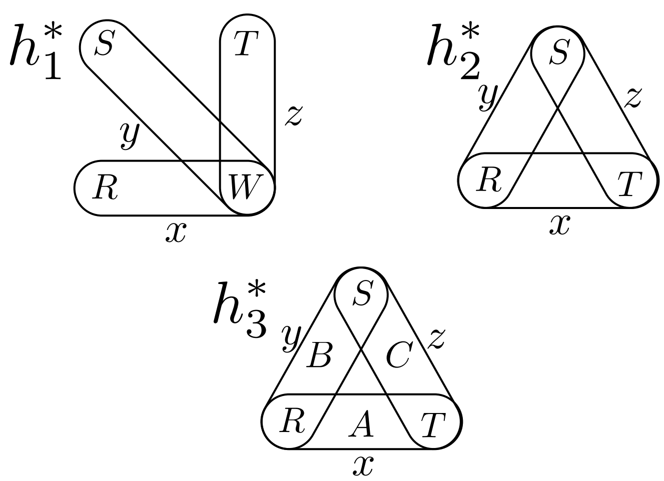
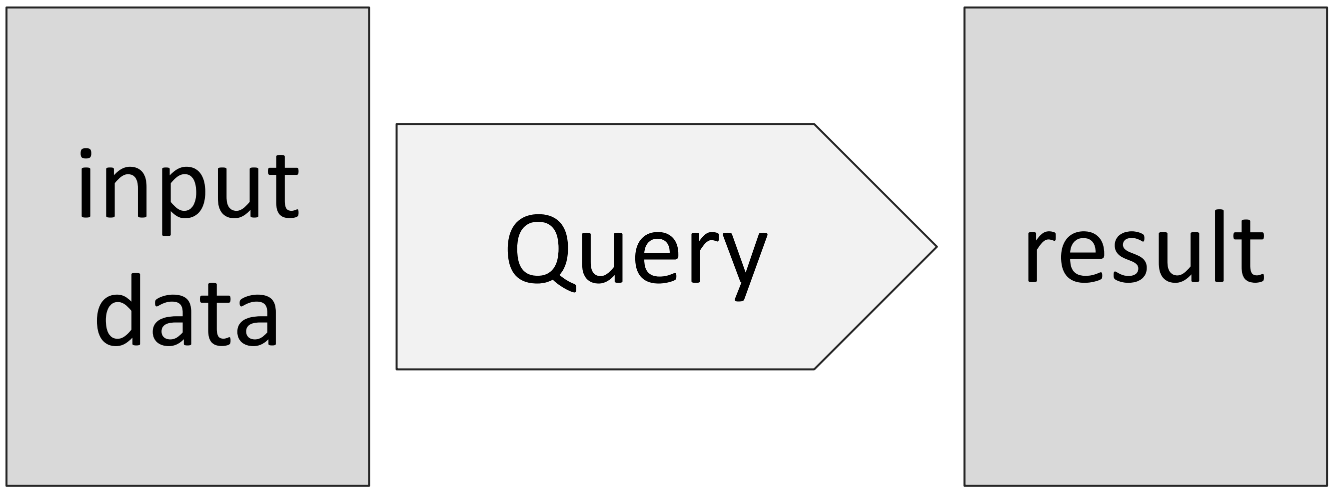




Responsibility in practice



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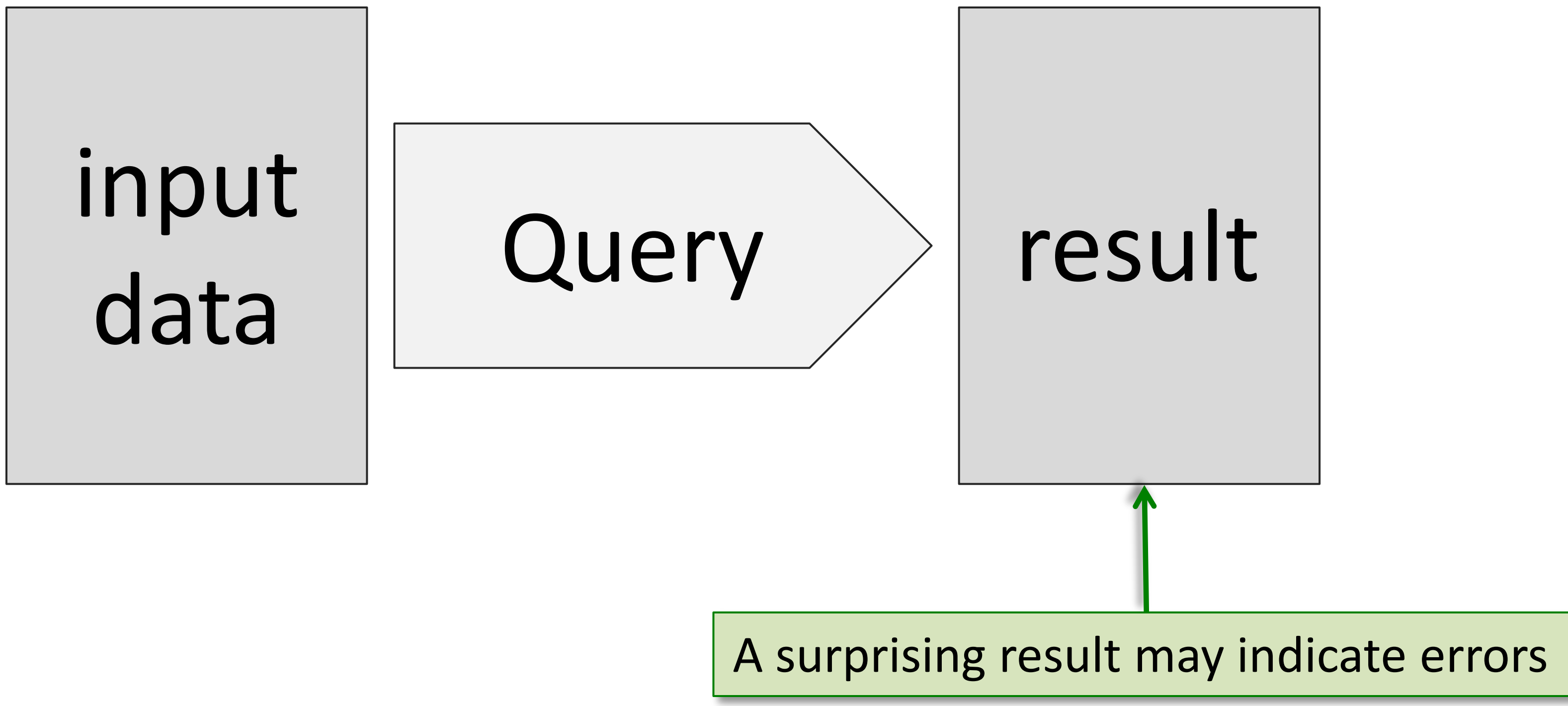

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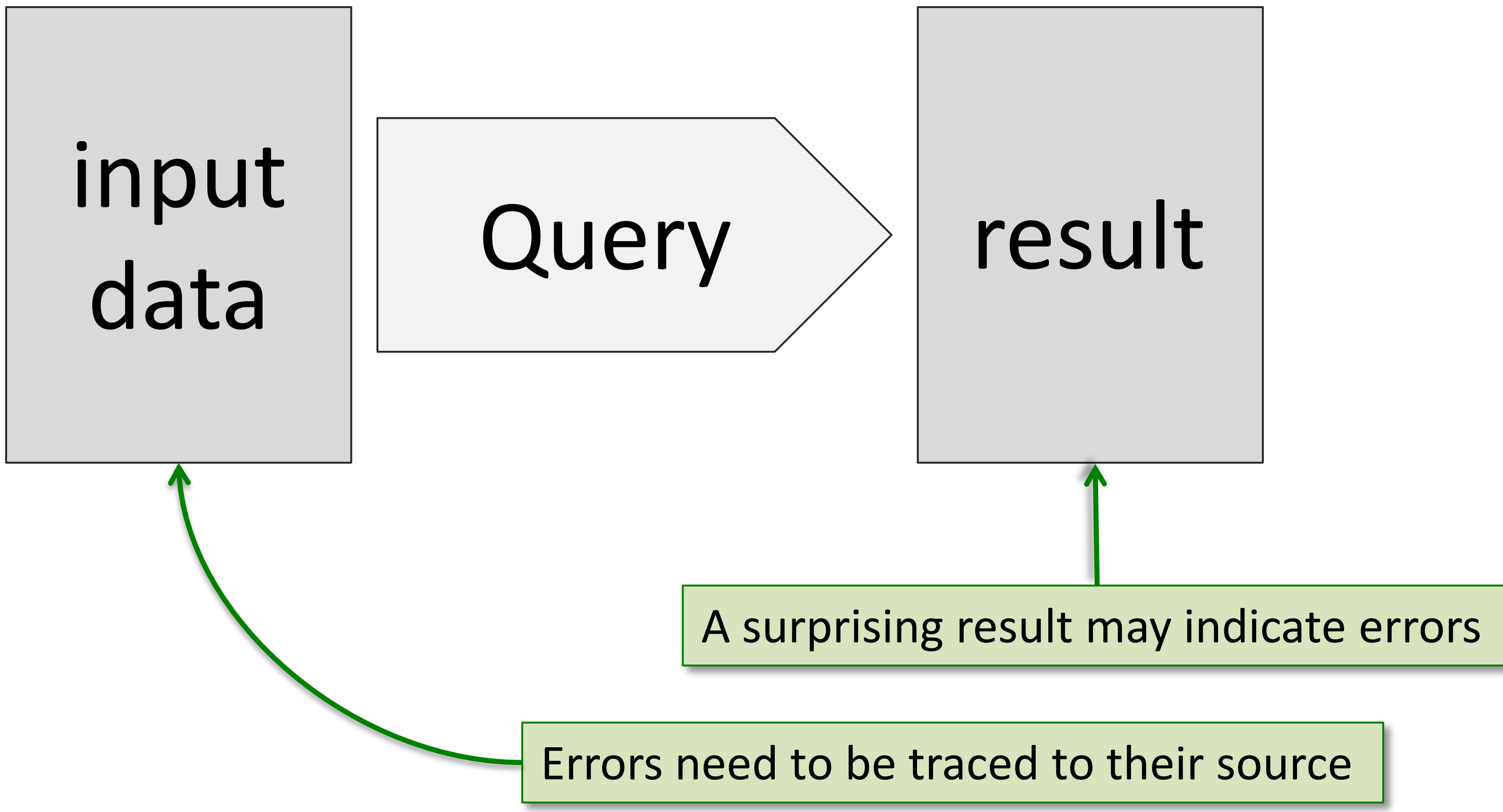

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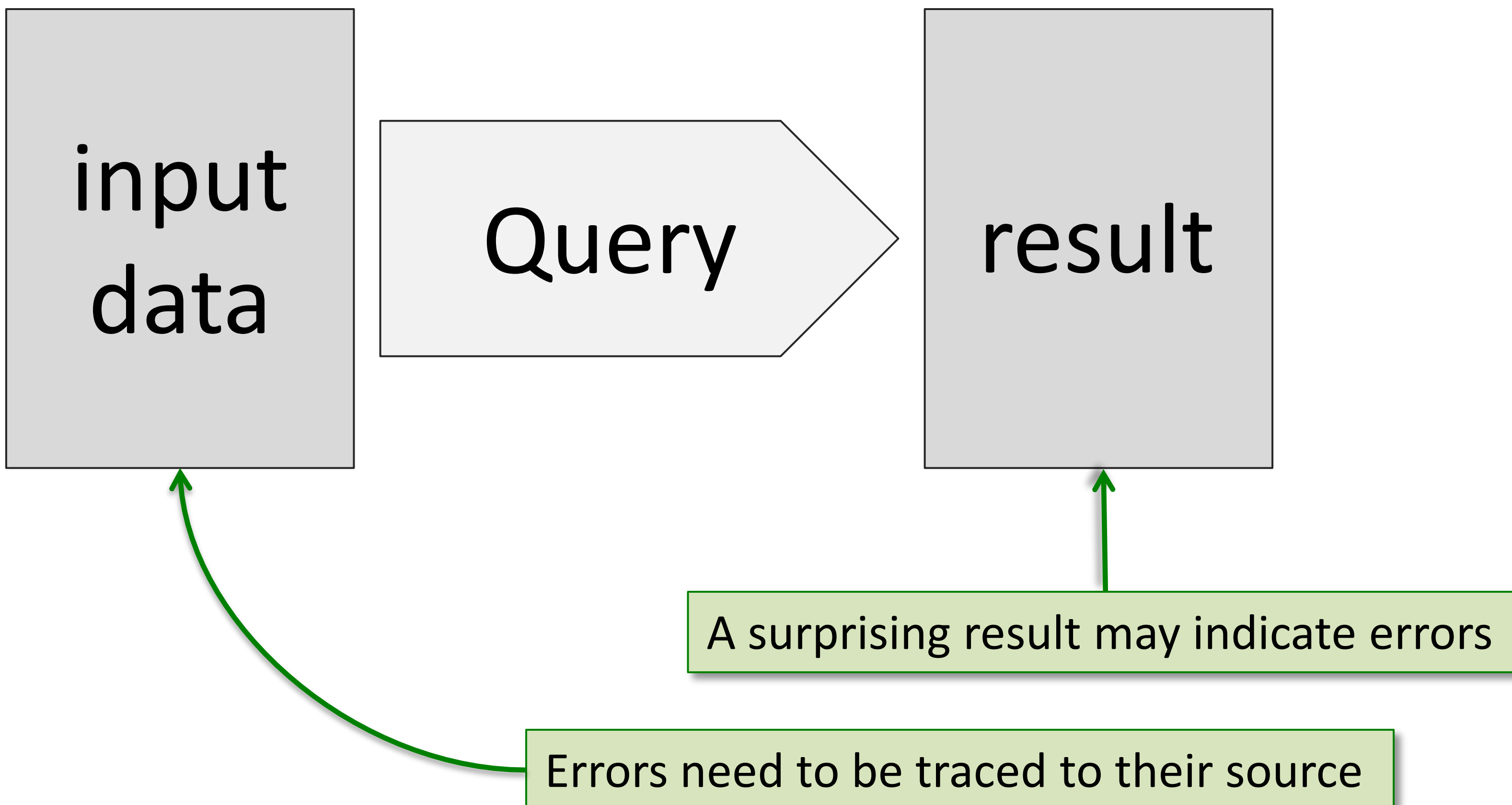

Post-factum data cleaning

[Meliou et al., 2011]

Context Aware Recommendations

Data

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Context Aware Recommendations

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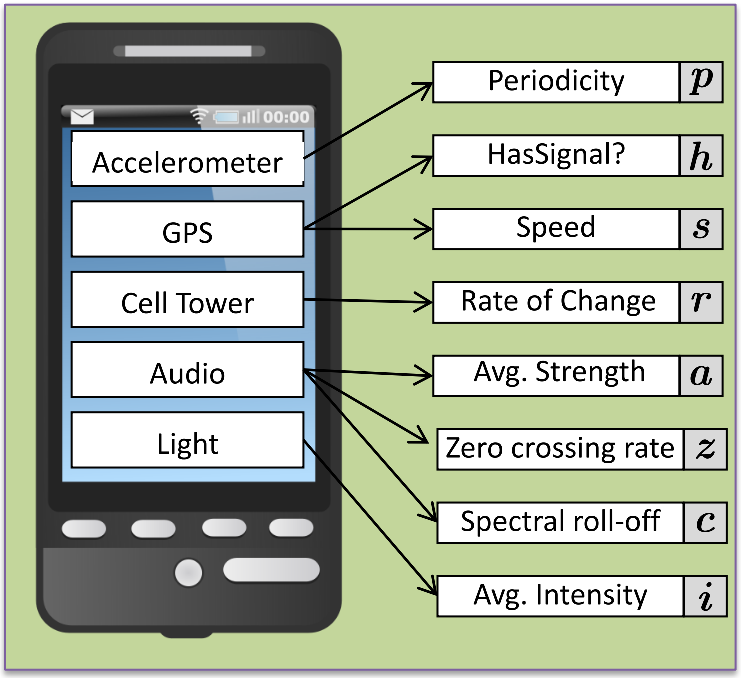
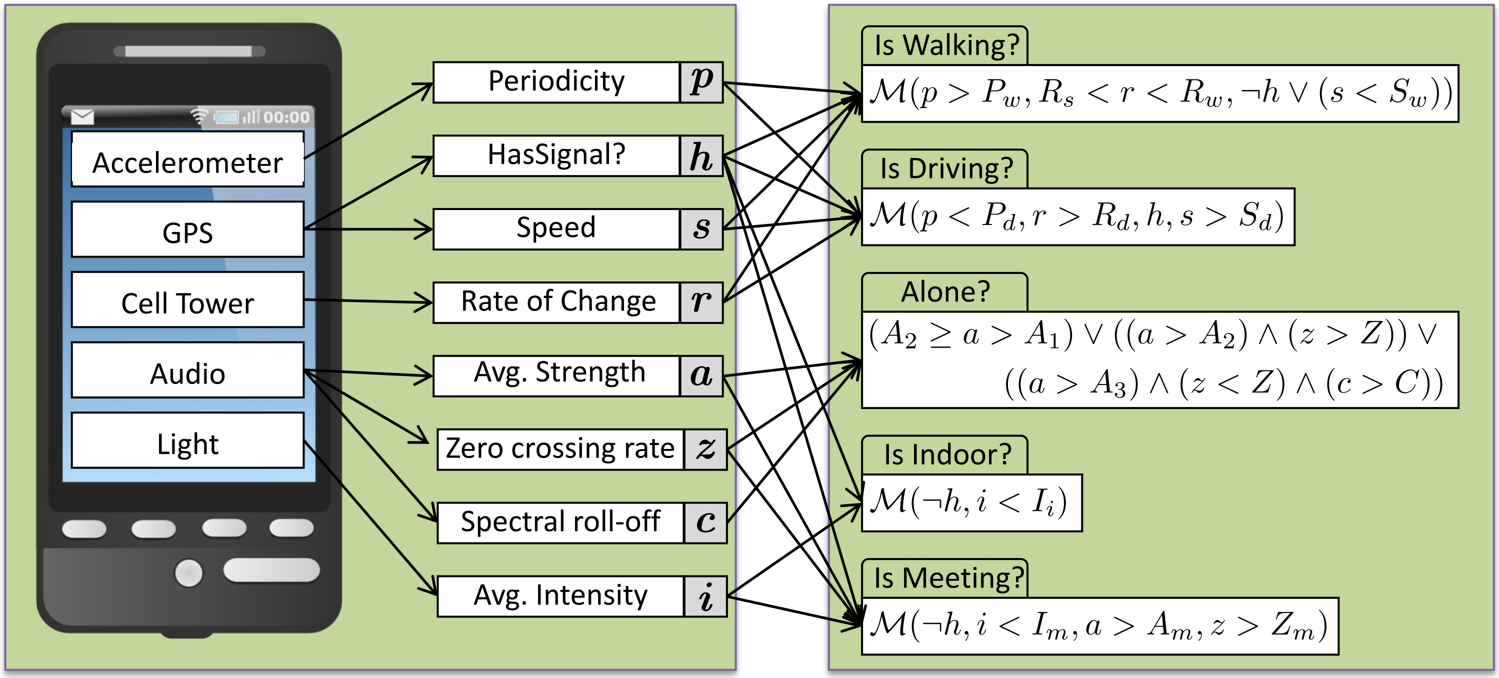


[Meliou et al., 2011]

Context Aware Recommendations

Data

Transformations



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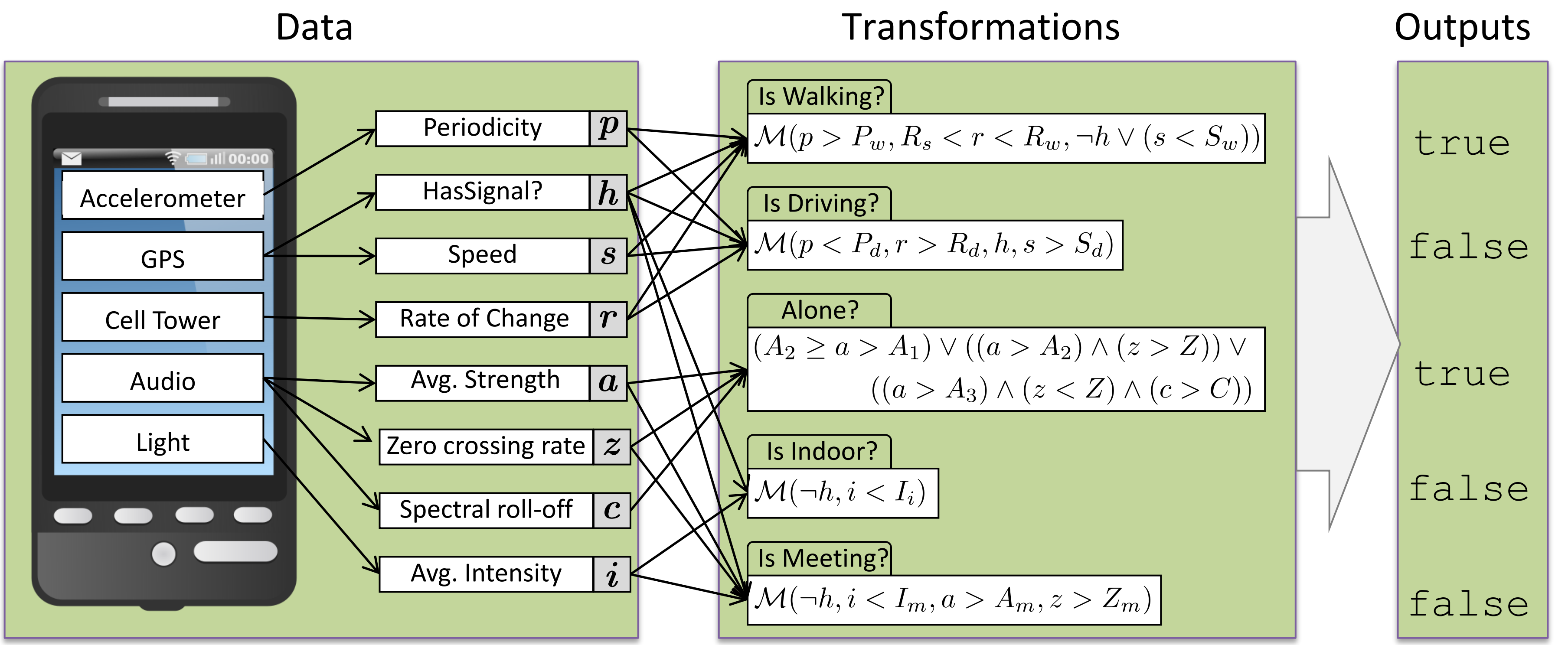

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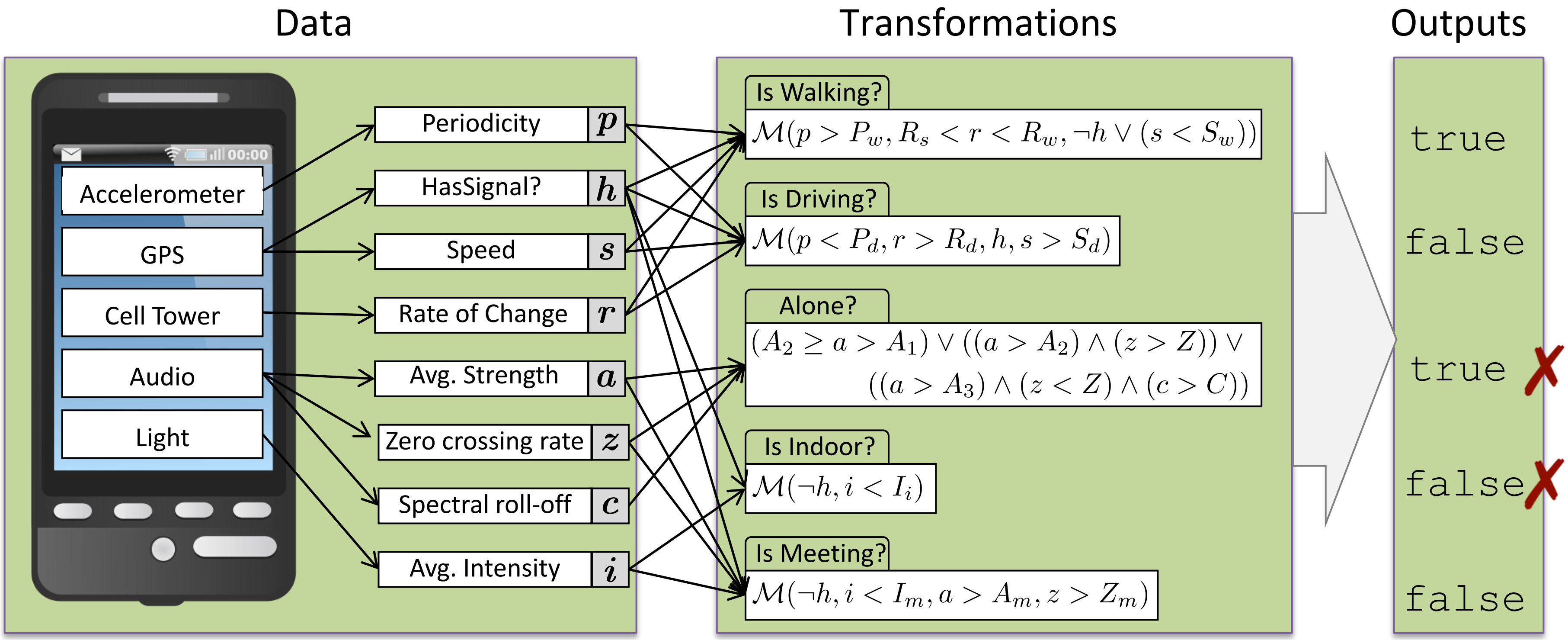

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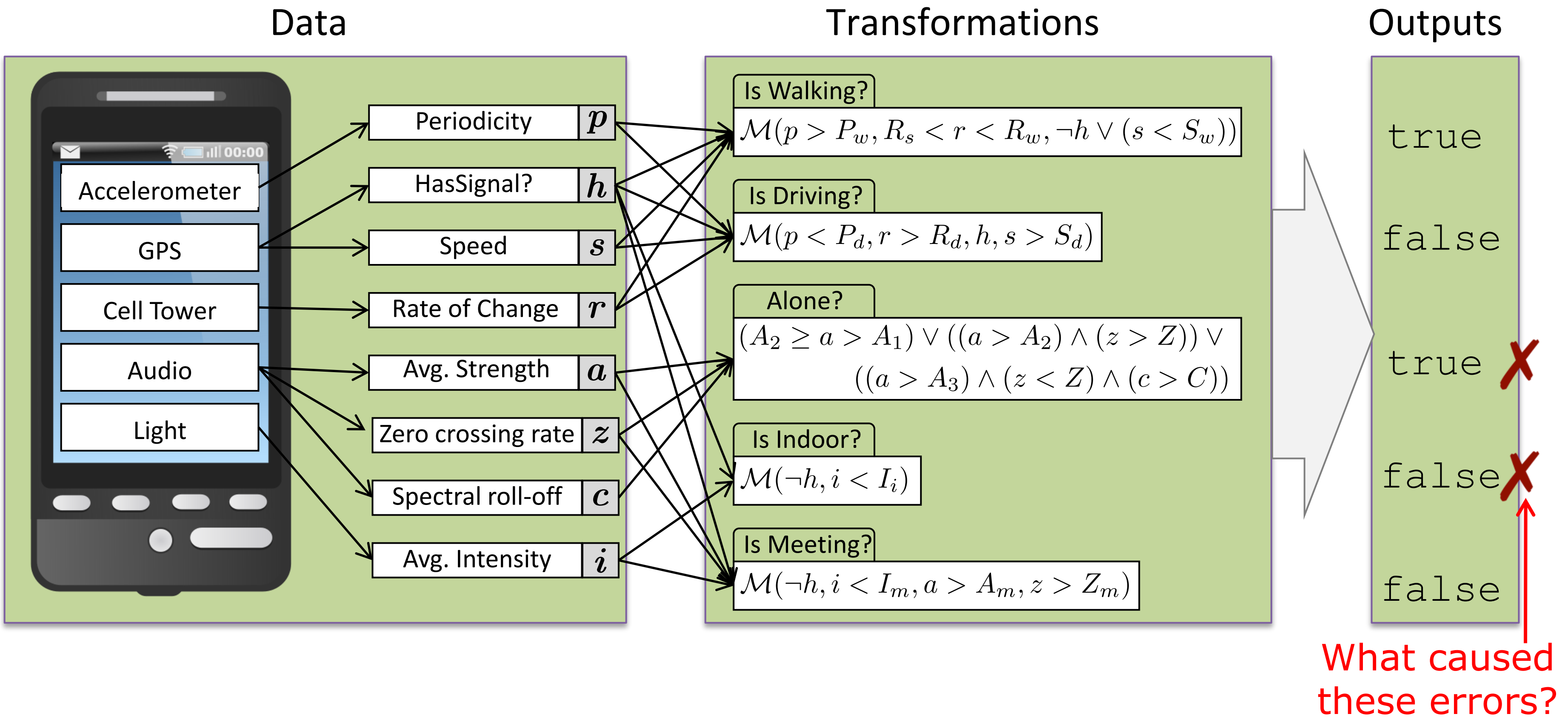

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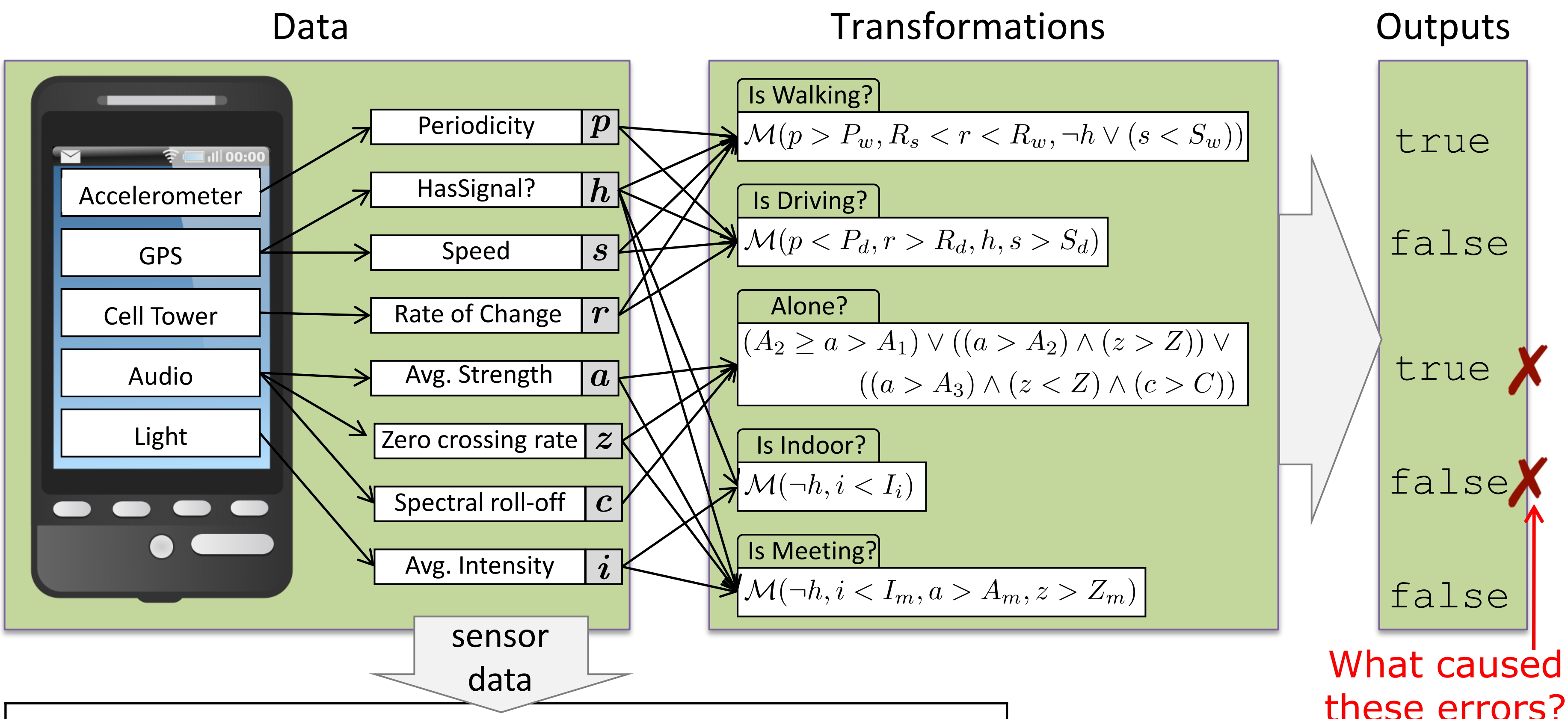
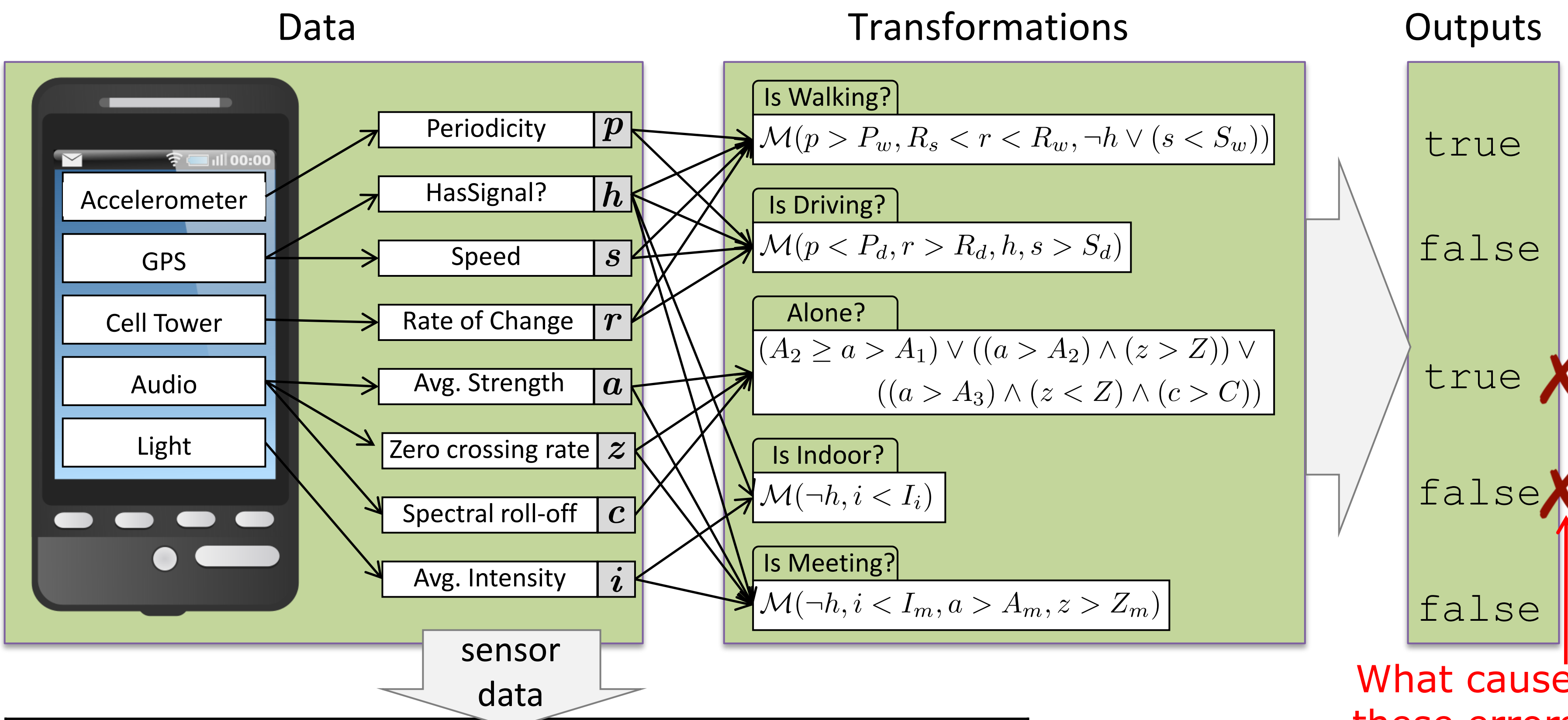


0.016	True	0.067	0	0.4	0.004	0.86	0.036	10
0.0009	False	0	0	0.2	0.0039	0.81	0.034	68
0.005	True	0.19	0	0.03	0.003	0.75	0.033	17
0.0008	True	0.003	0	0.1	0.003	0.8	0.038	18

[Meliou et al., 2011]

Context Aware Recommendations



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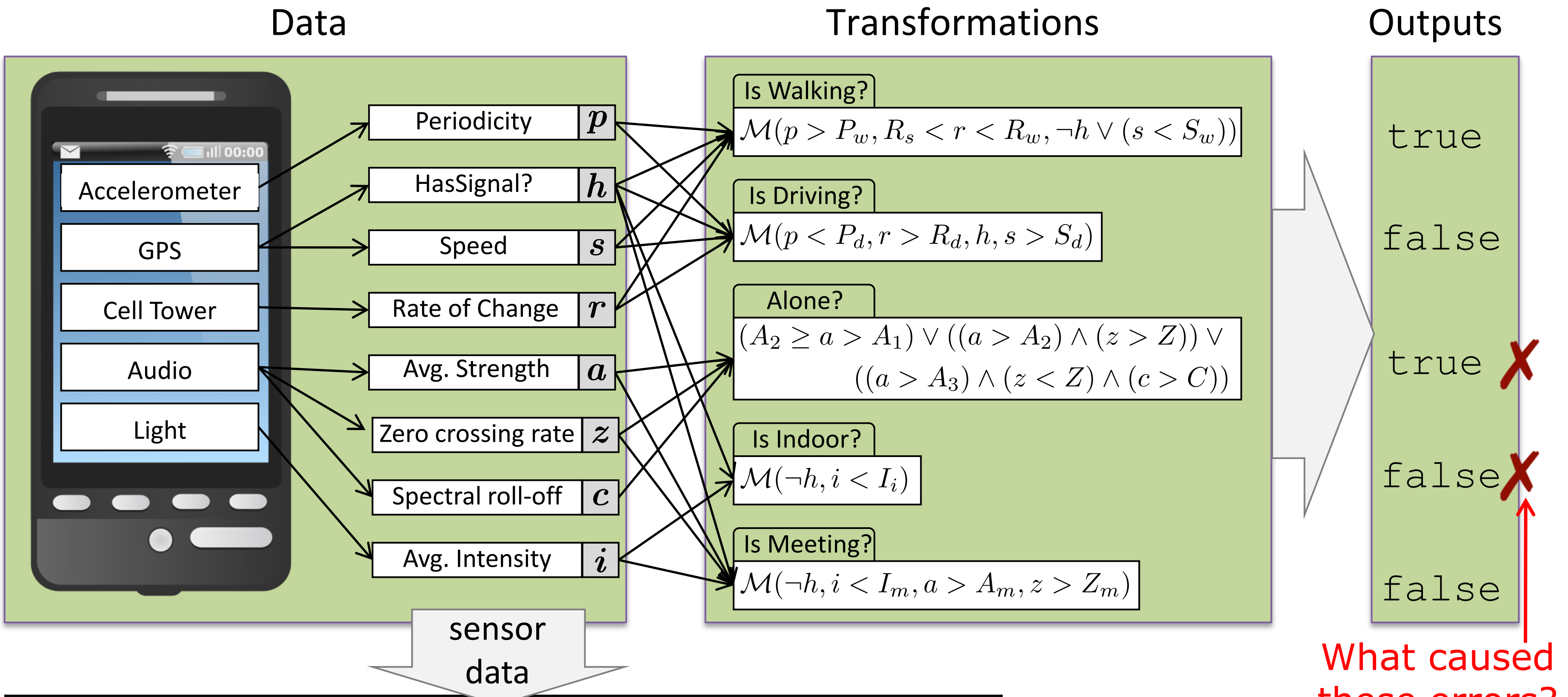
What caused these errors?

Sensors may be faulty or inhibited

[Meliou et al., 2011]

Context Aware Recommendations



0.016	True	0.067	0	0.4	0.004	0.86	0.036	10
0.0009	False	0	0	0.2	0.0039	0.81	0.034	68
0.005	True	0.19	0	0.03	0.003	0.75	0.033	17
0.0008	True	0.003	0	0.1	0.003	0.8	0.038	18

Sensors may be faulty or inhibited

It is not straightforward to spot such errors in the provenance

[Meliou et al., 2011]

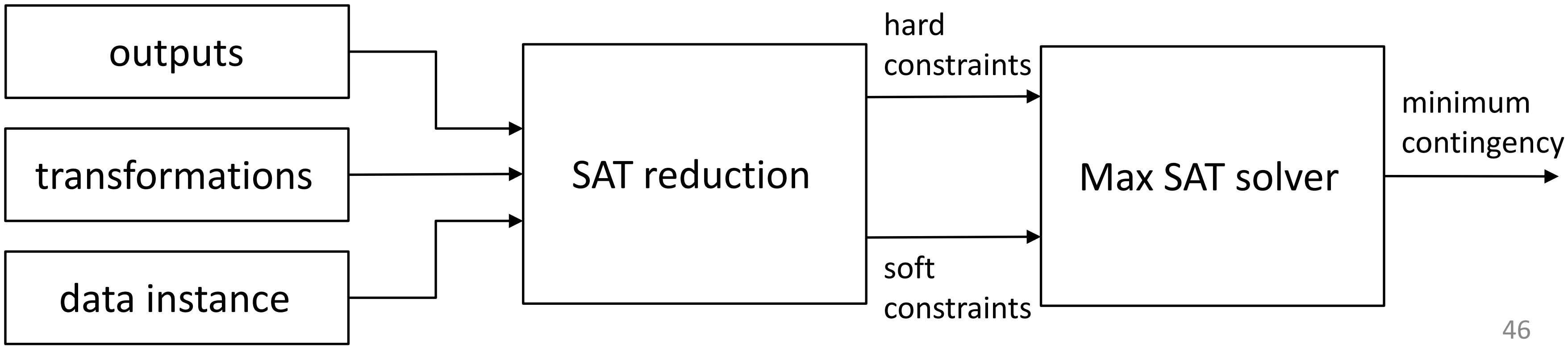
Solution

- Extension to view-conditioned causality
  - Ability to condition on multiple correct or incorrect outputs

[Meliou et al., 2011]

Solution

- Extension to view-conditioned causality
  - Ability to condition on multiple correct or incorrect outputs
- Reduction of computing responsibility to a Max SAT problem
  - Use state-of-the-art tools



Reasoning with causality
vs
Learning causality

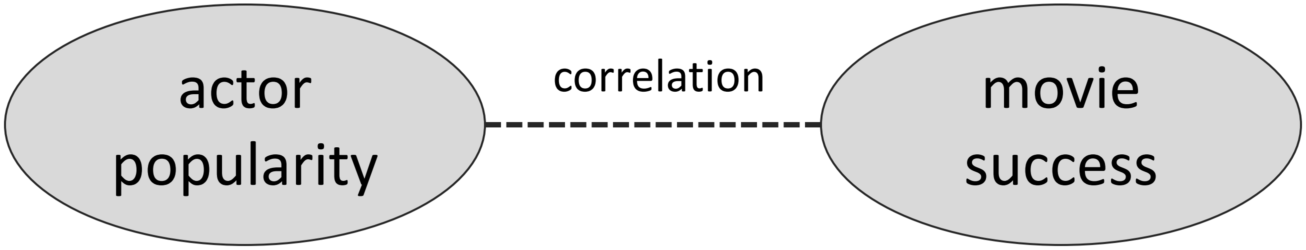
Reasoning with causality

vs

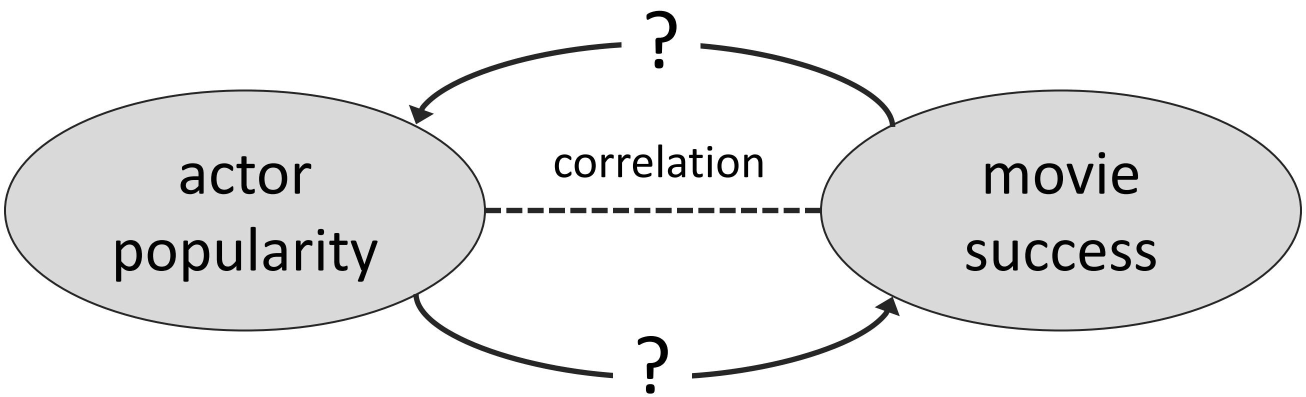
Learning causality

[Silverstein et al., 1998] [Maier et al., 2010]

Learning causal structures

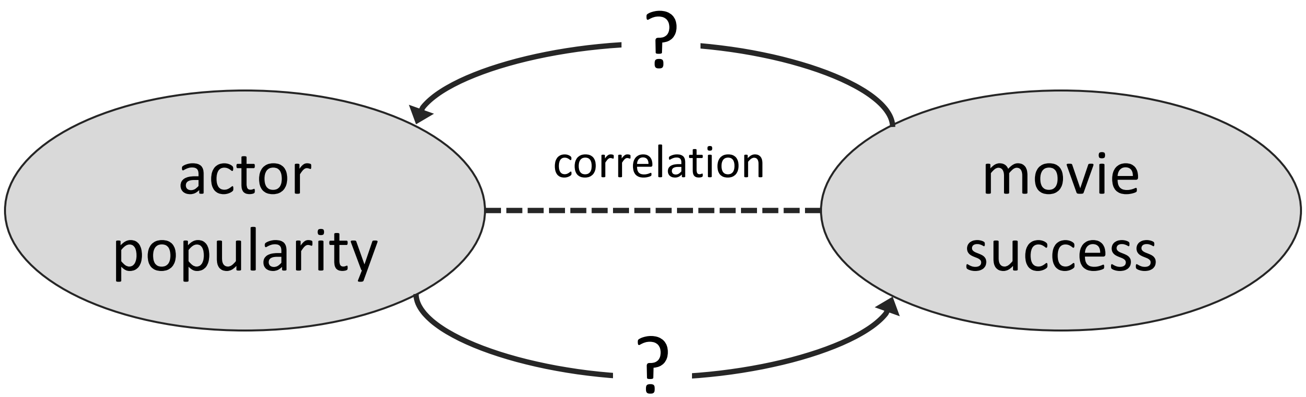


Learning causal structures



[Silverstein et al., 1998] [Maier et al., 2010]

Learning causal structures



Conditional independence:
Is one actor's popularity conditionally independent of the popularity of other actors appearing in the same movie, given that movie's success

Application of the Markov condition

[Mayrhofer et al., 2008]

Learning causal structures

Causal intuition in humans:
Understand it to discover better causal models from data

- Experimentally test how humans make associations
- Discovery: Humans use context, often violating Markovian conditions

Causality in databases: summary

- Provenance as causal network, tuples as causes
- Complexity for a query (rather than a data instance)
  - Many tractable cases
- Inferring causal relationships in data

Part 2: Explanations

a. Explanations for general DB query answers

b. Application-Specific DB Explanations

Part 2.a

• EXPLANATIONS FOR GENERAL DB QUERY ANSWERS

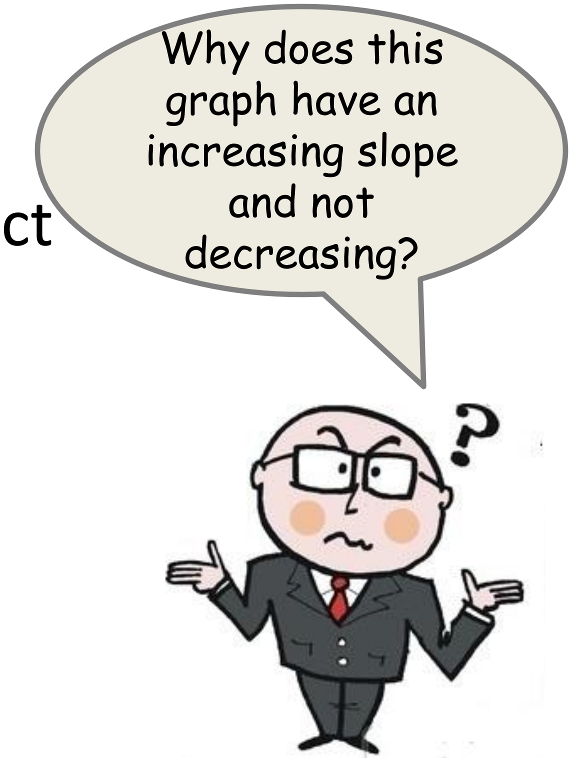
So far,

Fine-grained Actual Cause = Tuples

- Causality in AI and DB
  - defined by intervention

- In DB, goal was to compute the “responsibility” of individual input tuples in generating the output and rank them accordingly

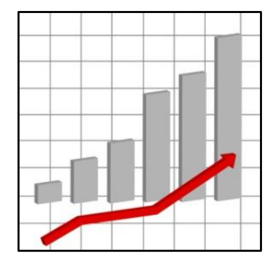
Coarse-grained Explanations = Predicates



- For "big data",
  individual input tuples may have little effect in explaining outputs. We need broader, coarse-grained explanations,
  e.g., given by predicates

- More useful to answer questions on aggregate queries visualized as graphs

- Less formal concept than causality
  - definition and ranking criteria sometimes depend on applications (more in part 2.b)

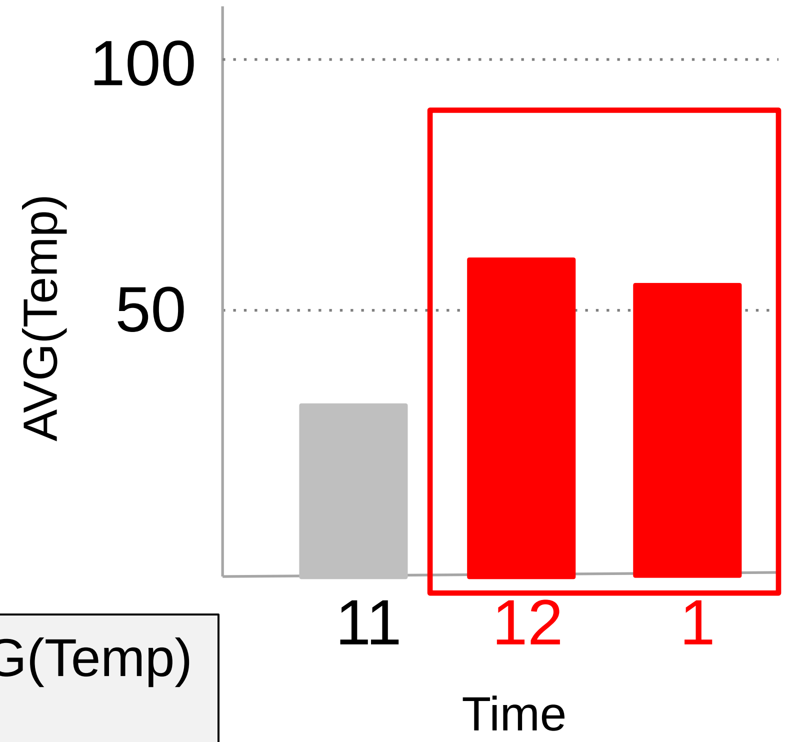


[Wu-Madden, 2013]

Example Question #1

Question on aggregate output

Time	Sensor	Volt	Humid	Temp
11	1	2.64	0.4	34
11	2	2.65	0.3	40
11	3	2.63	0.3	35
12	1	2.7	0.5	35
12	2	2.7	0.4	38
12	3	2.2	0.3	100
1	1	2.7	0.5	35
1	2	2.65	0.5	38
1	3	2.3	0.5	80

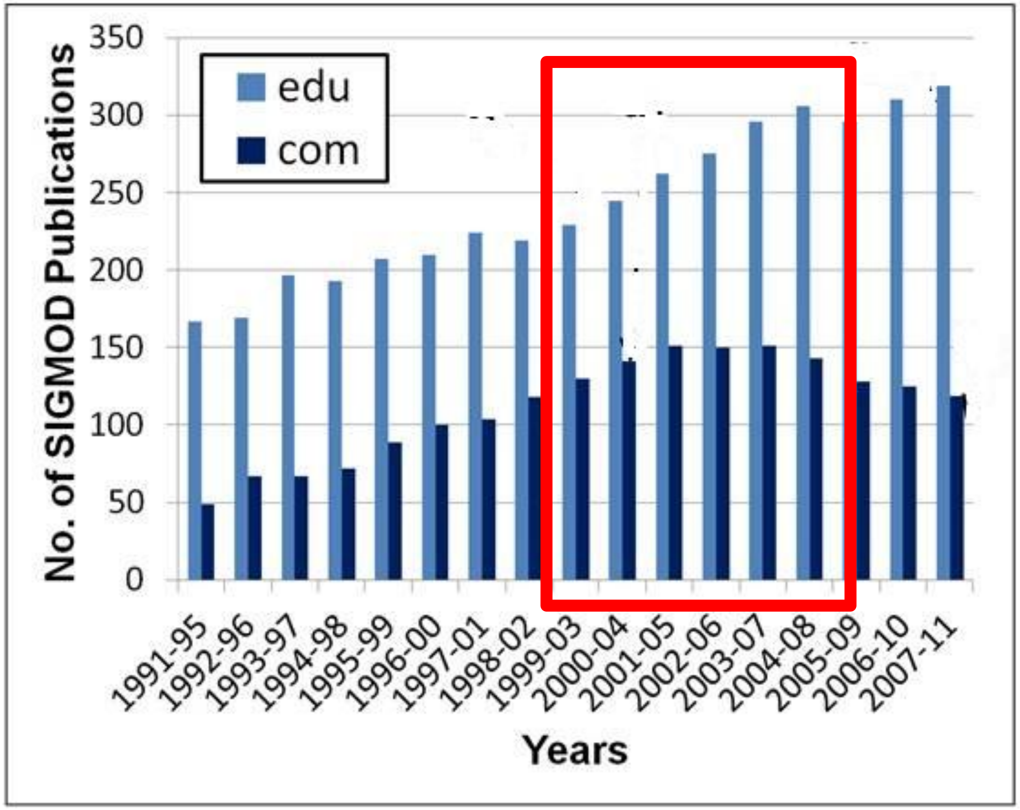



```
SELECT time, AVG(Temp)
FROM readings
GROUP BY time
```

Why is the avg. temp. high at time 12 pm and 1 pm, and low at time 11 am?

[Roy-Suciu, 2014]

Example Question #2



Question on aggregate output

Dataset:
Pre-processed DBLP
+ Affiliation data

(not all authors have affiliation info)

Why is there a peak for #sigmod papers from industry in 2000-06, while #academia papers kept increasing?

Ideal goal: Why $\equiv$ Causality

But, TRUE causality is difficult…

- True causality needs controlled, randomized experiments (repeat history)
- The database often does not even have all variables that form actual causes
- Given a limited database, broad explanations are more informative than actual causes (next slide)

Broad Explanations are more informative than Actual Causes

- We cannot repeat history and individual tuples are less informative

Time	Sensor	Volt	Humid	Temp
11	1	2.64	0.4	34
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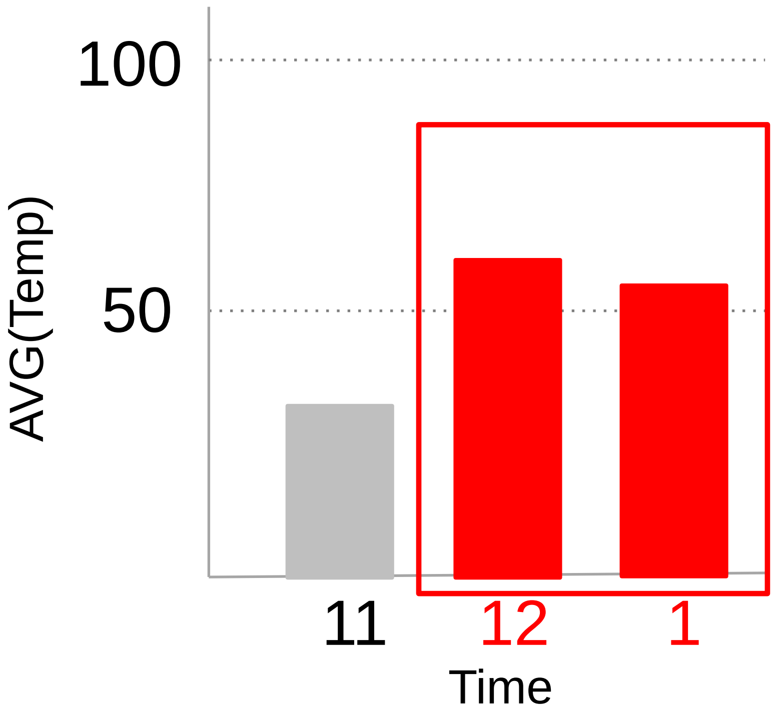

Less informative

Broad Explanations are more informative than Actual Causes

- We cannot repeat history and individual tuples are less informative

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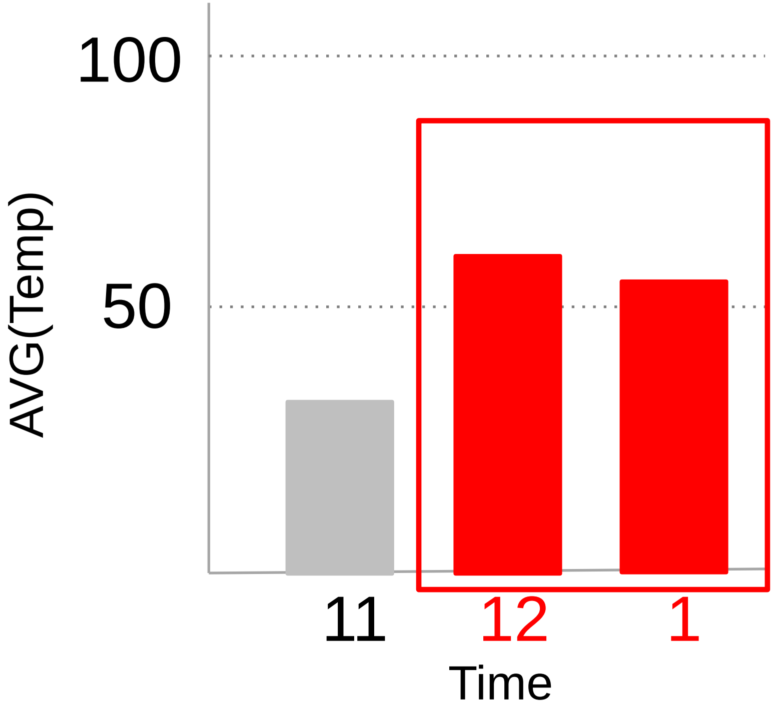

More informative

predicate:
Volt < 2.5 & Sensor = 3

Explanation can still be defined using "intervention" like causality!

Explanation by Intervention

- **Causality (in AI) by intervention:**

X is

a cause of Y,

if removal of X

also removes Y

keeping other conditions unchanged

Explanation by Intervention

- **Causality (in AI) by intervention:**

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- **Explanation (in DB) by intervention:**

Explanation by Intervention

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- **Explanation (in DB) by intervention:**

A predicate X is

Explanation by Intervention

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A predicate X is

an explanation of one or more outputs Y,

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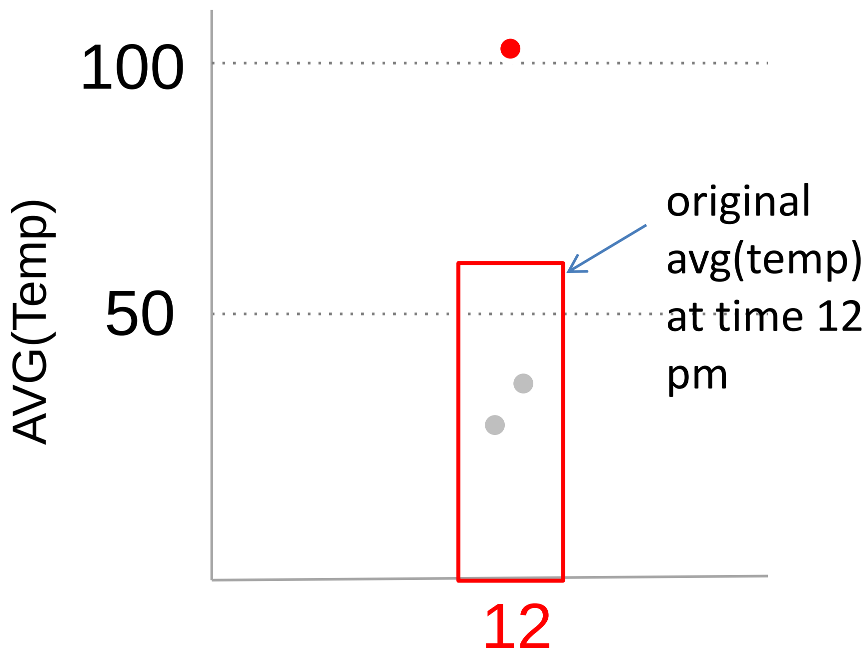

Why is the AVG(temp.) at 12pm so <u>high</u>?

predicate: Sensor = 3

[Wu-Madden, 2013]

Time	Sensor	Volt	Humid	Temp
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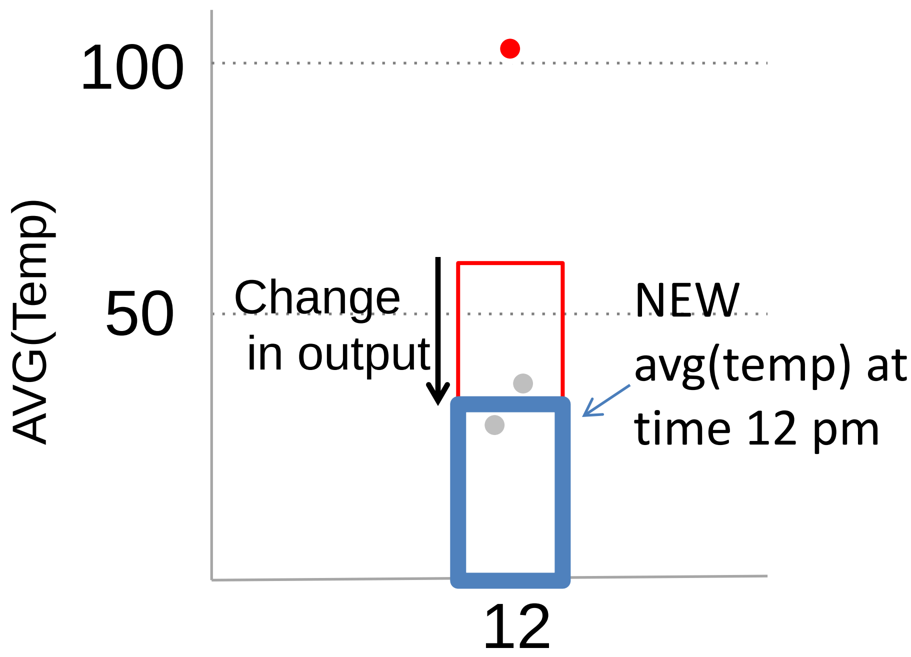
Intervention!



Why is the AVG(temp.) at 12pm so <u>high</u>?

predicate: Sensor = 3

Now lower!

We need a scoring function for ranking and returning top explanations…

Scoring Function: Influence

$$\text{infl}_{\text{agg}}(p) \quad = \quad \frac{\text{Change in output}}{\text{(\# of records to make the change)}}$$

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Sensor = 3

$$\frac{21.1}{1} = 21.1$$

One tuple
causes the change

[Wu-Madden, 2013]

Scoring Function: Influence

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One tuple
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Sensor = 3 or 2

$$\frac{22.6}{2} = 11.3$$

Two tuples
cause the change

[Wu-Madden, 2013]

Scoring Function: Influence

$$\mathrm{infl}_{agg}(p) = \frac{\text{Change in output}}{\text{(\# of records to make the change)}}$$

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Leave the choice to the user

[Wu-Madden, 2013]

Scoring Function: Influence

$$\text{infl}_{agg}(p) = \frac{\text{Change in output}}{(\text{\# of records to make the change})^{\lambda}}$$

Sensor = 3

$$\frac{21.1}{1} = 21.1$$

One tuple
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Sensor = 3 or 2

$$\frac{22.6}{2} = 11.3$$

Two tuples
cause the change

Leave the choice to the user

[Wu-Madden, 2013]

Scoring Function: Influence

$$\text{infl}_{agg}(p) = \frac{\text{Change in output}}{(\text{\# of records to make the change})^{\lambda}}$$

Top explanation for λ = 1

Sensor = 3

$$\frac{21.1}{1} = 21.1$$

One tuple
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Sensor = 3 or 2

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Two tuples
cause the change

Leave the choice to the user

[Wu-Madden, 2013]

Scoring Function: Influence

$$\text{infl}_{agg}(p) = \frac{\text{Change in output}}{(\text{\# of records to make the change})^{\lambda}}$$

Top explanation for λ = 1

Sensor = 3

$$\frac{21.1}{1} = 21.1$$

One tuple
causes the change

Top explanation for λ = 0

Sensor = 3 or 2

$$\frac{22.6}{2} = 11.3$$

Two tuples
cause the change

Leave the choice to the user

Summary: System "Scorpion"

- Input: SQL query, outliers, normal values, λ, …
- Output: predicate p having highest influence

[Wu-Madden, 2013]

Summary: System “Scorpion”

- Input: SQL query, outliers, normal values, λ, …
- Output: predicate p having highest influence
- Uses a top-down decision tree-based algorithm that recursively partitions the predicates and merges similar predicates
  - Naïve algo is too slow as the search space of predicates is huge

[Wu-Madden, 2013]

Summary: System “Scorpion”

- Input: SQL query, outliers, normal values, λ, …
- Output: predicate p having highest influence
- Uses a top-down decision tree-based algorithm that recursively partitions the predicates and merges similar predicates
  - Naïve algo is too slow as the search space of predicates is huge
- Simple notion of intervention (implicit):

  Delete tuples that satisfy a predicate

[Roy-Suciu, 2014]

More Complex Intervention: Causal Paths in Data

Intervention in general due to a given predicate:

Delete the tuples that satisfy the predicate,

also delete tuples that directly or indirectly depend on them through causal paths

[Roy-Suciu, 2014]

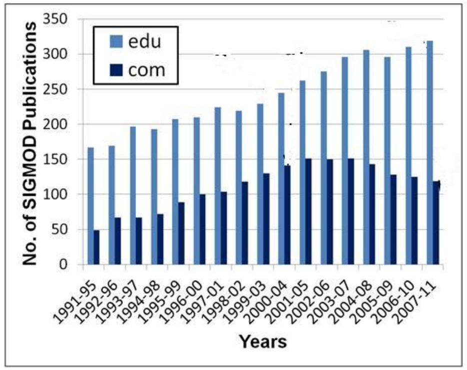
More Complex Intervention: Causal Paths in Data

Intervention in general due to a given predicate:

Delete the tuples that satisfy the predicate,

also delete tuples that directly or indirectly depend on them through causal paths

- Causal path is inherent to the data and is independent of the DB query or question asked by the user



- Next: Illustration with the DBLP example

[Roy-Suciu, 2014]

Causal Paths by Foreign Key Constraints

- Causal path $X \rightarrow Y$: removing X removes Y
- Analogy in DB:

Foreign key constraints and cascade delete semantics

[Roy-Suciu, 2014]

Causal Paths by Foreign Key Constraints

- Causal path X $\rightarrow$ Y: removing X removes Y
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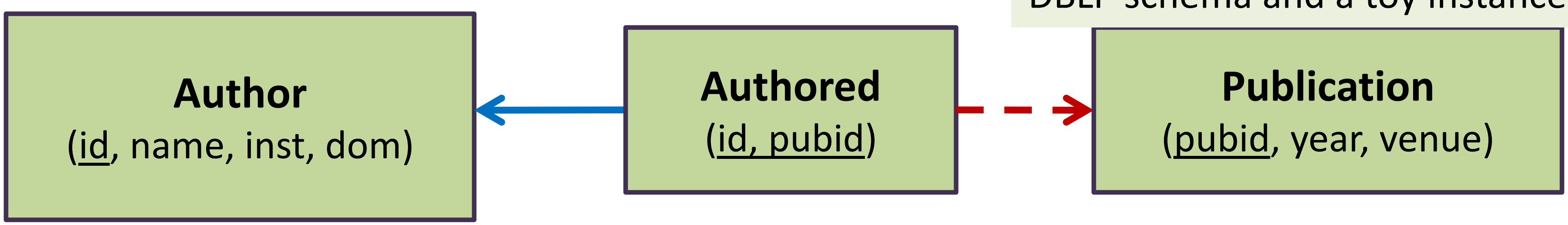
DBLP schema and a toy instance



Author

id	name	inst	dom
A1	JG	C.edu	edu
A2	RR	M.com	com
A3	CM	I.com	com

Publication

pubid	year	venue
P1	2001	SIGMOD
P2	2011	VLDB
P3	2001	SIGMOD

Authored

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[Roy-Suciu, 2014]

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Author (id, name, inst, dom) $\leftarrow$ **Authored** (id, pubid) $\dashrightarrow$ **Publication** (pubid, year, venue)

Standard F.K. (cascade delete)

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[Roy-Suciu, 2014]

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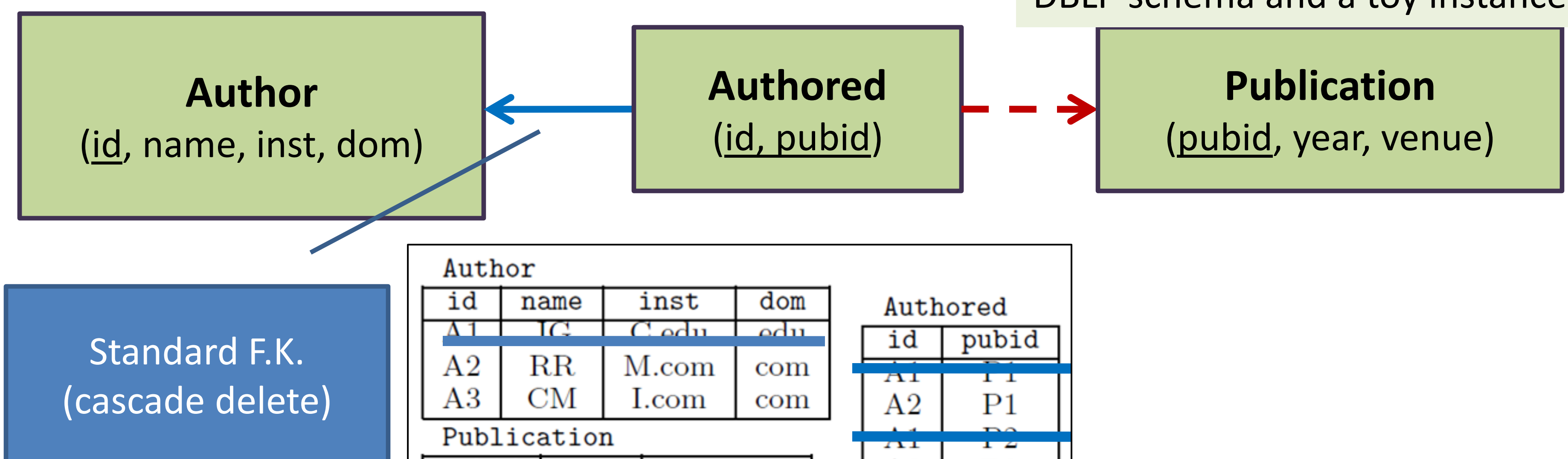

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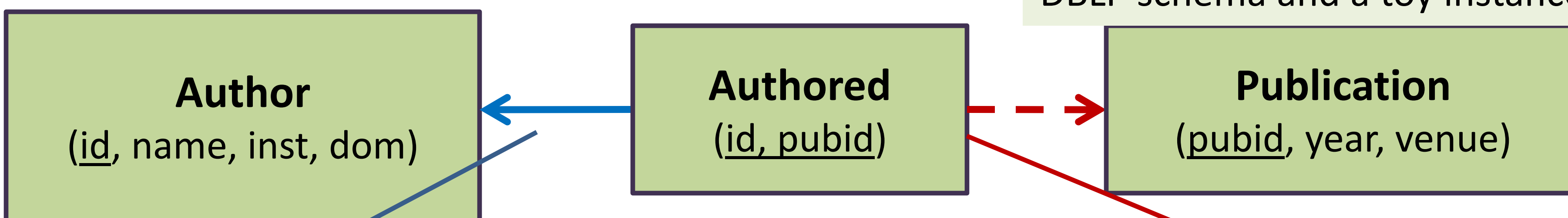

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Back and Forth F.K.
(cascade delete
+
reverse cascade delete)

[Roy-Suciu, 2014]

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[Roy-Suciu, 2014]

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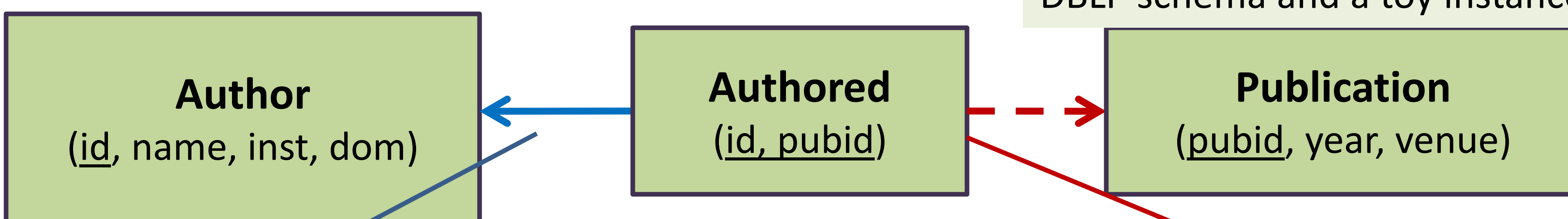

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[Roy-Suciu, 2014]

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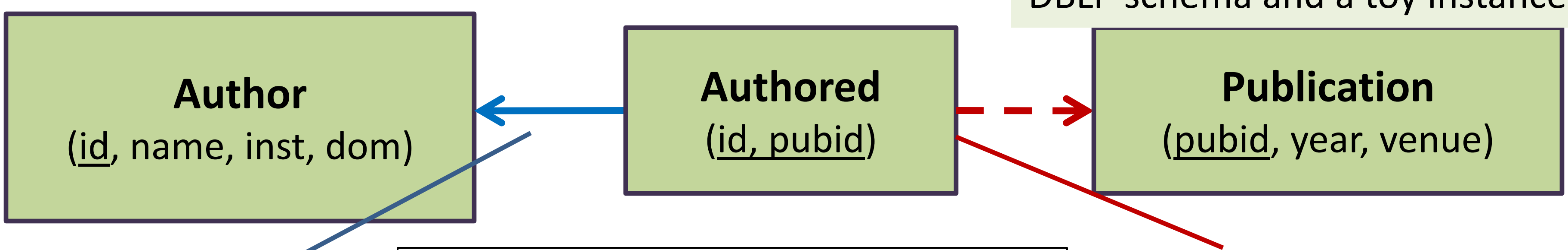

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Back and Forth F.K.
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[Roy-Suciu, 2014]

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Authored
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A3	P2
~~A2~~	~~P3~~
A3	P3

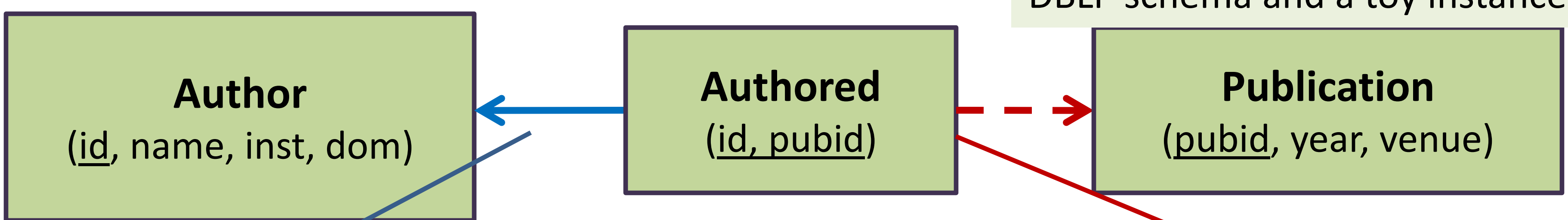
[Roy-Suciu, 2014]

Causal Paths by Foreign Key Constraints

Intuition:
- An author **can exist** if one of her papers is deleted
- A paper **cannot exist** if any of its co-authors is deleted

Note: Both F.K.s could be standard

DBLP schema and a toy instance



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A3	P2
~~A2~~	~~P3~~
A3	P3

Back and Forth F.K.
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[Roy-Suciu, 2014]

Intervention through Causal Paths

Forward
Reverse

Author

id	name	inst	dom
A1	JG	C.edu	edu
A2	RR	M.com	com
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Publication

pubid	year	venue
P1	2001	SIGMOD
P2	2011	VLDB
P3	2001	SIGMOD

Authored

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[Roy-Suciu, 2014]

Intervention through Causal Paths

Candidate explanation predicate **ϕ : [name = ‘RR’]**

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Tuples T_0 that satisfy ϕ + Tuples reachable from T_0

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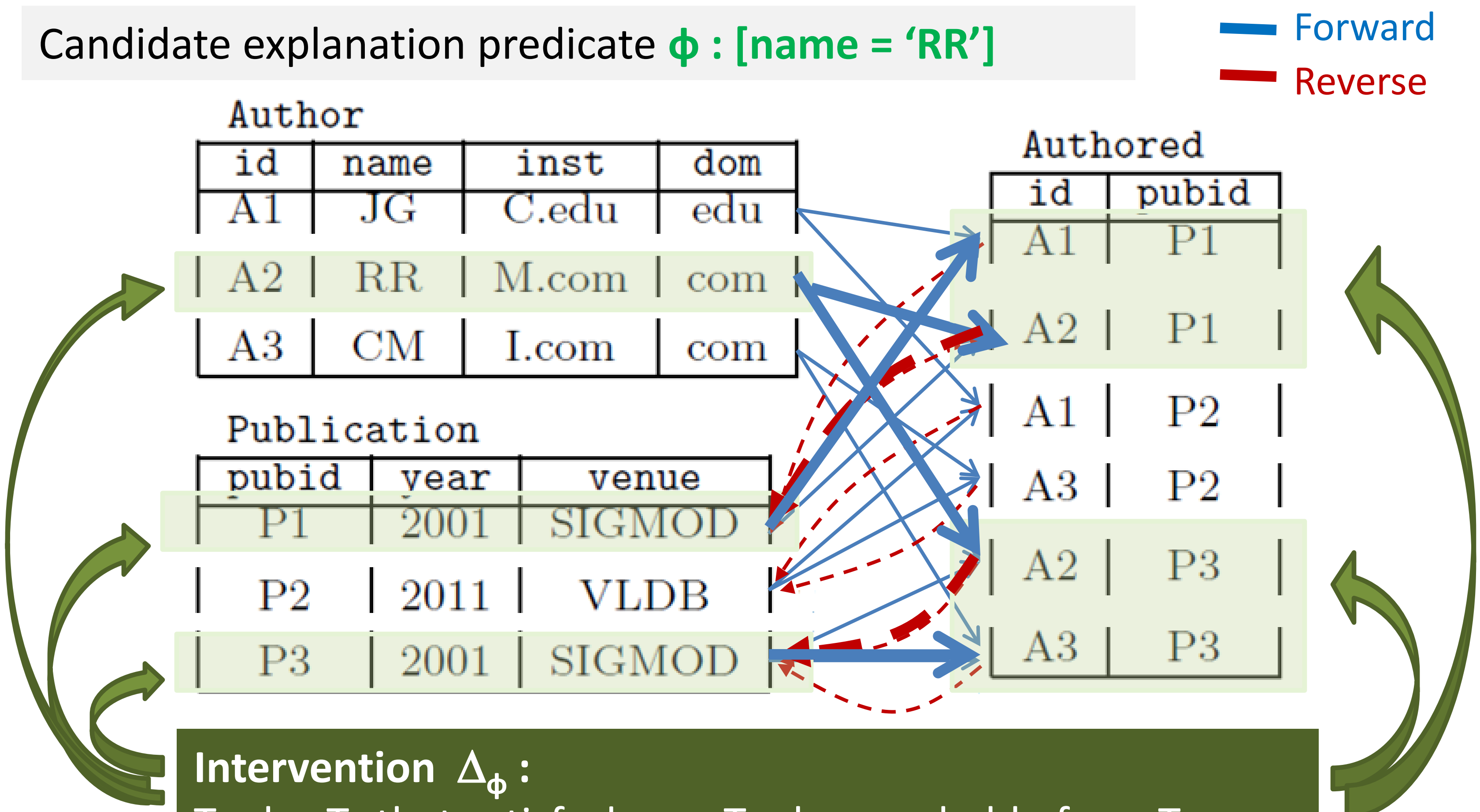

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Predicates on multiple tables require **universal relation**

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Predicates on multiple tables require **universal relation**

Intervention Δ_ϕ :
Tuples T_0 that satisfy ϕ + Tuples reachable from T_0

Given ϕ, computation of Δ_ϕ requires a recursive query

[Roy-Suciu, 2014]

Two sources of complexity

1. Huge search space of predicates (standard)
2. For any such predicate, run a recursive query to compute intervention (new)
   - The recursive query is poly-time, but still not good enough

[Roy-Suciu, 2014]

Two sources of complexity

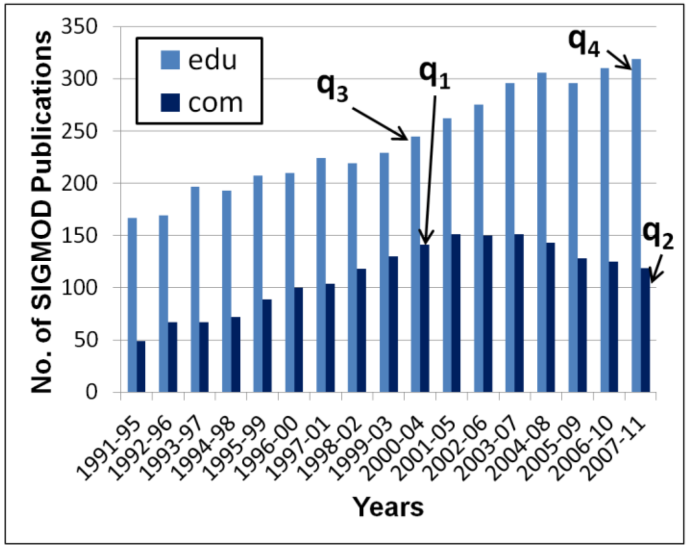
1. Huge search space of predicates (standard)
2. For any such predicate, run a recursive query to compute intervention (new)
   – The recursive query is poly-time, but still not good enough

- Data-cube-based bottom-up algorithm to address both challenges
  – Matches the semantic of recursive query for certain inputs, heuristic for others (open problem: efficient algorithm that matches the semantic for all inputs)

[Roy-Suciu, 2014]

Qualitative Evaluation (DBLP)

Hard due to lack of gold standard



Q. Why is there a peak for #sigmod papers from industry during 2000-06, while #academia papers kept increasing?

[Roy-Suciu, 2014]

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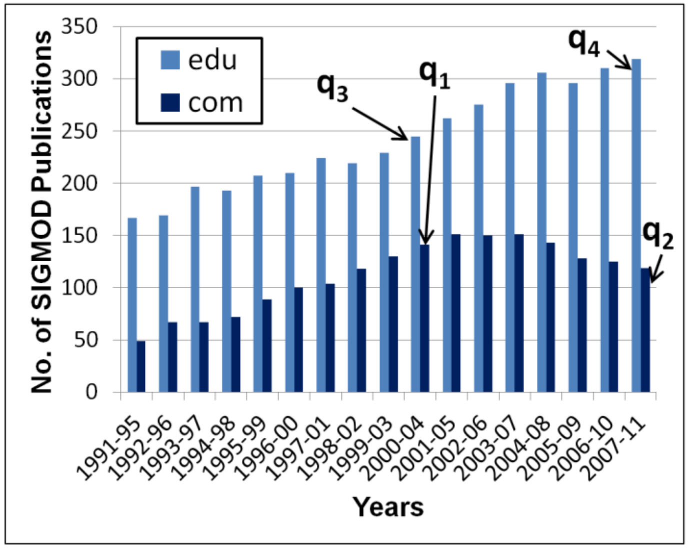

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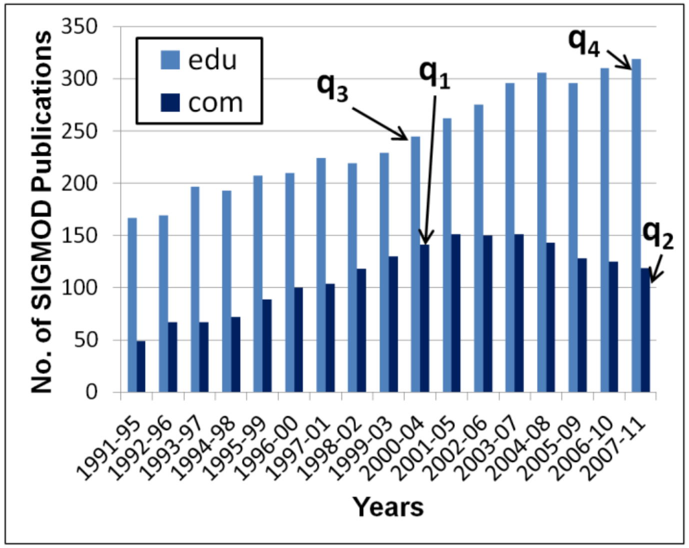

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Intuition:

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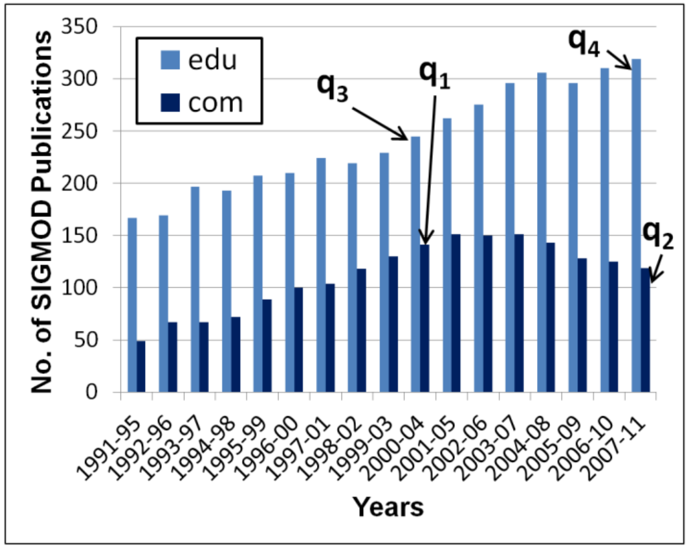

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Intuition:

1. If we remove these industrial labs and their senior researchers, the peak during 2000-04 is more flattened

2. If we remove these universities with relatively new but highly prolific db groups, the curve for academia is less increasing

Summary: Explanations for DB

In general, follow these steps:

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- **Define explanation**
  - Simple predicates, complex predicates with aggregates, comparison operators, …

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  - Delete tuples
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  - Independent of query/user question
- **Define intervention**
  - Delete tuples
  - Insert/update tuples (future direction)
  - Propagate through causal paths
- **Define a scoring function**
  - to rank the explanations based on their intervention
- **Find top-k explanations efficiently**

Part 2.b

• APPLICATION-SPECIFIC DB EXPLANATIONS

Application-Specific Explanations

1. Map-Reduce
2. Probabilistic Databases
3. Security
4. User Rating

We will discuss their notions of explanation and skip the details

Disclaimer:

- There are many applications/research papers that address explanations in one form or another; we cover only a few of them as representatives

1. Explanations for Map Reduce Jobs

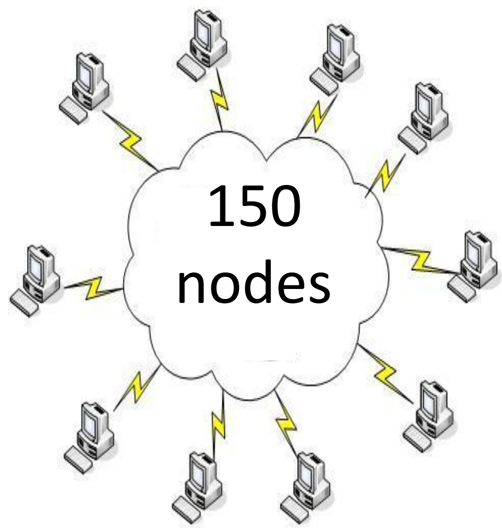
[Khoussainova et al., 2012]

[Khoussainova et al, 2012]

A MapReduce Scenario

```
map():
…

reduce():
…
```



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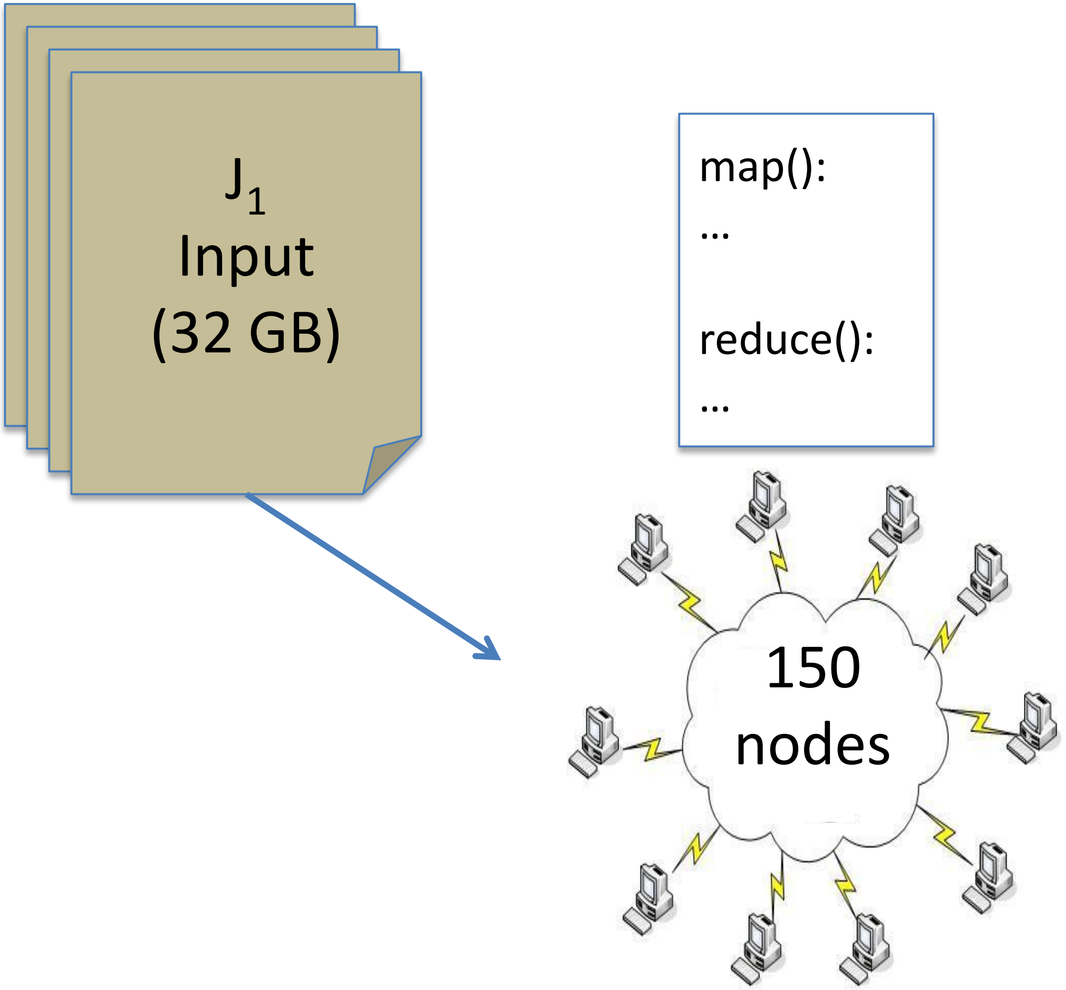

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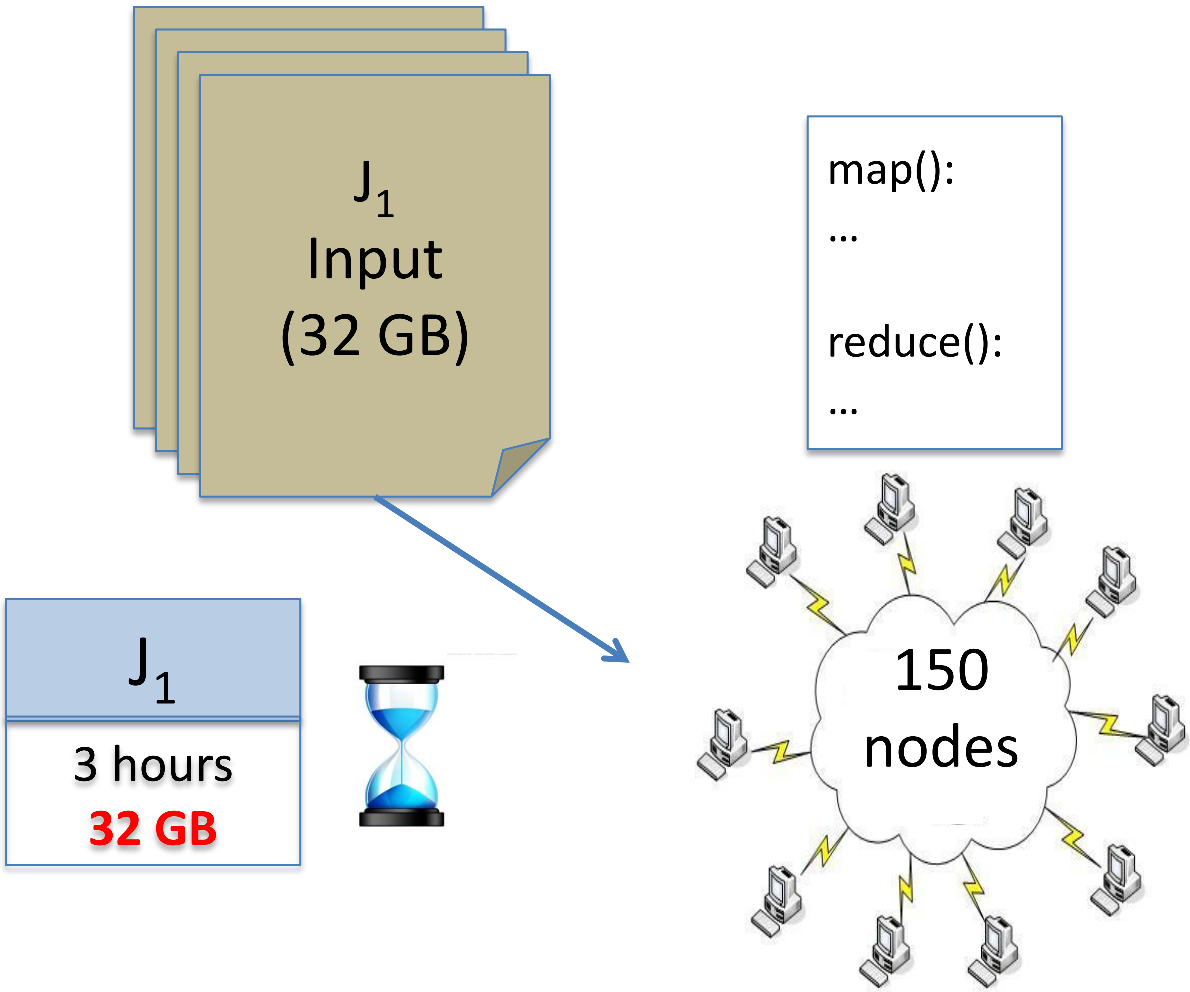

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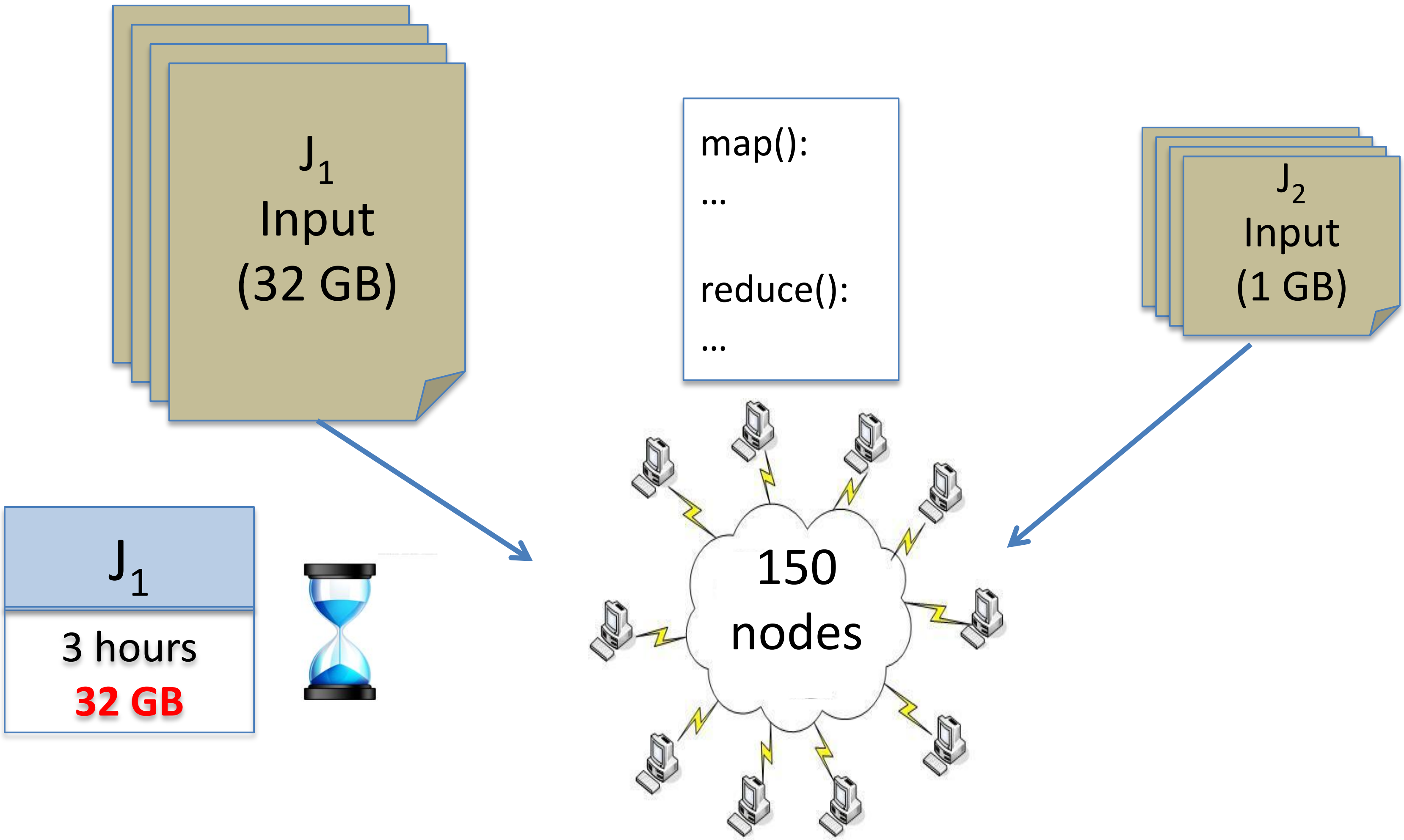

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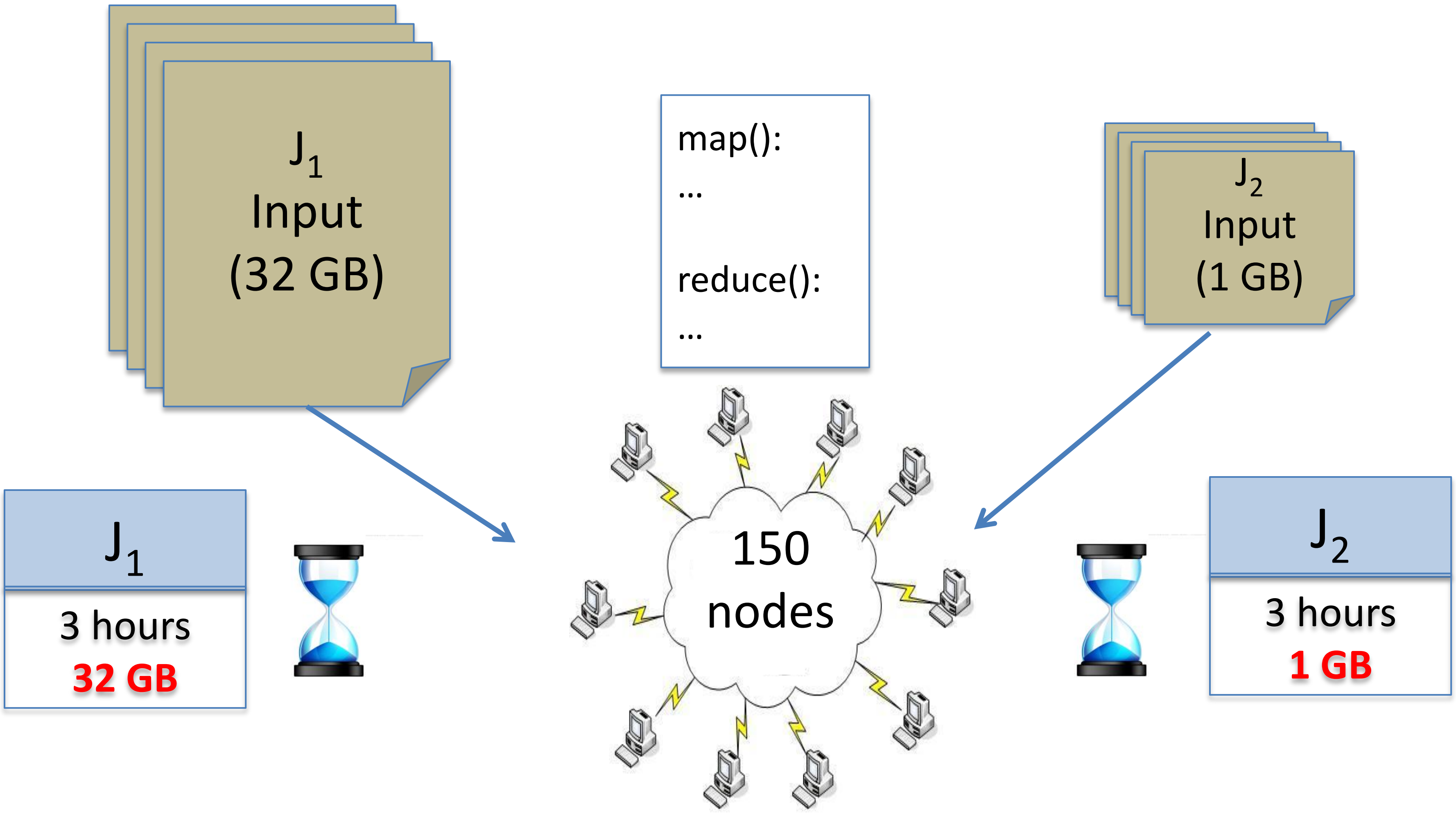

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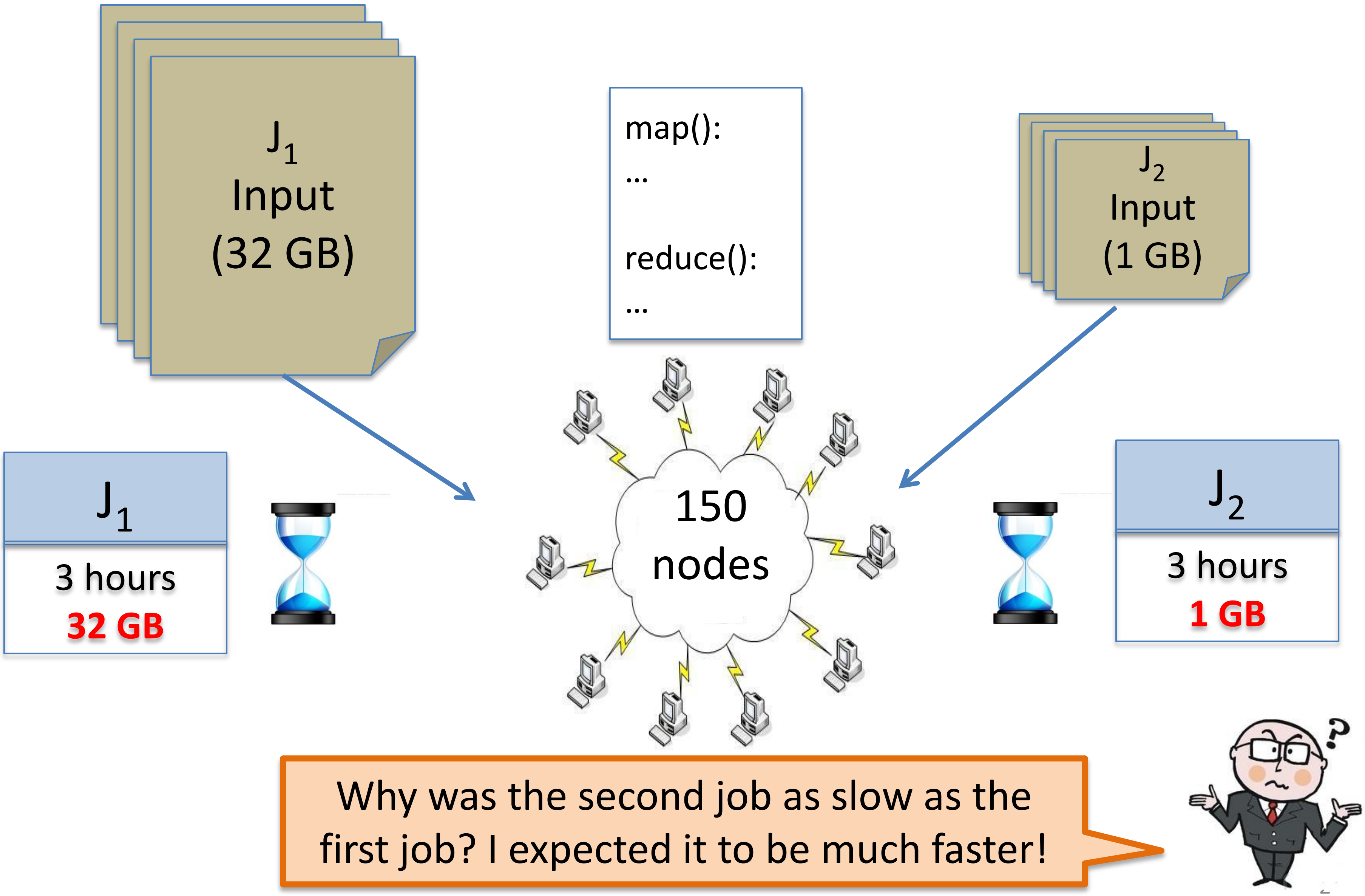

[Khoussainova et al, 2012]

Explanation by "PerfXPlain"

DFS block size >= 256 MB and #nodes = 150

J_1
3 hours
32 GB

J_2
3 hours
1 GB

Why was the second job as slow as the first job? I expected it to be much faster!

[Khoussainova et al, 2012]

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32 GB / 256 MB = 128 blocks.
There are 150 nodes!
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PerfXPlain uses a log of past job history and returns predicates on cluster config, job details, load etc. as explanations

2. Explanations for Probabilistic Database

[Kanagal et al, 2012]

Review: Query Evaluation in Prob. DB.

Probability

	AsthmaPatient	
x_1	Ann	0.1
x_2	Bob	0.4

	Friend		
y_1	Ann	Joe	0.9
y_2	Ann	Tom	0.8
y_3	Bob	Tom	0.2

	Smoker	
z_1	Joe	0.3
z_2	Tom	0.7

Probabilistic Database D

Boolean query **Q:** $\exists x \exists y$ **AsthmaPatient(x)** $\wedge$ **Friend (x, y)** $\wedge$ **Smoker(y)**

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Lineage: $F_{Q,D} = (x_1 \wedge y_1 \wedge z_1) \vee (x_1 \wedge y_2 \wedge z_2) \vee (x_2 \wedge y_3 \wedge z_2)$

- **Q** is true on **D** $\Leftrightarrow$ $F_{Q,D}$ is true

$$\Pr[F_{Q,D}] = \Pr[Q(D)]$$

[Kanagal et al, 2012]

Explanations for Prob. DB.

Explanation for Q(D) of size k:

- A set S of tuples in D, |S| = k, such that Pr[Q(D)] changes the most when we set the probabilities of all tuples in S to 0
  - i.e. when tuples in S are deleted (intervention)

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Example

Lineage: $(a \wedge b) \vee (c \wedge d)$

Probabilities: Pr[a] = Pr[b] = **0.9**, Pr[c] = Pr[d] = **0.1**

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Explanation of size 1: {a} or {b}

Explanation of size 2:

Any of four combinations {a,b} x {c, d} that makes Pr[Q(D)] = 0 and **NOT** {a, b}

[Kanagal et al, 2012]

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  - i.e. when tuples in S are deleted (intervention)

Example

NP-hard, but
poly-time for special cases

Lineage: **$(a \wedge b) \vee (c \wedge d)$**

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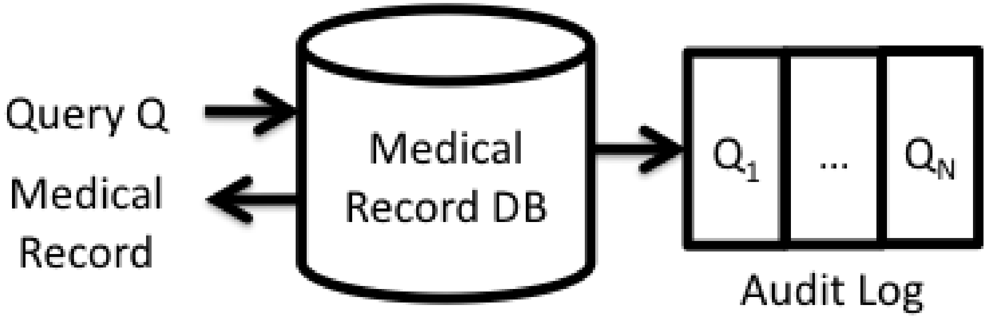
3. Explanations for Security and Access Logs

[Fabbri-LeFevre, 2011]
[Bender et al., 2014]

[Fabbri-LeFevre, 2011]

3a. Medical Record Security

- Security of patient data is immensely important
- Hospitals monitor accesses and construct an audit log
- Large number of accesses, difficult for compliance officers monitor the audit log
- Goal: Improve the auditing system so that it is easier to find inappropriate accesses by "explaining" the reason for access



[Fabbri-LeFevre, 2011]

Explanation by Existence of Paths

Consider this sample audit log and associated database:

Lid	Date	User	Patient
1	1/1/12	Dr. Bob	Alice
2	1/2/12	Dr. Mike	Alice
2	1/3/12	Dr. Evil	Alice

Audit Log

Patient	Date	Doctor
Alice	1/1/12	Dr. Bob

Appointments

Doctor	Department
Dr. Bob	Pediatrics
Dr. Mike	Pediatrics

Departments

[Fabbri-LeFevre, 2011]

Explanation by Existence of Paths

An access is explained if there exists a path:

- From the data accessed (Patient) to the user accessing the data (User)
- Through other tables/tuples stored in the DB

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Audit Log

Patient	Date	Doctor
Alice	1/1/12	Dr. Bob

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[Fabbri-LeFevre, 2011]

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Audit Log

Patient	Date	Doctor
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Appointments

Doctor	Department
Dr. Bob	Pediatrics
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Departments

Why did **Dr. Bob** access **Alice**'s record?

[Fabbri-LeFevre, 2011]

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Audit Log

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Alice	1/1/12	Dr. Bob

Appointments

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Departments

Because of an appointment

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[Fabbri-LeFevre, 2011]

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Audit Log

Patient	Date	Doctor
Alice	1/1/12	Dr. Bob

Appointments

Doctor	Department
Dr. Bob	Pediatrics
Dr. Mike	Pediatrics

Departments

Why did **Dr. Mike** access **Alice**'s record?

[Fabbri-LeFevre, 2011]

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An access is explained if there exists a path:

- From the data accessed (Patient) to the user accessing the data (User)
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Audit Log

Patient	Date	Doctor
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Appointments

Doctor	Department
Dr. Bob	Pediatrics
Dr. Mike	Pediatrics

Departments

Alice had an appointment with Dr. Bob, and Dr. Bob and Dr. Mike are Pediatricians *(same department)*

Why did **Dr. Mike** access **Alice**'s record?

[Fabbri-LeFevre, 2011]

Explanation by Existence of Paths

An access is explained if there exists a path:

- From the data accessed (Patient) to the user accessing the data (User)
- Through other tables/tuples stored in the DB

Lid	Date	User	Patient
1	1/1/12	Dr. Bob	Alice
2	1/2/12	Dr. Mike	Alice
2	1/3/12	**Dr. Evil**	**Alice**

Audit Log

Patient	Date	Doctor
Alice	1/1/12	Dr. Bob

Appointments

Doctor	Department
Dr. Bob	Pediatrics
Dr. Mike	Pediatrics

Departments

Why did **Dr. Evil** access **Alice**'s record?

[Fabbri-LeFevre, 2011]

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An access is explained if there exists a path:

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1	1/1/12	Dr. Bob	Alice
2	1/2/12	Dr. Mike	Alice
2	1/3/12	**Dr. Evil**	**Alice**

Audit Log

Patient	Date	Doctor
Alice	1/1/12	Dr. Bob

Appointments

Doctor	Department
Dr. Bob	Pediatrics
Dr. Mike	Pediatrics

Departments

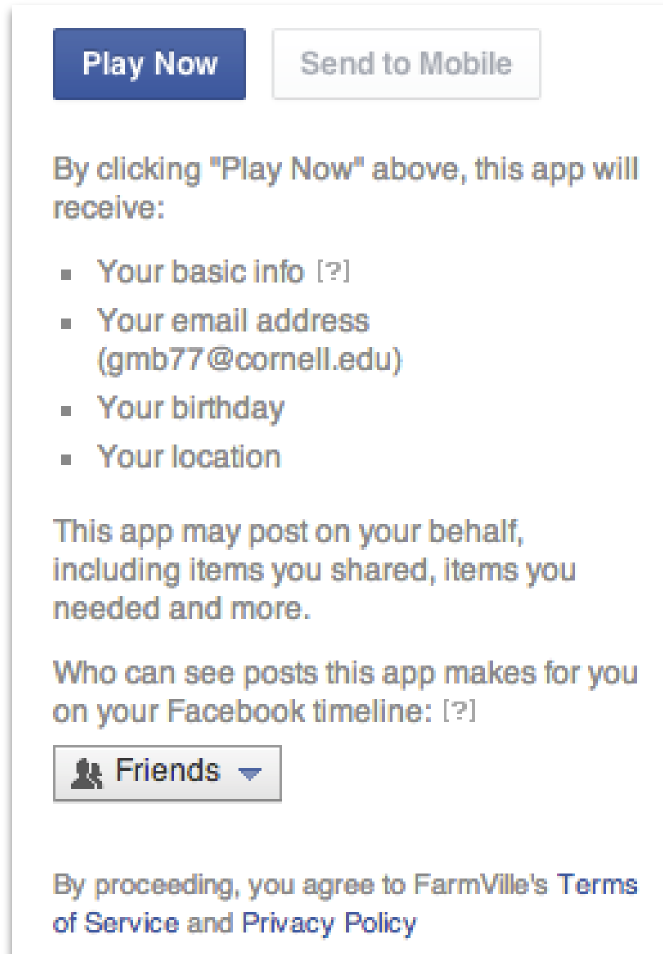
No path exists,
suspicious access!!

Why did **Dr. Evil** access **Alice**'s record?

[Bender et al., 2014]

3b. Explainable security permissions

- Access policies for social media/smartphone apps can be complex and fine-grained
- Difficult to comprehend for application developers
- Explain “NO ACCESS” decisions by what permissions are needed for access



[Bender et al., 2014]

Example: Base Table

User

uid	name	email
4	Zuck	zuck@fb.com
10	Marcel	marcel@fb.com
12347	Lucja	lucja@cornell.edu

[Bender et al., 2014]

Example: Security Views

```
CREATE VIEW V1 AS
SELECT * FROM User
 WHERE uid = 4

CREATE VIEW V2 AS
SELECT uid, name
  FROM User

CREATE VIEW V3 AS
SELECT name, email
  FROM User
```

User

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[Bender et al., 2014]

Example: Security Policy

✓
```
CREATE VIEW V1 AS
SELECT * FROM User
 WHERE uid = 4
```

✗
```
CREATE VIEW V2 AS
SELECT uid, name
  FROM User
```

✓
```
CREATE VIEW V3 AS
SELECT name, email
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```

User

uid	name	email
4	Zuck	zuck@fb.com
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✓ Permitted

✗ Not Permitted

[Bender et al., 2014]

Example: Security Policy Decisions

✓
```
CREATE VIEW V1 AS
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✗
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```

✓
```
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SELECT name, email
  FROM User
```

```
SELECT name
 FROM User
 WHERE uid = 4
```

Query issued by app

User

uid	name	email
4	Zuck	zuck@fb.com
10	Marcel	marcel@fb.com
12347	Lucja	lucja@cornell.edu

✓ Permitted

✗ Not Permitted

[Bender et al., 2014]

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Query issued by app

[Bender et al., 2014]

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[Bender et al., 2014]

Example: Why-Not Explanations

✗
```
CREATE VIEW V1 AS
SELECT * FROM User
 WHERE uid = 4
```

✗
```
CREATE VIEW V2 AS
SELECT uid, name
  FROM User
```

✓
```
CREATE VIEW V3 AS
SELECT name, email
  FROM User
```

✗
```
SELECT name
 FROM User
 WHERE uid = 4
```

Query issued by app

V1	V2	V3	Q
✗	✗	✓	✗
✗	✓	✓	✓
✓	✗	✓	✓
✓	✓	✓	✓

[Bender et al., 2014]

Example: Why-Not Explanations

✗
```
CREATE VIEW V1 AS
SELECT * FROM User
 WHERE uid = 4
```

✗
```
CREATE VIEW V2 AS
SELECT uid, name
  FROM User
```

✓
```
CREATE VIEW V3 AS
SELECT name, email
  FROM User
```

✗
```
SELECT name
 FROM User
 WHERE uid = 4
```

Query issued by app

V1	V2	V3	Q
✗	✗	✓	✗
✗	✓	✓	✓
✓	✗	✓	✓
✓	✓	✓	✓

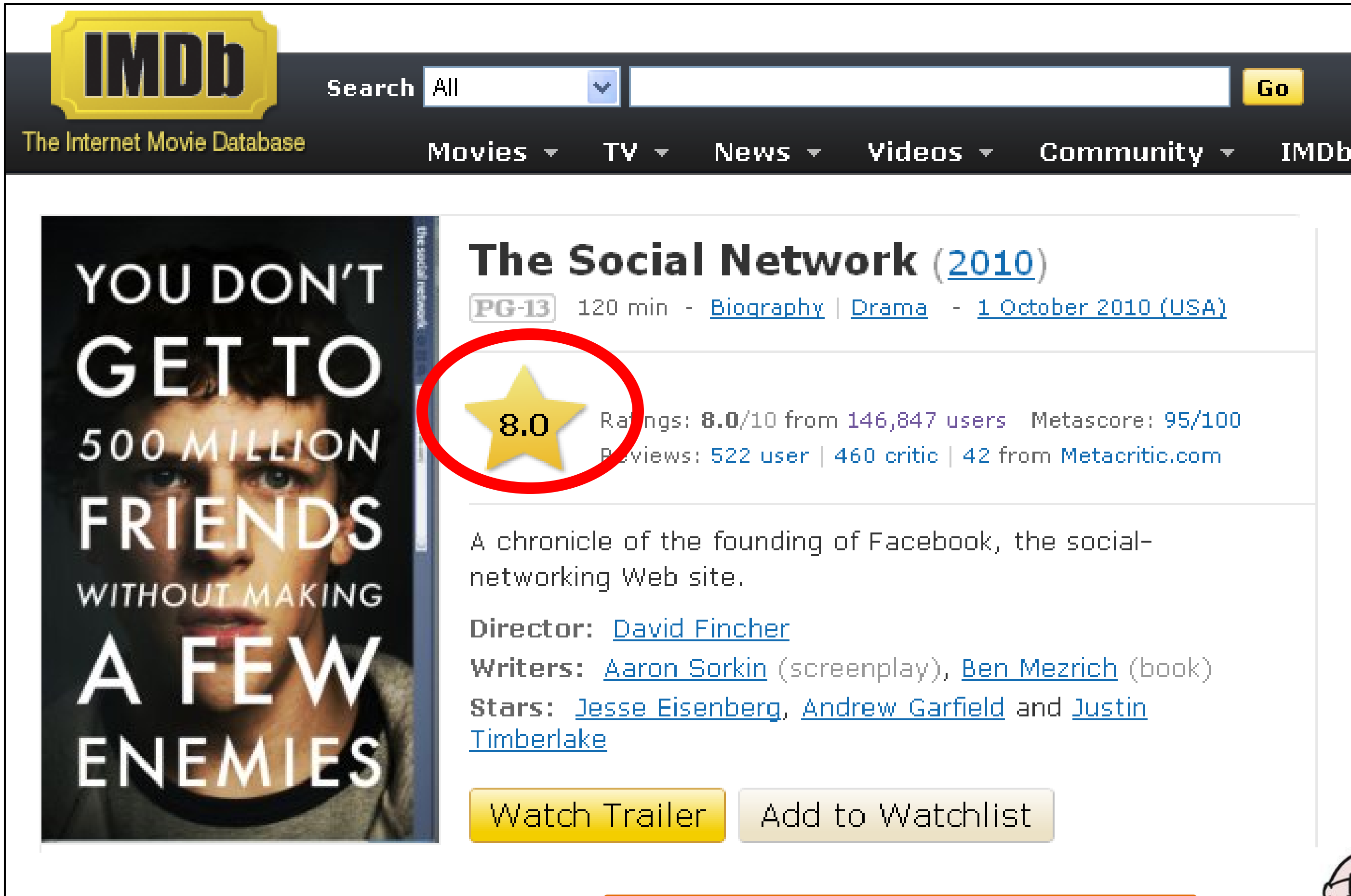
Why-not explanation:
V1 or V2

4. Explanations for User Ratings

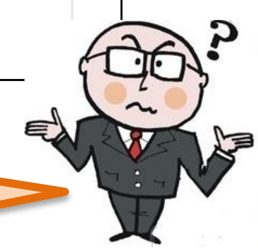
[Das et al., 2012]

[Das et al., 2012]

How to meaningfully explain user rating?

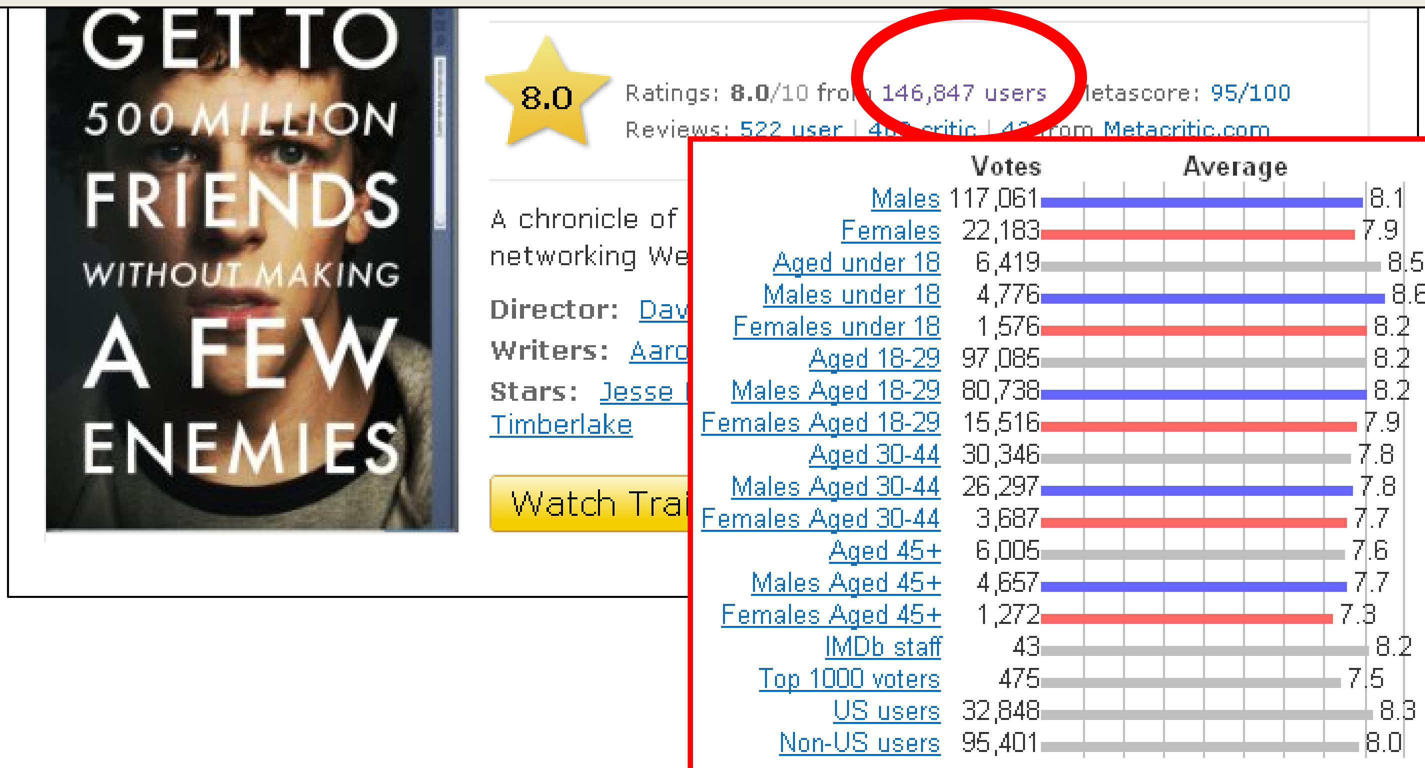


Why is the average rating 8.0?



How to meaningfully explain user rating?

- IMDB provides demographic information of the users, but it is limited
- Need a balance between individual reviews (too many) and final aggregate (less informative)



Meaningful User Rating

- **Solution:**
  Explain ratings by leveraging information about users and item attributes (data cube)

OUTPUT

Black Swan (2010)

R 108 min - Drama | Mystery | Thriller - 17 December 2010 (USA)

8.3 Ratings: **8.3**/10 from 156,148 users Metascore: **79**/100
Reviews: 892 user | 523 critic | 42 from Metacritic.com

Young female reviewers love this movie, average rating: 9.3

Reviewers from New York love this movie, average rating: 8.7

Young male student reviewers hate this movie, average rating: 6.1

Summary

- Causality is fine-grained (actual cause = single tuple), explanations for DB query answers are coarse-grained (explanation = a predicate)
  - There are other application-specific notions of explanations
- Like causality, explanation is defined by intervention

Part 3:

Related Topics
and
Future Directions

Part 3.a:

- **RELATED TOPICS**

Related Topics

- Causality/explanations:
  - how the inputs affect and explain the output(s)

- Other formalisms in databases that capture the connection between inputs and outputs:

1. Provenance/Lineage

2. Deletion Propagation

3. Missing Answers/Why-Not

[Cui et al., 2000] [Buneman et al., 2001] [EDBT 2010 keynote by Val Tannen]
[Green et al., 2007] [Cheney et al., 2009] [Amsterdamer et al. 2011] .....

1. (Boolean) Provenance/Lineage

- Tracks the source tuples that produced an output tuple and how it was produced

R

r1	a1	b1
r2	a1	b2
r3	a2	b2

S

b1	c1	s1
b2	c1	s2
b2	c2	s3

T = R ⋈ S

a1	**c1**	**r1s1 + r2s2**
a1	c2	r2s3
a2	c2	r3s3

- Why/how is T(a1, c1) produced?
- Ans: Either
  by r1 AND s1
  OR
  by r2 AND s2

Provenance vs. Causality/Explanations

- Provenance is a useful tool in finding causality/explanations
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  – Explanations return high-level abstractions as predicates which also help in comparing two or more output aggregate values

Example
For questions of the form
"Why is avg(temp) at time 12 pm so high?"
"Why is avg(temp) at time 12 pm higher than that at time 11 am?"

Provenance returns individual tuples, whereas a predicate is more informative:
"Sensor = 3"

[Buneman et al. 2002] [Cong et al. 2011] [Kimelfeld et al. 2011]

2. Deletion propagation

- An output tuple is to be deleted
- Delete a set of source tuples to achieve this
- Find a set of source tuples, having minimum side effect in
  - output (view): delete as few other output tuples as possible, or
  - source: delete as few source tuples as possible

[Buneman et al. 2002] [Cong et al. 2011] [Kimelfeld et al. 2011]

Deletion Propagation: View Side Effect

- To delete T(a1, c1)
- Need to delete one of 4 combinations: {r1, s1} x {r2, s2}

R

r1	a1	b1
r2	a1	b2
r3	a2	b2

S

b1	c1	s1
b2	c1	s2
b2	c2	s3

T = R ⋈ S

a1	c1	**r1s1 + r2s2**
a1	c2	r2s3
a2	c2	r3s3

[Buneman et al. 2002] [Cong et al. 2011] [Kimelfeld et al. 2011]

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b1	c1	s1
b2	c1	s2
b2	c2	s3

T = R $\bowtie$ S

a1	c1	**r1s1 + r2s2**
a1	c2	r2s3
a2	c2	r3s3

Delete **{r1, r2}**

[Buneman et al. 2002] [Cong et al. 2011] [Kimelfeld et al. 2011]

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$R \bowtie S$

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~~a1~~	~~c1~~	**r1s1 + r2s2**
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a2	c2	r3s3

Delete **{r1, r2}**
View Side Effect = 1
as T(a1, c2) is also deleted

[Buneman et al. 2002] [Cong et al. 2011] [Kimelfeld et al. 2011]

Deletion Propagation: View Side Effect

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T =

R S

~~a1~~	~~c1~~	r1s1 + r2s2
a1	c2	r2s3
a2	c2	r3s3

Delete **{r1, s2}**
View Side Effect = 0
(optimal)

[Buneman et al. 2002] [Cong et al. 2011] [Kimelfeld et al. 2011]

Deletion Propagation: Source Side Effect

- To delete T(a1, c1)
- Need to delete one of 4 combinations: {r1, s1} x {r2, s2}

R

r1	~~a1~~	~~b1~~
r2	a1	b2
r3	a2	b2

S

b1	c1	s1
~~b2~~	~~c1~~	s2
b2	c2	s3

T = $R \bowtie S$

~~a1~~	~~c1~~	r1s1 + r2s2
a1	c2	r2s3
a2	c2	r3s3

Source side effect =
#source tuples to be deleted **= 2**
(**optimal** for any of these four combinations)

Deletion Propagation vs. Causality

- Deletion propagation with source side effects:
  - Minimum set of source tuples to delete that deletes an output tuple
- Causality:
  - Minimum set of source tuples to delete that together with a tuple t deletes an output tuple

- Easy to show that causality is as hard as deletion propagation with source side effect

  (exact relationship is an open problem)

3. Missing Answers/Why-Not

- Aims to explain why a set of tuples does not appear in the query answer

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- **Data-based** (explain in terms of database tuples)
  - Insert/update certain input tuples such that the missing tuples appear in the answer
    [Herschel-Hernandez, 2009] [Herschel et al., 2010] [Huang et al., 2008]

3. Missing Answers/Why-Not

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    [Herschel-Hernandez, 2009] [Herschel et al., 2010] [Huang et al., 2008]

- **Query-based** (explain in terms of the query issued)
  - Identify the operator in the query plan that is responsible for excluding the missing tuple from the result

    [Chapman-Jagadish, 2009]
  - Generate a refined query whose result includes both the original result tuples as well as the missing tuples

    [Tran-Chan, 2010]

3. Why-Not vs. Causality/Explanations

- In general, why-not approaches use intervention
  - on the database, by inserting/updating tuples
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  - or, on the query, by proposing a new query

- **Future direction:**

  A unified framework for explaining missing tuples or high/low aggregate values using why-not techniques
  - e.g. [Meliou et al., 2010] already handles missing tuples

Other Related Work

- OLAP/Data cube exploration
  e.g. [Sathe-Sarawagi, 2001] [Sarawagi, 2000] [Sarawagi-Sathe, 2000]
  - Get insights about data by exploring along different dimensions

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- Connections between causality, diagnosis, repairs, and view-updates
  [Bertossi-Salimi, 2014] [Salimi-Bertossi, 2014]

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- Causal inference and learning for computational advertising e.g. [Bottou et al., 2013]
  - Uses causal inference and intervention in controlled experiments for better ad placement in search engines

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- Explanations in AI [Pacer et al., 2013] [Pearl, 1988] [Yuan et al., 2011]
  – Given a set of observed values of variables in a Bayesian network, find a hypothesis (an assignment to other variables) that best explains the observed values

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  – Given a set of observed values of variables in a Bayesian network, find a hypothesis (an assignment to other variables) that best explains the observed values
- Lamport's causality [Lamport, 1978]
  – to determine the causal order of events in distributed systems

Part 3.b:

- **FUTURE DIRECTIONS**

Extending causality

- Study broader query classes
  - e.g. for aggregate queries, can we define counterfactuals/responsibility in terms of increasing/decreasing the value of an output tuple instead of deleting it totally?

- Analyze causality under the presence of constraints
  - E.g., FDs restrict the lineage expressions that a query can produce. How does this affect complexity?

Refining the definition of cause

- Do we need preemption?
  - Preemption can model intermediate results/views that perhaps cannot be modified
  - Some complexity of the Halpern-Pearl definition may be valuable

- Causality/explanations for queries:
  - Looking for causes/explanations in a query, rather than the data

Find complex explanations efficiently

- Complex explanations
  - Beyond simple predicates,
    e.g. avg(salary) $\geq$ avg(expenditure)

- Efficiently explore the huge search space of predicates
  - Pre-processing/pruning to return explanations in real time

Ranking and Visualization

- Study ranking criteria
  - for simple, general, and diverse explanations
- Visualization and Interactive platform
  - View how the returned explanations affect the original answers
  - Filter out uninteresting explanations

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- All references are at the end of this tutorial
- The tutorial is available to download from www.cs.umass.edu/~ameli and homes.cs.washington.edu/~sudeepa

Acknowledgements

- Authors of all papers
  - We could not cover many relevant papers due to time limit

- Big thanks to Gabriel Bender, Mahashweta Das, Daniel Fabbri, Nodira Khoussainova, and Eugene Wu for sharing their slides!

- Partially supported by

  NSF Awards IIS-0911036 and CCF-1349784.

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Thank you!

Questions?