Probabilistic Models for Scene Interpretation

1

Uncertainty in Scene Interpretation

Causes for uncertainty in scene interpretation:

- Images give incomplete evidence for 3D scenes, allowing for multiple interpretations
  - spatial and temporal clipping
  - occlusion
- Image data may be corrupted by noise, image analysis will result in uncertain data
- Image analysis procedures may be coarse, allowing for multiple interpretations
- Models of the knowledge base may lack differentiation, allowing for multiple interpretations
- Logics of scene interpretation allow multiple interpretations

3D scene

↓ sensors

2D data

↓ image analysis

symbolic primitives

↓ knowledge base

scene interpretation

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Probabilistic Approaches for Scene Interpretation

Several ways to use probabilistic representations for scene interpretation:

- **Sensor modelling and sensor fusion**
- **Feature-based object classification**
- **Scene modelling (stationary + dynamic)**
- **Preference measure for logic-based interpretation**

treated in this course

Sage & Buxton 2005
http://www.ecvision.org/education/On-line_Cognitive_Vision_Course.htm

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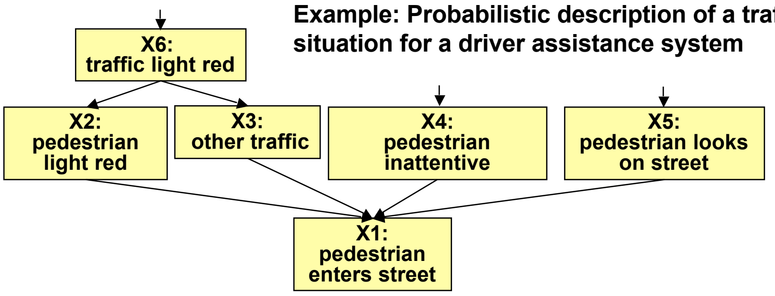
Probabilistic Scene Modelling

- **Random variables assigned to scene components:**
  - **events, occurrences**
  - **objects**
  - **properties**
  - **reified relations**
- **Probabilistic dependencies via joint distributions**

Example: Probabilistic description of a traffic situation for a driver assistance system



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Random Variables and Chain Rule

Modelling probabilistic dependencies (causalities) and independencies between components of a scene

X_i random variable *models uncertain propositions about a scene*

$X_i = a$ hypothesis

Decomposition of joint probabilities:

$P(X_1, X_2, X_3, \ldots, X_N) = P(X_1 \mid X_2, X_3, \ldots, X_N) \bullet P(X_2 \mid X_3, X_4, \ldots, X_N) \bullet \ldots \bullet P(X_{N-1} \mid X_N) \bullet P(X_N)$

Simplification in the case of statistical independence:

X independent of X_i

$P(X \mid X_1, \ldots X_{i-1}, X_i, X_{i+1}, \ldots, X_N) = P(X \mid X_1, \ldots X_{i-1}, X_{i+1}, \ldots, X_N)$

Joint probability of N variables may be simplified by ordering the variables according to their direct dependence (causality).

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Independence Causes Complexity Reduction

Assume that all random variables X_n of the JPD $P(X_1, X_2, X_3, \ldots, X_N)$ have a domain size K. Then a fully general JPD requires K^N entries.

Example: N = 20, K = 10 => 10^{20} entries must be specified!

If all random variables are statistically independent, we have
$P(X_1, X_2, X_3, \ldots, X_N) = P(X_1) \bullet P(X_2) \bullet \ldots \bullet P(X_N)$ and only KN entries are required.

Exploiting independencies can greatly reduce the size of a probability table!

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Conditional Independence

It is useful to determine direct influences Y_i on a random variable X, because given the Y_i, X is independent of other Variables Z_k "upstream" to the Y_i.

Let dom(X) be the domain of X, i.e. the set of possible values of X.

A random variable X is independent of Z given Y
if for all x_i e dom(X), for all y_j e dom(Y), and for all z_k e dom(Z),

$$P(X=x_i \mid Y=y_j, Z=z_k) = P(X=x_i \mid Y=y_j)$$

<u>Example</u>: X=plate_in_view, Y=plate_on_table, Z=want_to_eat

X Y Z	P(XYZ)	X Y Z	P(XYZ)
T T T	.096	F T T	.024
T T F	.064	F T F	.016
T F T	.0	F F T	.08
T F F	.0	F F F	.72

Check whether X is independent of Z given Y!

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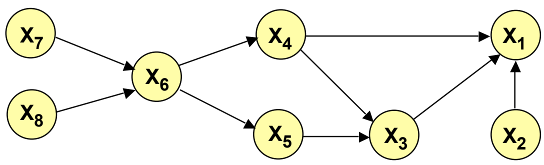
Causality Graph

Conditional dependencies (causality relations) of random variables define partial order. Representation as a directed acyclic graph (DAG):



For each node X we need P(X | parents of X) to obtain a specification of the JPD of all nodes.

$P(X_1, X_2, X_3, \dots, X_8) =$
$P(X_1 \mid X_2, X_3, X_4) \cdot P(X_2) \cdot P(X_3 \mid X_4, X_5) \cdot P(X_4 \mid X_6) \cdot P(X_5 \mid X_6) \cdot P(X_6 \mid X_7 X_8) \cdot P(X_7) \cdot P(X_8)$

For any DAG, we obtain the JPD as follows:

$Pa(X_i)$ parents of node X_i

$$P(X_1 \dots X_N) = \prod_i P(X_i \mid Pa(X_i))$$

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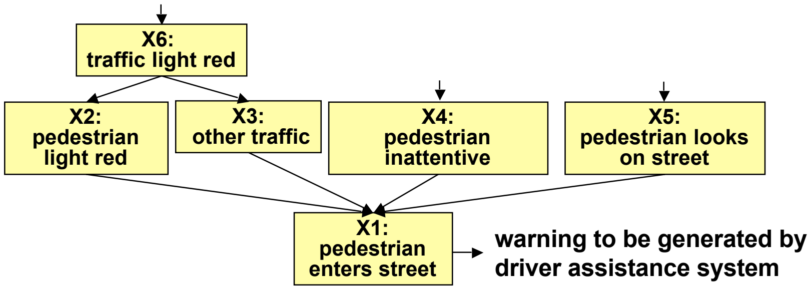
Example: Traffic Situation



Conditional probability table for each node must be known

P(X1 | X2, X3, X4, X5)

X1	X2	X3	X4	X5	P
T	T	T	T	T	0.3
F	T	T	T	T	0.7
T	F	T	T	T	0.9
F	F	T	T	T	0.1
⋮	⋮	⋮	⋮	⋮	⋮

P(X2 | X6)

X2	X6	P
T	T	0.2
F	T	0.8
T	F	1.0
F	F	0.0

P(X3 | X6)

X3	X6	P
T	T	0.01
F	T	0.99
T	F	0.6
F	F	0.4

P(X4)

X4	P
T	0.1
F	0.9

P(X5)

X5	P
T	0.7
F	0.3

P(X6)

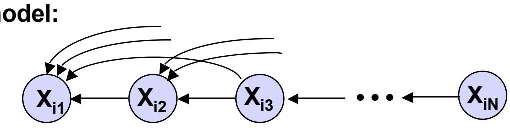
X6	P
T	0.7
F	0.3

Bayes Nets are not Unique

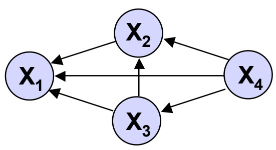
Using the chain rule, a JPD $P(X_1, X_2, \dots, X_N)$ may be expanded in N! ways:

$$P(X_1, X_2, \dots, X_N) = P(X_{i1} \mid X_{i2}, \dots, X_{iN}) \bullet P(X_{i2} \mid X_{i3}, \dots, X_{iN}) \bullet \dots \bullet P(X_{iN})$$

Even with no independencies, each chain rule expansion can be drawn as a graphical model:



<u>Example</u>:



Any JPD $P(X_1, X_2, X_3, X_4)$ can be represented by this Bayes Net.

For efficient inferences with a given JPD, it is important to find a Bayes Net with a low number of dependencies.

Constructing a Bayes Net

By domain analysis:

1. Select discrete variables X_i relevant for domain
2. Establish partial order of variables according to causality
3. In the order of decreasing causality:
   (i) Generate node X_i in net
   (ii) As predecessors of X_i choose the smallest subset of nodes which are already in the net and from which X_i is causally dependent
   (iii) determine a table of conditional probabilities for X_i

By data analysis:

Use a learning method to establish a Bayes Net approximating the empirical joint probablity distribution.

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Computing Inferences

We want to use a Bayes Net for probabilistic inferences of the following kind:

Given a joint probability $P(X_1, \dots, X_N)$ represented by a Bayes Net, and evidence $X_{m_1}=a_{m_1}, \dots, X_{m_K}=a_{m_K}$ for some of the variables, what is the probability $P(X_n = a_i \mid X_{m_1}=a_{m_1}, \dots, X_{m_K}=a_{m_K})$ of an unobserved variable to take on a value a_i ?

In general this requires

- expressing a conditional probability by a quotient of joint probabilities

$$P(X_n = a_i \mid X_{m_1}=a_{m_1}, \dots, X_{m_K}=a_{m_K}) = \frac{P(X_n = a_i, X_{m_1}=a_{m_1}, \dots, X_{m_K}=a_{m_K})}{P(X_{m_1}=a_{m_1}, \dots, X_{m_K}=a_{m_K})}$$

- determining partial joint probabilities from the given total joint probability by summing out unwanted variables

$$P(X_{m_1}=a_{m_1}, \dots, X_{m_K}=a_{m_K}) = \sum_{X_{n_1}, \dots, X_{n_K}} P(X_{m_1}=a_{m_1}, \dots, X_{m_K}=a_{m_K}, X_{n_1}, \dots, X_{n_K})$$

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Normalization

Basic formula for computing the probability of a query variable X_n from a JPD $P(X_1, \dots, X_N)$ given evidence $X_{m_1}=a_{m_1}, \dots, X_{m_K}=a_{m_K}$:

$$P(X_n = a_i \mid X_{m_1}=a_{m_1}, \dots, X_{m_K}=a_{m_K}) = \frac{P(X_n = a_i, X_{m_1}=a_{m_1}, \dots, X_{m_K}=a_{m_K})}{P(X_{m_1}=a_{m_1}, \dots, X_{m_K}=a_{m_K})}$$

The denominator on the right is independent of a_i and constitutes a normalizing factor α. It can be computed by requiring that the conditional probabilities of all a_i sum to unity.

$$P(X_n = a_i \mid X_{m_1}=a_{m_1}, \dots, X_{m_K}=a_{m_K}) = \alpha \{ P(X_n = a_i, X_{m_1}=a_{m_1}, \dots, X_{m_K}=a_{m_K}) \}$$

Formulae are often written in this simplified form with α as a normalizing factor.

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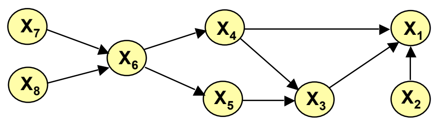
Factoring the JPD

JPDs can be computed from a Bayes Net more efficiently by ordering the "factors" so that only few summations and products must be computed.

<u>Example</u>:
Compute
$P(X_2=a, X_4=b \mid X_1=c, X_7=d)$



$$P(X_2=a, X_4=b \mid X_1=c, X_7=d) = \frac{P(X_2=a, X_4=b, X_1=c, X_7=d)}{P(X_1=c, X_7=d)}$$

$$P(X_2=a, X_4=b, X_1=c, X_7=d) = \sum_{X_3}\sum_{X_5}\sum_{X_6}\sum_{X_8} P(X_1=c, X_2=a, X_3, X_4=b, X_5, X_6, X_7=d, X_8)$$

$$= \sum_{X_3}\sum_{X_5}\sum_{X_6}\sum_{X_8} P(X_1=c \mid X_2=a, X_3, X_4=b) \cdot P(X_2=a) \cdot P(X_3 \mid X_4=b, X_5) \cdot P(X_4=b \mid X_6) \cdot P(X_5 \mid X_6) \cdot P(X_6 \mid X_7=d, X_8) \cdot P(X_7=d) \cdot P(X_8)$$

$$= P(X_2=a) \cdot P(X_7=d) \cdot \sum_{X_3} P(X_1=c \mid X_2=a, X_3, X_4=b) \cdot \sum_{X_5} P(X_3 \mid X_4=b, X_5) \cdot \sum_{X_6} P(X_4=b \mid X_6) \cdot P(X_5 \mid X_6) \cdot \sum_{X_8} P(X_6 \mid X_7=d, X_8) \cdot P(X_8)$$

one possible order for efficient computation

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Set-factoring Heuristic

Finding the best possible order for computing factors of a JPD is not tractable, in general. The set-factoring heuristic is a greedy (suboptimal) algorithm with often excellent results.

Given $\mathcal{X}$ set of random variables to be summed out

$\mathcal{F}$ set of factors to be combined

Set-factoring heuristic:

- Pick the pair of factors which produces the smallest probability table after combination and summing out as many variables of $\mathcal{X}$ as possible. Break ties by choosing the pair where most variables are summed out.
- Place resulting factor into set $\mathcal{F}$, remove summed-out variables from $\mathcal{X}$ and repeat procedure.

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Example for Set-factoring Heuristic (1)

Compute

$$P(X_2=a,X_4=b,X_1=c,X_7=d) = \sum_{X_3}\sum_{X_5}\sum_{X_6}\sum_{X_8} P(X_1=c \mid X_2=a,X_3,X_4=b) \cdot P(X_2=a) \cdot P(X_3 \mid X_4=b,X_5) \cdot$$
$$\cdot P(X_4=b \mid X_6) \cdot P(X_5 \mid X_6) \cdot P(X_6 \mid X_7=d,X_8) \cdot P(X_7=d) \cdot P(X_8)$$

Step 1: $\mathcal{X} = \{X_3, X_5, X_6, X_8\}$

$\mathcal{F} = \{P(X_1=c \mid X_2=a,X_3,X_4=b),\ P(X_2=a),\ P(X_3 \mid X_4=b,X_5),\ P(X_4=b \mid X_6),\ P(X_5 \mid X_6),$
$P(X_6 \mid X_7=d,X_8),\ P(X_7=d),\ P(X_8)\}$

After extracting the constant factors $P(X_2=a)$ and $P(X_7=d)$, 6 factors remain, hence 15 possible pairs may be formed. Assuming equally sized domains, the set-factoring heuristic prefers 2 combinations:

(i) $P(X_1=c \mid X_2=a,X_3,X_4=b) \cdot P(X_3 \mid X_4=b,X_5)$ and summing out X_3
(ii) $P(X_6 \mid X_7=d,X_8) \cdot P(X_8)$ and summing out X_8

Choosing (ii), the new factor $P(X_6 \mid X_7=d)$ is computed and the sets are updated:

Step 2: $\mathcal{X} = \{X_3, X_5, X_6\}$

$\mathcal{F} = \{P(X_1=c \mid X_2=a,X_3,X_4=b),\ P(X_3 \mid X_4=b,X_5),\ P(X_4=b \mid X_6),\ P(X_5 \mid X_6),\ P(X_6 \mid X_7=d)\}$

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Example for Set-factoring Heuristic (2)

The set-factoring heuristic prefers the combination:

$P(X_1{=}c|\ X_2{=}a, X_3, X_4{=}b) \cdot P(X_3|\ X_4{=}b, X_5)$ and summing out X_3

The new factor $P(X_1{=}c|\ X_2{=}a, X_4{=}b, X_5)$ is computed and the sets are updated:

Step 3: $\mathcal{X} = \{X_5, X_6\}$

$\mathcal{F} = \{P(X_1{=}c|\ X_2{=}a, X_4{=}b, X_5),\ P(X_4{=}b|\ X_6),\ P(X_5|\ X_6),\ P(X_6|\ X_7{=}d)\}$

The set-factoring heuristic prefers the combination:

$P(X_1{=}c|\ X_2{=}a, X_4{=}b, X_5) \cdot P(X_5|\ X_6)$ and summing out X_5

The new factor $P(X_1{=}c|\ X_2{=}a, X_4{=}b, X_6)$ is computed and the sets are updated:

Step 4: $\mathcal{X} = \{X_6\}$

$\mathcal{F} = \{P(X_1{=}c|\ X_2{=}a, X_4{=}b, X_6),\ P(X_4{=}b|\ X_6),\ P(X_6|\ X_7{=}d)\}$

The set-factoring heuristic ranks all combinations equal. Choosing

$P(X_4{=}b|\ X_6) \cdot P(X_6|\ X_7{=}d)$

we get the new factor $P(X_4{=}b, X_6|\ X_7{=}d)$ and the updated sets:

Step 5: $\mathcal{X} = \{X_6\}$

$\mathcal{F} = \{P(X_1{=}c|\ X_2{=}a, X_4{=}b, X_6),\ P(X_4{=}b, X_6|\ X_7{=}d)\}$

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Example for Set-factoring Heuristic (3)

The final result follows from reassembling the summations outwards:

$P(X_2{=}a, X_4{=}b, X_1{=}c, X_7{=}d) =$

$P(X_2{=}a) \cdot P(X_7{=}d)$

$\cdot [\sum_{X_6} P(X_4{=}b|\ X_6) \cdot P(X_6|\ X_7{=}d)$

$\cdot [\sum_{X_5} P(X_5 \mid X_6)$

$\cdot [\sum_{X_3} P(X_1{=}c \mid X_2{=}a, X_3, X_4{=}b) \cdot P(X_3 \mid X_4{=}b, X_5)$

$\cdot [\sum_{X_8} P(X_6 \mid X_7{=}d, X_8) \cdot P(X_8)\ ]\ ]\ ]\ ]$

If D is the size of the domains of the random variables, the number of multiplications is

$N_{mult} = D^2 + D^3 + D^2 + D$

This happens to be more than the number of multiplications for the manual ordering proposed earlier:

$N_{mult} = D^2 + D^2 + D^2 + D$

Obviously, the heuristic was not optimal in this case.

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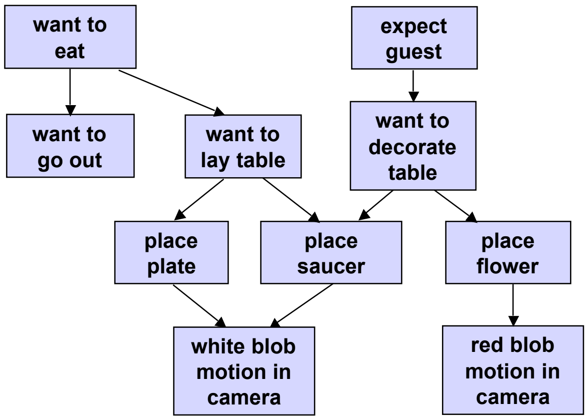
Dependance Analysis of Bayes Nets

The arcs in a Bayes Net indicate pairwise dependence. Can one infer dependencies and independencies between other nodes?

- in general?
- given partial evidence in terms of node values?



<u>Example</u>:
Given that a white blob motion has been observed, does this affect the probability of

- wanting to go out?
- red blob motion?

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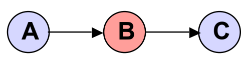
Blocking Evidence

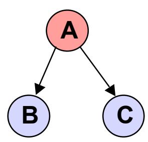
In general, (undirected) paths in a Bayes Net indicate possible flow of information. However, if hard evidence is given at an intermediate node, the path may be blocked.

Blocking situations:

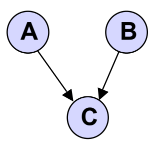
1. In a serial connection from A to C via B, evidence from A to C is blocked by hard evidence about B.



2. In a diverging connection from A to B and C, evidence from B to C is blocked by hard evidence about A.



3. In a converging situation from A and B to C, any evidence about C results in evidence transmitted between A and B.



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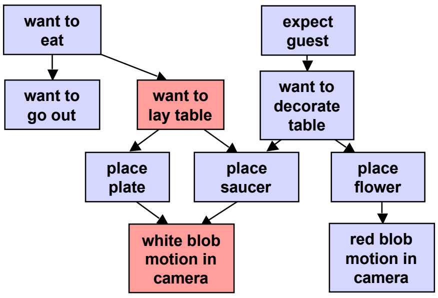
D-separation

"D-separation" = no flow of evidence from one node to another

Two nodes X and Y in a Bayes Net are d-separated if, for all paths between X and Y, there is an intermediate node Z for which either:

1. the connection is serial or diverging and the value of Z is known for certain; or
2. the connection is converging and neither Z (nor any of its descendants) have received any evidence at all.



Example:
Hard evidence for "want to lay table" blocks influence of evidence for "white blob motion in camera" on "want to eat" and "want to go out", but not on any other nodes.

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Basic Kinds of Inferences

1. Causal reasoning, prediction

Given upstream evidence, ask for downstream probability

Example: Given "want to eat" is true, what is the probability of "white blob motion"?

2. Evidential reasoning, explanation

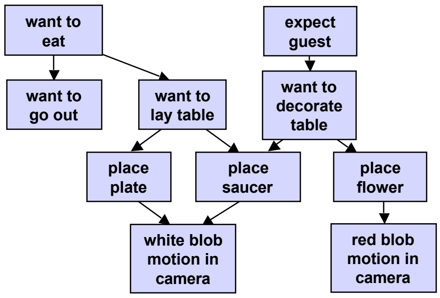
Given downstream evidence, ask for upstream probability

Example: Given "white blob motion" is true, what is the probability of "expect guest"?

3. Explaining away

Given evidence of a node with two parents and evidence for one of the parents, ask for probability of other parent node

Example: Given evidence for "place saucer" and "want to to eat", what is the probability of "want to decorate table"?



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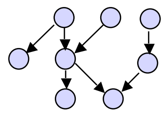
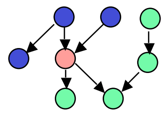
Evidence Propagation in Polytrees

polytree = DAG where each pair of distinct nodes is connected by a single (undirected) path



Any node X_k in a polytree separates the tree into an "upper" and "lower" part. Hence the marginal probability $P(X_k{=}c)$ can be computed from two factors.



$S^+ = \{X_i \text{ above } X_k\}$ $\quad S^- = \{X_i \text{ below } X_k\}$

$$P(X_k{=}c) = \sum_{X_i \neq X_k} P(X_1 \ldots X_k{=}c \ldots X_N)$$

$$= \sum_{X_i \neq X_k} P(X_k{=}c \mid Pa(X_k)) \prod_{\substack{X_i \neq X_k \\ X_k = c}} P(X_i \mid Pa(X_i))$$

$$= \Big[\sum_{X_i \in S^+} P(X_k{=}c \mid Pa(X_k)) \prod P(X_i \mid Pa(X_i)) \Big] \cdot \Big[\sum_{X_i \in S^-} \prod P(X_i \mid Pa(X_i))_{X_k = c} \Big]$$

$$= \lambda\,(X_k{=}c) \cdot \rho\,(X_k{=}c)$$

=> propagation scheme is possible

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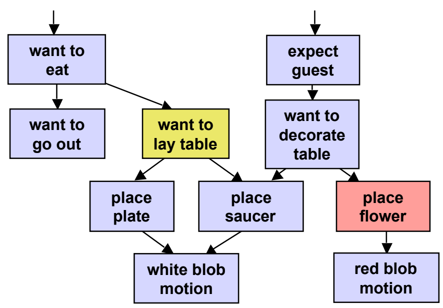
Approximate Inference in Bayesian Networks

- Inference in singly-connected Bayes Nets can be computed with O(N)
- Worst-case complexity in general Bayes Nets is exponential, hence approximate algorithms with less complexity are useful.

Basic idea:

Use random sampling (Monte Carlo method) to compute the approximate probability of an event based on a JPD and evidence.



Example: Determine P("place flower" | "want to lay table")

- Draw sample for each node based on probability conditioned on parent samples
- Repeat process many times
- Relative frequency of samples matching evidence converges to correct result in the limit.

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Sampling Methods

<u>Direct Sampling</u>:

Estimate the probability of an event without evidence by sampling a Bayes Net.

<u>Recommended Reading</u>:
Russell & Norvig: Artificial Intelligence - A Modern Approach, 2nd Ed., Prentice Hall, 2003

<u>Rejection Sampling</u>:

Estimate the probability of an event by sampling a Bayes Net and discarding all samples which do not match the evidence.

<u>Sampling with Likelihood Weighting</u>:

Estimate the probability of an event by sampling a Bayes Net and weighting all samples according to their likelihood to generate the evidence.

All three methods generate consistent estimates (which converge to the true value).

Hidden Markov Models

A sequence of observations may be governed by underlying probabilistic state transitions.

- A person laying a table may plan to first place the plates, then the cups, then the cutlery in a cyclic order (with a chance to deviate from this order).
- Observations of a moving robot depend on its changing pose

As usual in vision, observations may be disturbed and may provide uncertain evidence about the current state.

Such phenomena may be modelled by a <u>Hidden Markov Model</u> (HMM).

A (discrete) HMM is defined by
- a finite number of states $a_1, a_2, \dots, a_K$
- a sequence of state transition events $t_0, t_1, \dots, t_n$ (not necessarily times)
- probabilities of state transitions p_{ij} from state i to state j , each depending only on the previous state
- observations $b_1, b_2, \dots, b_M$ probabilistically related to each state
- probabilities q_{km} which map states into observations

Notation for HMM

- Sequence of random variables $X^{(1)}, \dots, X^{(n)}$ (state variables) with values from $\{a_1, \dots, a_K\}$
- Markov Chain property of $X^{(1)}, \dots, X^{(n)}$: $P(X^{(n)}|X^{(n-1)} \dots X^{(1)}) = P(X^{(n)}|X^{(n-1)})$
  - if $P(X^{(n)}|X^{(n-1)})$ is independent of n, the Markov Chain is homogeneous
  - transition probabilities $P(X^{(n)}=a_j|X^{(n-1)}=a_i)$ are represented by the state transition matrix

$$W^{(n)} = \begin{bmatrix} p_{11} & \dots & p_{1K} \\ \vdots & & \\ p_{K1} & \dots & p_{KK} \end{bmatrix}$$

- random variables $Y^{(1)}, \dots, Y^{(n)}$ (observations) with values from $\{b_1, \dots, b_M\}$
- observation probabilities $P(Y^{(n)}|X^{(n)})$ are represented by the matrix

$$Q = \begin{bmatrix} q_{11} & \dots & q_{1M} \\ \vdots & & \\ q_{K1} & \dots & q_{KM} \end{bmatrix}$$

- initial probabilities $\underline{p}^T = [\ P(X^{(1)}=a_1)\ \ P(X^{(1)}=a_2) \dots P(X^{(1)}=a_K)\ ]$

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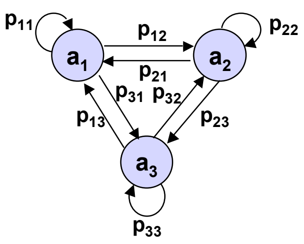
Properties of a Homogeneous HMM

Probability vector for state $X^{(2)}$: $\underline{\pi}^{(2)} = W^T\ \underline{\pi}$

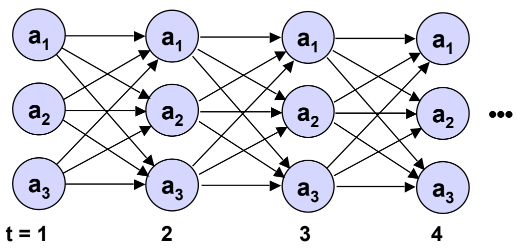
Probability vector for state $X^{(n)}$: $\underline{\pi}^{(n)} = (W^T)^{n-1}\ \underline{\pi}$

There is always a stationary distribution $\underline{\pi}_s$ such that $\underline{\pi}_s = W^T\ \underline{\pi}_s$

Graphical representation:



Trellis ("Spalier") representation:



- each (directed) path corresponds to a legal sequence of states
- the probability of a path is equal to the product of the transition probabilities

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Paths through a HMM

Given a sequence of N observations, we want to find the most probable sequence of states which may have led to the observations.

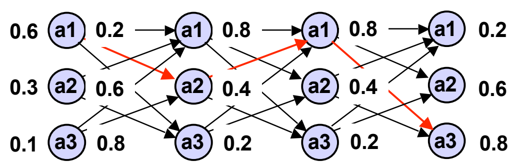
Extension of trellis representation

- **arc weights leading into states $X^{(n)}$:** ➡ **transition probabilities p_{ij}**
- **node weights of states $X^{(n)}$:** ➡ **observation likelihoods q_{jm} for given observations $Y^{(n)} = b_{m_n}$**
- **product of initial probability and node and arc probabilities along path:** ➡ **$P(Y^{(1)}=b_{m_1}, \dots, Y^{(N)}=b_{m_N}, X^{(1)}=a_{k_1}, \dots, X^{(N)}=a_{k_N})$ probability of observations and states**

Example:

$$W = \begin{bmatrix} 0.3 & 0.2 & 0.5 \\ 0.1 & 0.0 & 0.9 \\ 0.4 & 0.6 & 0.0 \end{bmatrix} \quad Q = \begin{bmatrix} 0.8 & 0.2 \\ 0.4 & 0.6 \\ 0.2 & 0.8 \end{bmatrix} \quad \pi = \begin{bmatrix} 0.6 \\ 0.3 \\ 0.1 \end{bmatrix}$$

observations b_2, b_1, b_1, b_2



probability of observations along path are
$P(Y^{(1)}=b_2, Y^{(2)}=b_1, Y^{(3)}=b_1, Y^{(4)}=b_2$, states of path) =
0.6• 0.2• 0.2• 0.4• 0.1• 0.8• 0.5• 0.8

Finding Most Probable Paths

The most probable sequence of states is found by maximizing

$$\max_{k_1 \dots k_N} P(X^{(1)}=a_{k_1}, \dots, X^{(N)}=a_{k_N} \mid Y^{(1)}=b_{m_1}, \dots, Y^{(N)}=b_{m_N}) = \max_{\underline{a}} P(\underline{a} \mid \underline{b})$$

Equivalently, the most probable sequence of states follows from

$$\max_{\underline{a}} P(\underline{a}\,\underline{b}) = \max_{\underline{a}} P(\underline{a} \mid \underline{b})\, P(\underline{b})$$

Hence the maximizing sequence of states can be found by exhaustive search of all path probabilities in the trellis. However, complexity is $O(K^N)$ with K = number of different states and N = length of sequence.

The Viterbi Algorithm does the job in O(KN)!

Overall maximization may be decomposed into a backward sequence of maximizations:

$$\max_{\underline{a}} P(\underline{a}\,\underline{b}) = \max_{k_1 \dots k_N} p_{k_1} q_{k_1 m_1} \prod_{n=2 \dots N} p_{k_{n-1} k_n} q_{k_{n-1} m_n}$$

$$= \max_{k_1} p_{k_1} q_{k_1 m_1} \left(\max_{k_2} p_{k_1 k_2} q_{i_2 m_2} \left(\dots \left(\max_{k_N} p_{k_{N-1} k_N} q_{k_{N-1} m_N} \right) \dots \right) \right)$$

Step N **Step N-1** **• • •** **Step 1**

Example for Viterbi Algorithm

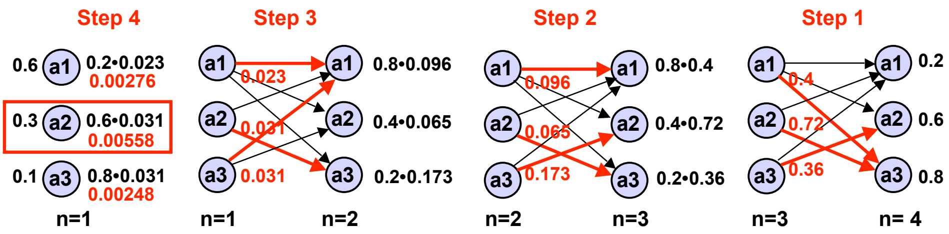
Typical maximization step of Viterbi algorithm:

$$\max_{k_n} \{ p_{k_{n-1}k_n} \bullet q_{k_{n-1}m_n} \bullet \text{<result of previous maximization step>} \}$$

Example as earlier:

$$W = \begin{bmatrix} 0.3 & 0.2 & 0.5 \\ 0.1 & 0.0 & 0.9 \\ 0.4 & 0.6 & 0.0 \end{bmatrix} \quad Q = \begin{bmatrix} 0.8 & 0.2 \\ 0.4 & 0.6 \\ 0.2 & 0.8 \end{bmatrix} \quad \pi = \begin{bmatrix} 0.6 \\ 0.3 \\ 0.1 \end{bmatrix}$$

observations b_2, b_1, b_1, b_2



red numbers show maximization results, red arrows maximizing transitions

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Model Evaluation for Given Observations

What is the likelihood that a particular HMM (out of several possible models) has generated the observations?

Likelihood of observations given model:

$$P(Y^{(1)}=b_{m_1}, \dots, Y^{(N)}=b_{m_N} \mid \text{model}) = P(\underline{b}) = \sum_{\underline{a}} P(\underline{a}\ \underline{b})$$

Instead of summing over all $\underline{a}$, one can use a forward algorithm based on a recursive formula:

$$P(b_{m_1}, \dots, b_{m_N}) = \sum_i P(a_i^{(n+1)}, b_{m_1}, \dots, b_{m_N})$$

$$\underline{P(a_j^{(n+1)}, b_{m_1}, \dots, b_{m_n}, b_{m_{n+1}})}$$

$$= P(a_j^{(n+1)}, b_{m_1}, \dots, b_{m_n}) \cdot P(b_{m_{n+1}} \mid a_j^{(n+1)})$$

observation depends only on current state

$$= \sum_i [P(a_j^{(n+1)}, a_i^{(n)}, b_{m_1}, \dots, b_{m_n})] \cdot P(b_{m_{n+1}} \mid a_j^{(n+1)})$$

$$= \sum_i [P(a_j^{(n+1)} \mid a_i^{(n)}, b_{m_1}, \dots, b_{m_n}) P(a_i^{(n)}, b_{m_1}, \dots, b_{m_n})] \cdot P(b_{m_{n+1}} \mid a_j^{(n+1)})$$

$$= \sum_i [P(a_j^{(n+1)} \mid a_i^{(n)}) \cdot P(a_i^{(n)}, b_{m_1}, \dots, b_{m_n})] \cdot P(b_{m_{n+1}} \mid a_j^{(n+1)})$$

current state depends only on previous state

$$= \sum_i [p_{ij} \cdot \underline{P(a_i^{(n)}, b_{m_1}, \dots, b_{m_n})}] \cdot q_{j\, m_{n+1}}$$

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Example for Model Evaluation (1)

Computing the probability of observations stepwise as they come in.

Example as earlier:

$$W = \begin{bmatrix} 0.3 & 0.2 & 0.5 \\ 0.1 & 0.0 & 0.9 \\ 0.4 & 0.6 & 0.0 \end{bmatrix} \quad Q = \begin{bmatrix} 0.8 & 0.2 \\ 0.4 & 0.6 \\ 0.2 & 0.8 \end{bmatrix} \quad \pi = \begin{bmatrix} 0.6 \\ 0.3 \\ 0.1 \end{bmatrix}$$

observations
b_2, b_1, b_1, b_2

Step 1

$$P(a_j^{(1)}, b_{m_1}) = \pi_j \cdot q_{j\,m_1}$$

$P(a_1^{(1)}, b_2) = 0.6 \cdot 0.2 = 0.12$
$P(a_2^{(1)}, b_2) = 0.3 \cdot 0.6 = 0.18$
$P(a_3^{(1)}, b_2) = 0.1 \cdot 0.8 = 0.08$

Note that $P(b_{m_1}, \ldots, b_{m_n})$ can be computed after each step by summing out the dependency on the state $X^{(n)}$.

Step 2

$$P(a_j^{(2)}, b_{m_1}, b_{m_2}) = \sum_i [\, p_{ij} \cdot P(a_i^{(1)}, b_{m_1})] \cdot q_{j\,m_2}$$

$P(a_1^{(2)}, b_2, b_1) = [\, 0.3 \cdot 0.12 + 0.1 \cdot 0.18 + 0.4 \cdot 0.08\,] \cdot 0.8 = 0.0314$
$P(a_2^{(2)}, b_2, b_1) = [\, 0.2 \cdot 0.12 + \quad 0.6 \cdot 0.08\,] \cdot 0.4 = 0.0288$
$P(a_3^{(2)}, b_2, b_1) = [\, 0.5 \cdot 0.12 + 0.9 \cdot 0.18 \quad] \cdot 0.2 = 0.0072$

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Example for Model Evaluation (2)

Example continued:

$$W = \begin{bmatrix} 0.3 & 0.2 & 0.5 \\ 0.1 & 0.0 & 0.9 \\ 0.4 & 0.6 & 0.0 \end{bmatrix} \quad Q = \begin{bmatrix} 0.8 & 0.2 \\ 0.4 & 0.6 \\ 0.2 & 0.8 \end{bmatrix} \quad \pi = \begin{bmatrix} 0.6 \\ 0.3 \\ 0.1 \end{bmatrix}$$

observations
b_2, b_1, b_1, b_2

Step 3

$$P(a_j^{(3)}, b_{m_1}, b_{m_2}, b_{m_3}) = \sum [\, p_{ij} \cdot P(a_j^{(2)}, b_{m_1}, b_{m_2})] \cdot q_{j\,m_3}$$

$P(a_1^{(3)}, b_2, b_1, b_1) = [\, 0.3 \cdot 0.0314 + 0.1 \cdot 0.0288 + 0.4 \cdot 0.0072\,] \cdot 0.8 = 0.01214$
$P(a_2^{(3)}, b_2, b_1, b_1) = [\, 0.2 \cdot 0.0314 + \quad 0.6 \cdot 0.0072\,] \cdot 0.4 = 0.00424$
$P(a_3^{(3)}, b_2, b_1, b_1) = [\, 0.5 \cdot 0.0314 + 0.9 \cdot 0.0288 \quad] \cdot 0.2 = 0.00832$

Step 4

$$P(a_j^{(4)}, b_{m_1}, b_{m_2}, b_{m_3}, b_{m_4}) = \sum [\, p_{ij} \cdot P(a_j^{(2)}, b_{m_1}, b_{m_2}, b_{m_3})] \cdot q_{j\,m_4}$$

$P(a_1^{(4)}, b_2, b_1, b_1, b_2) = [\, 0.3 \cdot 0.01214 + 0.1 \cdot 0.00424 + 0.4 \cdot 0.00832\,] \cdot 0.2 = 0.001479$
$P(a_2^{(4)}, b_2, b_1, b_1, b_2) = [\, 0.2 \cdot 0.01214 + \quad 0.6 \cdot 0.00832\,] \cdot 0.6 = 0.004452$
$P(a_3^{(4)}, b_2, b_1, b_1, b_2) = [\, 0.5 \cdot 0.01214 + 0.9 \cdot 0.00424 \quad] \cdot 0.4 = 0.003954$

Final step

$$P(b_{m_1}, b_{m_2}, b_{m_3}, b_{m_4}) = \sum P(a_j^{(4)}, b_{m_1}, b_{m_2}, b_{m_3}, b_{m_4}) = \boxed{0.009885}$$

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