

Artificial Intelligence²

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Today program

Agent in **partially observable environment** maintains a belief state from the percepts observed and a **sensor model** and using a **transition model** the agent can predict how the world might evolve in the next time step.

- a **belief state** represents which states of the world are currently possible (by explicit enumeration of states or by logical formulas)
- the probability theory allows to quantify the degree of belief in elements of the believe state
- we can also describe probability of state transitions

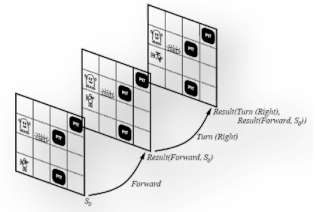
Probabilistic reasoning over time

- representation of state transitions
- basic inference tasks
- inference algorithms for temporal models
- specific kinds of models (hidden Markov models, dynamic Bayesian networks)



In **situation calculus**, we view the world as a series of snapshots (**time slices**).

A similar approach can be applied in probabilistic reasoning.



Each time slice (**state**) is described as a set of random variables:

- **hidden** (not observable) random **variables** X_t
- **observable** random **variables** E_t (with observed values e_t)

t is an identification of the time slice (we assume **discrete time** with uniform time steps)

Notation:

- $X_{a:b}$ denotes a set of variables from X_a to X_b

A model example (umbrella world)

You are the security guard stationed at a secret underground installation and you want to know whether it is **raining today**:

- hidden random variable R_t

But your only access to the outside world occurs each morning when you see the the director coming in **with, or without, an umbrella**.

- observable random variable U_t

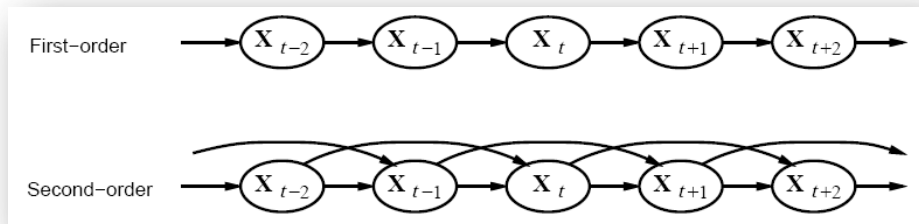


The **transition model** specifies the probability distribution over the latest state variables given the previous values.

This is given by $P(X_t | X_{0:t-1})$.

Problem #1: the set $X_{0:t-1}$ is unbounded in size as t increases

- we can make a **Markov assumption** – the current state depends only on a finite fixed number of previous states; processes satisfying this assumption are called **Markov processes or Markov chains**
- **first-order Markov chain** – the current state depends only on the previous state
 $P(X_t | X_{0:t-1}) = P(X_t | X_{t-1})$



Problem #2: there are infinitely many possible values of t

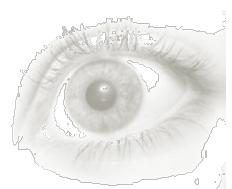
- We assume that changes in the world state are caused by a **stationary process** (a process of change is governed by laws that do not themselves change very time)
- the conditional probability tables $P(X_t | X_{t-1})$ are identical for all t

A **sensor (observation) model** describes how the evidence (observed) variables E_t depend on other variables.

They could depend on previous variables as well as the current state variables.

We make a **sensor Markov assumption** – the evidence variables depend only on the hidden state variables X_t from the same time.

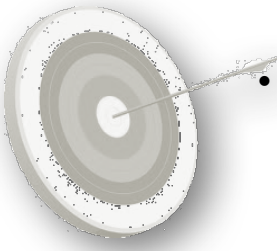
$$P(E_t | X_{0:t}, E_{1:t-1}) = P(E_t | X_t)$$



The first-order Markov assumption says that the state variables contain all the information needed to characterize the probability distribution for the next time slice.

What if this assumption is only approximate?

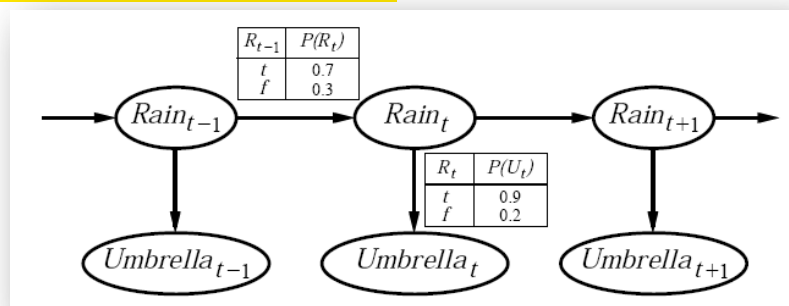
- **increase the order** of the Markov process model
- **increase the set** of state variables
 - For example we could add Season_t to incorporate historical records or we could add Temperature_t , Humidity_t , Pressure_t to use a physical model of rainy conditions.
 - The first solution (increasing the order) can always be reformulated as an increase in set of state variables.



A Bayesian network view

The transition and sensor models can be described using a **Bayesian network**.

In addition to $P(\mathbf{X}_t | \mathbf{X}_{t-1})$ and $P(\mathbf{E}_t | \mathbf{X}_t)$ we need to say how everything gets started $P(\mathbf{X}_0)$.



We have a specification of the complete joint distribution:

$$P(\mathbf{X}_{0:t}, \mathbf{E}_{1:t}) = P(\mathbf{X}_0) \prod_i P(\mathbf{X}_i | \mathbf{X}_{i-1}) P(\mathbf{E}_i | \mathbf{X}_i)$$

- **Filtering**: the task of computing the posterior distribution over the *most recent state*, given all evidence to date
 $P(X_t | e_{1:t})$
- **Prediction**: the task of computing the posterior distribution over the *future state*, given all evidence to date
 $P(X_{t+k} | e_{1:t})$ for $k > 0$
- **Smoothing**: the task of computing posterior distribution over a *past state*, given all evidence up to the present
 $P(X_k | e_{1:t})$ for $k: 0 \leq k < t$
- **Most likely explanation**: the task to find the sequence of states that is most likely generated a given sequence of observations
 $\text{argmax}_{x_{1:t}} P(x_{1:t} | e_{1:t})$



Filtering

The task of computing the posterior distribution over the *most recent state*, given all evidence to date – $P(X_t | e_{1:t})$.

A useful filtering algorithm needs to maintain a current state estimate and update it, rather than going back over (recursive estimation):

$$P(X_{t+1} | e_{1:t+1}) = f(e_{t+1}, P(X_t | e_{1:t}))$$

How to define the function f ?

$$\begin{aligned}
 P(X_{t+1} | e_{1:t+1}) &= P(X_{t+1} | e_{1:t}, e_{t+1}) \\
 &= \alpha P(e_{t+1} | X_{t+1}, e_{1:t}) P(X_{t+1} | e_{1:t}) \\
 &= \alpha P(e_{t+1} | X_{t+1}) P(X_{t+1} | e_{1:t}) \\
 &= \alpha P(e_{t+1} | X_{t+1}) \sum_{x_t} P(X_{t+1} | x_t, e_{1:t}) P(x_t | e_{1:t}) \\
 &= \alpha P(e_{t+1} | X_{t+1}) \sum_{x_t} P(X_{t+1} | x_t) P(x_t | e_{1:t})
 \end{aligned}$$

Bayes rule

sensor Markov assumption

conditioning
 $P(Y) = \sum_z P(Y|z) P(z)$

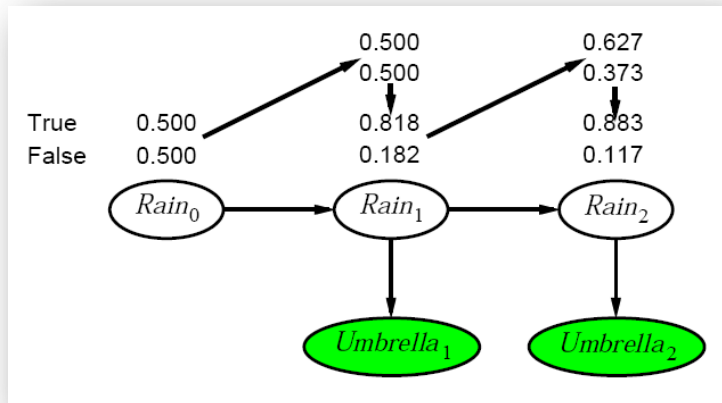
A message $f_{1:t}$ is propagated forward over the sequence:

$$\begin{aligned}
 P(X_t | e_{1:t}) &= f_{1:t} \\
 f_{1:t+1} &= \alpha \text{FORWARD}(f_{1:t}, e_{t+1}) \\
 f_{1:0} &= P(X_0)
 \end{aligned}$$



$$P(R_{t+1} | u_{1:t+1})$$

$$= \alpha P(u_{t+1} | R_{t+1}) P(R_{t+1} | u_{1:t}) = \alpha P(u_{t+1} | R_{t+1}) \sum_{r_t} P(R_{t+1} | r_t) P(r_t | u_{1:t})$$



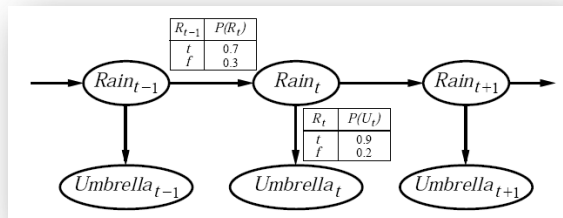
$$P(R_0) = \langle 0.5, 0.5 \rangle$$

$$P(R_1) = \sum_{r_0} P(R_1 | r_0) P(r_0) = \langle 0.5, 0.5 \rangle$$

$$P(R_1 | u_1) = \alpha P(u_1 | R_1) P(R_1) = \alpha \langle 0.9, 0.2 \rangle \langle 0.5, 0.5 \rangle \approx \langle 0.818, 0.182 \rangle$$

$$P(R_2 | u_1) = \sum_{r_1} P(R_2 | r_1) P(r_1 | u_1) = \langle 0.7, 0.3 \rangle \times 0.818 + \langle 0.3, 0.7 \rangle \times 0.182 \approx \langle 0.627, 0.372 \rangle$$

$$P(R_2 | u_1, u_2) = \alpha P(u_2 | R_2) P(R_2 | u_1) = \alpha \langle 0.9, 0.2 \rangle \langle 0.627, 0.372 \rangle = \langle 0.883, 0.117 \rangle$$



Prediction

The task of computing the posterior distribution over the *future state*, given all evidence to date – $P(X_{t+k} | e_{1:t})$ for some $k > 0$.

We can see this task as filtering without the addition of new evidence:

$$P(X_{t+k+1} | e_{1:t}) = \sum_{x_{t+k}} P(X_{t+k+1} | x_{t+k}) P(x_{t+k} | e_{1:t})$$

After some time (**mixing time**) the predicted distribution converges to the **stationary distribution** of the Markov process and remains constant.



The task of computing posterior distribution over a *past state*, given all evidence up to the present – $P(X_k | e_{1:t})$ for $k: 0 \leq k < t$.

We again exploit a recursive message-passing approach, now in two parts.

$$\begin{aligned} P(X_k | e_{1:t}) &= P(X_k | e_{1:k}, e_{k+1:t}) \\ &= \alpha P(X_k | e_{1:k}) P(e_{k+1:t} | X_k, e_{1:k}) \\ &= \alpha P(X_k | e_{1:k}) P(e_{k+1:t} | X_k) \\ &= \alpha f_{1:k} \times b_{k+1:t} \end{aligned}$$

Bayes rule

conditional independence

$$\begin{aligned} P(e_{k+1:t} | X_k) &= \sum_{x_{k+1}} P(e_{k+1:t} | X_k, x_{k+1}) P(x_{k+1} | X_k) \\ &= \sum_{x_{k+1}} P(e_{k+1:t} | x_{k+1}) P(x_{k+1} | X_k) \\ &= \sum_{x_{k+1}} P(e_{k+1}, e_{k+2:t} | x_{k+1}) P(x_{k+1} | X_k) \\ &= \sum_{x_{k+1}} P(e_{k+1} | x_{k+1}) P(e_{k+2:t} | x_{k+1}) P(x_{k+1} | X_k) \end{aligned}$$

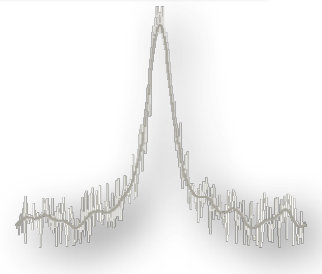
conditioning

conditional independence

conditional independence

Using the backward message-passing notation:

$$\begin{aligned} P(e_{k+1:t} | X_k) &= b_{k+1:t} \\ b_{k+1:t} &= \text{BACKWARD}(b_{k+2:t}, e_{k+1}) \\ b_{t+1:t} &= P(e_{t+1:t} | X_t) = P(| X_t) = 1 \end{aligned}$$



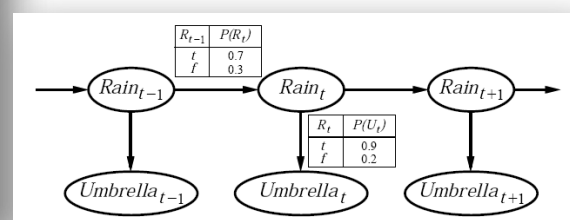
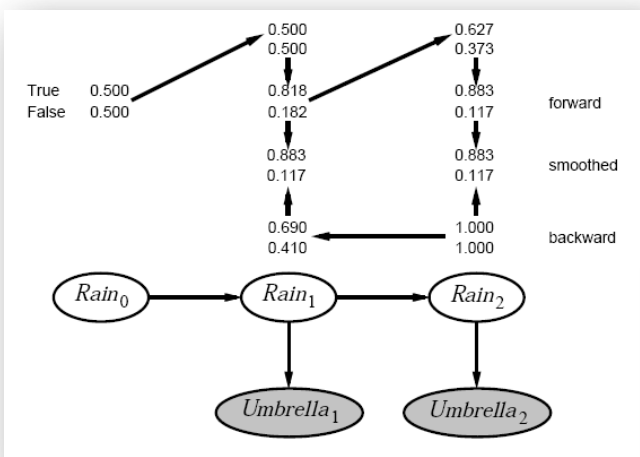
Smoothing (example)

$$P(R_k | u_{1:t+1}) = \alpha P(R_k | u_{1:k}) P(u_{k+1:t} | R_k)$$

$$P(u_{k+1:t} | R_k) = \sum_{r_{k+1}} P(u_{k+1} | r_{k+1}) P(u_{k+2:t} | r_{k+1}) P(r_{k+1} | R_k)$$

$$P(| R_2) = 1$$

$$\begin{aligned} P(u_2 | R_1) &= \sum_{r_2} P(u_2 | r_2) P(| r_2) P(r_2 | R_1) \\ &= 0.9 \times 1 \times \langle 0.7, 0.3 \rangle + 0.2 \times 1 \times \langle 0.3, 0.7 \rangle = \langle 0.69, 0.41 \rangle \end{aligned}$$



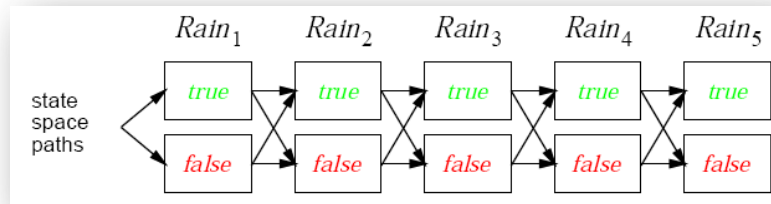
Most likely explanation/sequence

The task to find the sequence of states that is most likely generated a given sequence of observations

$$\operatorname{argmax}_{x_{1:t}} P(x_{1:t} | e_{1:t}).$$

This is different from smoothing for each past state and taking the sequence of most probable states!

We can see each sequence as a **path through a graph** whose nodes are possible states at each time step:



Because of the Markov property the most likely path to a given state consists of the most likely path to some previous state followed by a transition to that state.

This can be described using a **recursive formula**.

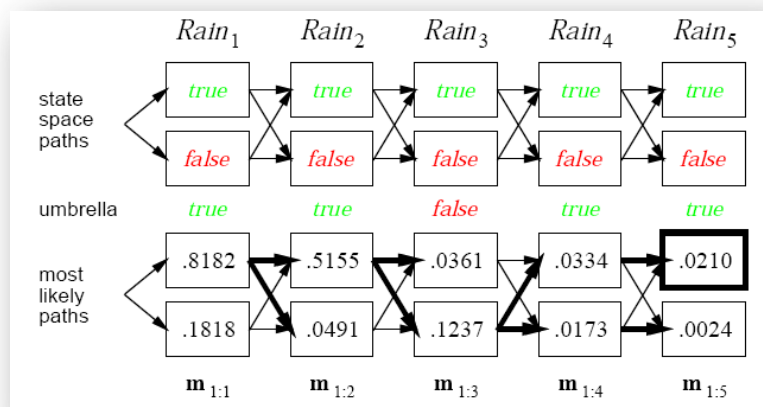
Viterbi algorithm

The most likely path to a given state consists of the most likely path to some previous state followed by a transition to that state.

$$\begin{aligned} & \max_{x_1, \dots, x_t} P(x_1, \dots, x_t, X_{t+1} | e_{1:t+1}) \\ &= \alpha P(e_{t+1} | X_{t+1}) \max_{x_t} (P(X_{t+1} | x_t) \max_{x_1, \dots, x_{t-1}} P(x_1, \dots, x_{t-1} | e_{1:t})) \end{aligned}$$

Again, we use an approach of forward message passing:

$$\begin{aligned} m_{1:t} &= \max_{x_1, \dots, x_{t-1}} P(x_1, \dots, x_{t-1}, X_t | e_{1:t}) \\ m_{1:t+1} &= P(e_{t+1} | X_{t+1}) \max_{x_t} (P(X_{t+1} | x_t) m_{1:t}) \end{aligned}$$



Assume that the state of process is described by a single discrete random variable X_t (there is also a single evidence variable E_t).

This is called a **hidden Markov model** (HMM).

This restricted model allows for a simple and elegant **matrix implementation** of all the basic algorithms.

Assume that variable X_t takes values from the set $\{1, \dots, S\}$, where S is the number of possible states.

The **transition model** $P(X_t | X_{t-1})$ becomes an $S \times S$ matrix T , where:

$$T_{(i,j)} = P(X_t = j | X_{t-1} = i)$$

We also put the **sensor model** in matrix form. Now we know the value of the evidence variable e_t so we describe $P(E_t = e_t | X_t = i)$, using a diagonal matrix O_t , where:

$$O_{t(i,i)} = P(E_t = e_t | X_t = i)$$

Matrix formulation of algorithms

The forward message propagation (from filtering)

$$P(X_t | e_{1:t}) = f_{1:t}$$

$$f_{1:t+1} = \alpha P(e_{t+1} | X_{t+1}) \sum_{x_t} P(X_{t+1} | x_t) P(x_t | e_{1:t})$$

can be reformulated using matrix operations (message $f_{1:t}$ is modelled as a one-column matrix) as follows:

$$T_{(i,j)} = P(X_t = j | X_{t-1} = i)$$

$$O_{t(i,i)} = P(E_t = e_t | X_t = i)$$

$$f_{1:t+1} = \alpha O_{t+1} T^T f_{1:t}$$

The backward message propagation (from smoothing)

$$P(e_{k+1:t} | X_k) = b_{k+1:t}$$

$$b_{k+1:t} = \sum_{x_{k+1}} P(e_{k+1} | x_{k+1}) P(e_{k+2:t} | x_{k+1}) P(x_{k+1} | X_k)$$

can be reformulated using matrix operations (message $b_{k:t}$ is modelled as a one-column matrix) as follows:

$$b_{k+1:t} = T O_{k+1} b_{k+2:t}$$

What if we need to **smooth the whole sequence of states?**

$$P(\mathbf{X}_k | \mathbf{e}_{1:t}) = \alpha \mathbf{f}_{1:k} \times \mathbf{b}_{k+1:t}$$

The time complexity of smoothing with respect to evidence $\mathbf{e}_{1:t}$ is $O(t)$

One obvious method to smooth the whole sequence is to run the smoothing algorithm for each time step – this results in time complexity $O(t^2)$.

A better approach uses **dynamic programming** (reuse already computed information) reducing the time complexity to $O(t)$.

- **forward-backward algorithm**
- the practical drawback of this approach is that its space complexity can be too high – it is $O(|\mathbf{f}|t)$.

Forward-backward algorithm

```

function FORWARD-BACKWARD(ev, prior) returns a vector of probability distributions
inputs: ev, a vector of evidence values for steps 1, ..., t
          prior, the prior distribution on the initial state,  $P(\mathbf{X}_0)$ 
local variables: fv, a vector of forward messages for steps 0, ..., t
                   b, a representation of the backward message, initially all 1s
                   sv, a vector of smoothed estimates for steps 1, ..., t

fv[0]  $\leftarrow$  prior
for  $i = 1$  to  $t$  do
    fv[ $i$ ]  $\leftarrow$  FORWARD(fv[ $i - 1$ ], ev[ $i$ ])
for  $i = t$  downto 1 do
    sv[ $i$ ]  $\leftarrow$  NORMALIZE(fv[ $i$ ]  $\times$  b)
    b  $\leftarrow$  BACKWARD(b, ev[ $i$ ])
return sv

```

Can be smoothing the whole sequence of states done with smaller memory consumption while keeping the time complexity $O(t)$?

Ideas:

- For message-passing in one direction we need constant space independent of t .
- Can the message $\mathbf{f}_{1:t}$ be obtained from the message $\mathbf{f}_{1:t+1}$?
- Then we can pass the forward message in the reverse (backward) direction together with the backward message.

Let us exploit **matrix operations**:

$$\mathbf{f}_{1:t+1} = \alpha \mathbf{O}_{t+1} \mathbf{T}^T \mathbf{f}_{1:t} \rightarrow \mathbf{f}_{1:t} = \alpha' (\mathbf{T}^T)^{-1} (\mathbf{O}_{t+1})^{-1} \mathbf{f}_{1:t+1}$$

Algorithm:

- first, run the forward-message propagation to get $\mathbf{f}_{1:t}$
- then during the backward stage compute both $\mathbf{f}_{1:k}$ and $\mathbf{b}_{k+1:t}$

Smoothing with a fixed time lag

Assume smoothing in an on-line setting where smoothed estimates must be computed for a fixed number d of back time steps – $\mathbf{P}(\mathbf{X}_{t-d} | \mathbf{e}_{1:t})$. This is called **fixed-lag smoothing**.

In the ideal case, we want incremental computation in a constant time per update.

we have $\mathbf{P}(\mathbf{X}_{t-d} | \mathbf{e}_{1:t}) = \alpha \mathbf{f}_{1:t-d} \times \mathbf{b}_{t-d+1:t}$

we need $\mathbf{P}(\mathbf{X}_{t-d+1} | \mathbf{e}_{1:t+1}) = \alpha \mathbf{f}_{1:t-d+1} \times \mathbf{b}_{t-d+2:t+1}$

An incremental approach:

- we can use $\mathbf{f}_{1:t-d+1} = \alpha \mathbf{O}_{t-d+2} \mathbf{T}^T \mathbf{f}_{1:t-d}$
- we need incremental computation of $\mathbf{b}_{t-d+2:t+1}$ from $\mathbf{b}_{t-d+1:t}$

$$\mathbf{b}_{t-d+1:t} = \mathbf{T} \mathbf{O}_{t-d+1} \mathbf{b}_{t-d+2:t} = (\prod_{i=t-d+1, \dots, t} \mathbf{T} \mathbf{O}_i) \mathbf{b}_{t+1:t} = \mathbf{B}_{t-d+1:t} \mathbf{1}$$

$$\mathbf{b}_{t-d+2:t+1} = (\prod_{i=t-d+2, \dots, t+1} \mathbf{T} \mathbf{O}_i) \mathbf{b}_{t+2:t+1} = \mathbf{B}_{t-d+2:t+1} \mathbf{1}$$

$$\mathbf{B}_{t-d+2:t+1} = (\mathbf{O}_{t-d+1})^{-1} \mathbf{T}^{-1} \mathbf{B}_{t-d+1:t} \mathbf{T} \mathbf{O}_{t+1}$$

```

function FIXED-LAG-SMOOTHING( $e_t$ , hmm, d) returns a distribution over  $\mathbf{X}_{t-d}$ 
  inputs:  $e_t$ , the current evidence for time step  $t$ 
           hmm, a hidden Markov model with  $S \times S$  transition matrix  $T$ 
           d, the length of the lag for smoothing
  static:  $t$ , the current time, initially 1
            $\mathbf{f}$ , a probability distribution, the forward message  $\mathbf{P}(X_t|e_{1:t})$ , initially  $\text{PRIOR}[hmm]$ 
            $B$ , the d-step backward transformation matrix, initially the identity matrix
            $e_{t-d:t}$ , double-ended list of evidence from  $t-d$  to  $t$ , initially empty
  local variables:  $\mathbf{O}_{t-d}$ ,  $\mathbf{O}_t$ , diagonal matrices containing the sensor model information

  add  $e_t$  to the end of  $e_{t-d:t}$ 
   $\mathbf{O}_t \leftarrow$  diagonal matrix containing  $\mathbf{P}(e_t|X_t)$ 
  if  $t > d$  then
     $\mathbf{f} \leftarrow \text{FORWARD}(\mathbf{f}, e_t)$ 
    remove  $e_{t-d-1}$  from the beginning of  $e_{t-d:t}$ 
     $\mathbf{O}_{t-d} \leftarrow$  diagonal matrix containing  $\mathbf{P}(e_{t-d}|X_{t-d})$ 
     $B \leftarrow \mathbf{O}_{t-d}^{-1} \mathbf{T}^{-1} B \mathbf{O}_t$ 
  else  $B \leftarrow B \mathbf{O}_t$ 
   $t \leftarrow t + 1$ 
  if  $t > d$  then return  $\text{NORMALIZE}(\mathbf{f} \times B\mathbf{1})$  else return null
  
```

