
# Managing Large, Uncertain Data Repositories with Probabilistic Graphical Models

Daisy Zhe Wang[+], Eirinaios Michelakis[+],
Minos Garofalakis[*+], Joseph M. Hellerstein[+]

University of California Berkeley[+], Yahoo! Research[*]

25th August 2008, VLDB

# Uncertainty in Real Systems

Sensor Networks

Data Extraction Systems

DBLife

Yahoo!/PSOX

IBM/Avatar/SystemT

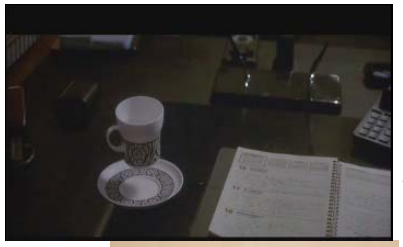
Social Networks


Data Integration Systems

# State of the Art – Probabilistic Data Management

- Machine Learning Research
  - Decision Tree, CRF Model
  - Bayesian Network
  - Probabilistic Relational Model

# Machine Learning Approach





Sensor/RFID streams

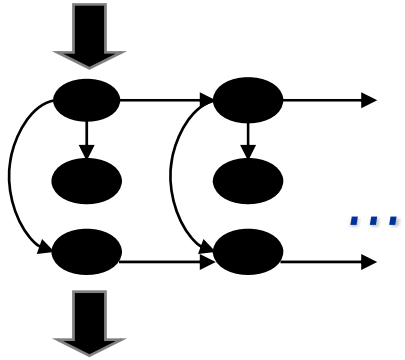
SELECT *
FROM RAWDATA

INPUT FILE

| time | id | temp |
|---|---|---|
| 10am | 1 | 20 |
| 10am | 2 | 21 |
| .. | .. | … |
| 10am | 7 | 29 |

Raw Data Tables

Relational DBMS



Inference, Classification, Aggregation, Filtering

OUTPUT FILE

# State of the Art – Probabilistic Data Management

- Machine Learning Research
  - Bayesian Network, Markov Network
  - Probabilistic Relational Model
  - Markov Network Model
- Probabilistic/Uncertain Database Research
  - MystiQ System [Dalvi&Suciu04]
  - Trio System [Wid05, Das06]
  - MauveDB [D&M, 2006]
  - MayBMS [ICDE07]

# BayesStore Data Model

1. Incomplete Relation -- $\mathbf{R^p}$
2. Distribution over Possible Worlds – **F**

**Sensor1(Time(T), Room(R), Sid, Temperature(Tp) $^p$, Light(L) $^p$)**

***Incomplete Relation of Sensor1$^p$***

| | T | R | Sid | Tp$^p$ | L$^p$ |
|---|---|---|---|---|---|
| t1 | 1 | 1 | 1 | Hot | X1 |
| t2 | 1 | 1 | 2 | Cold | Drk |
| t3 | 1 | 1 | 3 | X2 | X3 |
| t4 | 1 | 2 | 1 | X4 | Brt |
| t5 | 1 | 2 | 2 | Hot | X5 |
| t6 | 1 | 2 | 3 | X6 | X7 |

***Probabilistic Distribution of Sensor1$^p$***

$$F = Pr[X_1, \ldots, X_7]$$

N: number of missing values
|X|: size of the domain

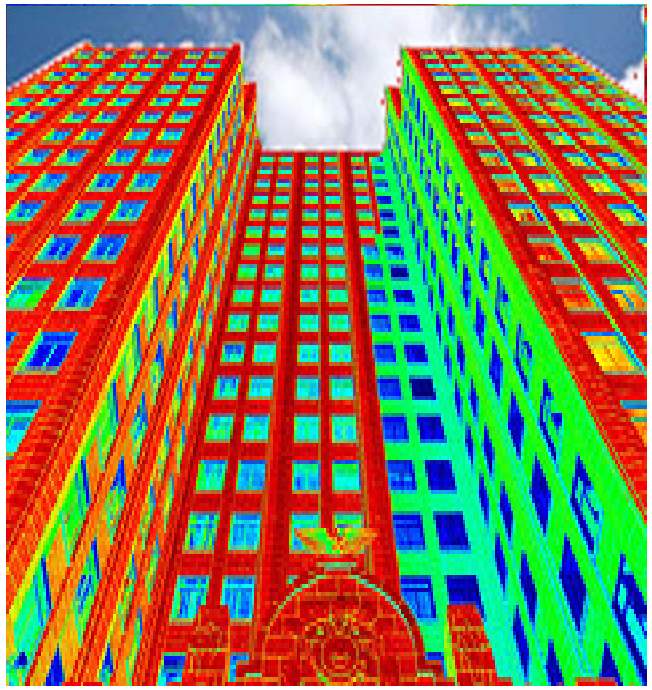
$$|F| = \Theta(|X|^N)$$

# The Skyscrapers Example

For all sensor in all rooms at all timestamp, Light and Temperature readings are correlated.

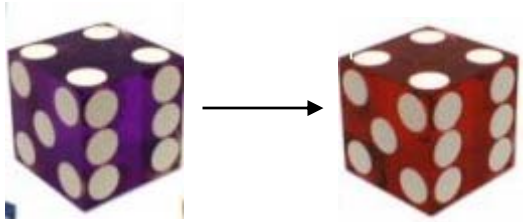
Light

Temperature



# Definitions

***Stripe:*** *A family of random variables from the same probabilistic attribute.*



***First-order Factor:*** *A family of local models, which share the same structure and conditional probability table(CPT).*

***BayesStore Data Type:*** *The input and output abstract data type of queries in BayesStore, which consists of data and model.*


***Possible Worlds***

# F as a First-order Bayesian Network (I)

***Sensor1$^p$***

| | T | R | Sid | Tp$^p$ | L$^p$ |
|---|---|---|---|---|---|
| †1 | 1 | 1 | 1 | H | X1 |
| †2 | 1 | 1 | 2 | Cold | Drk |
| †3 | 1 | 1 | 3 | X2 | X3 |
| †4 | 1 | 2 | 1 | X | Brt |
| †5 | 1 | 2 | 2 | Hot | X5 |
| †6 | 1 | 2 | 3 | X6 | X7 |
| †7 | 2 | 1 | 1 | H | X8 |
| †8 | 2 | 1 | 2 | Cold | Drk |
| †9 | 2 | 1 | 3 | X9 | X10 |
| †10 | 2 | 2 | 1 | X | Brt |
| †11 | 2 | 2 | 2 | Hot | X12 |
| †12 | 2 | 2 | 3 | X13 | X14 |

***Stripe (FO Variable) Definitions***

***All Tp values in Sensor1$^p$ with Sid=1***

# F as a First-order Bayesian Network (I)

***Sensor1$^p$***

| | T | R | Sid | Tp$^p$ | L$^p$ |
|---|---|---|---|---|---|
| t1 | 1 | 1 | 1 | H | X1 |
| t2 | 1 | 1 | 2 | C d | Dr |
| t3 | 1 | 1 | 3 | X | X3 |
| t4 | 1 | 2 | 1 | X | Br |
| t5 | 1 | 2 | 2 | H | X5 |
| t6 | 1 | 2 | 3 | X | X7 |
| t7 | 2 | 1 | 1 | H | X8 |
| t8 | 2 | 1 | 2 | C d | Dr |
| t9 | 2 | 1 | 3 | X | X1 |
| t10 | 2 | 2 | 1 | X | Br |
| t11 | 2 | 2 | 2 | H | X1 |
| t12 | 2 | 2 | 3 | X | X1 |

***Stripe (FO Variable) Definitions***

***All Tp values in Sensor1$^p$ with Sid=1***

***All Tp values in Sensor1$^p$ with Sid=2***

***All Tp values in Sensor1$^p$ with Sid !=2***

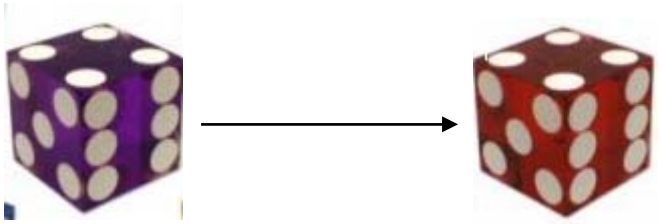
***All Tp values in Sensor1$^p$***

***All L values in Sensor1$^p$***

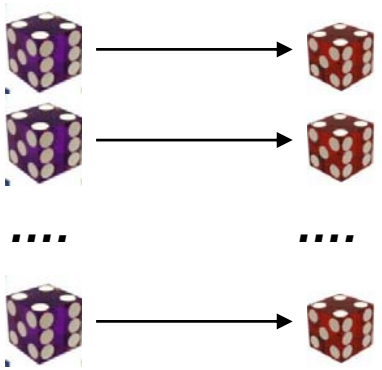
# F as a First-order Bayesian Model

***Mapping between Stripes***

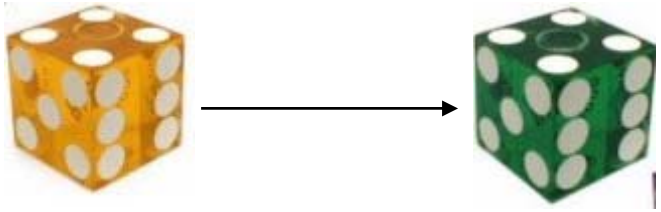
***All Tp values*** ***All L values***

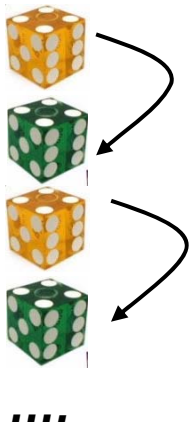


***All Tp values*** ***All L values***



***All Tp values with Sid=1*** ***All Tp values with Sid=2***





***All Tp values with Sid=1***

***All Tp values with Sid=2***

# F as a First-order Bayesian Model

***First-order Factor Definitions***

***All Tp values***

***All L values***

| Tp | L | p |
|---|---|---|
| Cold | Brt | 0.1 |
| Hot | Brt | 0.9 |
| Hot | Drk | 0.1 |
| Cold | Drk | 0.9 |

***All Tp values with Sid=1***

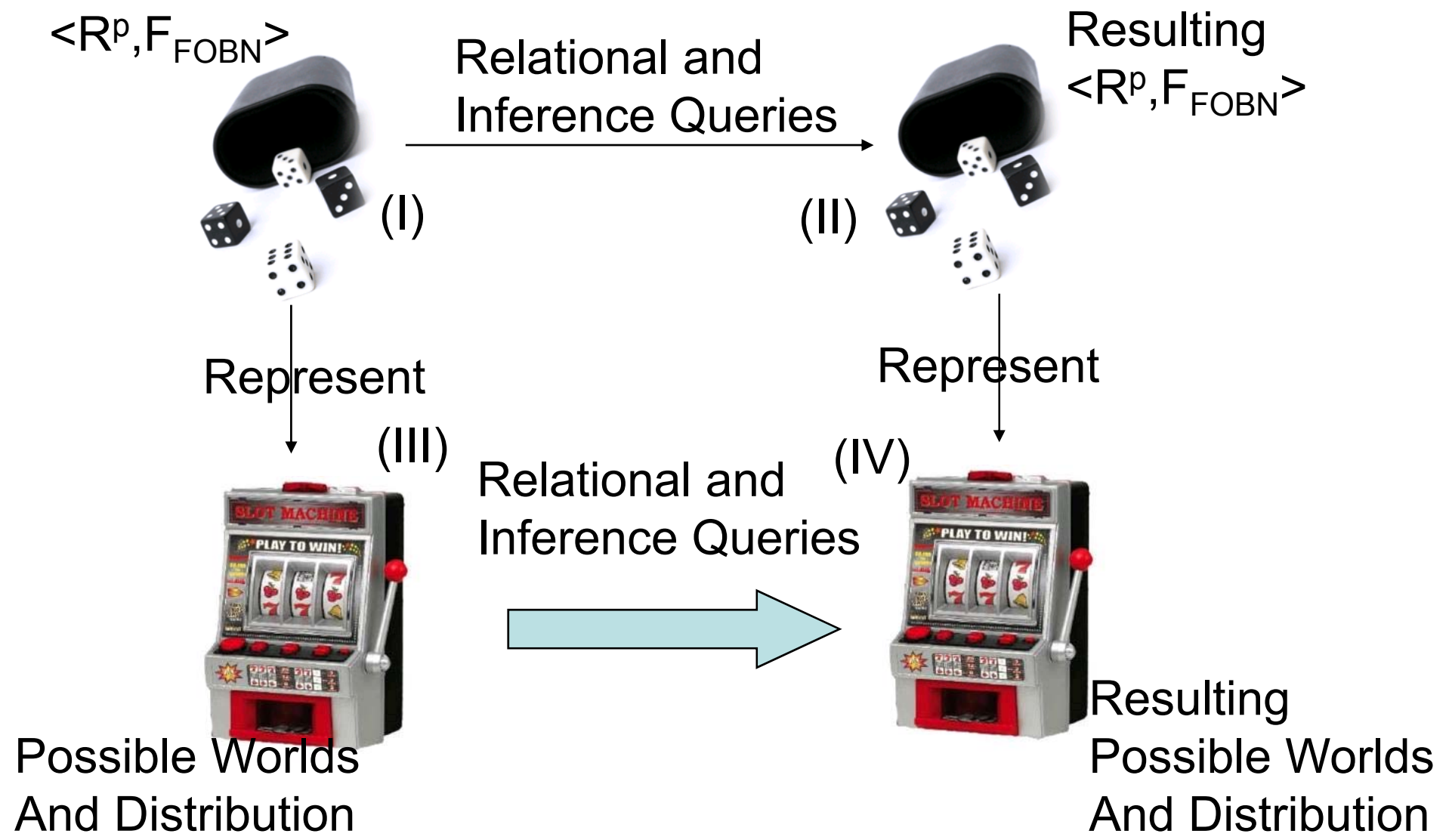
***All Tp values with Sid=2***

| Tp1 | Tp2 | p |
|---|---|---|
| Cold | Cold | 0.1 |
| Cold | Hot | 0.9 |
| Hot | Hot | 0.1 |
| Hot | Cold | 0.9 |

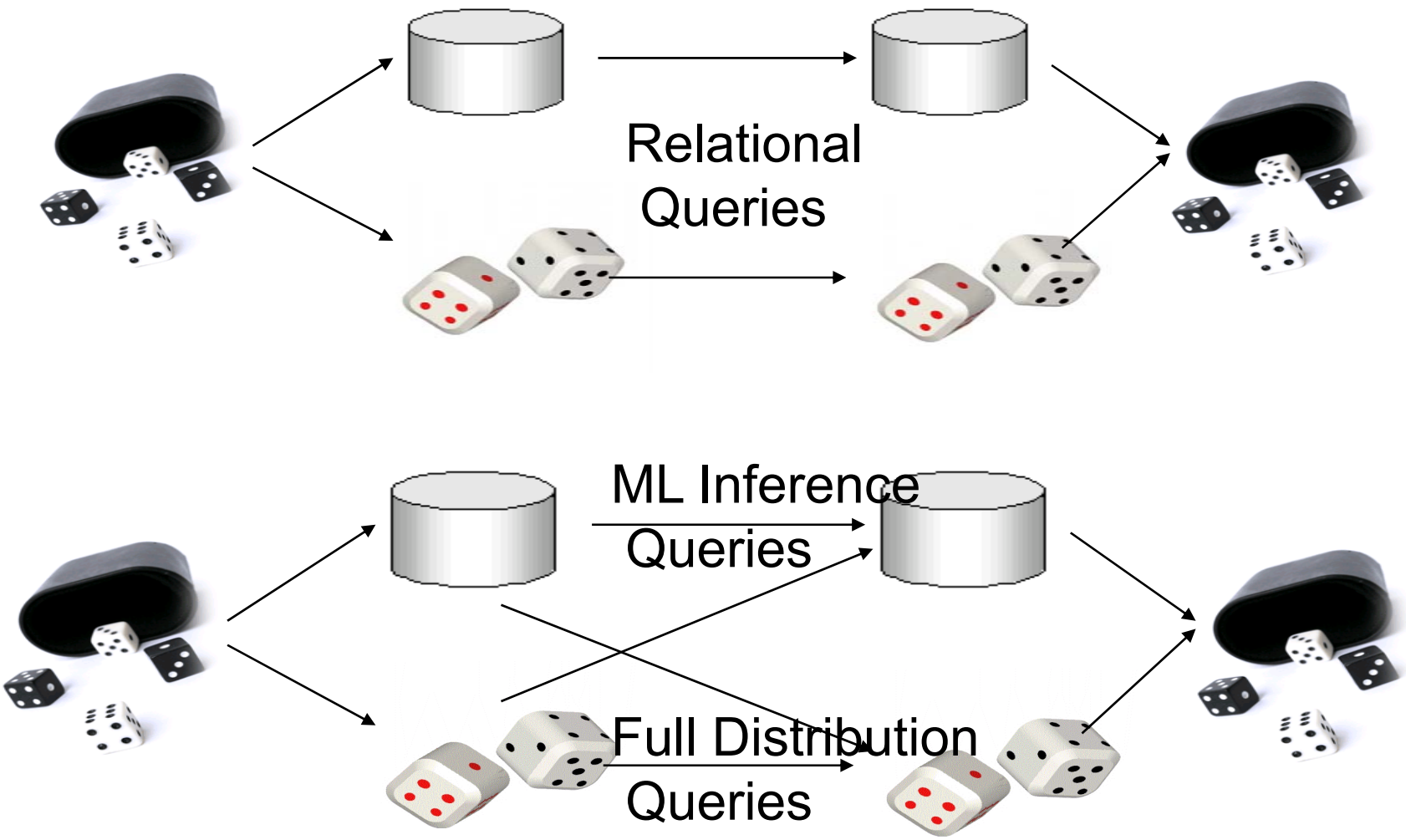
***All Tp values with Sid !=2***

| Tp | p |
|---|---|
| Cold | 0.6 |
| Hot | 0.4 |

# Query Semantics



# Query Algebra



# Selection

- **Selection over Incomplete Relation $R^p$**
- Selection over Model $M_{FOBN}$

***Sensor1$^p$***

| | T | R | Sid | $Tp^p$ | $L^p$ |
|---|---|---|---|---|---|
| t1 | 1 | 1 | 1 | Hot | X1 |
| t2 | 1 | 1 | 2 | Cold | Drk |
| t3 | 1 | 1 | 3 | X2 | X3 |
| t4 | 1 | 2 | 1 | X4 | Brt |
| t5 | 1 | 2 | 2 | Hot | X5 |
| t6 | 1 | 2 | 3 | X6 | X7 |

$\sigma_{Tp=Cold}$

***Sensor1$^p$***

| | T | R | Sid | $Tp^p$ | $L^p$ |
|---|---|---|---|---|---|
| t2 | 1 | 1 | 2 | Cold | Drk |
| t3 | 1 | 1 | 3 | X2 | X3 |
| t4 | 1 | 2 | 1 | X4 | Brt |
| t6 | 1 | 2 | 3 | X6 | X7 |

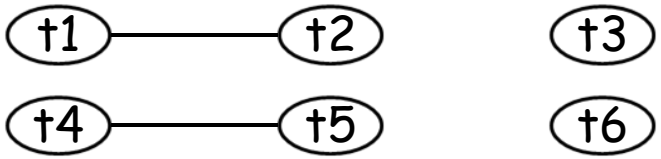
# Selection

- **Selection over Incomplete Relation $R^p$**
- Selection over Model $M_{FOBN}$

***Sensor1$^p$***

| | T | R | Sid | Tp$^p$ | L$^p$ |
|---|---|---|---|---|---|
| t1 | 1 | 1 | 1 | Hot | X1 |
| t2 | 1 | 1 | 2 | Cold | Drk |
| t3 | 1 | 1 | 3 | X2 | X3 |
| t4 | 1 | 2 | 1 | X4 | Brt |
| t5 | 1 | 2 | 2 | Hot | X5 |
| t6 | 1 | 2 | 3 | X6 | X7 |

**Tuple Correlation Graph (TCG) for $F_{FOBN}$ (Sensor1)**




$\sigma_{Tp=Cold|Null}$

| | T | R | Sid | Tp$^p$ | L$^p$ |
|---|---|---|---|---|---|
| t2 | 1 | 1 | 2 | Cold | Drk |
| t3 | 1 | 1 | 3 | X2 | X3 |
| t4 | 1 | 2 | 1 | X4 | Brt |
| t6 | 1 | 2 | 3 | X6 | X7 |

Compute Transitive Closure over TCG

| | T | R | Sid | Tp$^p$ | L$^p$ |
|---|---|---|---|---|---|
| t1 | 1 | 1 | 1 | Hot | X1 |
| t2 | 1 | 1 | 2 | Cold | Drk |
| t3 | 1 | 1 | 3 | X2 | X3 |
| t4 | 1 | 2 | 1 | X4 | Brt |
| t5 | 1 | 2 | 2 | Hot | X5 |
| t6 | 1 | 2 | 3 | X6 | X7 |

# Selection

- Selection over Incomplete Relation $R^p$
- **Selection over Model $M_{FOBN}$**

***Probabilistic Distribution $F_{FOBN}$ of Sensor1$^p$***

***All Tp values***

***All L values***

| Tp | L | p |
|---|---|---|
| Cold | Brt | 0.1 |
| Hot | Brt | 0.9 |
| Hot | Drk | 0.1 |
| Cold | Drk | 0.9 |

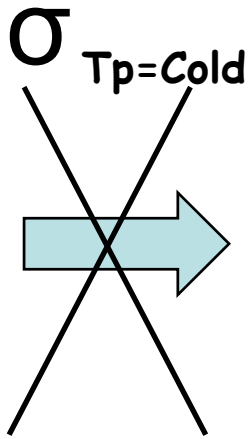
***All Tp values with Sid=1***

***All Tp values with Sid=2***

| Tp1 | Tp2 | p |
|---|---|---|
| Cold | Cold | 0.9 |
| Cold | Hot | 0.1 |
| Hot | Hot | 0.9 |
| Hot | Cold | 0.1 |

***All Tp values with Sid !=2***

| Tp | p |
|---|---|
| Cold | 0.6 |
| Hot | 0.4 |




***$F_{FOBN}$ | Tp=Cold***

# Selection

- Selection over Incomplete Relation $R^p$
- **Selection over Model $M_{FOBN}$**

***Sensor1(T, R, Sid, $Tp^p$, $L^p$, $Exist(E)^p$)***

***$F_{FOBN}$ of $Sensor1^p$***

$\sigma_{Tp=Cold}$

***All Tp values***

***All L values***

| Tp | L | p |
|---|---|---|
| Cold | Brt | 0.1 |
| Hot | Brt | 0.9 |

$\sigma_{Tp=Cold}$

***All Tp values***

***All Exist values***

***All Tp values with Sid=1***

***All Tp values with Sid=2***

| Tp1 | | |
|---|---|---|
| Cold | | 9 |
| Cold | Hot | 0.1 |
| Hot | | |
| Hot | | |

***pr(E=1)=1 iff Tp=Cold***
***pr(E=0) iff Tp=Hot***

***All Tp values with Sid !=2***

| Tp | p |
|---|---|
| Cold | 0.6 |
| Hot | 0.4 |

# Project & Join

- Project
  - Project over Incomplete Relation – projected attributes and correlated attributes
  - Project over Model – retrieve only part of the model relevant to the projected attributes
- Join
  - Join over Incomplete Relations with deterministic join condition (e.g. Sensor1.Sid = Sensor2.Sid)
  - Join over Models by merging the local models for $Exist^p$ attribute
  - Probabilistic selection with probabilistic join condition (e.g. $Sensor1.Light^p = Sensor2.Light^p$)

# Optimizations (I)

- Selection over Incomplete Relation $R^p$
  - **BayesBall Algorithm**
  - Model based Filtering

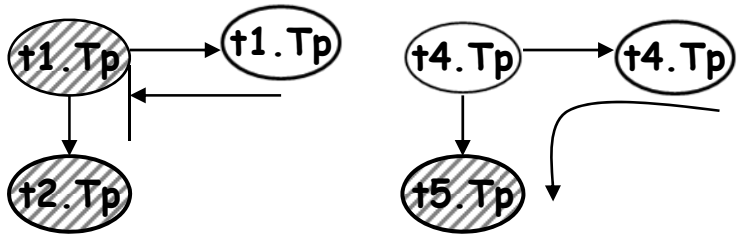
***Sensor1$^p$***

| | T | R | Sid | Tp$^p$ | L$^p$ |
|---|---|---|---|---|---|
| t1 | 1 | 1 | 1 | Hot | X1 |
| t2 | 1 | 1 | 2 | Cold | Drk |
| t3 | 1 | 1 | 3 | X2 | X3 |
| t4 | 1 | 2 | 1 | X4 | Brt |
| t5 | 1 | 2 | 2 | Hot | X5 |
| t6 | 1 | 2 | 3 | X6 | X7 |

$\sigma_{Tp=Cold|Null}$

| | T | R | Sid | Tp$^p$ | L$^p$ |
|---|---|---|---|---|---|
| t2 | 1 | 1 | 2 | Cold | Drk |
| t3 | 1 | 1 | 3 | X2 | X3 |
| t4 | 1 | 2 | 1 | X4 | Brt |
| t6 | 1 | 2 | 3 | X6 | X7 |

**Grounded Bayesian Network (GBN) for $F_{FOBN}$ (Sensor1)**

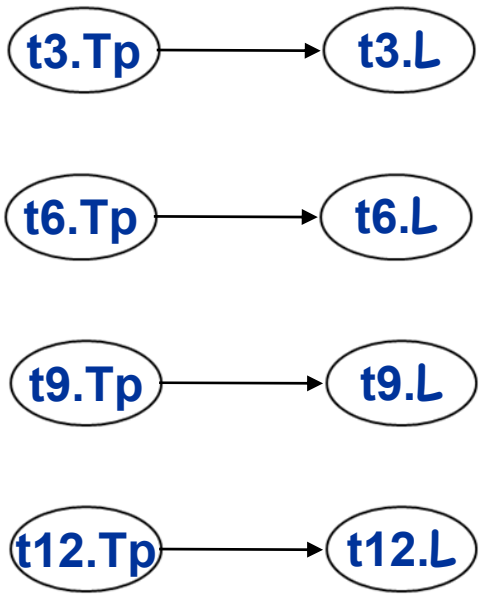



Compute BayesBall Algorithm over GBN

| | T | R | Sid | Tp$^p$ | L$^p$ |
|---|---|---|---|---|---|
| t2 | 1 | 1 | 2 | Cold | Drk |
| t3 | 1 | 1 | 3 | X2 | X3 |
| t4 | 1 | 2 | 1 | X4 | Brt |
| t5 | 1 | 2 | 2 | Hot | X5 |
| t6 | 1 | 2 | 3 | X6 | X7 |

# Optimizations (II)

- Selection over Incomplete Relation $R^p$
  - BayesBall Algorithm
  - Model based Filtering
- Simple First-order Inference Technique
  - **Sharing**

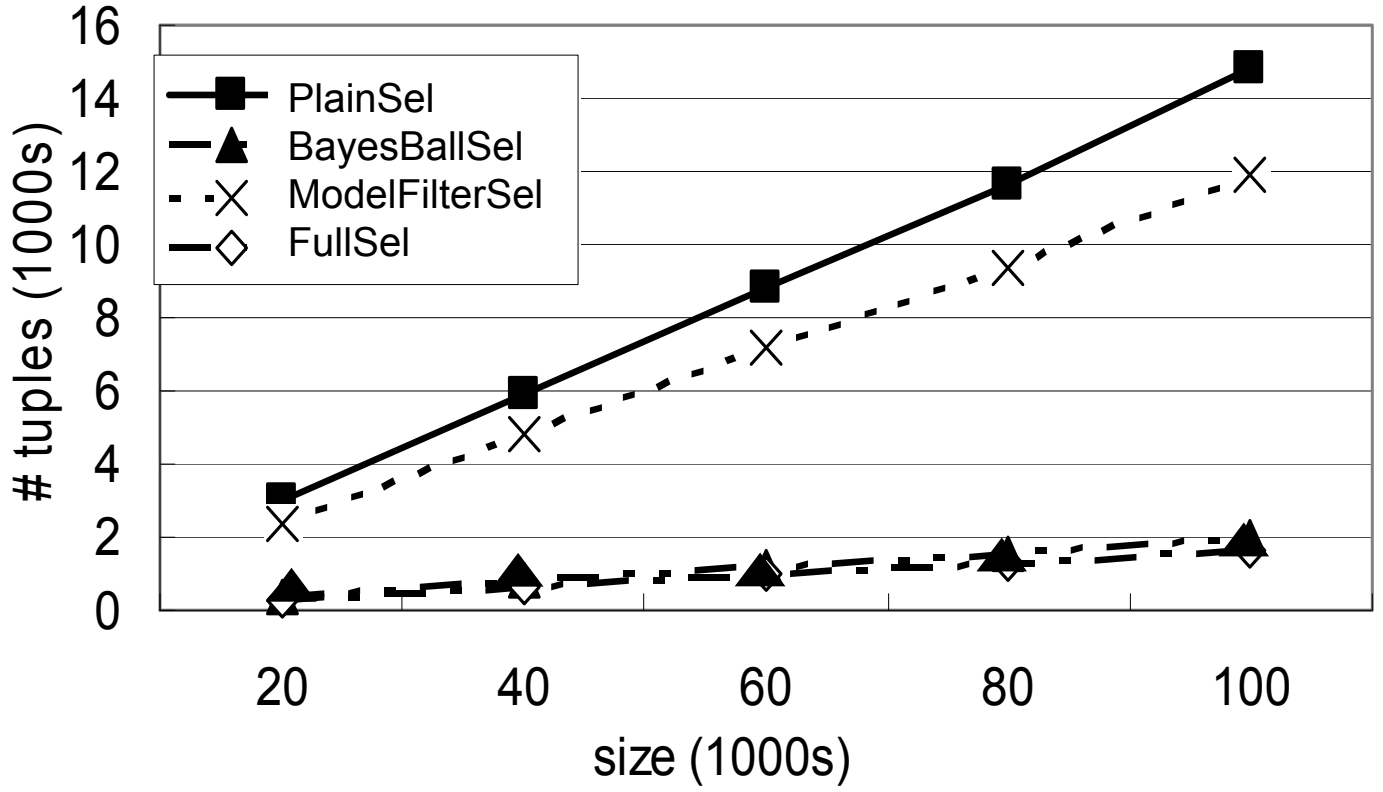



***Sensor1$^p$***

| | T | R | Sid | Tp$^p$ | L$^p$ |
|---|---|---|---|---|---|
| t1 | 1 | 1 | 1 | Hot | X1 |
| t2 | 1 | 1 | 2 | Cold | Drk |
| t3 | 1 | 1 | 3 | X2 | X3 |
| t4 | 1 | 2 | 1 | X4 | Brt |
| t5 | 1 | 2 | 2 | Hot | X5 |
| t6 | 1 | 2 | 3 | X6 | X7 |
| t7 | 2 | 1 | 1 | Hot | X8 |
| t8 | 2 | 1 | 2 | Cold | Drk |
| t9 | 2 | 1 | 3 | X9 | X10 |
| t10 | 2 | 2 | 1 | X11 | Brt |
| t11 | 2 | 2 | 2 | Hot | X12 |
| t12 | 2 | 2 | 3 | X13 | X14 |

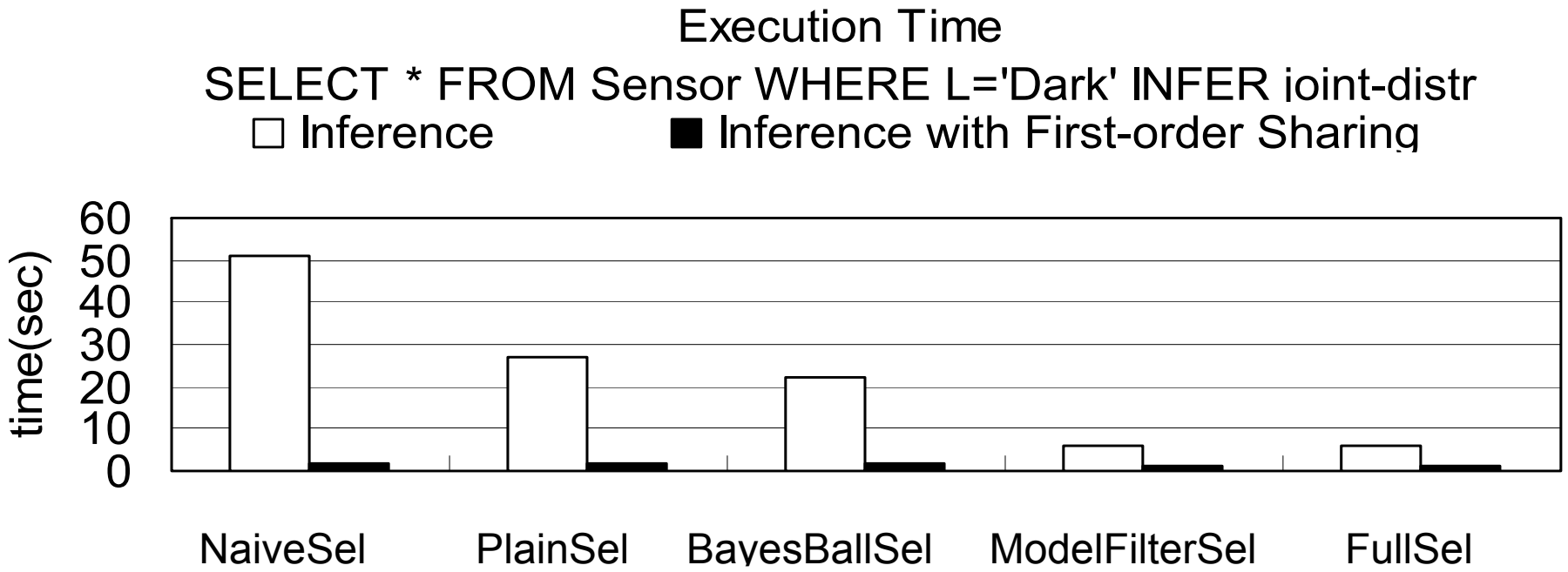
# Evaluation – Selection Algorithms

PlainSel: Selection over Incomplete Relation
BayesBallSel: Stop Transitive Closure using Bayes Ball Algorithm
ModelFilterSel: Filter tuples with zero satisfying probability using Model
FullSel: Both BayesBall and ModelFilter Optimizations are used



# Evaluation – Inference Algorithms

First-order model enables the first-order inference optimizations.



# Current and Future Work

- First-order Inference & Model Learning
- Full System Implementation
- Aggregation Operators
- Query Optimizations
- Lineage Compression
- API Design

Questions?

# Backup Slides

# Life of a Query