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Probabilistic Inferences in Partonomies

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Uncertainty Management for Scene Interpretation

Interpretations are based on partial and uncertain evidence
⇒ many interpretations possible ("hallucination")
⇒ measure of preference needed

Choice points of the interpretation process:

- assigning evidence to one of many possible scene objects
  e.g. tracking result => transport-object
- assigning a part to one of many aggregates
  e.g. transport-saucer => place-cover

} part-whole reasoning

- choosing one of many specializing concepts
  e.g. transport-object => transport-saucer
- ➡ choosing one of many feature values
  e.g. transport-object => transport-saucer

} speciali-zation

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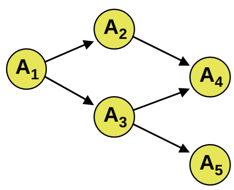
Belief Propagation

Bayesian networks (belief nets) are useful for determining the probability of an event from a joint probability distribution given some evidence.

JPD	$P(A_1, A_2, \ldots, A_N)$	⇒	$P(A_k = c \mid A_i = a, A_j = b)$
evidence	$A_i = a, A_j = b, \ldots$		

Solution procedures are known for general and special Bayes Nets (exact and approximate).



How can these techniques be applied to events defined in object-oriented taxonomies and partonomies?

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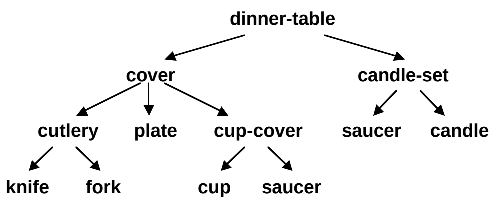
Tree-shaped Bayes Nets for Partonomies?



Binford 92
An aggregate causes parts

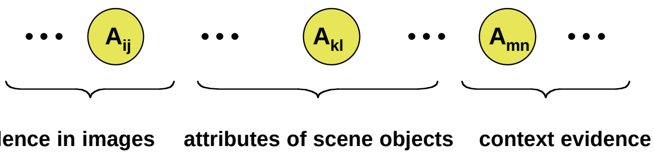
Rimey 93:
Tree-shaped part-of nets, is-a trees, expected-area nets, and task nets

Criticism:
- **Aggregate probabilities follow functionally from part probabilities**
- **Part dependencies are not modelled properly**
- **Coherent model of objects and object properties required**

Table Scenes as Probabilistic Events

Assume that a notion of "object" is given.

A table scene can be viewed as a probabilistic event in terms of the instantiation of a large number of correlated random variables A_{ij} describing attributes of objects (i ranging over objects, j over attributes).



Examples:

A_{kl} = location-of-plate
domain(A_{kl}) = {loc1, loc2, ... , no}

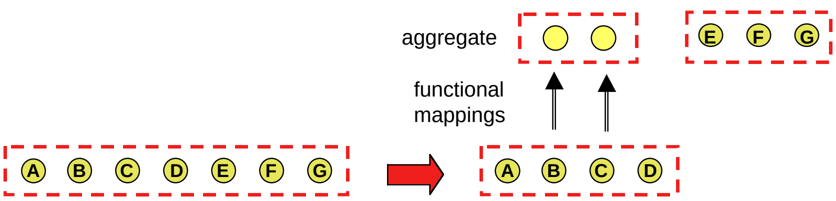
A_{kl} = color-of-cup
domain(A_{kl}) = {red, white, ... , no}

Coarsening and Aggregation

A partonomy is viewed as an artificial structure created to simplify reasoning with an otherwise overly large joint probability distribution.

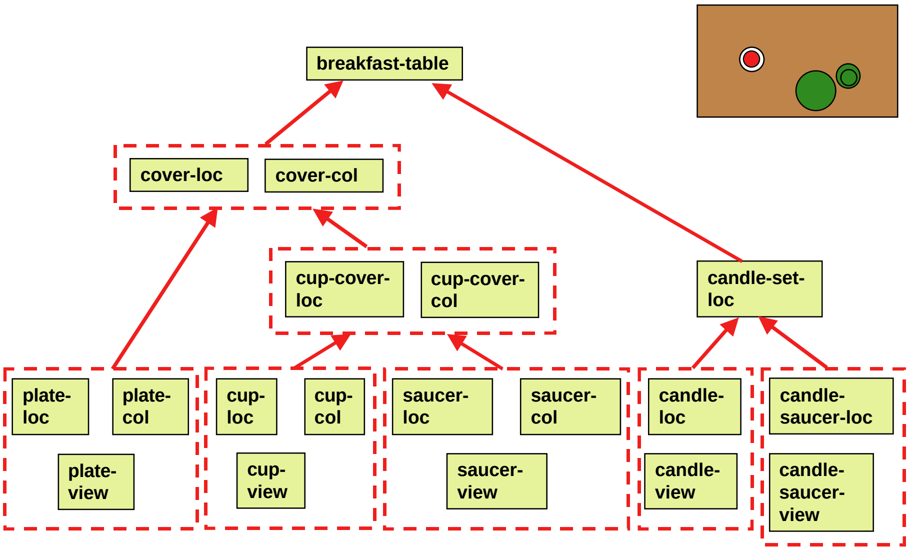
Basic design criteria:

- **Ignore weak correlations (poor predictive power)**
- **Cluster strongly correlated random variables into aggregates**
- **Provide representative aggregate descriptions**



Example: Joint probability table size of $|D|^7$ is changed to $|D|^4 + |D|^5$ (|D| = domain size).

Example: Dinner Table



Representative Aggregate Properties

<u>Shorthand</u>:

$$P(\underline{A}_1, \underline{A}_2, \ldots \underline{A}_M) = P(\overbrace{A_{11}A_{12} \ldots A_{1N_1}}^{\text{object 1}}\overbrace{A_{21}A_{22} \ldots A_{2N_2}}^{\text{object 2}} \ldots A_{M1}A_{M2} \ldots A_{MN_M})$$

Assume that objects $\underline{A}_1$ to $\underline{A}_K$ are clustered into an aggregate $\underline{B}_1$ with properties $B_{1n} = f_n(\underline{A}_1, \ldots \underline{A}_K)$, n = 1 … N. The B_{1n} are representative aggregate properties of $\underline{A}_1 \ldots \underline{A}_K$ with respect to $\underline{A}_{K+1} \ldots \underline{A}_M$ if

$$P(\underline{A}_{K+1} \ldots \underline{A}_M \mid \underline{A}_1, \ldots \underline{A}_K) \approx P(\underline{A}_{K+1} \ldots \underline{A}_M \mid \underline{B}_1)$$

We assume that all properties of an aggregate are representative of its parts w.r.t. the rest of the world.

Partonomy Probability Assignments

Given a basic JPD $P(\underline{A}_1, \underline{A}_2, \ldots \underline{A}_M)$, then the JPDs of all aggregates $\underline{B}_i$ are determined by the functional mappings $B_{in} = f_n(\underline{A}_1, \ldots \underline{A}_K)$.

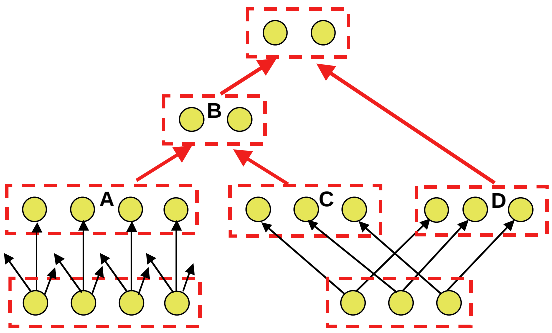
$$P(B_{in}) = \sum_{b_{in} = f_n(\underline{a}_1, \ldots \underline{a}_K)} P(\underline{A}_1, \ldots \underline{A}_K)$$

Similarly:

$$P(\underline{B}) = P(B_{i1} \ldots B_{iN}) = \sum_{\substack{b_{i1} = f_1(\underline{a}_1, \ldots \underline{a}_K) \\ \wedge b_{i2} = f_2(\underline{a}_1, \ldots \underline{a}_K) \\ \ldots \\ \wedge b_{iN} = f_N \underline{a}_1, \ldots \underline{a}_K)}} P(\underline{A}_1, \ldots \underline{A}_K)$$

Probabilistic Inferences

Context information:
$P(\underline{B}) \Rightarrow P'(\underline{B})$
- propagate up
- propagate horizontally
- propagate down



Unambiguous image evidence:
- $P(\underline{A}) \Rightarrow P'(\underline{A})$ by naive Bayes estimation
- propagate up

Ambiguous image evidence:
- network copies for each alternative
- $P(\underline{C}) \Rightarrow P'(\underline{C})$ by naive Bayes estimation
- propagate up

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Yes/no Context Information

"Aggregate B is present"

Assume binary mapping $f(\underline{b}) = \begin{cases} 1 & \text{if } \underline{b} \text{ satisfies aggregate properties} \\ 0 & \text{otherwise} \end{cases}$

Consistency constraint: $\Sigma P'(\underline{B}) = \Sigma P(\underline{B}) = 1$

All $P(\underline{B})$ with $f(\underline{b}) = 1$ are upscaled by constant factor $1 / \sum_{f(\underline{b})=1} P(\underline{B})$

$$P'(\underline{B}) = P(\underline{B}) / \sum_{f(\underline{b})=1} P(\underline{B})$$

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Propagating Down

$P(\underline{B}) \Rightarrow P'(\underline{B})$ with $B_{1n} = f_n(\underline{A}_1, \ldots \underline{A}_K)$, $n = 1 \ldots N$

How does the change of $P(B)$ affect $P(\underline{A}_1, \ldots \underline{A}_K)$?

Shorthand: $\underline{A} = \underline{A}_1, \ldots \underline{A}_K$ $\quad \underline{B} = \underline{f}(\underline{A})$

$P'(\underline{B}) = s(\underline{B})\, P(\underline{B})$

$$P'(\underline{A}) = s(\underline{B})\, P(\underline{A}) \quad \text{for all } \underline{b} = \underline{f}(\underline{a})$$

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Propagating Horizontally

Assume that $\underline{A}_1 \ldots \underline{A}_N$ are parts of an aggregate B.

Assume that $P(\underline{A}_1) \Rightarrow P'(\underline{A}_1)$

How does the change of $P(\underline{A}_1)$ affect $P(\underline{A}_1 \ldots \underline{A}_N)$?

$$P'(\underline{A}_1) = s(\underline{A}_1)\, P(\underline{A}_1)$$

$$\begin{aligned} P'(\underline{A}_1 \ldots \underline{A}_N) &= s(\underline{A}_1)\, P(\underline{A}_1)\, P'(\underline{A}_2 \ldots \underline{A}_N | \underline{A}_1) \\ &= s(\underline{A}_1)\, P(\underline{A}_1) P(\underline{A}_2 \ldots \underline{A}_N | \underline{A}_1) \\ &= s(\underline{A}_1)\, P(\underline{A}_1 \ldots \underline{A}_N) \end{aligned}$$

For Bayes Net representation:

$$P'(\underline{A}_1 | \underline{A}_i \ldots \underline{A}_k) = s(\underline{A}_1)\, P(\underline{A}_1 | \underline{A}_i \ldots \underline{A}_k)$$

$$\underset{n \neq 1}{P'(\underline{A}_n | \underline{A}_i \ldots \underline{A}_k)} = P(\underline{A}_n | \underline{A}_i \ldots \underline{A}_k)$$

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Propagating Up

Assume that $\underline{A}_1 \ldots \underline{A}_K$ are parts of an aggregate B.

Assume that $P(\underline{A}_1) \Rightarrow P'(\underline{A}_1)$

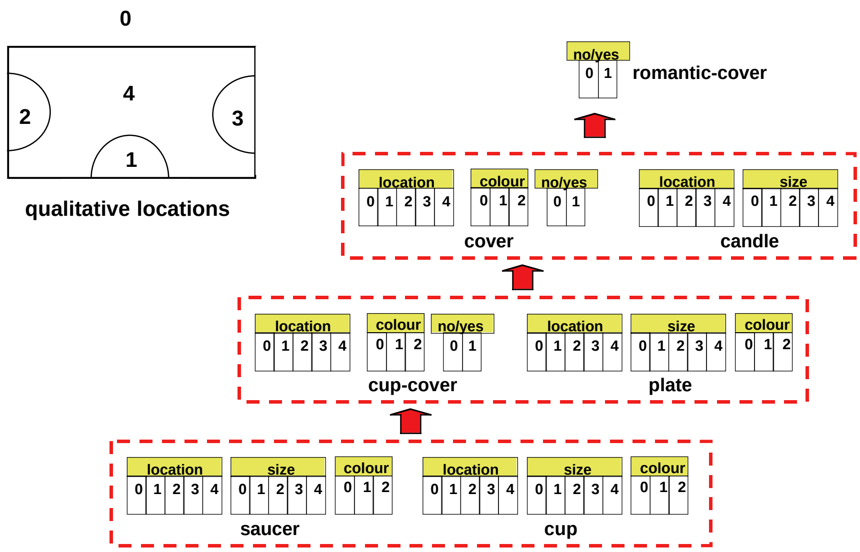
How does the change of $P(\underline{A}_1)$ affect $P(\underline{B})$?

From horizontal propagation we get

$$P'(\underline{A}_1 \ldots \underline{A}_K) = s(\underline{A}_1)\, P(\underline{A}_1 \ldots \underline{A}_K)$$

$$P'(\underline{B}) = \sum_{\substack{b_1 = f_1(\underline{a}_1, \ldots \underline{a}_K) \\ \wedge b_2 = f_2(\underline{a}_1, \ldots \underline{a}_K) \\ \ldots \\ \wedge b_N = f_N(\underline{a}_1, \ldots \underline{a}_K)}} P'(\underline{A}_1 \ldots \underline{A}_K)$$

Simulation Experiment



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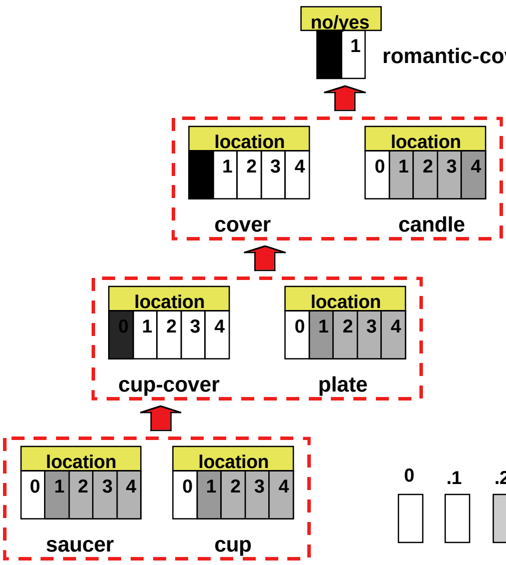
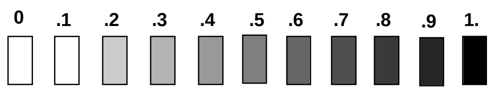
Location Probabilities of Partonomy Items (1)



initial distribution of marginal probabilities
(joint probabilities not shown)

probability colour code



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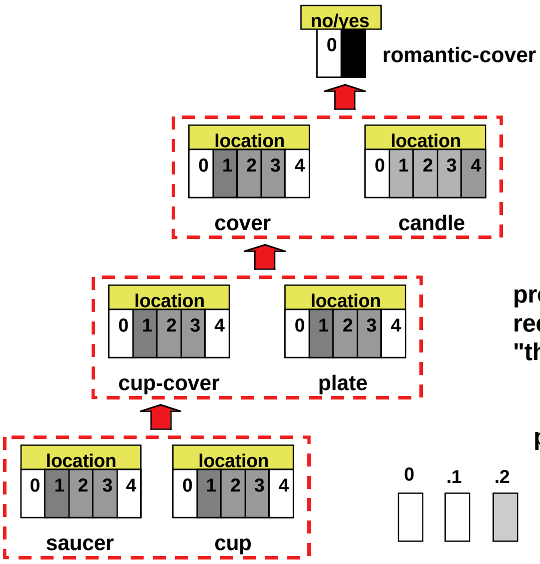
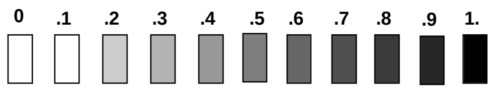
Location Probabilities of Partonomy Items (2)



probability distribution after receiving context information "there is a romantic-cover"

probability colour code



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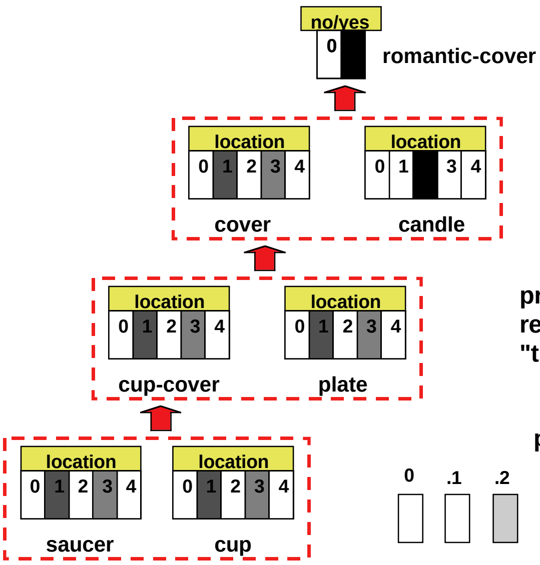
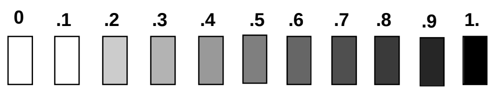
Location Probabilities of Partonomy Items (3)



probability distribution after receiving context information "there is a candle at Position 2"

probability colour code



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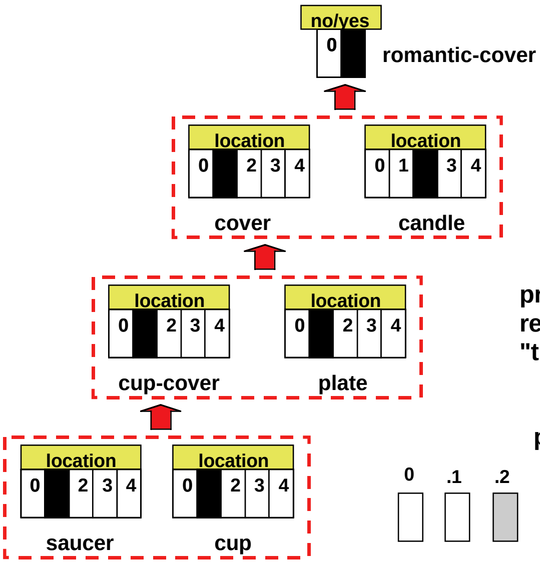
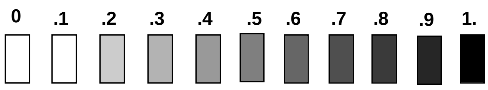
Location Probabilities of Partonomy Items (4)



probability distribution after receiving context information "there is a plate at Position 1"

probability colour code



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Conclusions

- Belief revision in partonomies can be achieved by local propagation
- Expected feature values can be made available at any time during the interpretation process
  - => educated guesses
  - => best-first search
  - => top-down control of image analysis
- "Weak" integration with logic-based interpretation

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Further Work

- Extend probabilistic reasoning to include taxonomical structures
- Develop preference measure for interpretation steps
- Develop resource-limited belief propagation
- System integration