# Topics in Probabilistic and Statistical Databases 

# Lecture 2: Representation of Probabilistic Databases 

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## Review: Definition

The set of all possible database instances:

$$
\text { Inst }=\left\{\mathrm{I}_{1}, \mathrm{I}_{2}, \mathrm{I}_{3}, \ldots, \mathrm{I}_{\mathrm{N}}\right\}
$$

Sample space ( $\Omega$ )

Definition A probabilistic database PDB $=(\mathbf{I n s t}, \mathrm{Pr})$ is a discrete probability distribution:

$$
\operatorname{Pr}: \text { Inst } \rightarrow[0,1] \quad \text { s.t. } \sum_{\mathrm{i}=1, \mathrm{~N}} \operatorname{Pr}\left(\mathrm{I}_{\mathrm{i}}\right)=1
$$

Definition A possible world is I s.t. $\operatorname{Pr}(\mathrm{I})>0$
A possible tuple is a tuple $\mathrm{t} \in \mathrm{I}$, for a possible world $\mathrm{I}^{2}$

## Representation System

Informally: it is a syntax + semantics that allows us to represent a probabilistic database concisely

Definition A representation system for ProbDB is ( $\mathbf{S}$, Rep), where $\mathbf{S}$ is a set of representations and Rep: $\mathbf{S} \boldsymbol{\rightarrow}$ (set of PDBs) assigns a probabilistic database to each representation

## Review: <br> Disjoint-Independent Databases

Definition A PDB is disjoint-independent if for any set T of possible tuples one of the following holds:

- T is an independent set, or
- T contains two disjoint tuples

A disjoint-independent database can be fully specified by:

- all marginal tuple probabilities
- an indication of which tuples are disjoint or independent


## Representations Systems for D/IDatabases

- MystiQ's representation
- Trio's xor-, maybe- tuples
- Attribute-level probabilities


## D/I Relations in MystiQ

At the schema level:

- Possible worlds key = set of attributes
- Probability = expression on attributes

Constraint at the instance level:

- For each key value, sum of probabilities $\leq 1$



## X-Relations in Trio

- Maybe tuple is $t$ ?, meaning it may be missing
- X-tuple is $<\mathrm{t} 1, \mathrm{t} 2, \ldots>$ meaning it may be any of $\mathrm{t} 1, \mathrm{t} 2, \ldots$
- An X-relation is a collection of X-tuples and maybe-tuples


## Maybe- and X-tuples in Trio

$\mathrm{S}=$

| ID | Saw(witness, car) |
| :---: | :---: |
| 11 | (Amy, Acura) $: 0.8$ |
| 12 | (Betty,Acura) $: 0.4$ | (Betty, Mazda) $: 0.6$ ?


| ID | Drives(person, car) |
| :---: | :---: |
| 51 | (Hank, Acura) :0.6 ? |

$$
\operatorname{Rep}(S)=?
$$

## Attribute-level Uncertainty

- For some attribute A, give a probability distribution on possible values
- Note: sum of probabilities must be 1
- More generally, for a set of attributes A1, A2, ... give a probability distribution on possible values
[Barbara'92]


## Attribute-Level Uncertainty

| $\mathrm{S}=$ | TABLE 1 <br> Example Probabilistic Relation |  |  |
| :--- | :--- | :--- | :--- |
| Key | Independent | Interdependent | Independent |
|  | Deterministic | Stochastic | Stochastic |
| EMPLOYEE | DEPARTMENT | QUALITY BONUS | SALES |
| Jon Smith | Toy | 0.4 [Great Yes] | $0.3[\$ 30-34 \mathrm{~K}]$ |
|  |  | 0.5 [Good Yes] | $0.7[\$ 35-39 \mathrm{~K}]$ |
|  |  | 0.1 [Fair No] | 1.0 [Good Yes] |

$$
\operatorname{Rep}(S)=?
$$

## Review Query Semantics

Semantics 1: Possible Sets of Answers
A probability distributions on sets of tuples

$$
\forall \mathrm{A} \cdot \operatorname{Pr}(\mathrm{Q}=\mathrm{A})=\sum_{\mathrm{I} \in \text { Inst. } \mathrm{Q}(\mathrm{I})=\mathrm{A}} \operatorname{Pr}(\mathrm{I})
$$

Semantics 2: Possible Tuples
A probability function on tuples

$$
\forall \mathrm{t} . \operatorname{Pr}(\mathrm{t} \in \mathrm{Q})=\sum_{\mathrm{I} \in \text { Inst. } \mathrm{t} \in \mathrm{Q}(\mathrm{I})} \operatorname{Pr}(\mathrm{I})
$$

## The Representation Problem

- How do we represent correlations between tuples in a probdb?
- How do we represent query answers (views)?


## Main Techniques

- Incomplete databases
- Concerned with representing possible worlds, i.e. no probabilities
- Probabilistic Networks
- Concerned with representing correlations, i.e. no databases

Incomplete Databases

## [Imilelinski\&Lipsi’1984, Green\&Tannen'2006]

## Incomplete Databases

Let Inst $=$ the set of all possible instances over domain D
Definition An incomplete database is a set of possible worlds

$$
\mathbf{I}=\left\{\mathrm{I}_{1}, \mathrm{I}_{2}, \mathrm{I}_{3}, \ldots\right\} \subseteq \text { Inst }
$$

Definition A representation system is ( $\mathbf{S}$, Rep) where $\mathbf{S}$ is a set of representations described by some syntax, and:

$$
\text { Rep : } \mathbf{S} \rightarrow 2^{\text {Inst }}
$$

## Discussion

- We often denote an incomplete database $\left\{\mathrm{I}_{1}, \mathrm{I}_{2}, \ldots\right\}$ with $<\mathrm{I}_{1}, \mathrm{I}_{2}, \ldots>$
- This is called an OR-set: the true state can be any $\mathrm{I} \in<\mathrm{I}_{1}, \mathrm{I}_{2}, \ldots>$


## Rule of Thumb \#1

A ProbDB = an Incomplete DB + probabilities

## Discussion

- Question: what does $<>$ mean (the empty set of worlds)?


## Discussion

- Question: what does $<>$ mean (the empty set of worlds)?
- Answer: inconsistency !
- We do not allow $<>$


## Examples

- Every traditional database instance I is also an incomplete database $\mathbf{I}=<\mathrm{I}>$
- The no-information, or zero-information incomplete database is:
$\mathbf{N}=<\mathrm{I} \mid \mathrm{I} \in$ Inst $>$
(in other words: $\mathbf{N}=\mathbf{I n s t}$ )


## Four Representation Systems

- Codd-tables
- V-tables
- C-tables
- OR-sets


## Codd-Tables

## $\mathrm{T}=$

SUPPLIER LOCATION PRODUCT QUANTITY

| Smith | London | Nails | B |
| :--- | :---: | :--- | :---: |
| Brown | $@$ | Bolts | Nuts |
| Jones | $@$ | 40,000 |  |
|  |  |  |  |
| NULL or $\perp$ |  |  |  |

$$
\operatorname{Rep}(T)=?
$$

## V-Tables

## $\mathrm{T}=$



## C-Tables

## $\mathrm{T}=$

| SUPPLIER | LOCATION | PRODUCT | con |
| :---: | :---: | :---: | :---: |
| $x$ | London | Nails | $x=$ Smith |
| Brown | New York | Nails | $x \neq$ Smith |

$$
\operatorname{Rep}(\mathrm{T})=?
$$

## Boolean C-Tables: Vars only in Cond

$$
\mathrm{T}=
$$

| A | B | Cond |
| :--- | :--- | :--- |
| a1 | b 1 | $(\mathrm{x}=1) \wedge(\mathrm{y}=2) \vee(\mathrm{z}=1)$ |
| a 1 | b 2 | $\mathrm{x}=2$ |
| a 2 | b 2 | $\mathrm{z}=1$ |

We often state explicitly the domain of each variable:
$\operatorname{Dom}(\mathrm{X})=\{1,2\}$
$\operatorname{Dom}(\mathrm{Y})=\{1,2,3\}$
$\operatorname{Dom}(Z)=\{0,1\} \ldots$

$$
\operatorname{Rep}(T)=?
$$

In G\&T's definition all vars are Boolean; minor distinction.

## OR-Sets

## Review of Nested Relational Algebra NRA:

## Types: <br> $\mathrm{T}::=$ baseType $|\mathrm{T} \times \mathrm{T}|\{\mathrm{T}\}$ <br> Operations (in class):...

## OR-Sets

Types:

$$
\mathrm{T}::=\text { baseType }|\mathrm{T} \times \mathrm{T}|\{\mathrm{T}\} \mid<\mathrm{T}>
$$

Operations (in class):...

## OR-Sets Examples

What are their types? What do they mean?

- $\{[$ Gizmo, $<99,110>]$, [Camera, $<10,12,19>]\}$
- $\{<3,5>,<3,7>,<5,8,12>\}$
- $\{<\{<1,2>,<3>\},\{<4>\}>,<\{<1>\},\{<2,3>,<4>\}>\}$


## Discussion

Which concepts from incomplete databases where borrowed by the three simple representation systems for ProbDB ?

- MystiQ's disjoint/independent tables
- Trio's X-tuples
- Attribute level probabilities


## Two Important Properties

- Completeness: can a representation system represent all incomplete databases ?
- Closure: can the result of a query also be represented in the same system ?


## Closure and Completeness



Definition A representation system is complete if for any incomplete database $\mathbf{I}$ there exists a representation $S$ s.t. $\operatorname{Rep}(S)=\mathbf{I}$.

## Which Are Complete? Why ?

- Codd-Tables ?
- V-Tables?
- C-Tables ?
- OR-Sets ?


## Which Are Complete ? Why ?

- Codd-Tables ? NO: constant cardinality
- V-Tables ? NO: constant cardinality
- C-Tables? YES
- OR-Sets? YES


## Closure

Definition A representation system is closed w.r.t. a query language Q , if for every representation S and query $q$ in Q , there exists $S^{\prime}$ s.t. $\operatorname{Rep}\left(S^{\prime}\right)=q(\operatorname{Rep}(S)$


## Which Are Closed w.r.t. RA ?

- Codd-Tables ?
- V-Tables?
- C-Tables ?
- OR-Sets ?


## Which Are Closed w.r.t. RA ?

- Codd-Tables? NO - in class
- V-Tables? NO - in class
- C-Tables ? YES - in class
- OR-Sets ? YES - in class


## Completeness $\boldsymbol{\rightarrow}$ Closure

- Fact: every complete system is closed w.r.t. the Relational Algebra
- Why?


## Completeness $\leftarrow$ Closure ?

- Challenge: give an example of a system that is closed w.r.t. Relational Algebra but is not complete!


## Completeness $\leftarrow$ Closure ?

Consider a representation system $\mathbf{S}$ s.t.

- S can represent any deterministic instance $<\mathrm{I}>$
- $S$ can represent $<\{0\},\{1\}>$
- $\mathbf{S}$ is closed under $\{\Pi, \times, \sigma\}$

Then $\mathbf{S}$ is complete

PROOF: in class

## Lineage

- Lineage $=$ a Boolean expression annotating a tuple that explains why the tuple is there
- Technically: lineage $=$ condition in a Boolean C-table
- A.k.a provenance


## [Benjelloun, VLDBJ'2008]

## Example

## Start from Trio's X-relations:

```
ID 
X1 <[Amy, Mazda], [Amy, Toyota]> ?
X2 <[Betty, Honda]>
```

| ID | Drives(Person, Car) |
| :--- | :--- |
| Y1 | $<$ [Jimmy, Mazda], [Jimmy, Toyota] $>$ |
| Y2 | $<$ [Billy, Mazda], [Billy, Honda] $>$ |

## [Benjelloun, VLDBJ’2008]

## Example

## Convert to Boolean C-Tables

Saw

| Witness | Car | Cond |
| :--- | :--- | :--- |
| Amy | Mazda | $\mathrm{X} 1=1$ |
| Amy | Toyota | $\mathrm{X} 1=2$ |
| Betty | Honda | $\mathrm{X} 2=1$ |


| Person | Car | Cond |
| :--- | :--- | :--- |
| Jimmy | Mazda | $\mathrm{Y} 1=1$ |
| Jimmy | Toyota | $\mathrm{Y} 1=2$ |
| Billy | Mazda | $\mathrm{Y} 2=1$ |
| Billy | Honda | $\mathrm{Y} 2=2$ |

Q: How do we say
"Amy is a maybe tuple",
"Betty is a certain tuple"?
Drives

## Example

Answer:
$\operatorname{Dom}(\mathrm{X} 1)=\{0,1,2\}$
$\operatorname{Dom}(\mathrm{X} 2)=\{1\}$
$\operatorname{Dom}(\mathrm{Y} 1)=\{1,2\}$
$\operatorname{Dom}(\mathrm{Y} 2)=\{1,2\}$

## [Benjelloun, VLDBJ’2008]

## Example

Compute the query $q(w, p):-\operatorname{Saw}(w, c), \operatorname{Drives}(c, p)$

Saw

| Witness | Car | Cond |
| :--- | :--- | :--- |
| Amy | Mazda | $\mathrm{X} 1=1$ |
| Amy | Toyota | $\mathrm{X} 1=2$ |
| Betty | Honda | $\mathrm{X} 2=1$ |

Drives

| Person | Car | Cond |
| :--- | :--- | :--- |
| Jimmy | Mazda | $\mathrm{Y} 1=1$ |
| Jimmy | Toyota | $\mathrm{Y} 1=2$ |
| Billy | Mazda | $\mathrm{Y} 2=1$ |
| Billy | Honda | $\mathrm{Y} 2=2$ |


| Witness | Person | Cond |
| :--- | :--- | :--- |
| Amy | Jimmy | $\mathrm{X} 1=1 \wedge \mathrm{Y} 1=1 \vee \mathrm{X} 1=2 \wedge \mathrm{Y} 1=2$ |
| Betty | Billy | $\mathrm{X} 2=1 \wedge \mathrm{Y} 2=2$ |

## Uniform Lineage

Call a lineage expression uniform if:

- It is in DNF
- All conjuncts have the same number $k$ of literals
- Each literal is of the form $\mathrm{X}=\mathrm{v}$

Representation of uniform lineage: add 2 k columns!

## Example

Compute the query $q(w, p):-\operatorname{Saw}(w, c), \operatorname{Drives}(c, p)$

Saw

| Witness | Car | X | V |
| :--- | :--- | :--- | :--- |
| Amy | Mazda | X1 | 1 |
| Amy | Toyota | X1 | 2 |
| Betty | Honda | X2 | 1 |

Drives

| Person | Car | Y | $\mathbf{W}$ |
| :--- | :--- | :--- | :--- |
| Jimmy | Mazda | Y1 | 1 |
| Jimmy | Toyota | Y1 | 2 |
| Billy | Mazda | Y2 | 1 |
| Billy | Honda | Y2 | 2 |


| Witness | Person | $\mathbf{X}$ | $\mathbf{V}$ | $\mathbf{Y}$ | $\mathbf{w}$ |
| :--- | :--- | :--- | :--- | :--- | :--- |
| Amy | Jimmy | X 1 | 1 | Y 1 | 1 |
| Amy | Jimmy | X 1 | 2 | Y 1 | 2 |
| Betty | Billy | X 2 | 1 | Y 2 | 2 |$\quad$| $\mathrm{X} 1=1$ ^Y1=1 V |
| ---: |
| $\mathrm{X} 1=2$ ^Y1=2 |

## Summary of Incomplete DBs

- Main goal: specify a set of possible worlds
- Very relevant to ProbDBs !
- Key concepts: closure and completeness
- Turn out to be equivalent, except trivial cases
- Boolean C-tables closed\&complete; others not
- Lineage: important tool in ProbDB, is derived from C-tables
- Some open questions next. Want to tell \& show? $\rightarrow$ Email by Wed.


## Open Questions in Incomplete/ Probabilistic Databases

- Variables
- OWA v.s. CWA
- Certain tuples, possible tuples
- Partial information order
- Strong v.s. weak representation systems

Homework: pick one and apply to probdbs. Tell us next time your thoughts

## Variables as Attribute Values

$$
\mathrm{T}=\begin{array}{|l|l|}
\hline \mathbf{A} & \mathbf{B} \\
\hline \perp & \mathrm{b} 1 \\
\hline \mathrm{a} 2 & \mathrm{~b} 1 \\
\hline
\end{array}
$$

$$
\operatorname{Rep}(T)=
$$

A large, or infinite set

ProbDBs don't use variables as attribute values

What if we allow ProbDBs to have variables?

## OWA v.s. CWA

- CWA: if $R(a, b, c)$ is not mentioned in the knowledge/data base, then $\neg \mathrm{R}(\mathrm{a}, \mathrm{b}, \mathrm{c})$ is assumed
- OWA: $\neg \mathrm{R}(\mathrm{a}, \mathrm{b}, \mathrm{c})$ is inferred only if it is explicitly stated in the knowledge/data base Which one is standard semantics in DB? And in KR ?


## OWA v.s. CWA in Incomplete DB

$\mathrm{T}=$| $\mathbf{A}$ | $\mathbf{B}$ |
| :---: | :---: |
| $\perp$ | b 1 |
| a 2 | b 1 |

CWA: $\operatorname{Rep}(\mathrm{T})=$

| A | $\mathbf{B}$ |
| :--- | :--- |
| a1 | b 1 |
| a 2 | b 1 |


| A | $\mathbf{B}$ |
| :--- | :--- |
| a1 | b 1 |


| A | $\mathbf{B}$ |
| :--- | :--- |
| a3 | b1 |
| a2 | b1 |


| A | $\mathbf{B}$ |
| :--- | :--- |
| a4 | b 1 |
| a 2 | b 1 |

OWA: $\operatorname{Rep}(T)=$

| A | $\mathbf{B}$ | $\mathbf{A}$ | $\mathbf{B}$ |
| :--- | :--- | :--- | :--- |
| a 1 | b 1 | a 1 | b 1 |
| a 2 | b 1 | a 2 | b 1 |

What would OWA mean for ProbDBs?

## Certain v.s. Possible Tuples

Consider an incomplete database $\quad \mathbf{I}=\left\{\mathrm{I}_{1}, \mathrm{I}_{2}, \mathrm{I}_{3}, \ldots\right\}$

Definition The certain tuples $\square \mathbf{I}=I_{1} \cap I_{2} \cap I_{3} \cap \ldots$
Definition The possible tuples $\diamond \mathbf{I}=I_{1} \cup I_{2} \cup I_{3} \cup \ldots$

What do certain/possible tuples correspond to in ProbDB?

## Certain v.s. Possible Tuples

- Two incomplete databases I, J are equivalent if $\square \mathbf{I}=\square \mathbf{J}$
- Two incomplete databases I, J are equivalent w.r.t. a query language $Q$ if forall q in $\mathrm{Q}, \square \mathrm{q}(\mathbf{I})=\square \mathrm{q}(\mathbf{J})$
- These notions are used to define "weak representation systems" (see [AHV])..

Are there similar notions of equivalences between ProbDBs?

## Partial Information Order

Let $(\mathrm{D}, \leq)$ be an ordered set.
Consider two sets $A=\left\{a_{1}, \ldots, a_{m}\right\}, B=\left\{b_{1}, \ldots, b_{n}\right\}$.
When can we say $\mathrm{A} \leq \mathrm{B}$ ?

## Definition [Smythe or upper] A $\leq$ B if $\forall b_{j} \exists a_{i}: a_{i} \leq b_{j}$

Definition [Hoare or lower] $A \leq{ }^{b} B$ if $\forall a_{i} \exists b_{j}: a_{i} \leq b_{j}$
Definition [Plotkin or convex] $\mathrm{A} \leq{ }^{\natural} \mathrm{B}$ if $\mathrm{A} \leq \neq \mathrm{B}$ and $\mathrm{A} \leq^{\mathrm{b}} \mathrm{B}$

## Partial Information Order

Let's order OR-sets

- Values of base type: $\mathrm{a} \leq \mathrm{a}$ and $\perp \leq \mathrm{a}$
- Records: $[\mathrm{x}, \mathrm{y}] \leq[\mathrm{u}, \mathrm{v}]$ when ?
- OR-sets $<\mathrm{a} 1, \mathrm{a} 2, \mathrm{a} 3>\leq<\mathrm{b} 1, \mathrm{~b} 2>$ when ?
- Sets: $\{\mathrm{a} 1, \mathrm{a} 2, \mathrm{a} 3\} \leq\{\mathrm{b} 1, \mathrm{~b} 2\}$ when ?


## Partial Information Order

Let's order OR-sets

- Values of base type: $\mathrm{a} \leq \mathrm{a}$ and $\perp \leq \mathrm{a}$
- Records: $[\mathrm{x}, \mathrm{y}] \leq[\mathrm{u}, \mathrm{v}]$ when ?
- When $x \leq u$ and $y \leq v$
- OR-sets $<\mathrm{a} 1, \mathrm{a} 2, \mathrm{a} 3>\leq<\mathrm{b} 1, \mathrm{~b} 2>$ when ?
- Smythe
- Sets: $\{\mathrm{a} 1, \mathrm{a} 2, \mathrm{a} 3\} \leq\{\mathrm{b} 1, \mathrm{~b} 2\}$ when ?
- Hoare (for OWA), or equality (for CWA)


## Partial Information Order

What is the partial information order on ProbDBs ?

## Probabilistic Networks

## Probabilistic Models

Problem setting:

- Given $m$ random variables $\mathrm{V}_{1}, \ldots, \mathrm{~V}_{\mathrm{m}}$
- Each with domain D (same for all $\mathrm{V}_{\mathrm{i}}$ )
- A probability space over $\mathrm{D}^{\mathrm{m}}: \operatorname{Pr}: \mathrm{D}^{\mathrm{m}} \rightarrow[0,1]$, st $\sum_{\mathrm{v} 1, \ldots, \mathrm{vm} \text { in } \mathrm{D}} \operatorname{Pr}\left(\mathrm{v}_{1}, \ldots, \mathrm{v}_{\mathrm{m}}\right)=1$
- Called the joint probability distribution

Problem: give a compact representation of Pr

## Example

| V1 | V2 | P |
| :--- | :--- | :--- |
| 1 | 1 | 0.06 |
| 1 | 2 | 0.14 |
| 2 | 1 | 0.24 |
| 2 | 2 | 0.56 |



Here $\mathrm{m}=2$, but in general m is large, need compact rep.

## Background

- Marginal probability:

$$
\operatorname{Pr}\left(\mathrm{V}_{\mathrm{i}}=\mathrm{a}\right)=\sum_{\mathrm{v} 1, \ldots, \mathrm{vm} \text { in } \mathrm{D}, \mathrm{vi}=\mathrm{a}} \operatorname{Pr}\left(\mathrm{v}_{1}, \ldots, \mathrm{v}_{\mathrm{m}}\right)
$$

- What does this mean $? \operatorname{Pr}\left(\mathrm{~V}_{\mathrm{i}}\right), \operatorname{Pr}\left(\mathrm{V}_{\mathrm{i}} \mathrm{V}_{\mathrm{j}}\right)$
- Conditional prob: $\quad \operatorname{Pr}(\mathrm{E} \mid \mathrm{F})=\operatorname{Pr}(\mathrm{EF}) / \operatorname{Pr}(\mathrm{F})$
- Independence: $\operatorname{Pr}(\mathrm{EF})=\operatorname{Pr}(\mathrm{E}) * \operatorname{Pr}(\mathrm{~F})$ Equivalently: $\operatorname{Pr}(\mathrm{E} \mid \mathrm{F})=\operatorname{Pr}(\mathrm{E})$
- Conditional indep: $\operatorname{Pr}(\mathrm{E}, \mathrm{F} \mid \mathrm{G})=\operatorname{Pr}(\mathrm{E} \mid \mathrm{G}) * \operatorname{Pr}\left(\mathrm{~F}_{62} \mathrm{G}\right)$


## Independence

| V1 | V2 | $\mathbf{P}$ |
| :--- | :--- | :--- |
| 1 | 1 | 0.06 |
| 1 | 2 | 0.14 |
| 2 | 1 | 0.24 |
| 2 | 2 | 0.56 |


| V1 | $\mathbf{P}$ |
| :--- | :--- |
| 1 | 0.2 |
| 2 | 0.8 |


| V2 | $\mathbf{P}$ |
| :--- | :--- |
| 1 | 0.3 |
| 2 | 0.7 |

Marginal probabilities

Are $\mathrm{V} 1, \mathrm{~V} 2$ independent, i.e. $\operatorname{Pr}(\mathrm{V} 1, \mathrm{~V} 2)=\operatorname{Pr}(\mathrm{V} 1) * \operatorname{Pr}(\mathrm{~V} 2)$ ? Note: need to check 4 equalities (why ?)

## Factored Representation

More general: if $\mathrm{P}(\mathrm{V} 1=\mathrm{a}, \mathrm{V} 2=\mathrm{b})=\mathrm{p}(\mathrm{a}) * \mathrm{q}(\mathrm{b})$ forall $\mathrm{a}, \mathrm{b}$ then $\mathrm{V} 1, \mathrm{~V} 2$ are independent

| V1 | $\mathbf{V 2}$ | $\mathbf{P}$ |
| :--- | :--- | :--- |
| $\mathrm{a}_{1}$ | $\mathrm{~b}_{1}$ | $\mathrm{p}_{1} \mathrm{q}_{1}$ |
| $\mathrm{a}_{1}$ | $\mathrm{~b}_{2}$ | $\mathrm{p}_{1} \mathrm{q}_{2}$ |
| $\mathrm{a}_{2}$ | $\mathrm{~b}_{1}$ | $\mathrm{p}_{2} \mathrm{q}_{1}$ |
| $\mathrm{a}_{2}$ | $\mathrm{~b}_{2}$ | $\mathrm{p}_{2} \mathrm{q}_{2}$ |
| $\ldots$ | $\ldots$ |  |$=$| $\mathbf{V 1}$ | $\mathbf{P}$ |
| :--- | :--- | :--- | :--- |
| $\mathrm{a}_{1}$ | $\mathrm{p}_{1}$ |
| $\mathrm{a}_{2}$ | $\mathrm{p}_{2}$ |
| $\ldots$ |  |$\times$| $\mathbf{V 2}$ | $\mathbf{P}$ |
| :--- | :--- | :--- |
| $\mathrm{b}_{1}$ | $\mathrm{q}_{1}$ |
| $\mathrm{~b}_{2}$ | $\mathrm{q}_{2}$ |
| $\ldots$ |  |$\quad$| Factors |
| :--- |

## $1^{\text {st }}$ Connection to ProbDBs: Variable $\rightarrow$ Attribute

- Every joint distribution over variables $\mathrm{V}_{1}$, $\ldots, \mathrm{V}_{\mathrm{m}}$ corresponds to a trivial probabilistic table with attributes $\mathrm{V}_{1}, \ldots, \mathrm{~V}_{\mathrm{m}}$
- What's "trivial" about it?


## $1^{\text {st }}$ Connection to ProbDBs: Variable $\leftarrow$ Attribute

- Conversely: each block in a disjoint/ independent relation defines a joint distribution on the values of its attribute

| Object | Time | Person | $P$ |
| :--- | :--- | :--- | :--- |
| LaptopX77 | $9: 07$ | John | 0.5 |
|  |  | Jim | 0.5 |
| Book302 | $9: 18$ | Mary | 0.2 |
|  |  | John | 0.4 |
|  |  | 0.4 |  |

## Independence

TABLE 1
Example Probabilistic Relation

| Key | Independent | Interdependent | Independent |
| :--- | :--- | :--- | :--- |
|  | Deterministic | Stochastic | Stochastic |
| EMPLOYEE | DEPARTMENT | OUALITY BONUS | SALES |
| Jon Smith | Toy | 0.4 [Great Yes] | $0.3[\$ 30-34 \mathrm{~K}]$ |
|  |  | 0.5 [Good Yes] | $0.7[\$ 35-39 \mathrm{~K}]$ |
|  |  | $1.0[$ Good Yes] | $0.5[\$ 20-24 \mathrm{~K}]$ |
|  |  |  | $0.5[\$ 25-29 \mathrm{~K}]$ |

## Independence

| Employee | Department | Quality | Bonus | Sales | $\mathbf{P}$ |
| :--- | :--- | :--- | :--- | :--- | :--- |
| John Smith | Toy | Great | Yes | $30 \mathrm{k}-34 \mathrm{k}$ | $0.4^{*} 0.3$ |
| John Smith | Toy | Good | Yes | $30 \mathrm{k}-34 \mathrm{k}$ | $0.5 * 0.3$ |
| John Smith | Toy | Fair | No | $30 \mathrm{k}-34 \mathrm{k}$ | $0.1 * 0.3$ |
| John Smith | Toy | Great | Yes | $35 \mathrm{k}-39 \mathrm{k}$ | $0.4^{*} 0.7$ |
| John Smith | Toy | Good | Yes | $35 \mathrm{k}-39 \mathrm{k}$ | $0.5 * 0.7$ |
| John Smith | Toy | Fair | No | $35 \mathrm{k}-39 \mathrm{k}$ | $0.1 * 0.7$ |
| Fre Jones | Houseware | Good | Yes | $20 \mathrm{k}-24 \mathrm{k}$ | 0.5 |
| Fre Jones | Houseware | Good | Yes | $24 \mathrm{k}-29 \mathrm{k}$ | 0.5 |

## Independence

Factors are disjoint/indep. Tables !

| Employee | Department | Quality | Bonus | P |
| :--- | :--- | :--- | :--- | :--- |
| John Smith | Toy | Great | Yes | 0.4 |
| John Smith | Toy | Good | Yes | 0.5 |
| John Smith | Toy | Fair | No | 0.1 |
| Fre Jones | Houseware | Good | Yes | 1 |


| Employee | Department | Sales | $\mathbf{P}$ |
| :--- | :--- | :--- | :--- |
| John Smith | Toy | $30 \mathrm{k}-34 \mathrm{k}$ | 0.3 |
| John Smith | Toy | $35 \mathrm{k}-39 \mathrm{k}$ | 0.7 |
| Fre Jones | Houseware | $20 \mathrm{k}-24 \mathrm{k}$ | 0.5 |
| Fre Jones | Houseware | $24 \mathrm{k}-29 \mathrm{k}$ | 0.5 |

## Rule of Thumb \#2

## Correlated table $=$ Independent tables + join

Same principle as in traditional schema normalization

- Decompose big table into small tables with independent attributes
- Big table = a view (single join !) over the small tables


## Database 101

- Assume that (Quality, Bonus) is independent from (Sales)
- Drop the $\mathbf{P}$ column $\rightarrow$ a traditional table (no more probabilities)
Question What 'functional dependency' holds in this table?


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Question What 'functional dependency' holds in this table?

A Multivalued FD !:
Emp, Dept $\rightarrow$ Quality, Bonus Sales

## Rule of Thumb \#3

Factor decomposition $=$ MVD decomposition + probability identities

## Conditional Independence

| V1 | V2 | W | $\mathbf{P}$ |
| :--- | :--- | :--- | :--- |
| 1 | 1 | a | 0.03 |
| 1 | 2 | a | 0.07 |
| 2 | 1 | a | 0.12 |
| 2 | 2 | a | 0.28 |
| 1 | 1 | b | 0.125 |
| 1 | 2 | b | 0.125 |
| 2 | 1 | b | 0.125 |
| 2 | 2 | b | 0.125 |

Are V1, V2 independent given W , i.e.
$\operatorname{Pr}(\mathrm{V} 1, \mathrm{~V} 2 \mid \mathrm{W})=\operatorname{Pr}(\mathrm{V} 1 \mid \mathrm{W}) * \operatorname{Pr}(\mathrm{~V} 2 \mid \mathrm{W})$ ?

## Conditional Independence

| V1 | V2 | W | P |
| :--- | :--- | :--- | :--- |
| 1 | 1 | a | 0.03 |
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| 2 | 1 | b | 0.125 |
| 2 | 2 | b | 0.125 |

$$
\mathrm{P}(\mathrm{~W}=\mathrm{a})=0.5 ; \mathrm{P}(--\mid \mathrm{W}=\mathrm{a}):
$$

| V1 | V2 | $\mathbf{P}$ |
| :--- | :--- | :--- |
| 1 | 1 | 0.06 |
| 1 | 2 | 0.14 |
| 2 | 1 | 0.24 |
| 2 | 2 | 0.56 |

$\mathrm{P}(\mathrm{W}=\mathrm{b})=0.5 ; \mathrm{P}(--\mid \mathrm{W}=\mathrm{b})$ :

| V1 | V2 | $\mathbf{P}$ |
| :--- | :--- | :--- |
| 1 | 1 | 0.25 |
| 1 | 2 | 0.25 |
| 2 | 1 | 0.25 |
| 2 | 2 | $0.25 \quad 75$ |

They: they are conditional independent

## Conditional Independence

| V1 | V2 | $\mathbf{W}$ | $\mathbf{P}$ |
| :--- | :--- | :--- | :--- |
| 1 | 1 | a | 0.03 |
| 1 | 2 | a | 0.07 |
| 2 | 1 | a | 0.12 |
| 2 | 2 | a | 0.28 |
| 1 | 1 | b | 0.125 |
| 1 | 2 | b | 0.125 |
| 2 | 1 | b | 0.125 |
| 2 | 2 | b | 0.125 |


$=$| $\mathbf{W}$ | $\mathbf{P}$ |
| :--- | :--- |
| a | 0.5 |
| b | 0.5 |


| V1 | $\underline{\mathbf{W}}$ | $\mathbf{P}$ |
| :--- | :--- | :--- |
| 1 | a | 0.2 |
| 2 | a | 0.8 |
| 1 | b | 0.5 |
| 2 | b | 0.5 |$\diamond$| $\mathbf{V 2}$ | $\underline{\mathbf{W}}$ | $\mathbf{P}$ |
| :--- | :--- | :--- |
| 1 | a | 0.3 |
| 2 | a | 0.7 |
| 1 | b | 0.5 |
| 2 | b | 0.5 |

## Representing Conditional Independent Vars

More general: if $\mathrm{P}(\mathrm{V} 1=\mathrm{a}, \mathrm{V} 2=\mathrm{b}, \mathrm{W}=\mathrm{c})=\mathrm{p}(\mathrm{a}, \mathrm{c}) * \mathrm{q}(\mathrm{b}, \mathrm{c})$ forall $\mathrm{a}, \mathrm{b}, \mathrm{c}$ then $\mathrm{V} 1, \mathrm{~V} 2$ are independent given c

| V1 | $\mathbf{V 2}$ | $\mathbf{W}$ | $\mathbf{P}$ |
| :--- | :--- | :--- | :--- |
| $\mathrm{a}_{1}$ | $\mathrm{~b}_{1}$ | $\mathrm{c}_{1}$ | $\mathrm{p}_{11} \mathrm{q}_{11}$ |
| $\mathrm{a}_{1}$ | $\mathrm{~b}_{2}$ | $\mathrm{c}_{1}$ | $\mathrm{p}_{11} \mathrm{q}_{21}$ |
| $\mathrm{a}_{2}$ | $\mathrm{~b}_{1}$ | $\mathrm{c}_{1}$ | $\mathrm{p}_{21} \mathrm{q}_{11}$ |
| $\mathrm{a}_{2}$ | $\mathrm{~b}_{2}$ | $\mathrm{c}_{1}$ | $\mathrm{p}_{21} \mathrm{q}_{21}$ |
| $\ldots$ | $\ldots$ | $\mathrm{c}_{2}$ | $\mathrm{P}_{12} \mathrm{q}_{12}$ |
| $\ldots$ | $\ldots$ |  |  |



| $\mathbf{V} 2$ | $\underline{\mathbf{W}}$ | $\mathbf{P}$ |
| :--- | :--- | :--- |
| $\mathrm{~b}_{1}$ | $\mathrm{c}_{1}$ | $\mathrm{q}_{11} / \mathrm{Q}_{1}$ |
| $\mathrm{~b}_{2}$ | $\mathrm{c}_{1}$ | $\mathrm{q}_{21} / \mathrm{Q}_{1}$ |
| $\ldots$ | $\mathrm{c}_{2}$ | $\mathrm{q}_{12} / \mathrm{Q}_{2}$ |
| $\ldots$ |  |  |

## Summary of Prob Networks

- $($ Conditional $)$ indep. $=$ MVDs + prob ident.
- Factored decomposition $=$ base tables + joins
- Next time:
- Discuss the networks in probabilistic networks; WSdecomposition, U-relations
- Partial/approximate representations
- Begin query evaluation
- Send email by Wed. if want to show\&tell

