

Aggregate Queries for Discrete and Continuous Probabilistic XML

S. Abiteboul,¹ T-H. H. Chan,² E. Kharlamov,^{1,3} W. Nutt,³ P. Senellart⁴

¹INRIA Saclay – Île-de-France ³Free University of Bozen-Bolzano

²The University of Hong Kong ⁴Télécom ParisTech

ICDT, March 2010

Outline

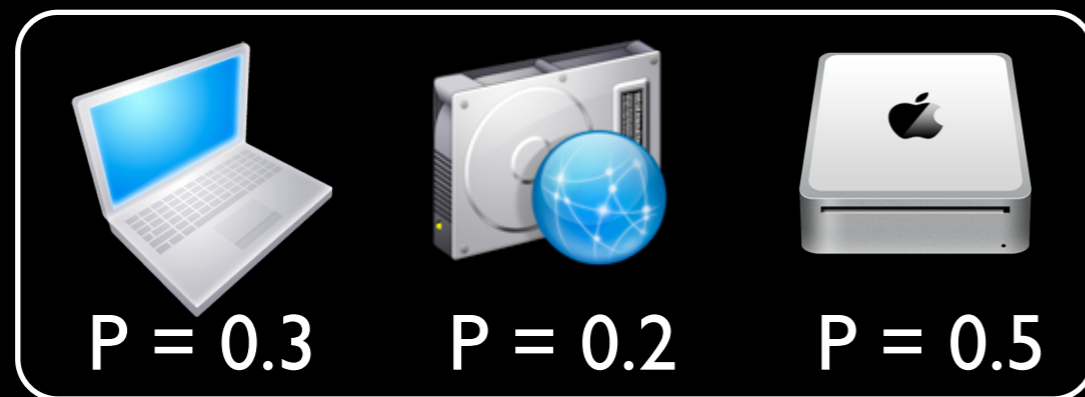
1. Probabilistic data
2. Problem definition
3. Aggregating discrete Probabilistic XML
4. Aggregating continuous Probabilistic XML

Applications of Probabilistic Data

- **Approximate query processing:** ranking, linkage
- **Information extraction:** approximate search for entities (e.g. names) in text
- **Sensor data:** imprecise or missing readings
- ...

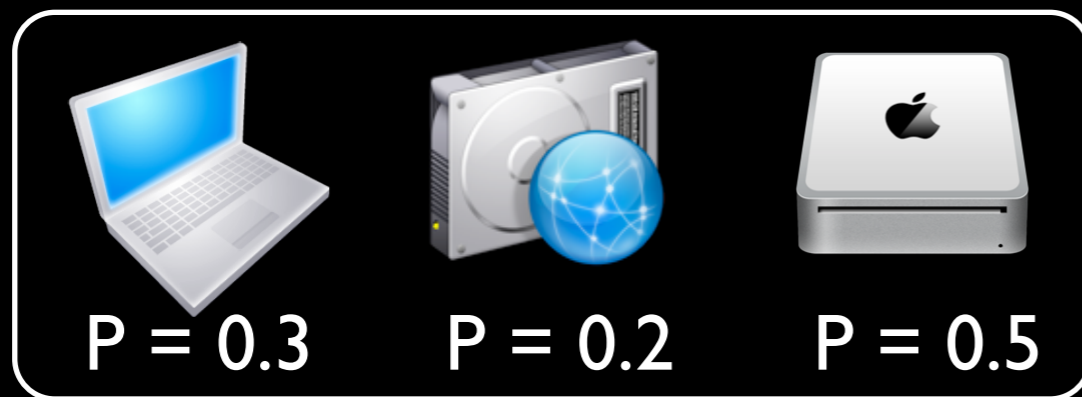
Probabilistic Database

Probabilistic DB:



Probabilistic Database

Probabilistic DB:



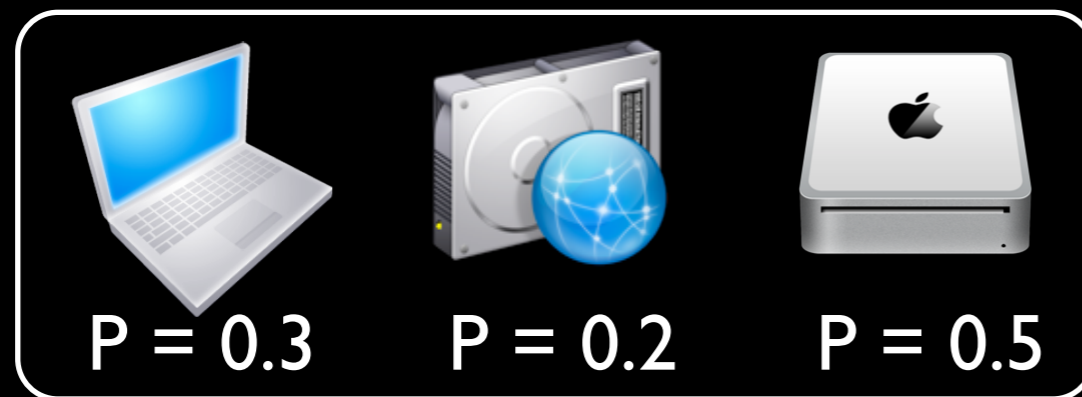
Q ↓
a

Q ↓
a

Q ↓
a

Probabilistic Database

Probabilistic DB:



Q ↓
a

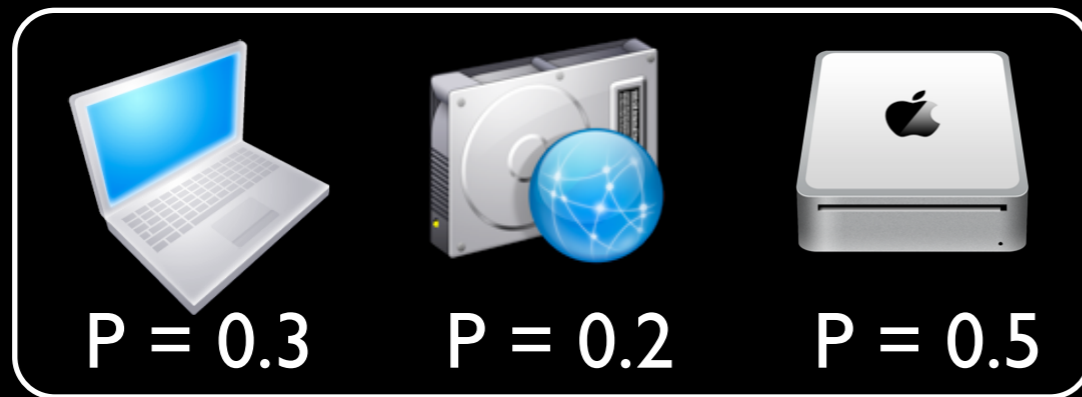
Q ↓
a

Q ↓
a

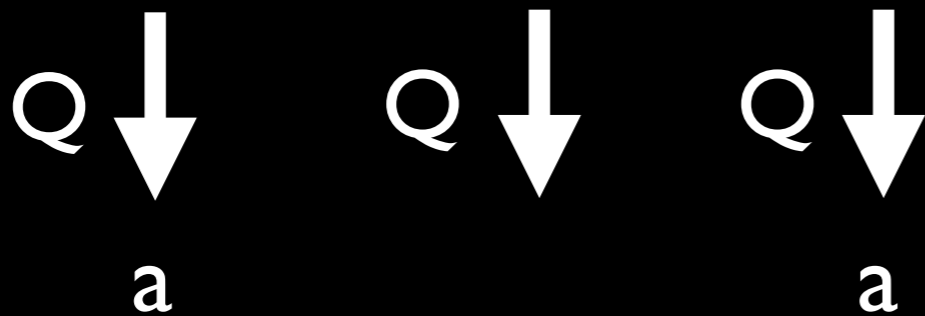
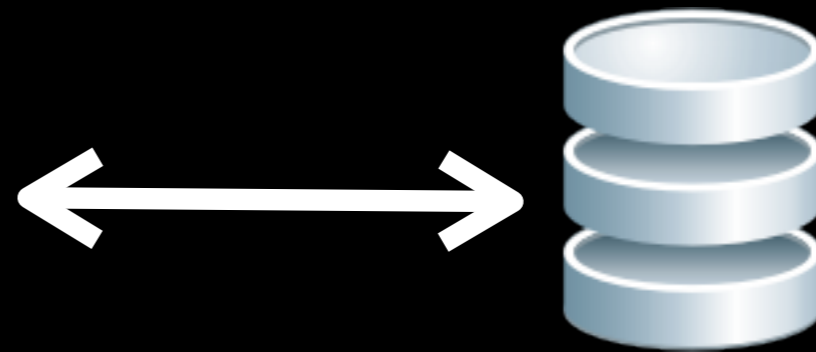
Answer: (a, 0.8)

Probabilistic Database

Probabilistic DB:



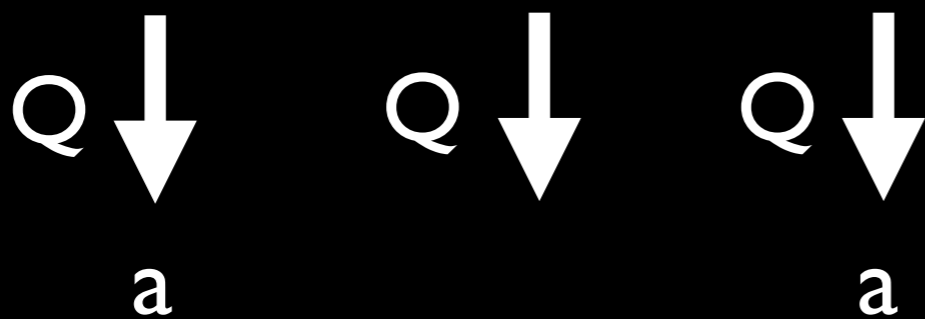
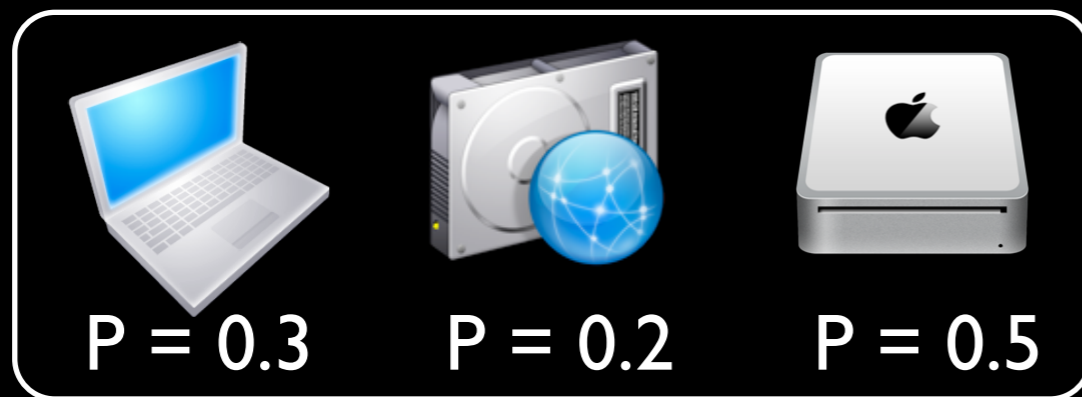
Representation
of Prob DB:



Answer: (a, 0.8)

Probabilistic Database

Probabilistic DB:



Answer: $(a, 0.8)$

Representation
of Prob DB:

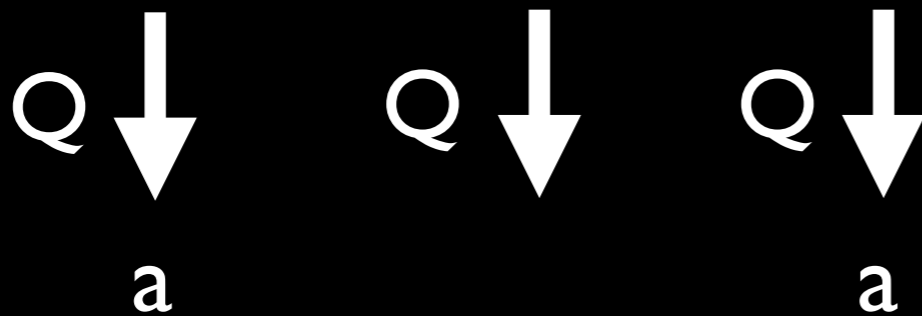
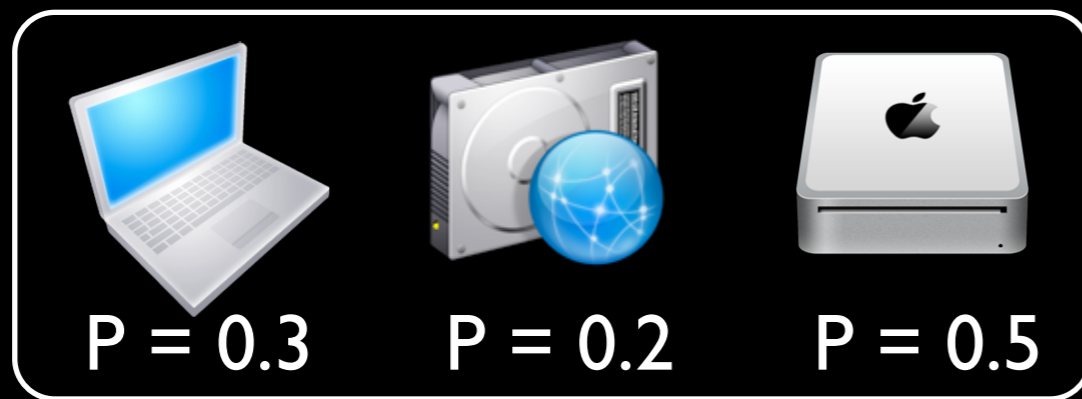


Q

$(a, 0.8)$

Probabilistic Database

Probabilistic DB:



Answer: (a, 0.8)

Representation
of Prob DB:



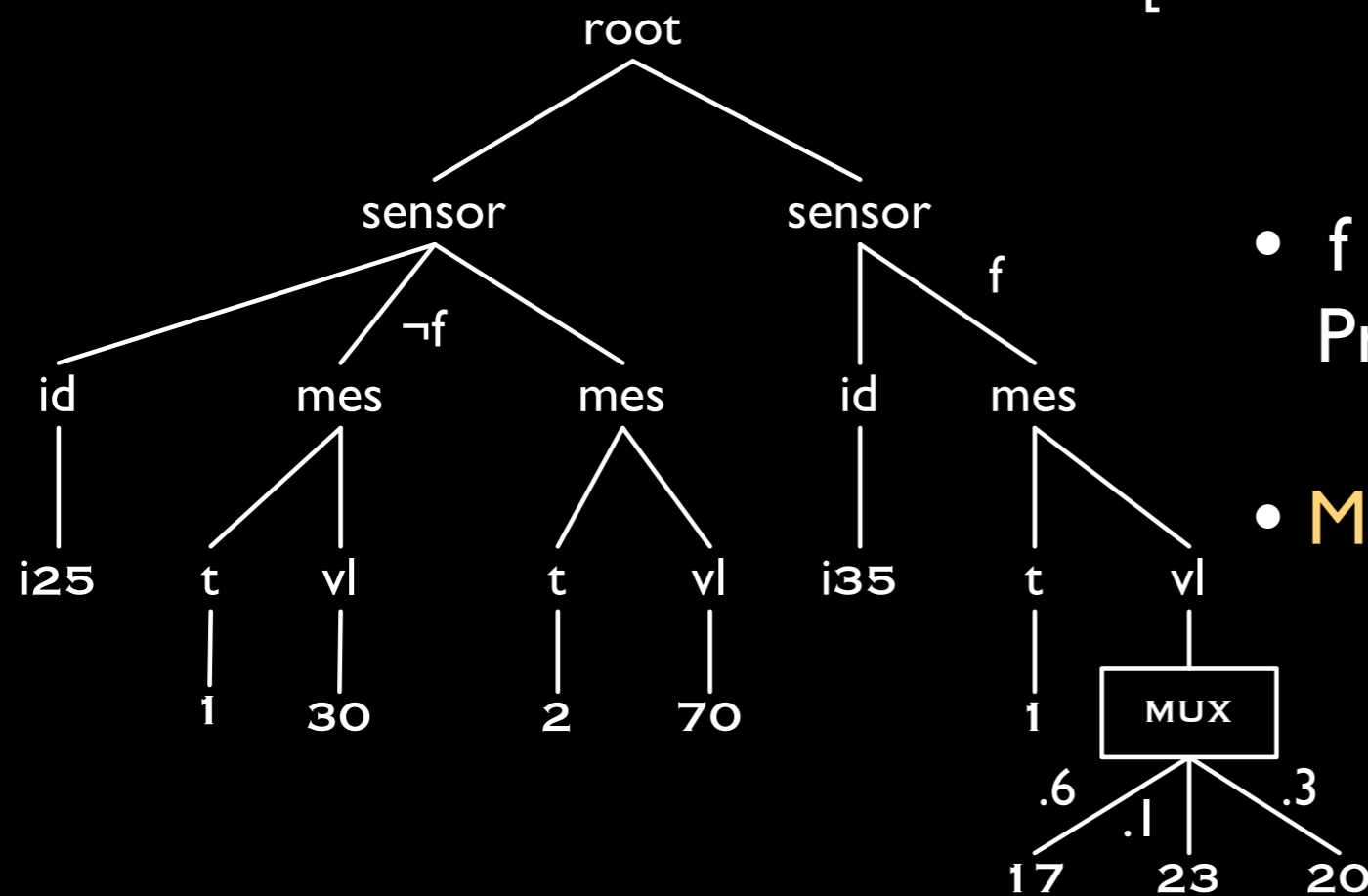
Q

(a, 0.8)

PXML with Events and Distributional Nodes

[Kimelfed&al:2007]

[Senellart&al:2007]

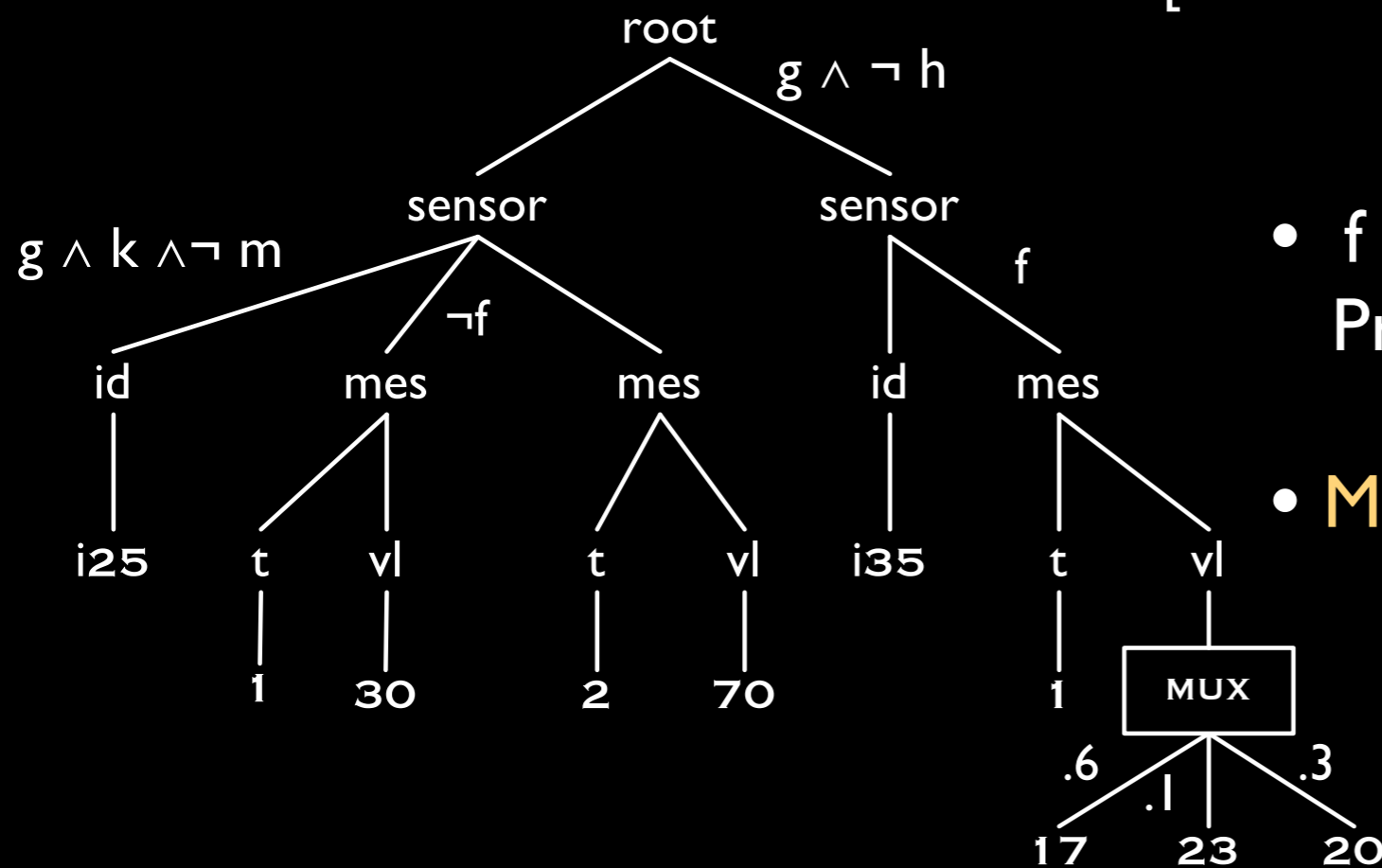


- **f - event**: “weather is fine”
 $\Pr(f) = .4$
- **MUX** - mutually exclusive options

PXML with Events and Distributional Nodes

[Kimelfed&al:2007]

[Senellart&al:2007]

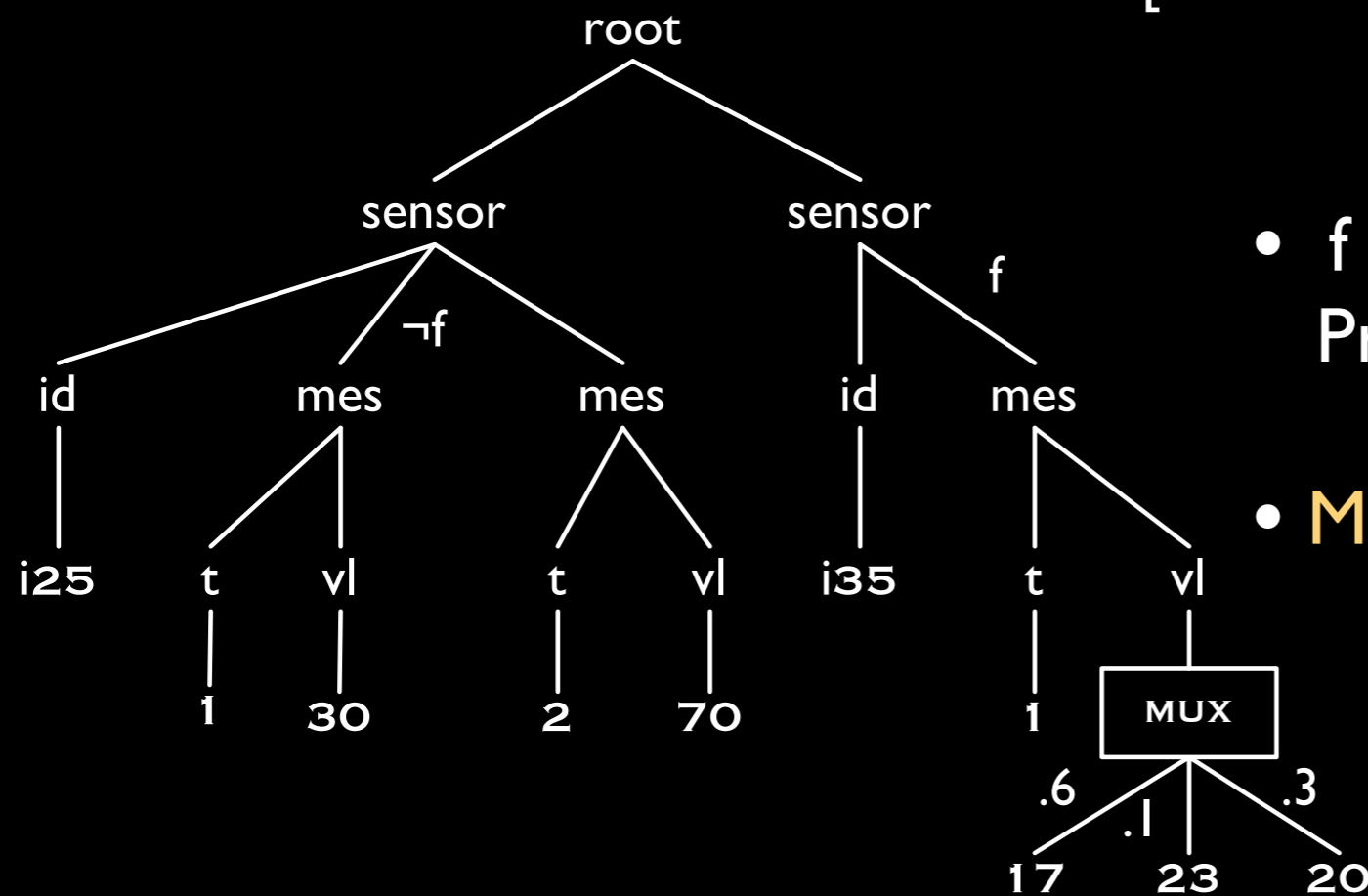


- **f - event**: “weather is fine”
Pr(f) = .4
- **MUX** - mutually exclusive options

PXML with Events and Distributional Nodes

[Kimelfed&al:2007]

[Senellart&al:2007]



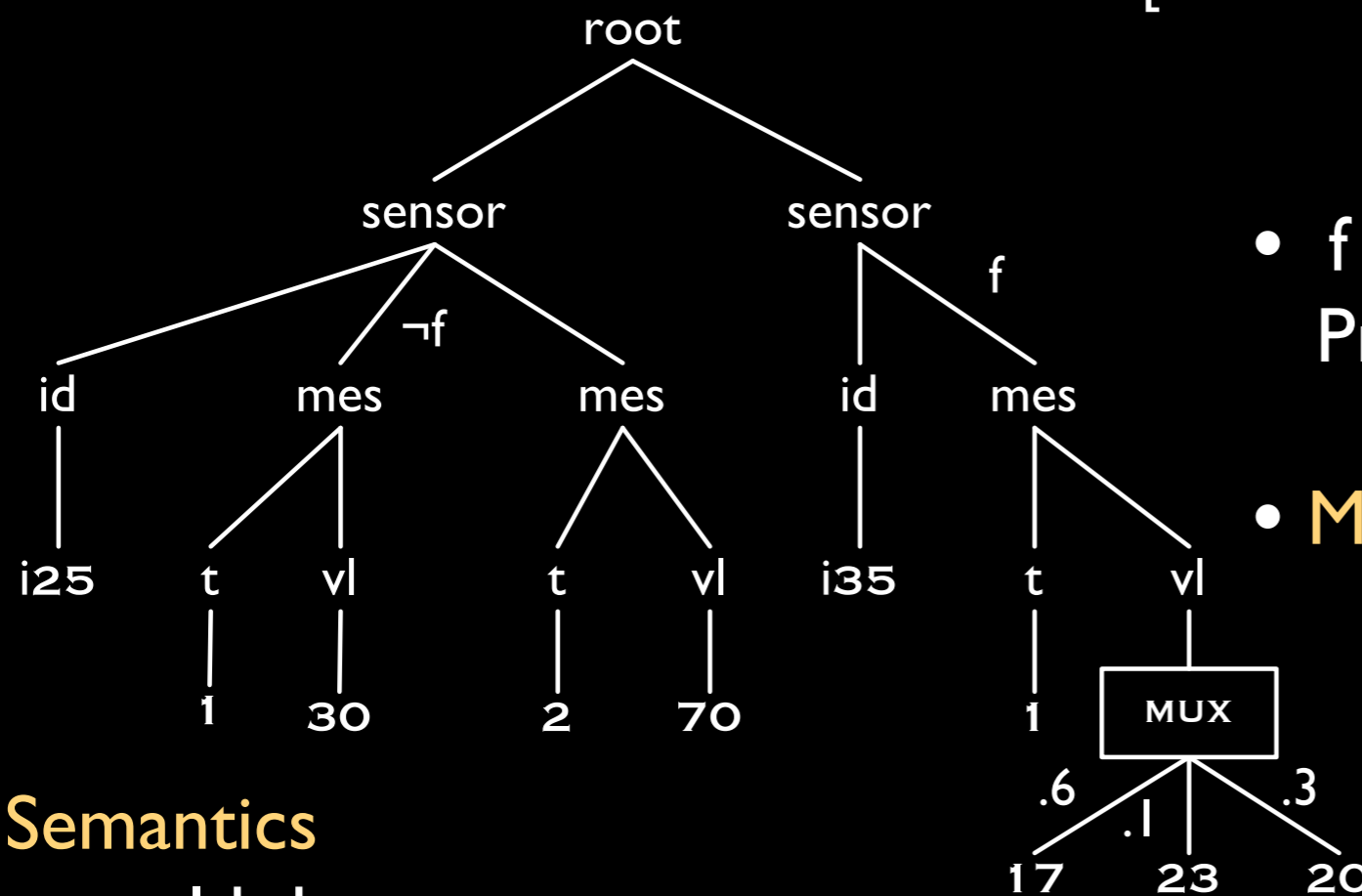
- **f - event**: “weather is fine”
 $\Pr(f) = .4$

- **MUX** - mutually exclusive options

PXML with Events and Distributional Nodes

[Kimelfed&al:2007]

[Senellart&al:2007]



- **f - event**: “weather is fine”
 $\Pr(f) = .4$

- **MUX** - mutually exclusive options

Semantics

a world d :

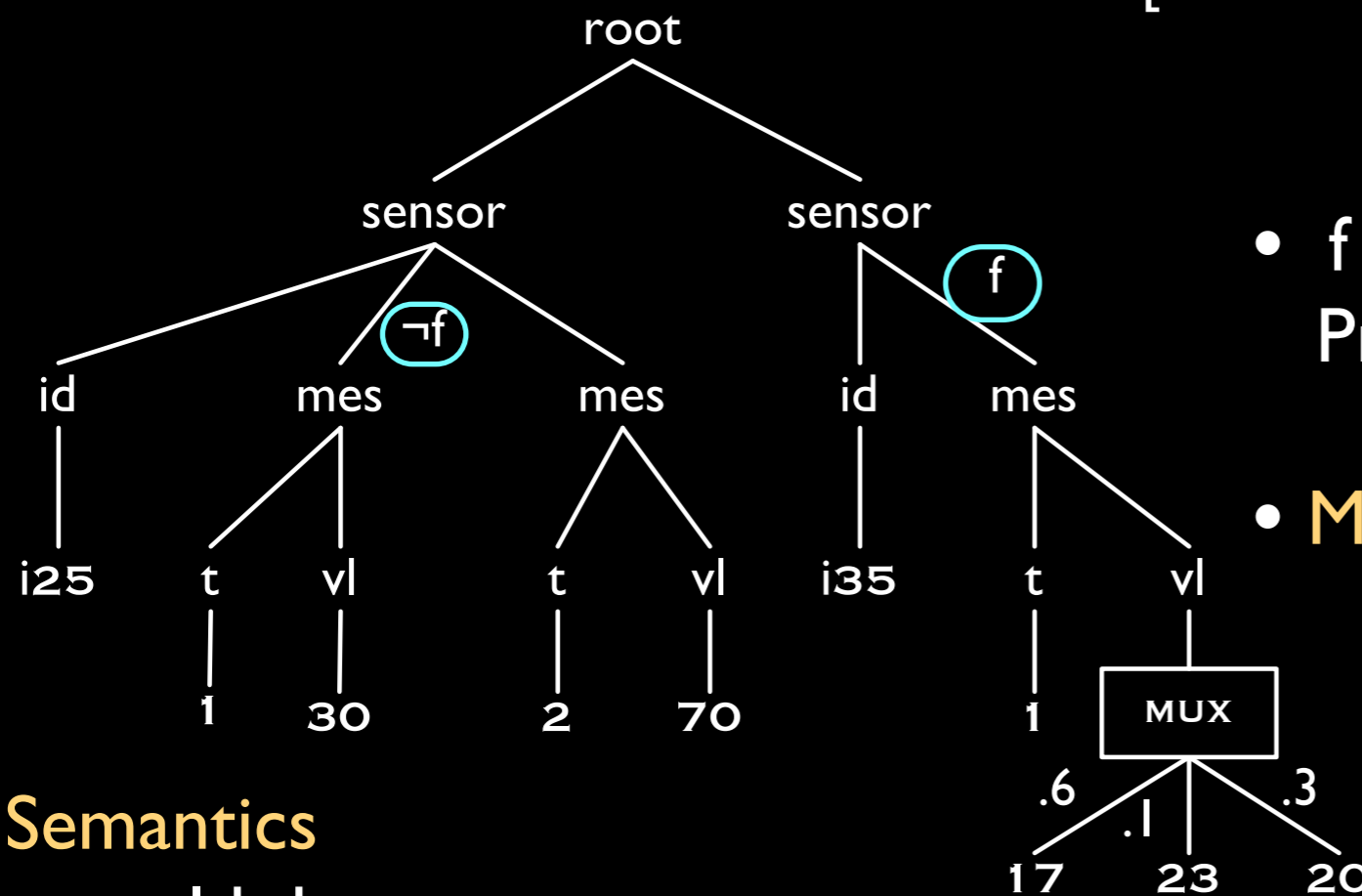
- $f = \text{true}$, $\Pr(f) = 0.4$
- **MUX**: 23, $\Pr(23) = 0.1$

$$\Pr(d) = 0.4 \times 0.1$$

PXML with Events and Distributional Nodes

[Kimelfed&al:2007]

[Senellart&al:2007]



- **f - event**: “weather is fine”
 $\Pr(f) = .4$

- **MUX** - mutually exclusive options

Semantics

a world d :

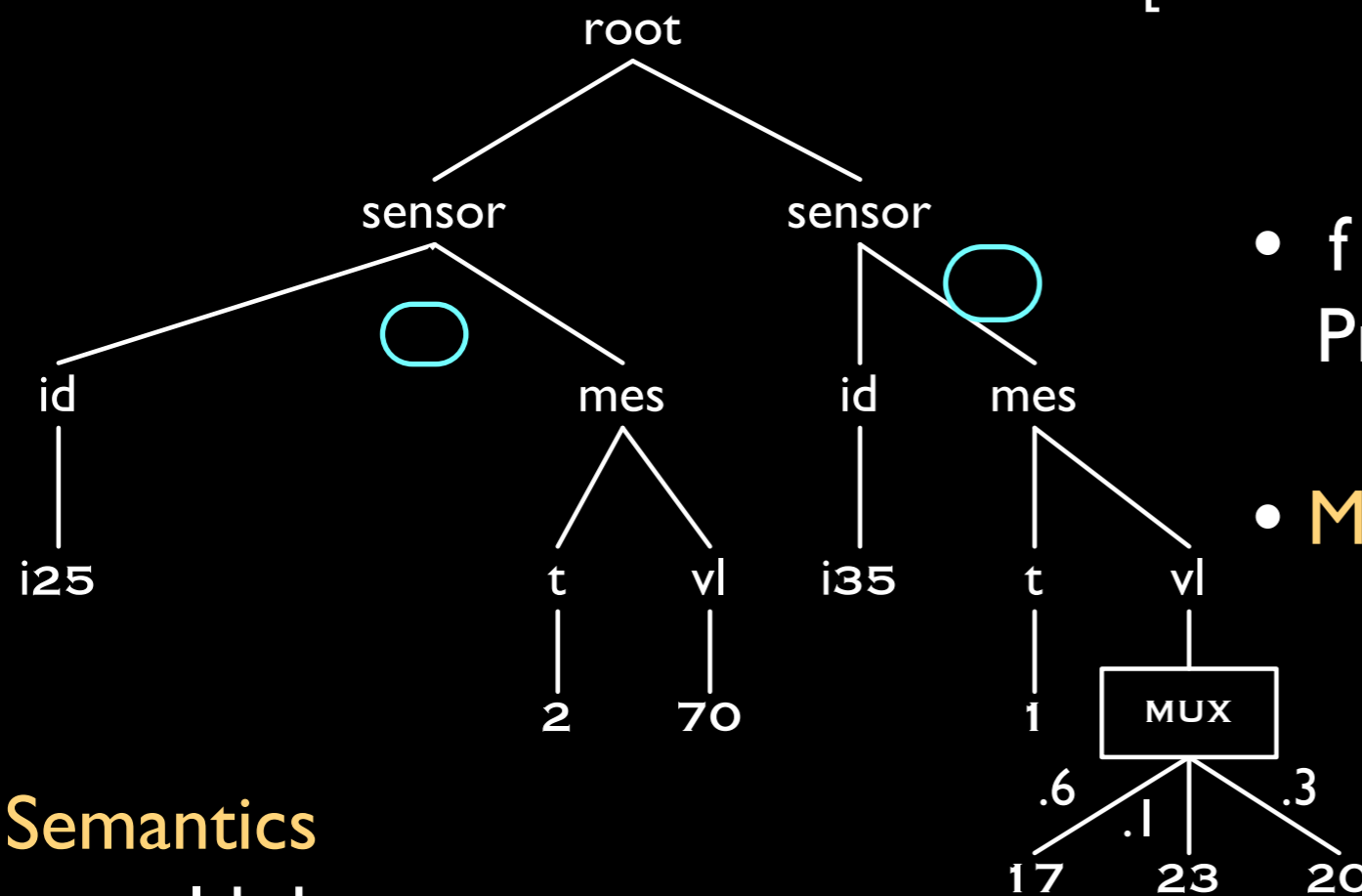
- **f = true**, $\Pr(f) = 0.4$
- **MUX: 23**, $\Pr(23) = 0.1$

$$\Pr(d) = 0.4 \times 0.1$$

PXML with Events and Distributional Nodes

[Kimelfed&al:2007]

[Senellart&al:2007]



- **f - event**: “weather is fine”
 $\Pr(f) = .4$
- **MUX** - mutually exclusive options

Semantics

a world d :

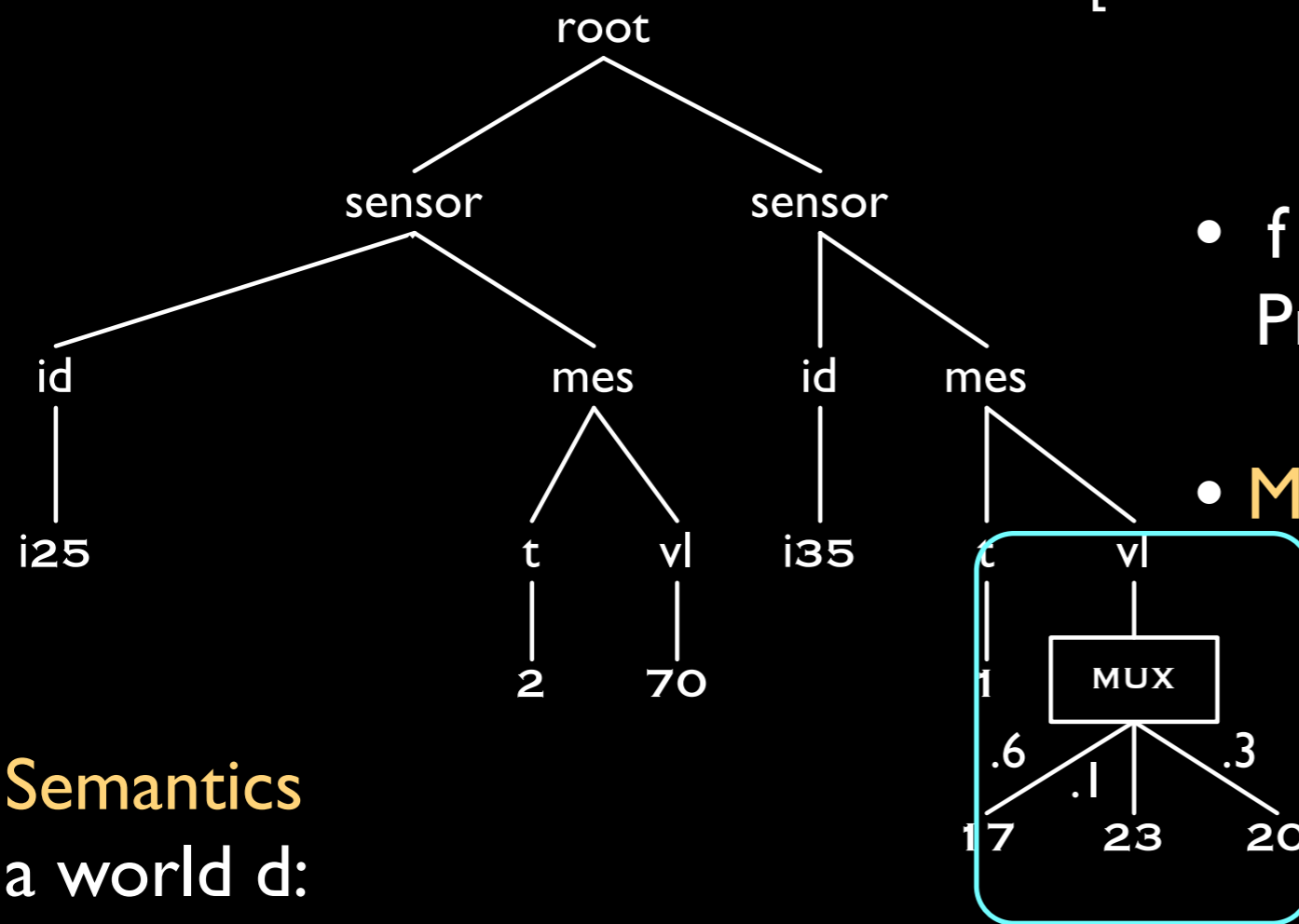
- **f = true**, $\Pr(f) = 0.4$
- **MUX: 23**, $\Pr(23) = 0.1$

$$\Pr(d) = 0.4 \times 0.1$$

PXML with Events and Distributional Nodes

[Kimelfed&al:2007]

[Senellart&al:2007]



- **f - event**: “weather is fine”
 $\Pr(f) = .4$

- **MUX** - mutually exclusive options

Semantics

a world d :

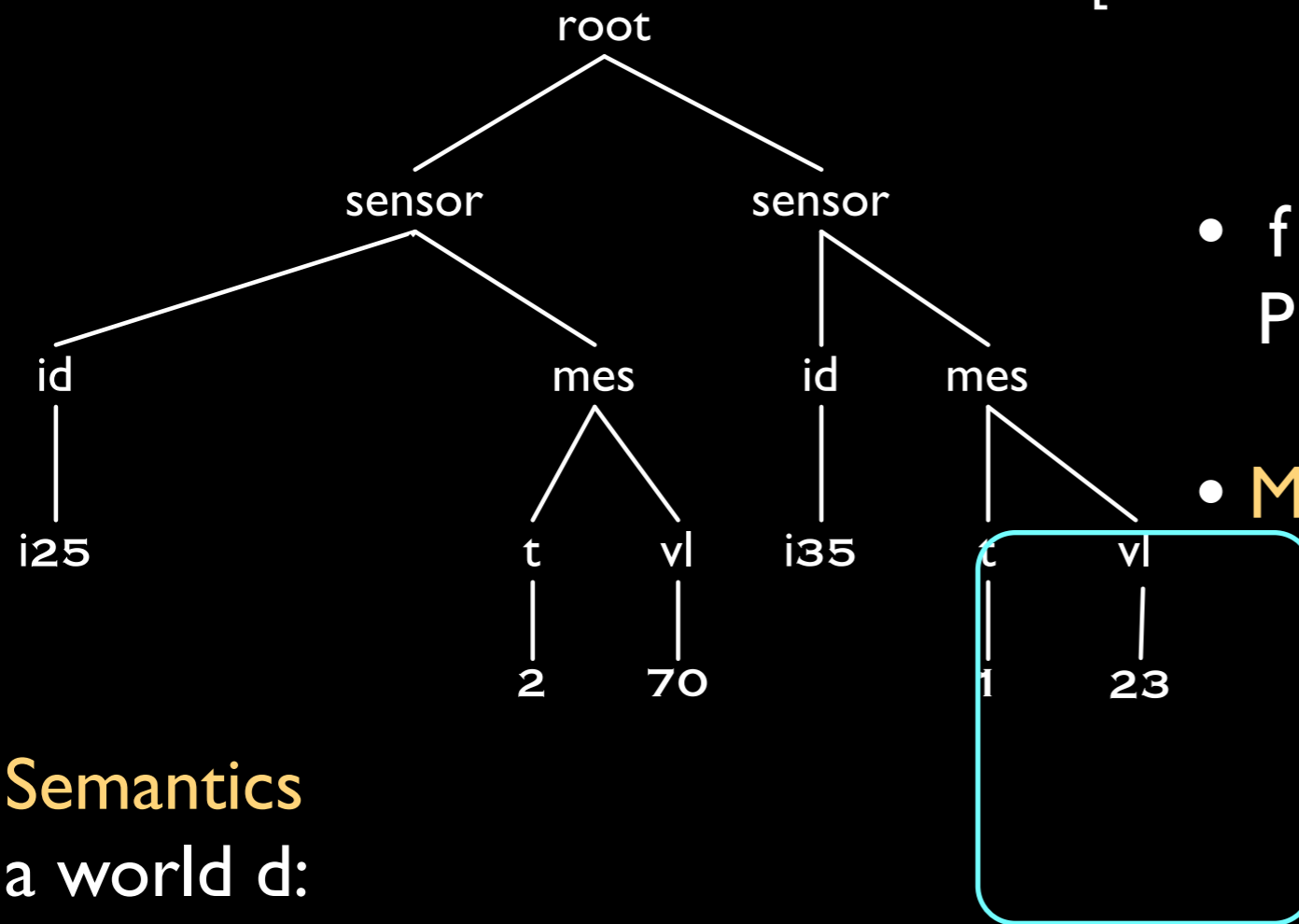
- $f = \text{true}$, $\Pr(f) = 0.4$
- **MUX: 23**, $\Pr(23) = 0.1$

$$\Pr(d) = 0.4 \times 0.1$$

PXML with Events and Distributional Nodes

[Kimelfed&al:2007]

[Senellart&al:2007]



- **f - event**: “weather is fine”
 $\Pr(f) = .4$

- **MUX** - mutually exclusive options

Semantics

a world d :

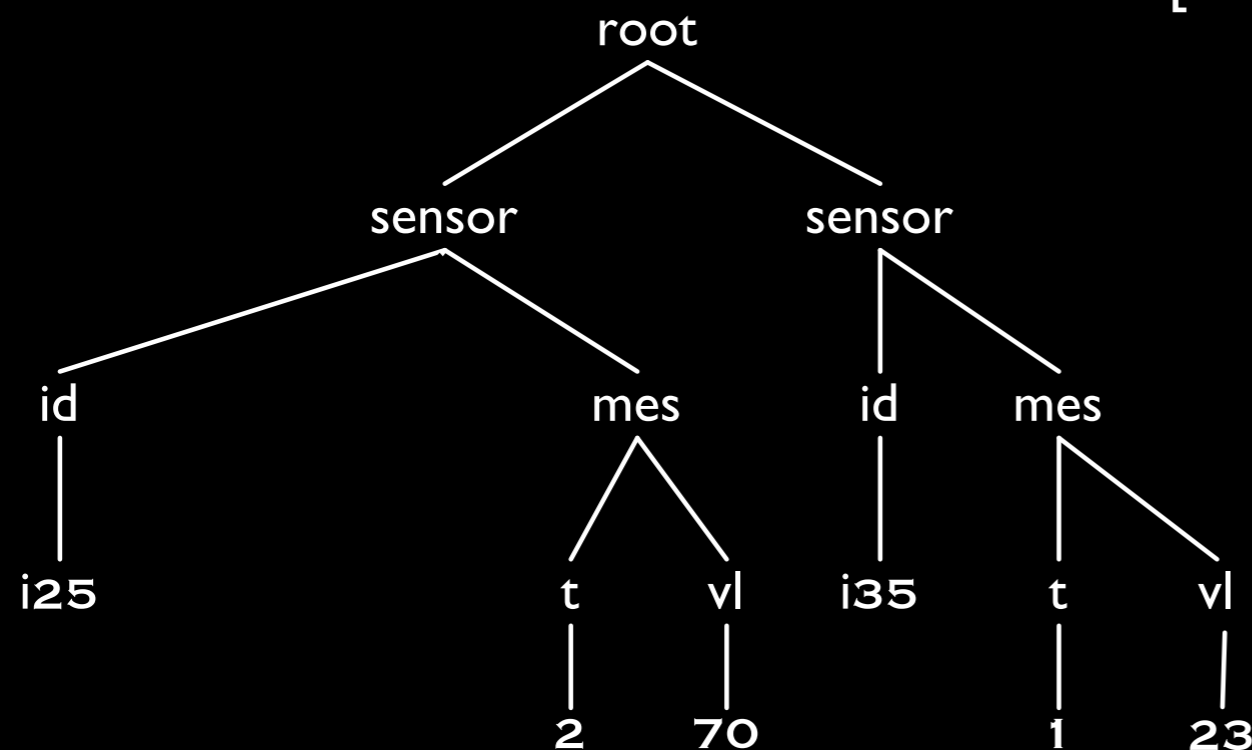
- $f = \text{true}$, $\Pr(f) = 0.4$
- **MUX: 23**, $\Pr(23) = 0.1$

$\Pr(d) = 0.4 \times 0.1$

PXML with Events and Distributional Nodes

[Kimelfed&al:2007]

[Senellart&al:2007]



- **f - event**: “weather is fine”
 $\Pr(f) = .4$
- **MUX** - mutually exclusive options

Semantics

a world d :

- $f = \text{true}$, $\Pr(f) = 0.4$
- **MUX**: 23, $\Pr(23) = 0.1$

$\Pr(d) = 0.4 \times 0.1$

Discrete Probabilistic XML Documents

- Probabilistic XML document D
 - represents (exponentially) many documents d
 - each with a probability $\Pr(d)$
- It is achieved by
 - **Conjunctions of event literals** on edges.
Capture **long-distance** dependencies
 - **Distributional** nodes: Mux, Ind, Det, Exp.
Capture **local** (hierarchical) dependencies

Discrete Probabilistic XML Documents

- Probabilistic XML document D
 - represents (exponentially) many documents d
 - each with a probability $\Pr(d)$
- It is achieved by
 - **Conjunctions of event literals** on edges.
Capture **long-distance** dependencies. Special case of event formulas
 - **Distributional** nodes: Mux, Ind, Det, Exp.
Capture **local** (hierarchical) dependencies

What is Known?

- Answering simple XPath queries [Kimelfed&al:2007]
[Senellart&al:2007]
- Distributional nodes: PTIME
- Events: $FP^{\#P}$ -complete
- Simple XPath over Mux-Det PXML with HAVING constraints: [Cohen&al:2008]
[Re&al:2007]
- PTIME for COUNT and MIN
- NP-hard for SUM and AVG

What is Known?

- Answering simple XPath queries [Kimelfed&al:2007]
[Senellart&al:2007]
- Distributional nodes: PTIME
- Events: $FP^{\#P}$ -complete
- Simple XPath over Mux-Det PXML with HAVING constraints: [Cohen&al:2008]
[Re&al:2007]
 - PTIME for COUNT and MIN
 - NP-hard for SUM and AVG

NO events

Outline

1. Probabilistic data
2. Problem definition
3. Aggregating discrete Probabilistic XML
4. Aggregating continuous Probabilistic XML

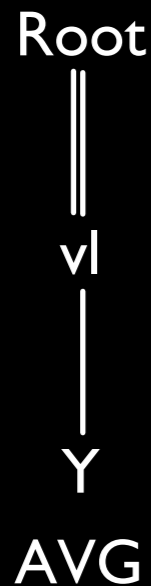
Aggregate Queries

1. What is the **average** temperature across sensors?
 2. What is the **average** temperature for sensor i25?
 3. **How often** did sensors i25 and i33 give the same measurement simultaneously?
- ⇒ we want to answer queries with **aggregate** functions:
MIN/MAX, TopK, COUNT, SUM, COUNTD, AVG

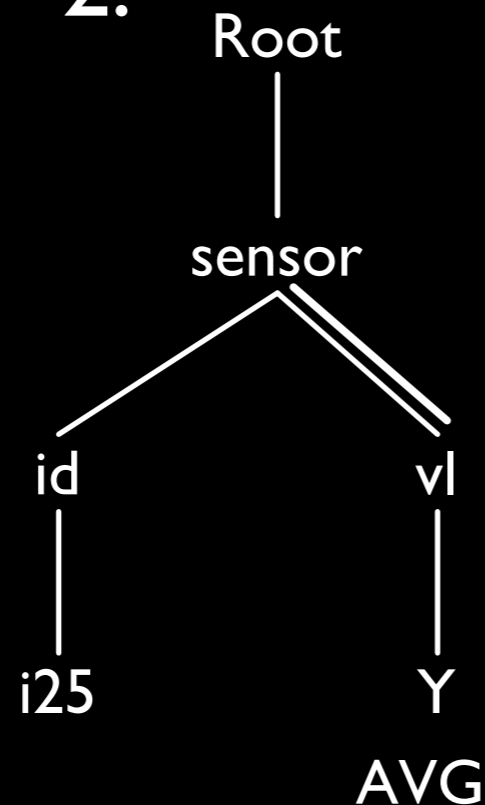
Query Models

1. What is the **average** temperature across sensors?
2. What is the **average** temperature for sensor i25?
3. **How often** did sensors i25 and i33 give the same measurement simultaneously?

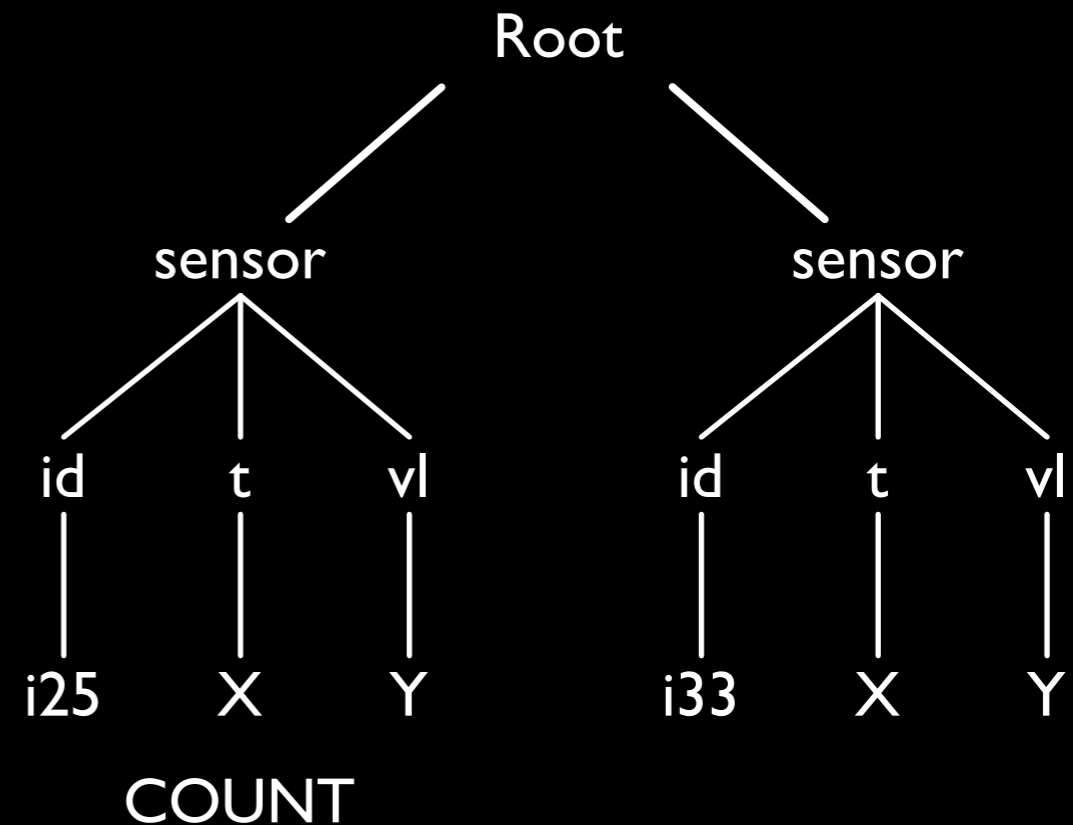
1.



2.



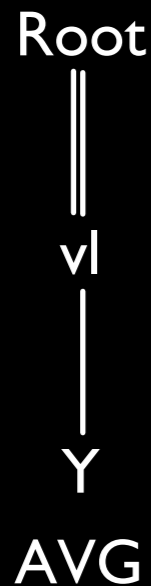
3.



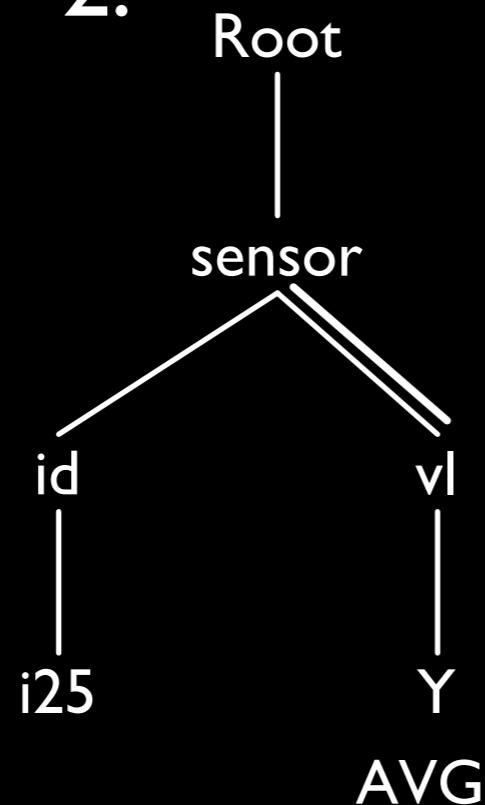
Query Models

1. What is the **average** temperature across sensors?
2. What is the **average** temperature for sensor i25?
3. **How often** did sensors i25 and i33 give the same measurement simultaneously?

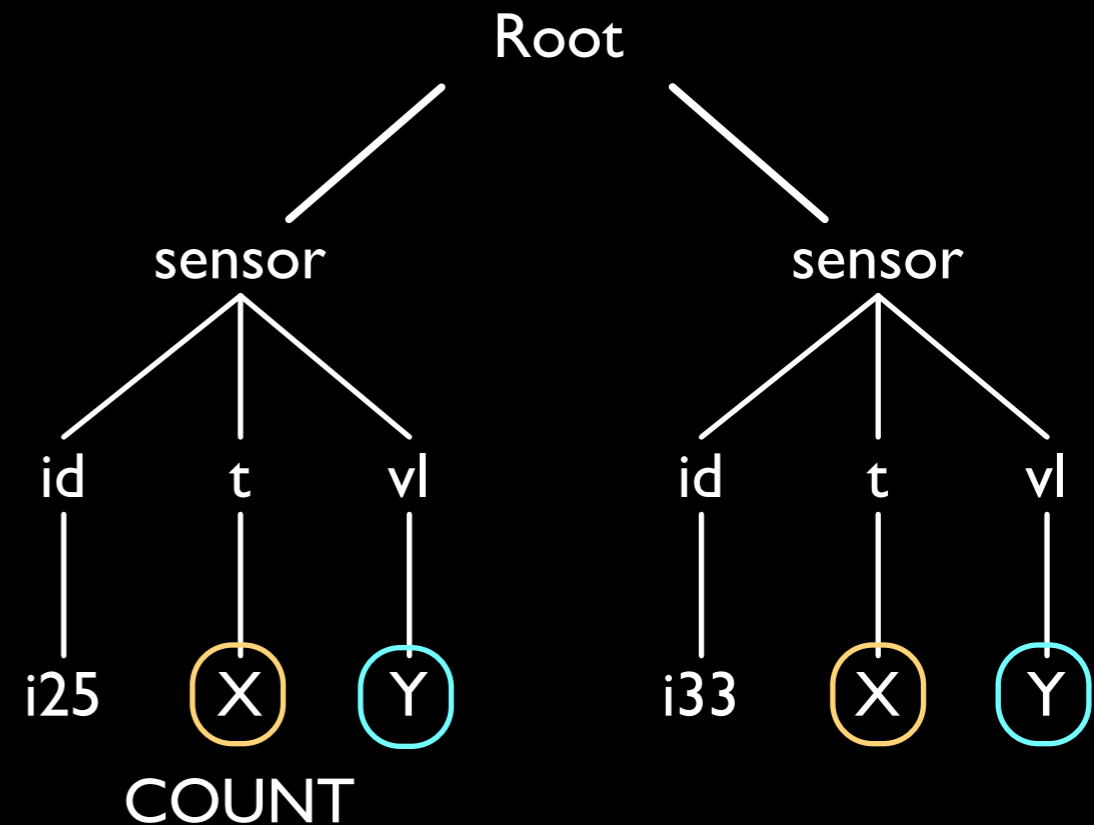
1.



2.



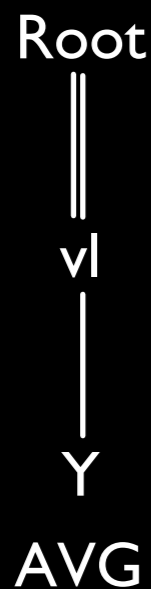
3.



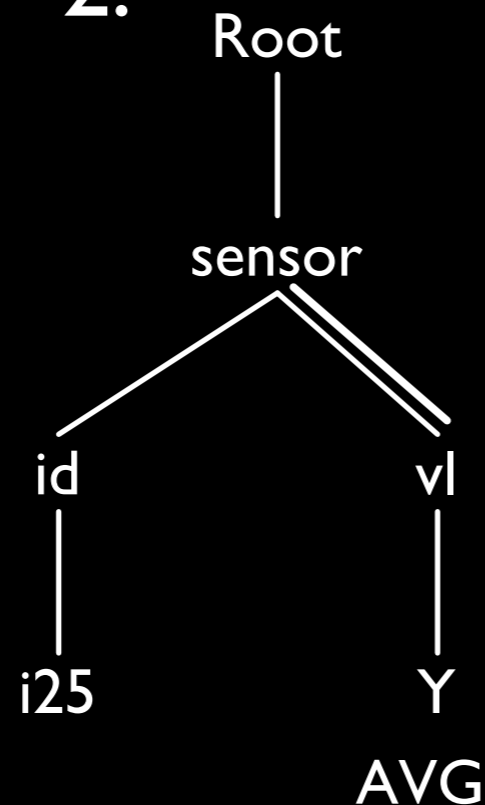
Query Models

1. Single-Path queries - **SP**
2. Tree-Pattern queries - **TP**
3. Tree-Pattern queries with Joins - **TPJ**

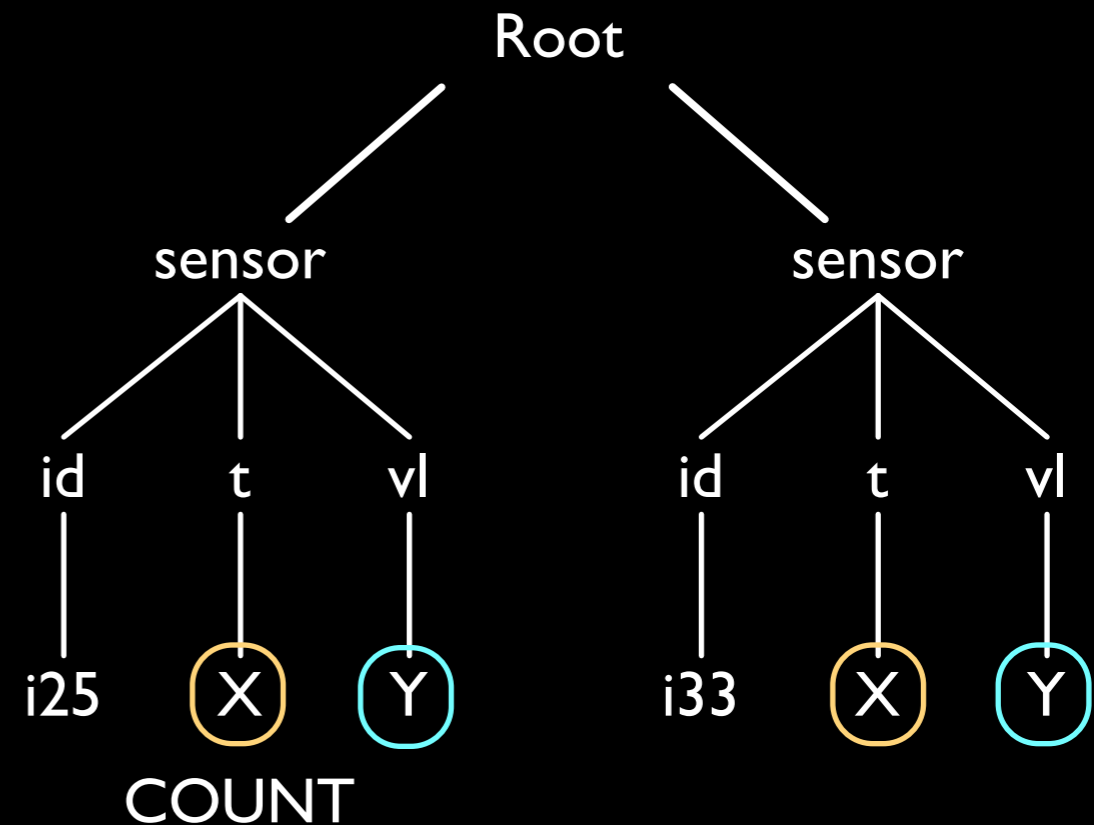
1.



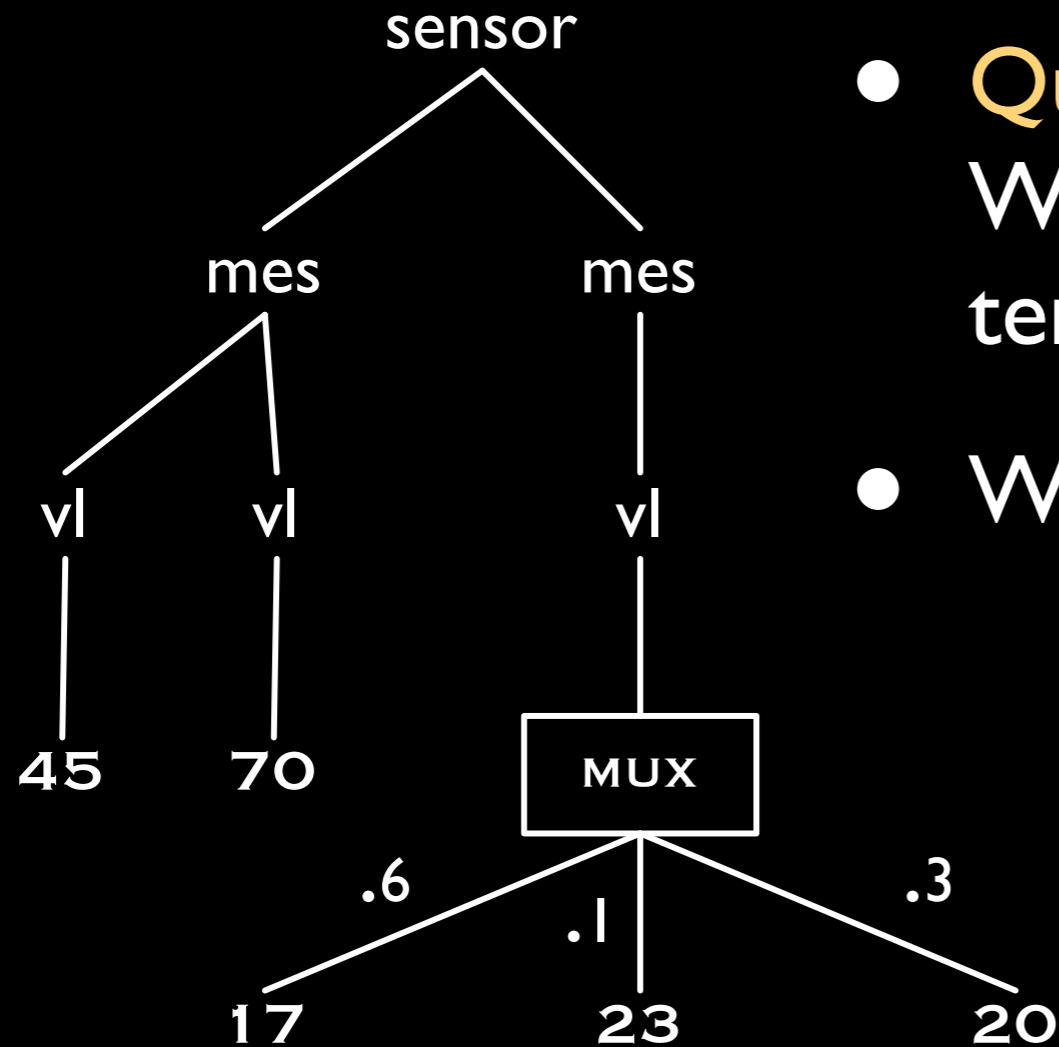
2.



3.



Semantics of AQs



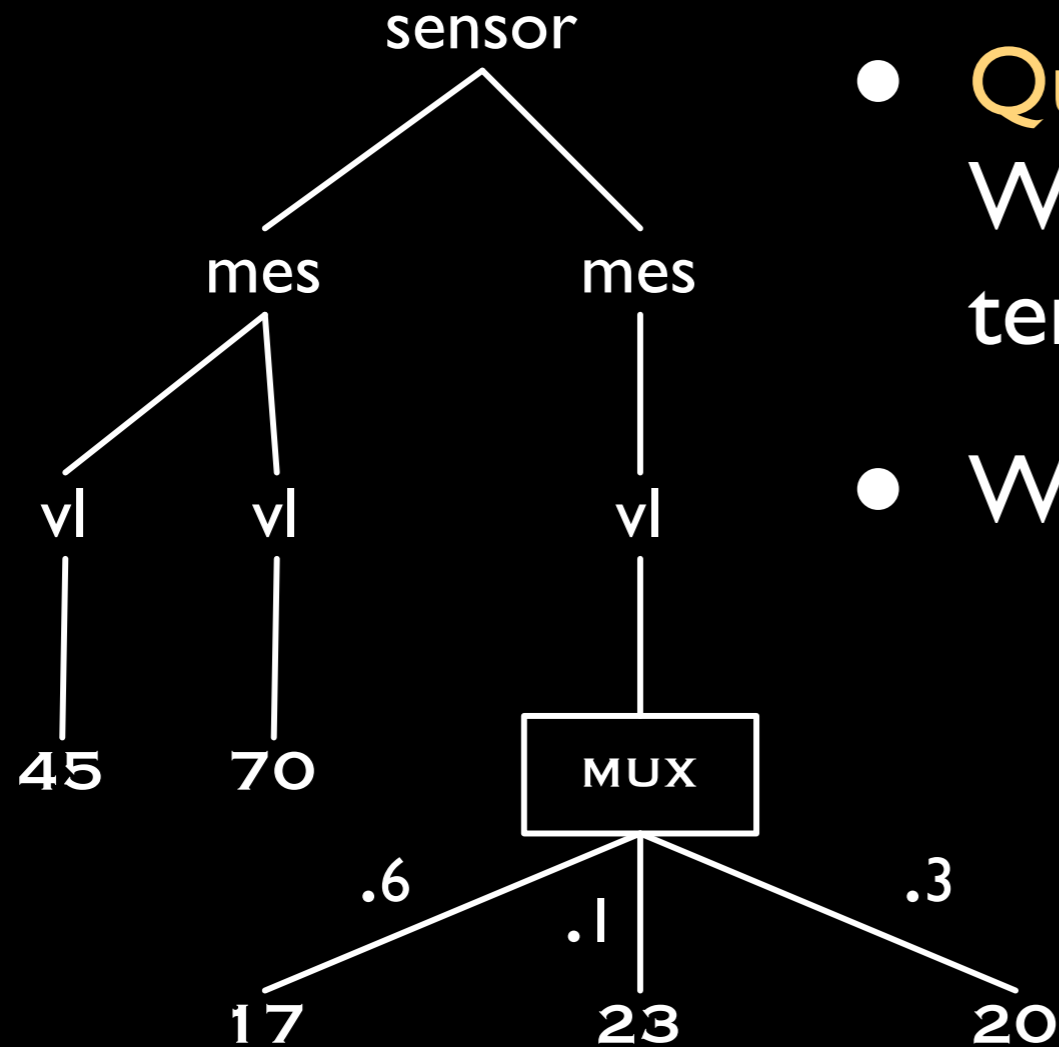
- **Query:**
What is the **average** temperature?
- What should be an **answer**?

$$\text{AVG}(d17) = 44, \text{Pr}(d17) = .6$$

$$\text{AVG}(d23) = 46, \text{Pr}(d23) = .1$$

$$\text{AVG}(d20) = 45, \text{Pr}(d20) = .3$$

Semantics of AQs



- **Query:**
What is the **average** temperature?
- What should be an **answer**?

$$\text{AVG}(d17) = 44, \text{Pr}(d17) = .6$$

$$\text{AVG}(d23) = 46, \text{Pr}(d23) = .1$$

$$\text{AVG}(d20) = 45, \text{Pr}(d20) = .3$$

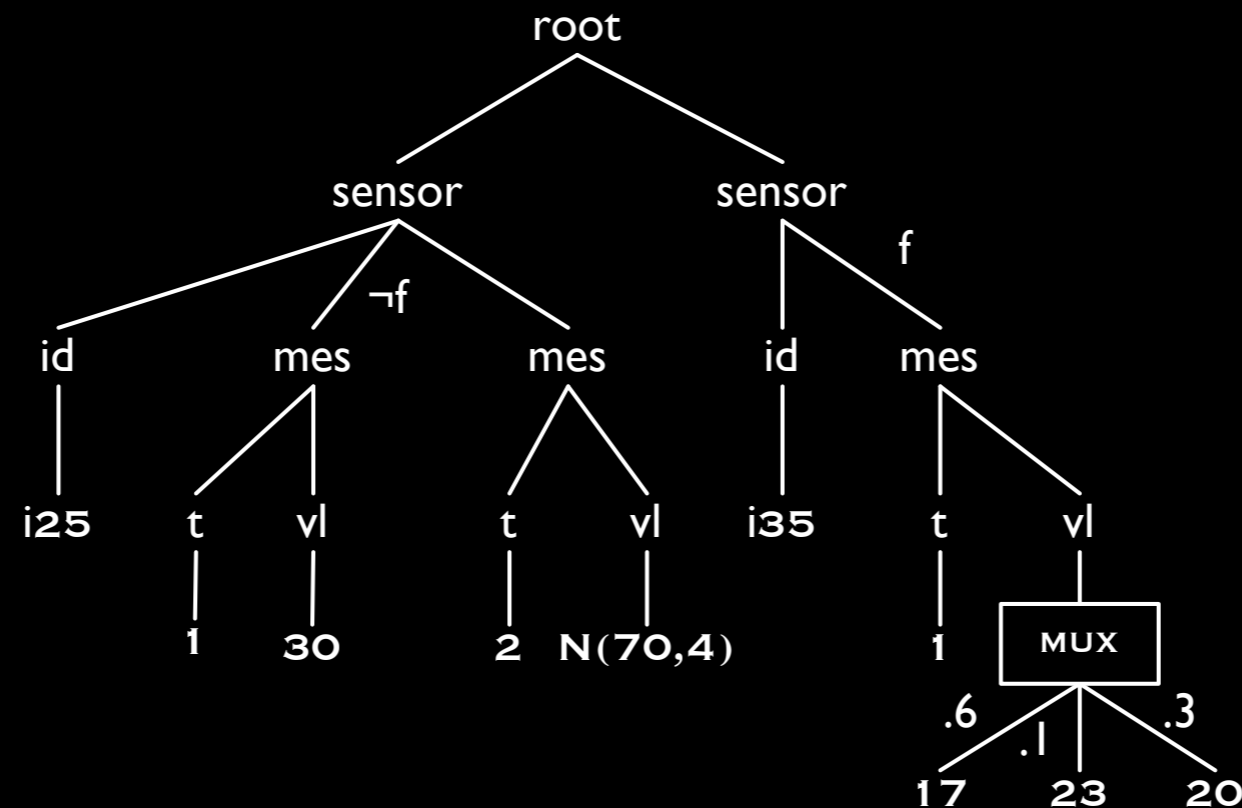
Distribution of aggregate values over all documents represented by the PXML document

Problems to Investigate for Discrete PXML

For PXML document D , constant C

- **Possible answers:**
decide $\Pr(Q(D)=C) > 0$
- **Probability computation:**
compute $\Pr(Q(D)=C)$
- **Moment computation:**
compute $E(Q(D)^k)$ E is “expected value”

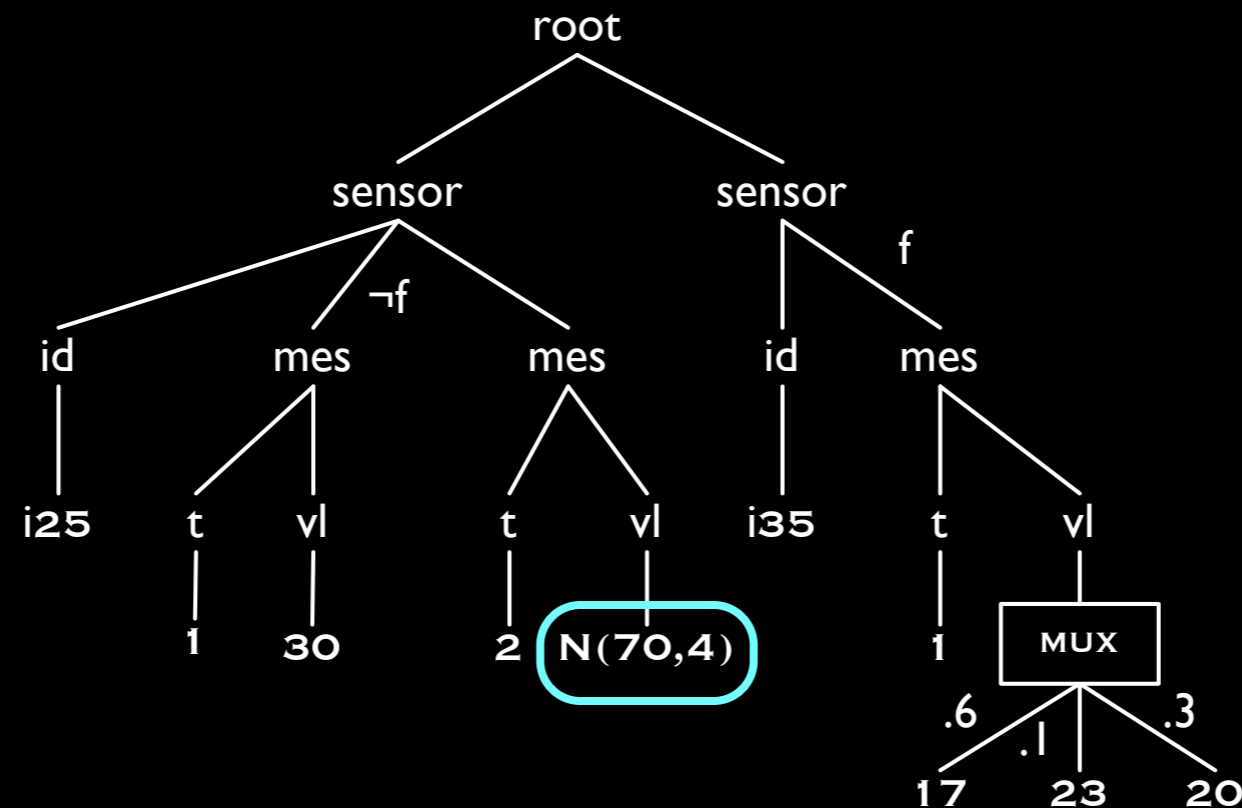
Continuous PXML



- Incorporate **continuous distributions** in PXML leaves
- **Aggregate** continuous PXML

At the moment there is **no** formal **semantics** for continuous probabilistic XML models

Continuous PXML



- Incorporate **continuous distributions** in PXML leaves
- **Aggregate** continuous PXML

At the moment there is **no** formal **semantics** for continuous probabilistic XML models

Outline

1. Probabilistic data
2. Problem definition
3. Aggregating discrete Probabilistic XML
4. Aggregating continuous Probabilistic XML

Data Complexity of Query Answering

	Query Language		
PXML Model	Single Path	Tree Pattern	Tree Pat. Joins
Event Conjunctions	$FP^{\#P}$ -complete		
Distributional Nodes	P		$FP^{\#P}$ -complete

What is difficult?

- **joins** in queries
- **events** in data

Data Complexity of Query Answering

	Query Language		
PXML Model	Single Path	Tree Pattern	Tree Pat. Joins
Event Conjunctions	$FP^{\#P}$ -complete		
Distributional Nodes	P		$FP^{\#P}$ -complete

What is difficult?

- **joins** in queries
- **events** in data

Is it getting more difficult with aggregation?

Aggregating PXML-Events

	Aggregate Query Language		
Problems	Single Path	Tree Pattern	Tree Pat. Joins
Possible Answers	NP-complete		
Probability Computation	FP ^{#P} -complete		
Moment Computation	COUNT, SUM: PTIME MIN, AVG COUNTD: FP ^{#P} -comp	FP ^{#P} -complete	

Data-complexity

Aggregates: COUNT, SUM, MIN, COUNTD, AVG

Aggregating PXML-Events

	Aggregate Query Language		
Problems	Single Path	Tree Pattern	Tree Pat. Joins
Possible Answers	NP-complete		
Probability Computation	FP ^{#P} -complete		
Moment Computation	COUNT, SUM, PTIME MIN, AVG COUNTD: FP ^{#P} -comp	FP ^{#P} -complete	

Data-complexity

Aggregates: COUNT, SUM, MIN, COUNTD, AVG

Aggregating PXML with Distributional Nodes

	Aggregate Query Language		
Problems	Single Path	Tree Pattern	Tree Pat. Joins
Possible Answers	SUM,AVG, COUNTD: NP-complete		
	COUNT, MIN: PTIME		COUNT, MIN : NP
Probability Computation	SUM,AVG, COUNTD: $FP^{\#P}$ -complete COUNT, MIN: PTIME		$FP^{\#P}$ -complete
Probability SUM in $ input + output $	PTIME	$FP^{\#P}$	
Moment Computation		AVG: $FP^{\#P}$ others: PTIME	

Data-complexity

Aggregates: COUNT, SUM, MIN, COUNTD, AVG

Aggregating PXML with Distributional Nodes

				Aggregate Query Language		
Problems	Single Path	Tree Pattern	Tree Pat. Joins			
Possible Answers	SUM,AVG, COUNTD: NP-complete					
Probability Computation	COUNT, MIN: PTIME		COUNT, MIN : NP			
Probability SUM in input + output	SUM,AVG, COUNTD: FP ^{#P} -complete		FP ^{#P} -complete			
Moment Computation	COUNT, MIN: PTIME					

Data-complexity

Aggregates: COUNT, SUM, MIN, COUNTD, AVG

Tractable Cases

Key components of tractability:

- **Hierarchical** structure of PXML documents imposed by **distributional** nodes
- Some aggregate functions can exploit the hierarchy - **monoid functions**

Monoid: COUNT, SUM, MIN, TopK, PARITY, ...

Non Monoid: COUNTD, AVG

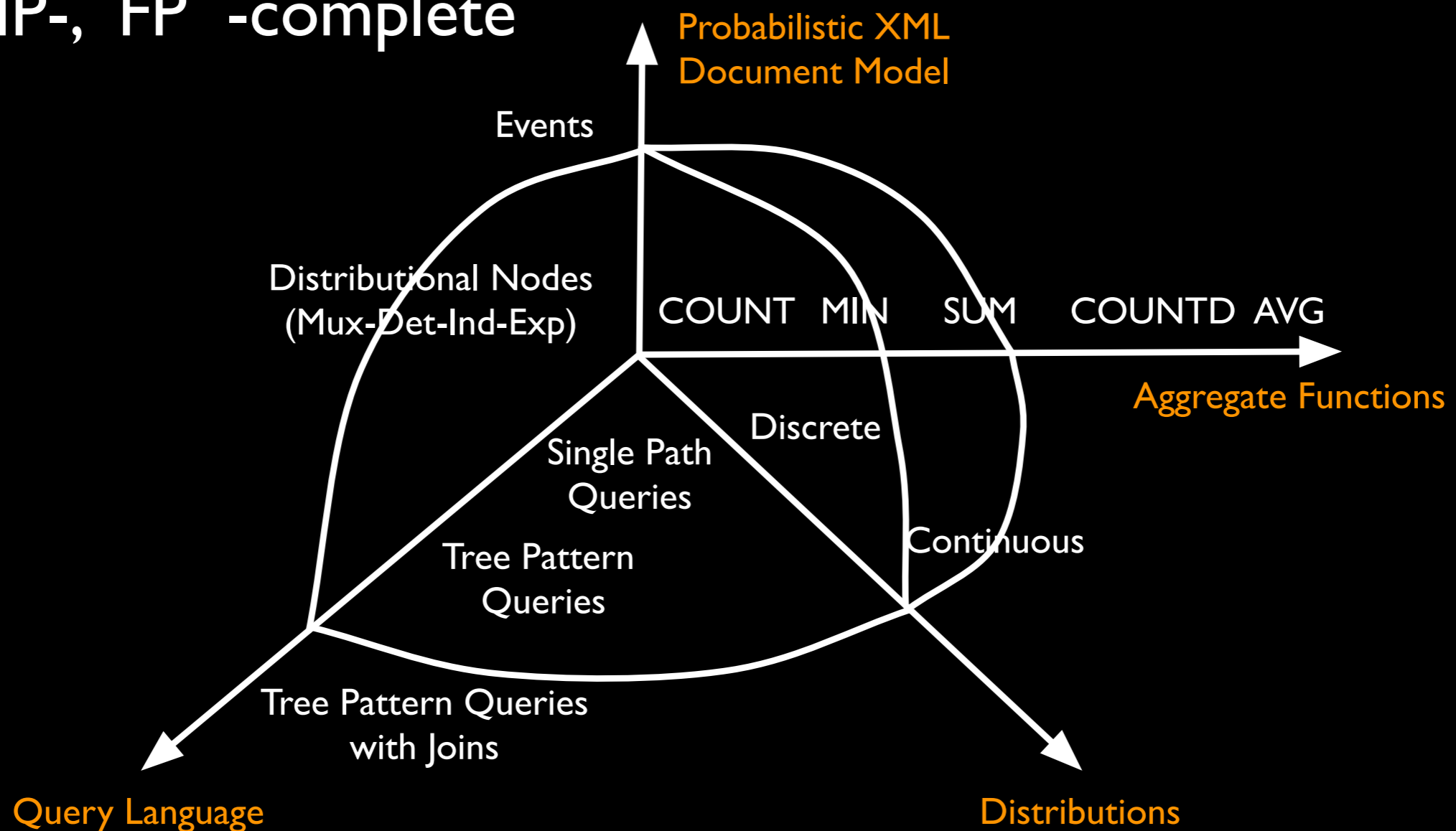
P-TIME algorithm to compute distributions:

Bottom-up evaluation using **convex sums** and **convolutions**

The Problem Space

Outside: intractable,
i.e., NP-, $FP^{\#P}$ -complete

Inside: PTIME



Approximating Query Answers

- Many problems are NP- or $\text{FP}^{\#P}$ -complete
How good are **Monte-Carlo** methods?

- By Hoeffding bound, to achieve

$$| E(\alpha(D)^k) - \text{Estimate} | < \varepsilon \text{ with } \text{Pr} = 1 - \delta$$

at most $O(R^{2k} 1/\varepsilon^2 \log(1/\delta))$ samples is needed

\Rightarrow for $\alpha = \text{COUNTD}$

quadratically many samples are needed

Approximating Query Answers

- Many problems are NP- or $\text{FP}^{\#P}$ -complete
How good are **Monte-Carlo** methods?

- By Hoeffding bound, to achieve

$$| E(\alpha(D)^k) - \text{Estimate} | < \varepsilon \text{ with } \text{Pr} = 1 - \delta$$

at most $O(R^{2k} 1/\varepsilon^2 \log(1/\delta))$ samples is needed

\Rightarrow for $\alpha = \text{COUNTD}$

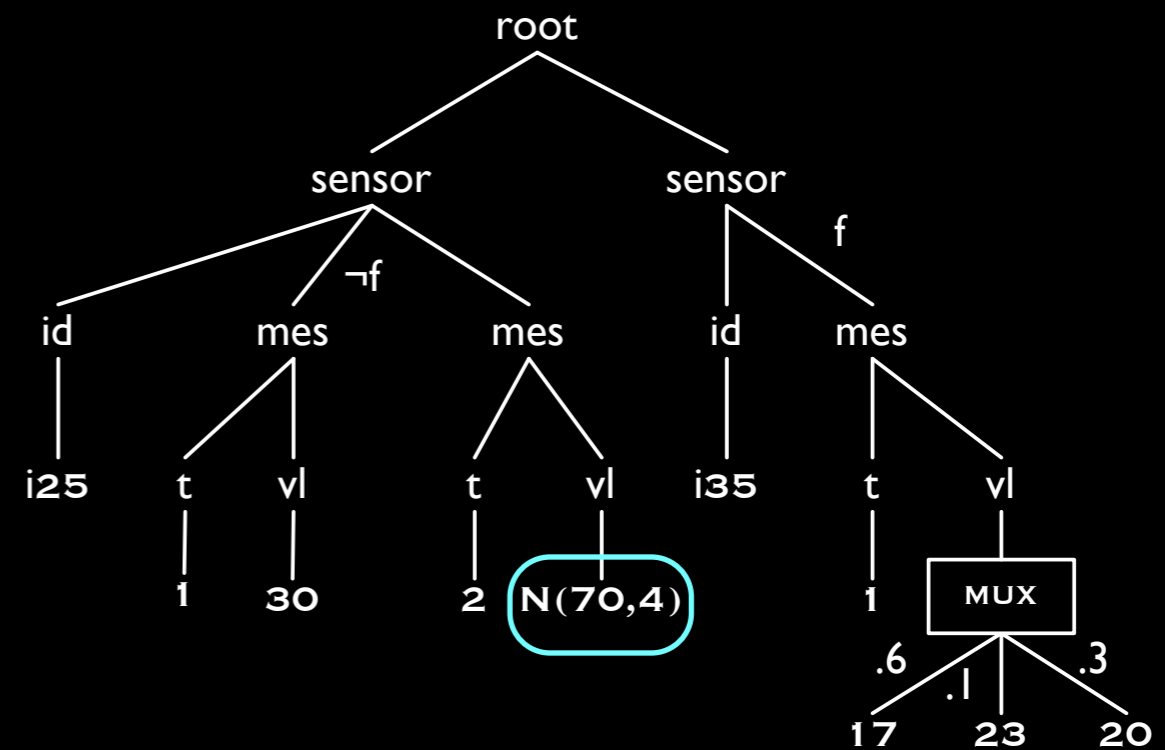
quadratically many samples are needed

Outline

1. Probabilistic data
2. Problem definition
3. Aggregating discrete Probabilistic XML
4. Aggregating continuous Probabilistic XML

Discrete vs Continuous Models

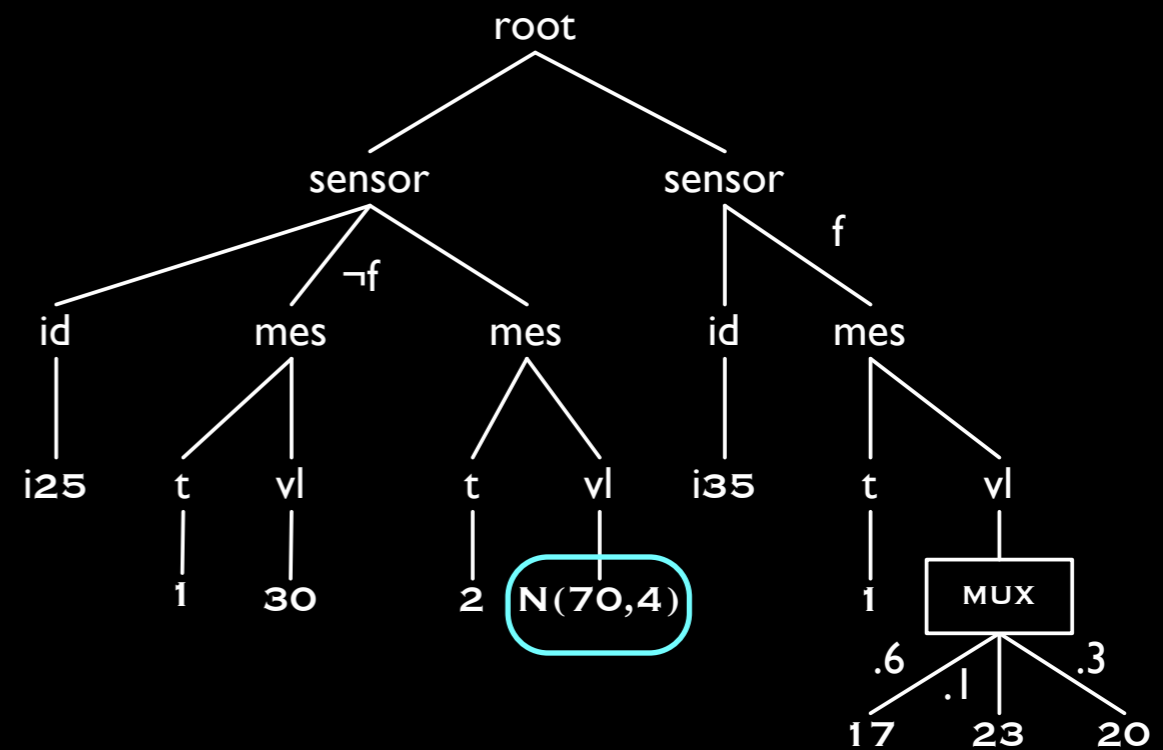
- Finite case:
 - **finite** sets of trees
 - where **every tree** has a non-zero probability



- Continuous case:
 - **infinite** sets of trees
 - where **some** (infinite) **subsets** of trees have non-zero probability measure

Discrete vs Continuous Models

- Finite case:
 - **finite** sets of trees
 - where **every tree** has a non-zero probability



- Continuous case:
 - **infinite** sets of trees
 - where **some** (infinite) **subsets** of trees have non-zero probability measure

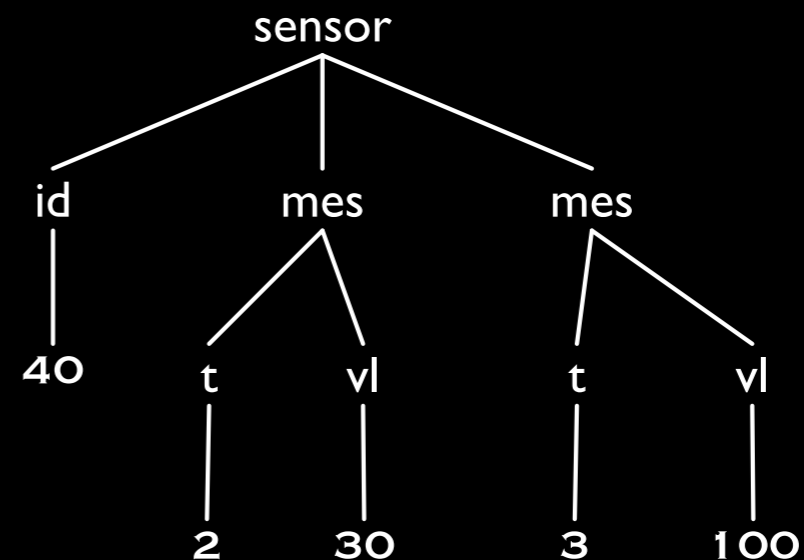
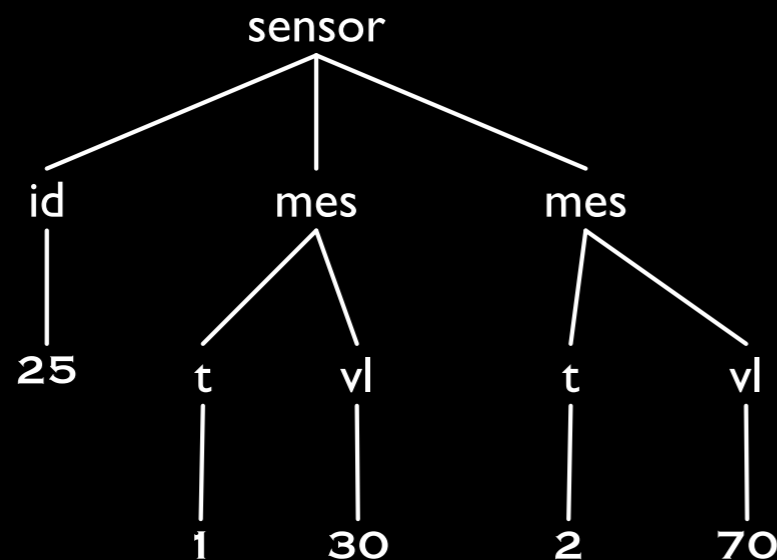
How to measure infinite sets of trees?

Measuring Infinite Sets of Trees

I. Take a set S of trees with

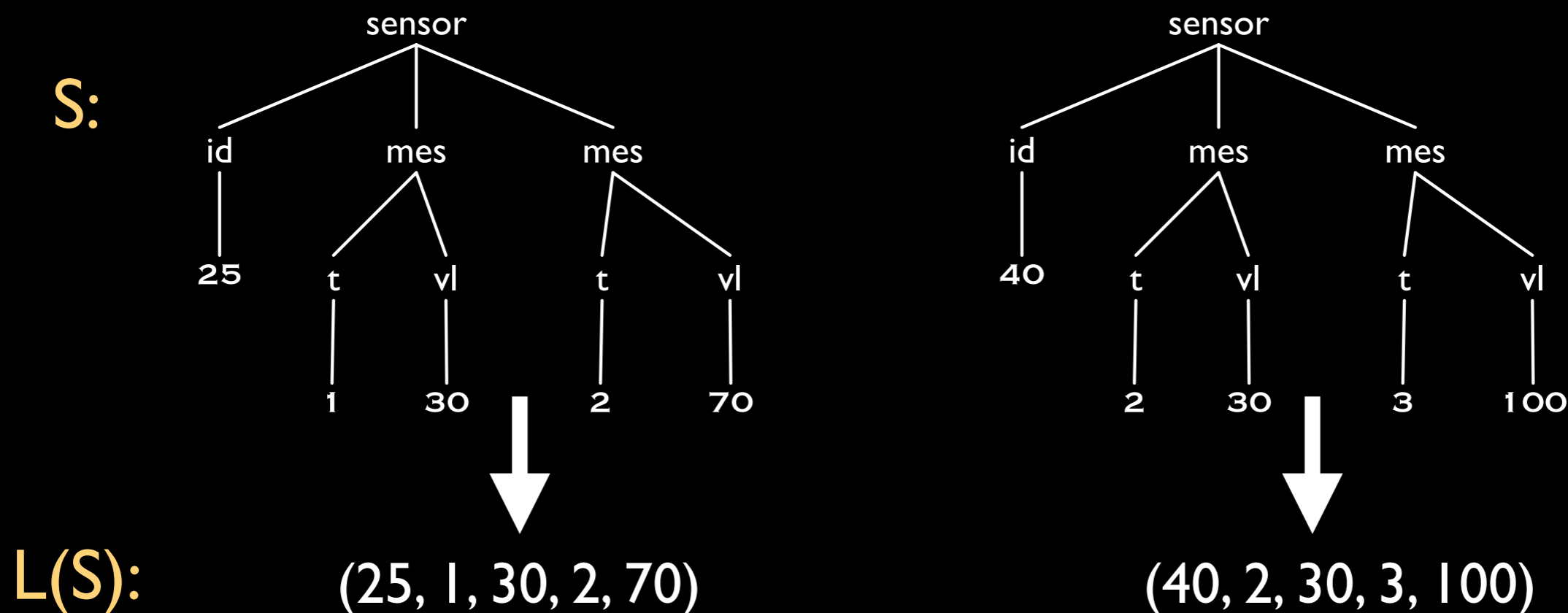
- **real values** on the leaves / **share** the same **structure**

S:



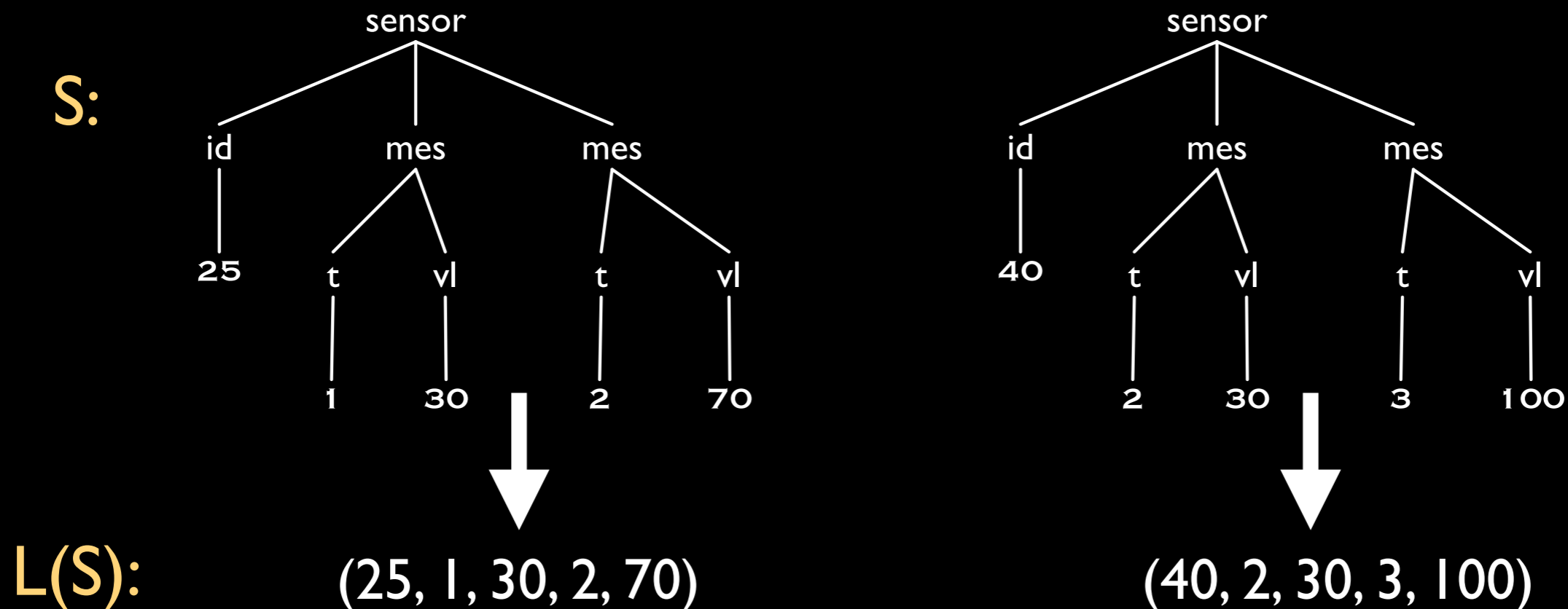
Measuring Infinite Sets of Trees

1. Take a set S of trees with
 - **real values** on the leaves / **share** the same **structure**
2. collect **labels** of leaves **as tuples** of values
 \Rightarrow Subset $L(S)$ of \mathbb{R}^n



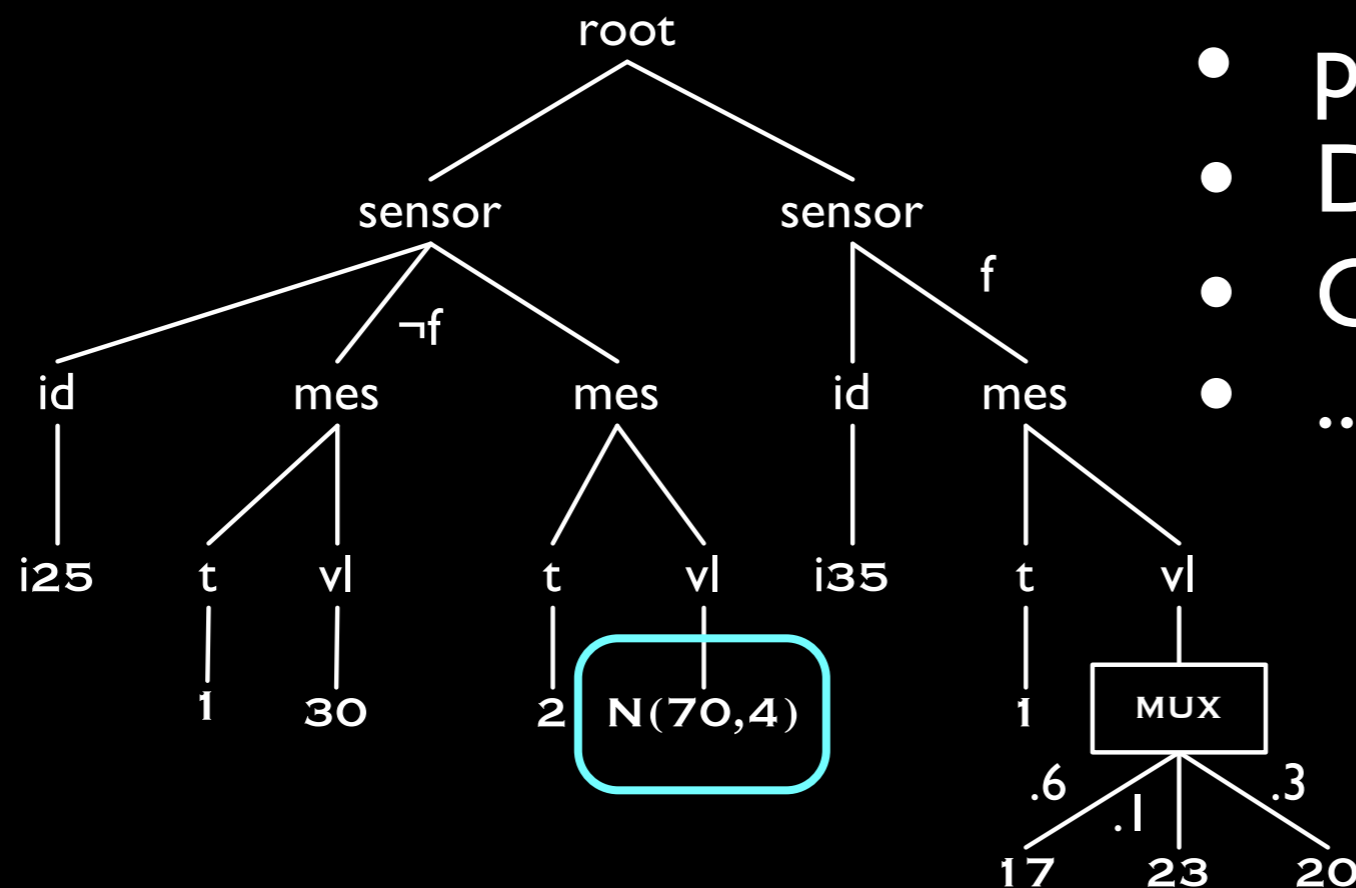
Measuring Infinite Sets of Trees

3. Take a **standard measure M** on Borel subsets of \mathbb{R}^n
4. **Use** the measure M on $L(S)$
5. **Lift M** from sets of tuples $L(S)$ to sets of trees S



Continuous PXML Documents

- Extension of discrete PXML with distribution functions attached to leaves



- piecewise polynomials
- Diracs
- Gaussian
- ...

Aggregation of CPXML: Probability Computation

- Tractable for
 1. Data: CPXML with distributional nodes
 2. Query: SP with monoid functions
- Bottom-up algorithms based on **convex sums** and **convolutions**
- Works when distributions on the leaves are **closed** under convolutions and convex sums
 - piecewise polynomials (SUM, MIN/MAX) **PTIME**

Summing Up

- **Comprehensive picture** of complexity for **discrete** PXML aggregation:
 - PXML models with local, global dependencies
 - SP, TP, TPJ queries
 - COUNT, SUM, MIN, COUNTD, AVG
- **Continuous** PXML model:
 - **formal** semantics
 - initial study of aggregation

Madam



- Thank you

References

- [Kimelfeld&al:2007] - Benny Kimelfeld, Yehoshua Sagiv: Matching Twigs in Probabilistic XML. VLDB 2007: 27-38
- [Senellart&al:2007] - Pierre Senellart, Serge Abiteboul: On the complexity of managing probabilistic XML data. PODS 2007: 283-292
- [Re&al:2007] - C. Ré and D. Suciu. Efficient evaluation of HAVING queries on a probabilistic database. DBPL 2007
- [Cohen&al:2008] - Sara Cohen, Benny Kimelfeld, Yehoshua Sagiv: Incorporating constraints in probabilistic XML. PODS 2008: 109-118