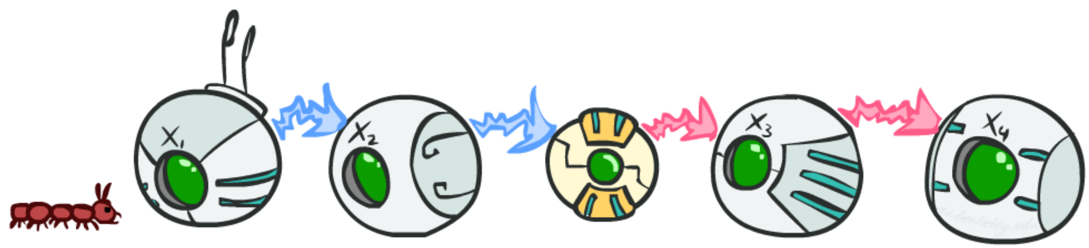
CS 188: Artificial Intelligence

Markov Models



Slides mostly from Stuart Russell and Dawn Song

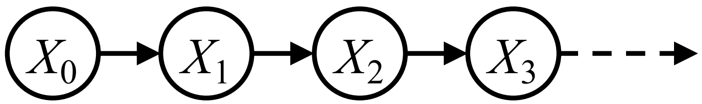
University of California, Berkeley

Uncertainty and Time

- Often, we want to reason about a ***sequence*** of observations where the state of the underlying system is ***changing***
  - Speech recognition
  - Robot localization
  - User attention
  - Medical monitoring
  - Global climate
- Need to introduce time into our models

Markov Models (aka Markov chain/process)

- Value of X at a given time is called the ***state*** (usually discrete, finite)



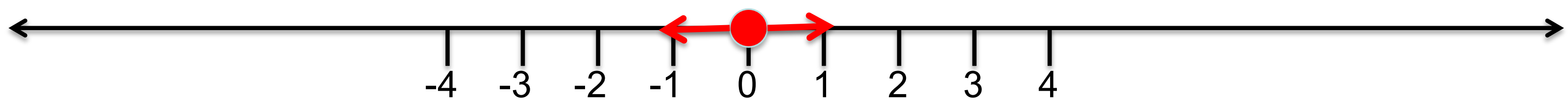
$P(X_0)$ $P(X_t \mid X_{t-1})$

- The ***transition model*** $P(X_t \mid X_{t-1})$ specifies how the state evolves over time
- ***Stationarity*** assumption: transition probabilities are the same at all times
- ***Markov*** assumption: "future is independent of the past given the present"
  - X_{t+1} is independent of $X_0, \ldots, X_{t-1}$ given X_t
  - This is a ***first-order*** Markov model (a kth-order model allows dependencies on k earlier steps)
- Joint distribution $P(X_0, \ldots, X_T) = P(X_0) \prod_t P(X_t \mid X_{t-1})$

Quiz: are Markov models a special case of Bayes nets?

- Yes and no!
- Yes:
  - Directed acyclic graph, joint = product of conditionals
- No:
  - Infinitely many variables (unless we truncate)
  - Repetition of transition model not part of standard Bayes net syntax

Example: Random walk in one dimension



- State: location on the unbounded integer line
- Initial probability: starts at 0
- Transition model: $P(X_t = k \mid X_{t-1} = k \pm 1) = 0.5$
- Applications: particle motion in crystals, stock prices, gambling, genetics, etc.
- Questions:
  - How far does it get as a function of t?
    - Expected distance is $O(\sqrt{t})$
  - Does it get back to 0 or can it go off for ever and not come back?
    - In 1D and 2D, returns w.p. 1; in 3D, returns w.p. 0.34053733

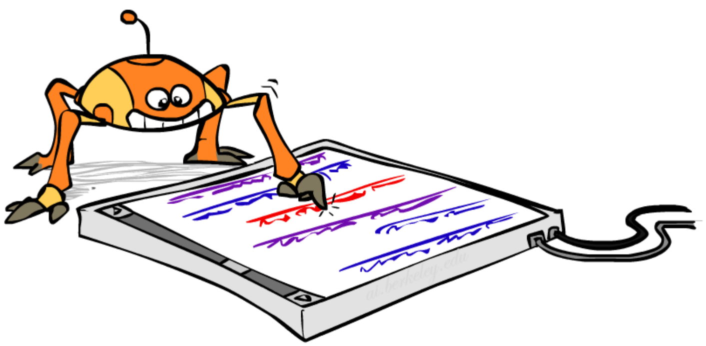
Example: n-gram models

We call ourselves *Homo sapiens*—man the wise—because our **intelligence** is so important to us.
For thousands of years, we have tried to understand *how we think*; that is, how a mere handful of matter can perceive, understand, predict, and manipulate a world far larger and more complicated than itself. ….

- State: word at position t in text (can also build letter n-grams)
- Transition model (probabilities come from empirical frequencies):
  - Unigram (zero-order): $P(Word_t = i)$
    - "logical are as are confusion a may right tries agent goal the was . . ."
  - Bigram (first-order): $P(Word_t = i \mid Word_{t-1} = j)$
    - "systems are very similar computational approach would be represented . . ."
  - Trigram (second-order): $P(Word_t = i \mid Word_{t-1} = j, Word_{t-2} = k)$
    - "planning and scheduling are integrated the success of naive bayes model is . . ."
- Applications: text classification, spam detection, author identification, language classification, speech recognition

Example: Web browsing

- State: URL visited at step *t*
- Transition model:
  - With probability *p*, choose an outgoing link at random
  - With probability (1-*p*), choose an arbitrary new page
- Question: What is the ***stationary distribution*** over pages?
  - I.e., if the process runs forever, what fraction of time does it spend in any given page?
- Application: Google page rank



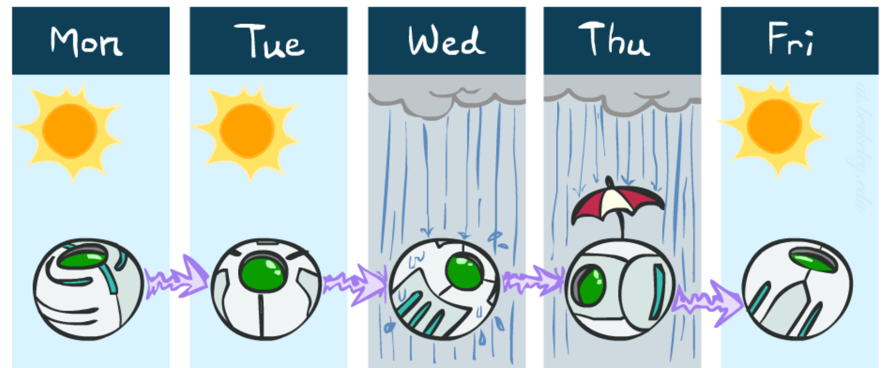
Example: Weather

- States {rain, sun}
- Initial distribution $P(X_0)$

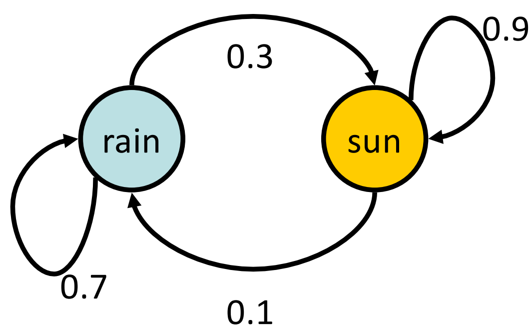
$P(X_0)$	
sun	rain
0.5	0.5

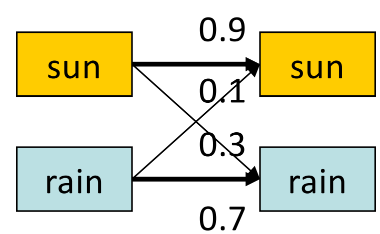
- Transition model $P(X_t \mid X_{t-1})$

X_{t-1}	$P(X_t \mid X_{t-1})$	
	sun	rain
sun	0.9	0.1
rain	0.3	0.7



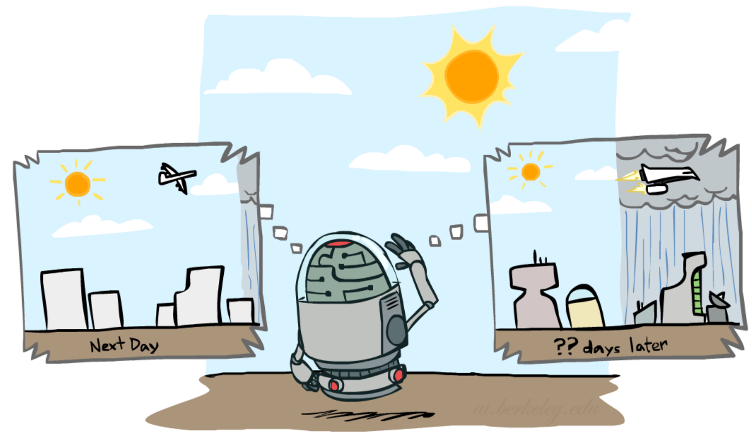
Two new ways of representing the same CPT





Weather prediction

X_{t-1}	$P(X_t \mid X_{t-1})$	
	sun	rain
sun	0.9	0.1
rain	0.3	0.7

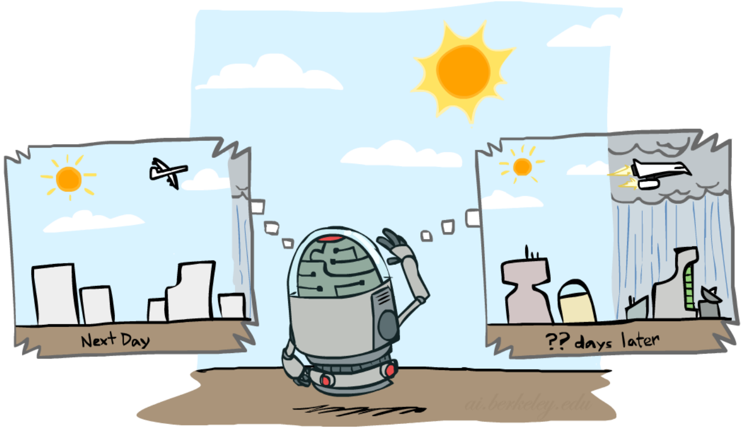


- Time 0: <0.5,0.5>
- What is the weather like at time 1?
  - $P(X_1) = \sum_{x_0} P(X_1, X_0{=}x_0)$
  - $\quad = \sum_{x_0} P(X_0{=}x_0)\, P(X_1 \mid X_0{=}x_0)$
  - $\quad = 0.5\langle 0.9, 0.1\rangle + 0.5\langle 0.3, 0.7\rangle = \langle 0.6, 0.4\rangle$

Weather prediction, contd.

- Time 1: <0.6,0.4>

X_{t-1}	$P(X_t \mid X_{t-1})$	
	sun	rain
sun	0.9	0.1
rain	0.3	0.7

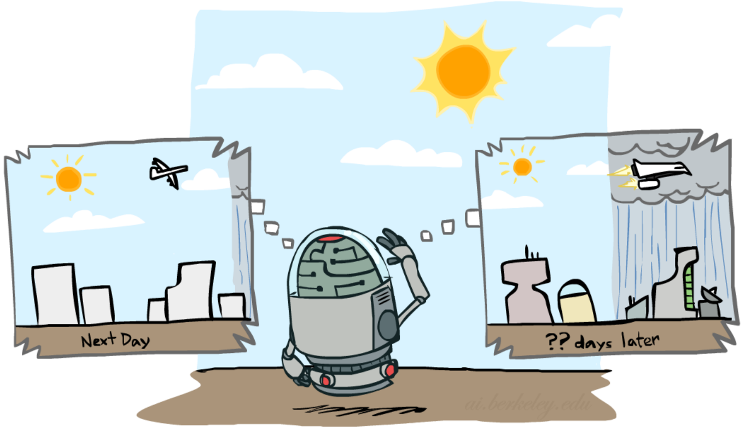


- What is the weather like at time 2?
  - $P(X_2) = \sum_{x_1} P(X_2, X_1{=}x_1)$
  - $\quad = \sum_{x_1} P(X_1{=}x_1)\, P(X_2 \mid X_1{=}x_1)$
  - $\quad = 0.6\langle 0.9,0.1\rangle + 0.4\langle 0.3,0.7\rangle = \langle 0.66,0.34\rangle$

Weather prediction, contd.

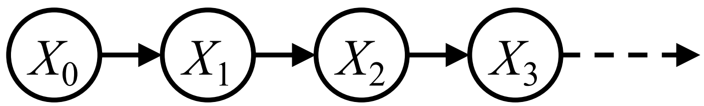
- Time 2: <0.66,0.34>

X_{t-1}	$P(X_t \mid X_{t-1})$	
	sun	rain
sun	0.9	0.1
rain	0.3	0.7



- What is the weather like at time 3?
  - $P(X_3) = \sum_{x_2} P(X_3, X_2 = x_2)$
  - $= \sum_{x_2} P(X_2 = x_2)\, P(X_3 \mid X_2 = x_2)$
  - $= 0.66\langle 0.9, 0.1\rangle + 0.34\langle 0.3, 0.7\rangle = \langle 0.696, 0.304\rangle$

Forward algorithm (simple form)



$P(X_0)$ $P(X_t \mid X_{t-1})$

Probability from previous iteration

Transition model

- What is the state at time t?
  - $P(X_t) = \sum_{x_{t-1}} P(X_t, X_{t-1}=x_{t-1})$
  - $= \sum_{x_{t-1}} P(X_{t-1}=x_{t-1})\, P(X_t \mid X_{t-1}=x_{t-1})$
- Iterate this update starting at t=0
  - This is called a ***recursive*** update: $P_t = g(P_{t-1}) = g(g(g(g(\ldots P_0))))$

And the same thing in linear algebra

- What is the weather like at time 2?
  - $P(X_2) = 0.6\langle 0.9,0.1\rangle + 0.4\langle 0.3,0.7\rangle = \langle 0.66,0.34\rangle$
- In matrix-vector form:
  - $P(X_2) = \begin{pmatrix} 0.9 & 0.3 \\ 0.1 & 0.7 \end{pmatrix} \begin{pmatrix} 0.6 \\ 0.4 \end{pmatrix} = \begin{pmatrix} 0.66 \\ 0.34 \end{pmatrix}$

X_{t-1}	$P(X_t \mid X_{t-1})$	
	sun	rain
sun	0.9	0.1
rain	0.3	0.7

- I.e., multiply by T^{T}, transpose of transition matrix

Stationary Distributions

- The limiting distribution is called the ***stationary distribution*** P_∞ of the chain
- It satisfies $P_\infty = P_{\infty+1} = T^T P_\infty$
- Solving for P_∞ in the example:

$$\begin{pmatrix} 0.9 & 0.3 \\ 0.1 & 0.7 \end{pmatrix} \begin{pmatrix} p \\ 1-p \end{pmatrix} = \begin{pmatrix} p \\ 1-p \end{pmatrix}$$

$0.9p + 0.3(1-p) = p$

$p = 0.75$

Stationary distribution is <0.75,0.25> ***regardless of starting distribution***

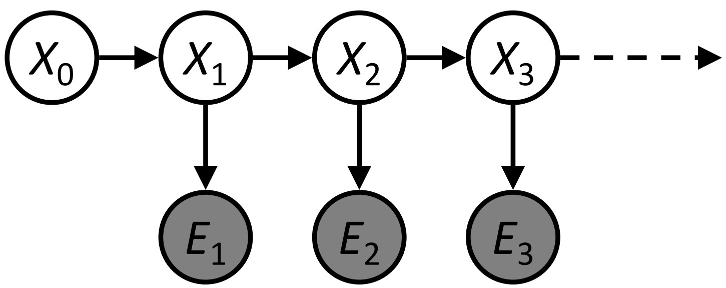
Consistency of Gibbs (see AIMA 13.4.2 for details)

- Gibbs sampling works because it uses a Markov chain where:
  - States are assignments of values to variables in the Bayes' net
  - Transition probabilities are easy to calculate – only use "local" information
  - Stationary distribution over states equals the desired conditional probability distribution
- Key fact: whenever we modify X_i, ratio of transition probabilities for transitioning to $X_i = x_i$ versus $X_i = x_i'$ is equal to the ratio:
- $P(x_1\, x_2 \ldots\, x_{i-1}\, x_i\, x_{i+1} \ldots\, x_n \mid \boldsymbol{e})$ versus $P(x_1\, x_2 \ldots\, x_{i-1}\, x_i'\, x_{i+1} \ldots\, x_n \mid \boldsymbol{e})$

Hidden Markov Models

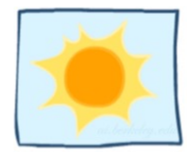
Hidden Markov Models

- Usually the true state is not observed directly
- Hidden Markov models (HMMs)
  - Underlying Markov chain over states X
  - You observe evidence E at each time step
  - X_t is a single discrete variable; E_t may be continuous and may consist of several variables

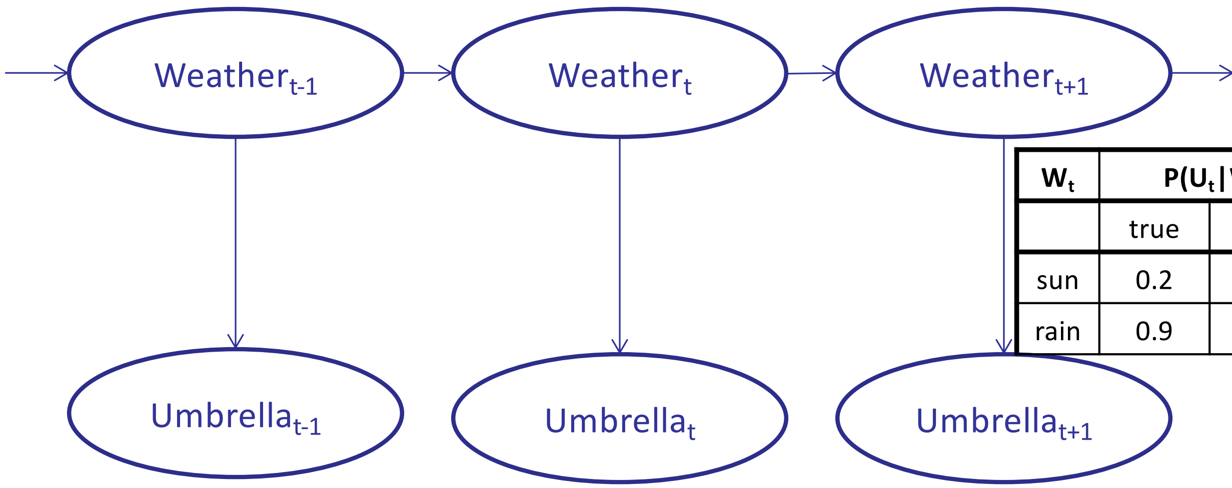


Example: Weather HMM

- An HMM is defined by:
  - Initial distribution: $P(X_0)$
  - Transition model: $P(X_t | X_{t-1})$
  - Sensor model: $P(E_t | X_t)$



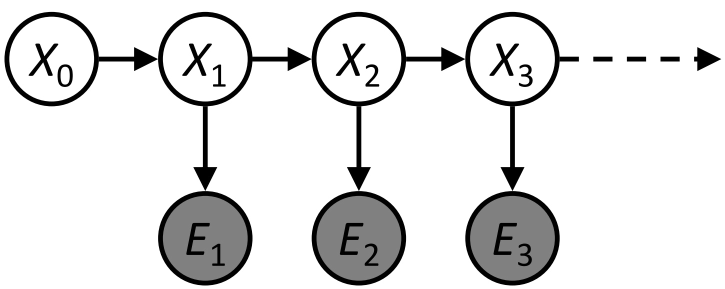
W_{t-1}	$P(W_t \mid W_{t-1})$	
	sun	rain
sun	0.9	0.1
rain	0.3	0.7



W_t	$P(U_t \mid W_t)$	
	true	false
sun	0.2	0.8
rain	0.9	0.1

HMM as probability model

- Joint distribution for Markov model: $P(X_0,\ldots, X_T) = P(X_0) \prod_{t=1:T} P(X_t \mid X_{t-1})$
- Joint distribution for hidden Markov model:
  $P(X_0,E_0,X_1,E_1,\ldots, X_T,E_T) = P(X_0) \prod_{t=1:T} P(X_t \mid X_{t-1})\, P(E_t \mid X_t)$
- Future states are independent of the past given the present
- Current evidence is independent of everything else given the current state
- Are evidence variables independent of each other?



Useful notation:

$X_{a:b} = X_a , X_{a+1}, \ldots, X_b$

Real HMM Examples

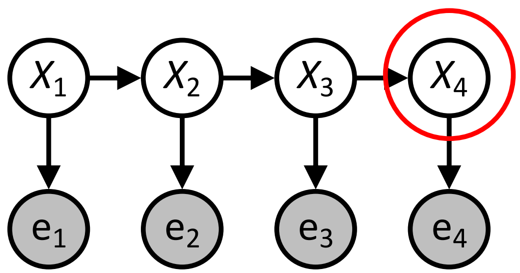
- Speech recognition HMMs:
  - Observations are acoustic signals (continuous valued)
  - States are specific positions in specific words (so, tens of thousands)
- Machine translation HMMs:
  - Observations are words (tens of thousands)
  - States are translation options
- Robot tracking:
  - Observations are range readings (continuous)
  - States are positions on a map (continuous)
- Molecular biology:
  - Observations are nucleotides ACGT
  - States are coding/non-coding/start/stop/splice-site etc.

Inference tasks

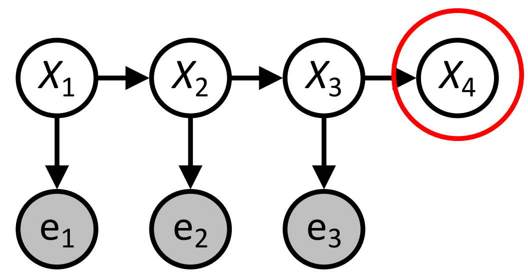
- ***Filtering***: $P(X_t | e_{1:t})$
  - ***belief state***—input to the decision process of a rational agent
- ***Prediction***: $P(X_{t+k} | e_{1:t})$ for $k > 0$
  - evaluation of possible action sequences; like filtering without the evidence
- ***Smoothing***: $P(X_k | e_{1:t})$ for $0 \leq k < t$
  - better estimate of past states, essential for learning
- ***Most likely explanation***: $\arg\max_{x_{1:t}} P(x_{1:t} \mid e_{1:t})$
  - speech recognition, decoding with a noisy channel

Inference tasks

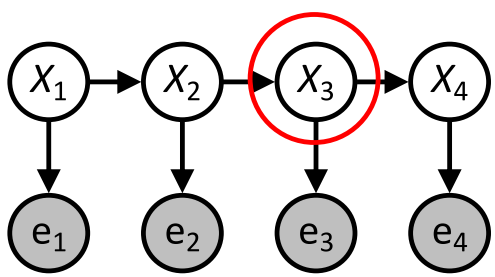
Filtering: $P(X_t | e_{1:t})$



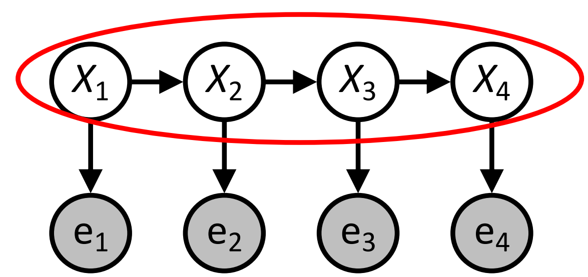
Prediction: $P(X_{t+k} | e_{1:t})$



Smoothing: $P(X_k | e_{1:t})$, $k<t$



Explanation: $P(X_{1:t} | e_{1:t})$

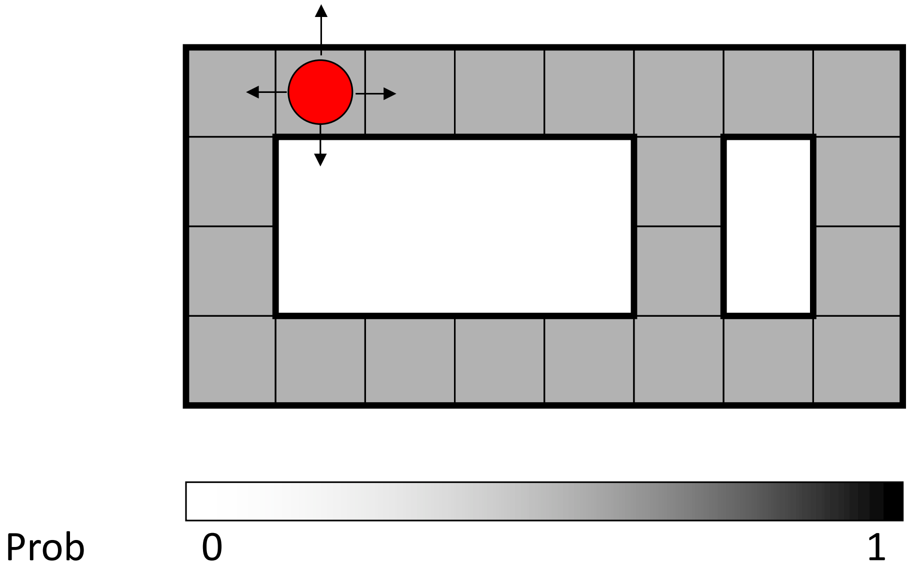


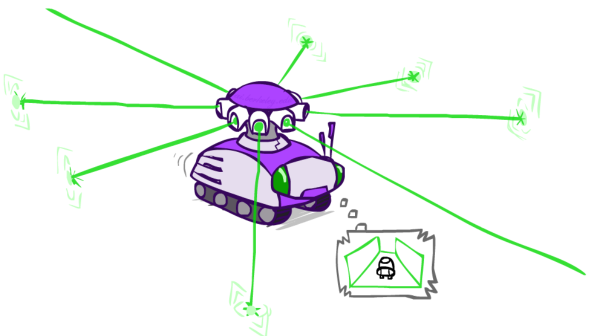
Filtering / Monitoring

- Filtering, or monitoring, or state estimation, is the task of maintaining the distribution $\boldsymbol{f}_{1:t} = P(X_t | e_{1:t})$ over time
- We start with $\boldsymbol{f}_0$ in an initial setting, usually uniform
- Filtering is a fundamental task in engineering and science
- The Kalman filter (continuous variables, linear dynamics, Gaussian noise) was invented in 1960 and used for trajectory estimation in the Apollo program; core ideas used by Gauss for planetary observations; ***>1,000,000*** papers on Google Scholar

Example: Robot Localization

Example from Michael Pfeiffer



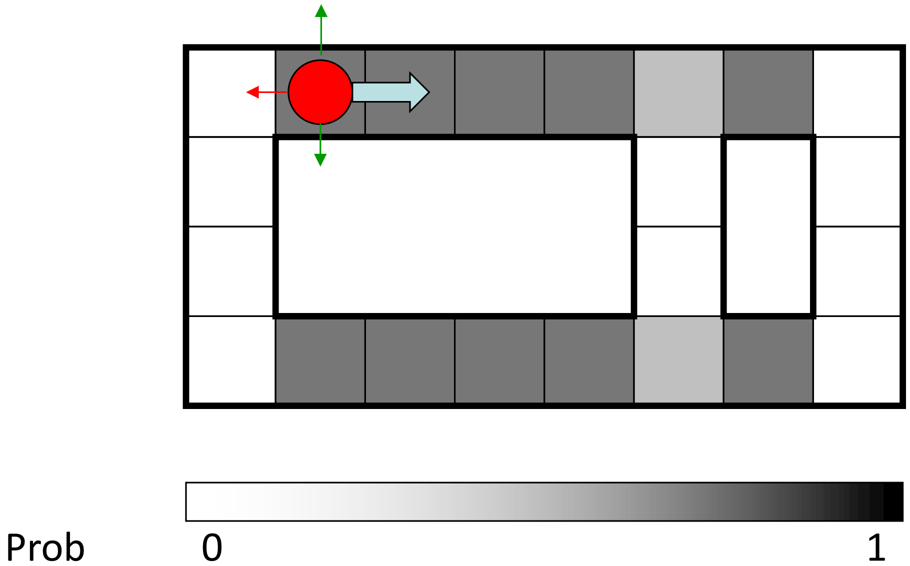


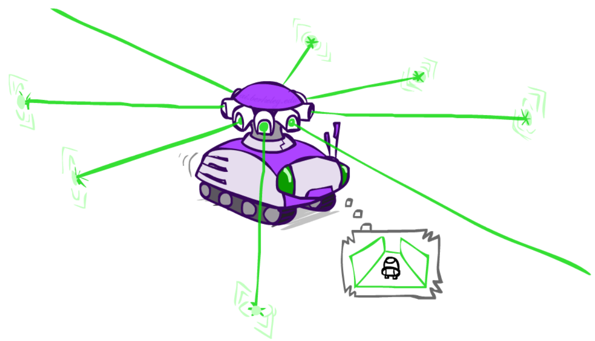
t=0

Sensor model: four bits for wall/no-wall in each direction, never more than 1 mistake

Transition model: action may fail with small prob.

Example: Robot Localization



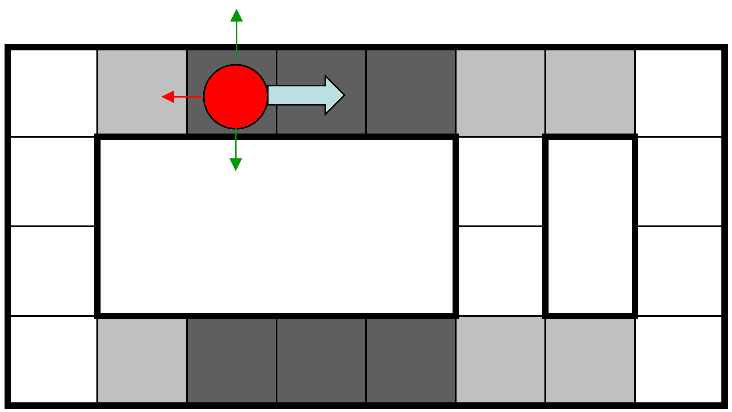


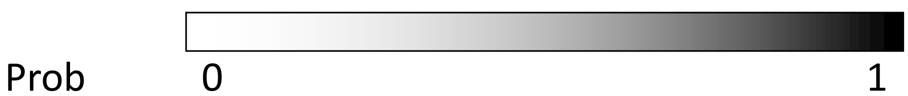
t=1

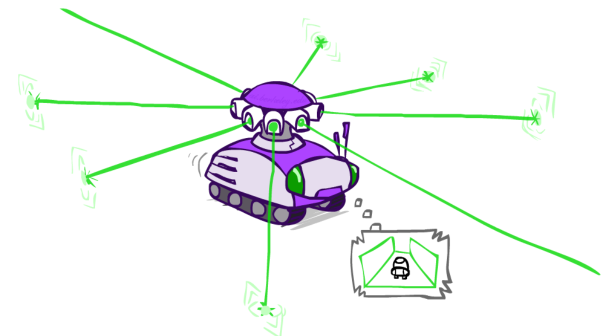
Lighter grey: was ***possible*** to get the reading,

but ***less likely*** (required 1 mistake)

Example: Robot Localization

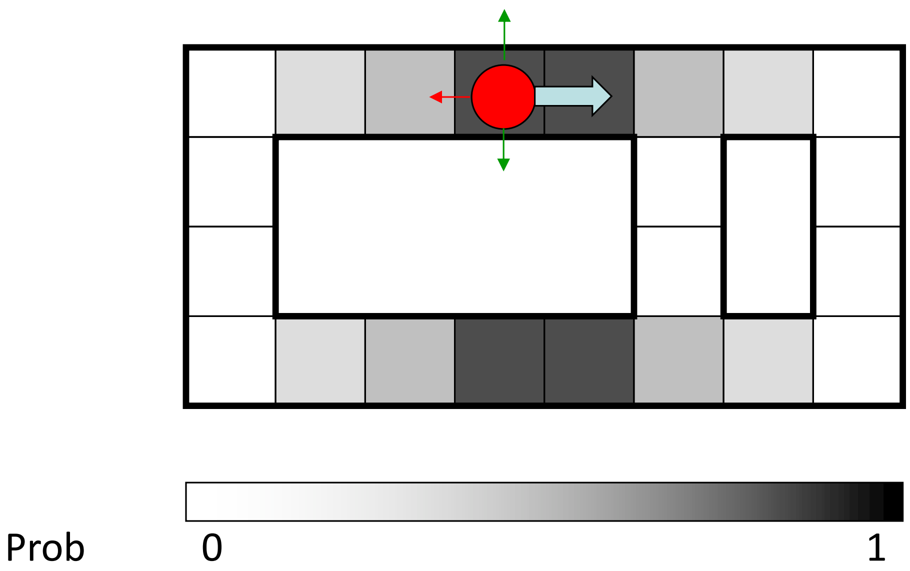


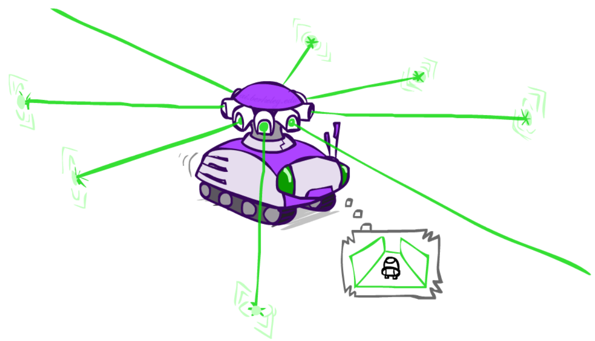




t=2

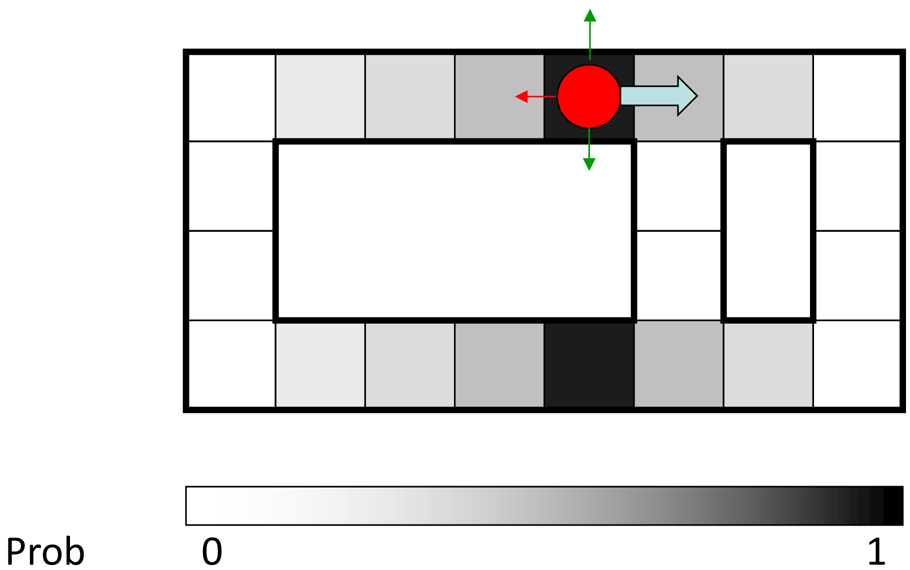
Example: Robot Localization



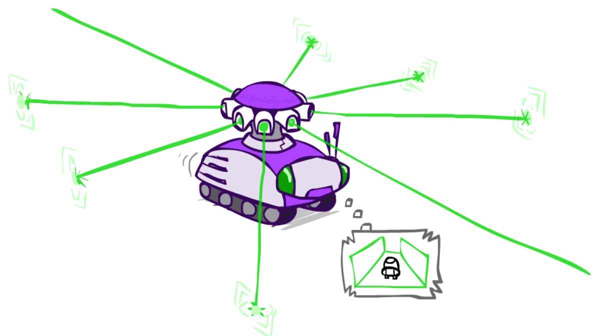


t=3

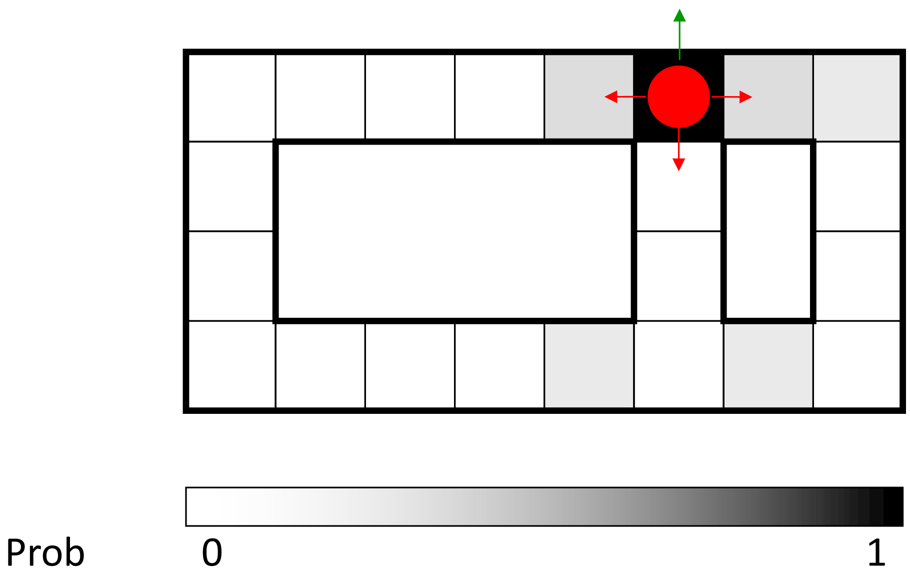
Example: Robot Localization

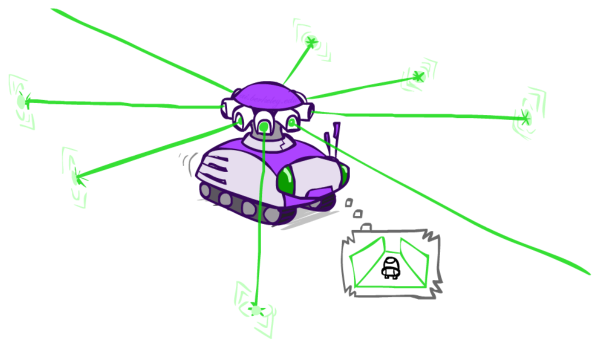


t=4



Example: Robot Localization

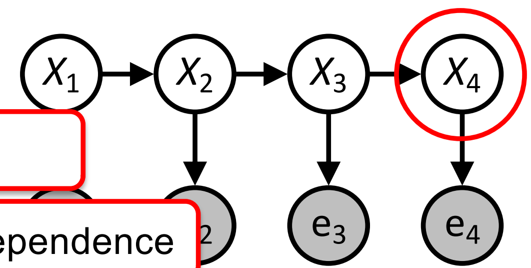




t=5

Filtering algorithm

- Aim: devise a ***recursive filtering*** algorithm of the form
  - $P(X_{t+1} | e_{1:t+1}) = g(e_{t+1}, P(X_t | e_{1:t}))$



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

Apply Bayes' rule

Apply conditional independence

Condition on X_t

Apply conditional independence

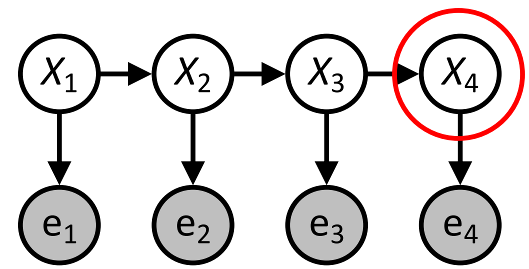
Normalize

Update

Predict

Filtering algorithm

- Aim: devise a ***recursive filtering*** algorithm of the form
  - $P(X_{t+1} | e_{1:t+1}) = g(e_{t+1}, P(X_t | e_{1:t}))$

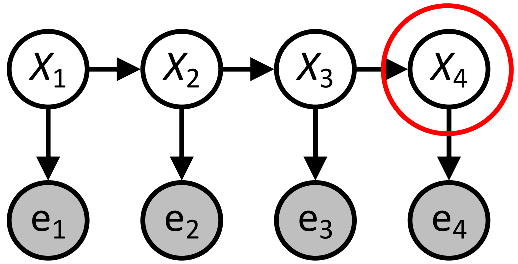


- $P(X_{t+1} | e_{1:t+1}) = P(X_{t+1} | e_{1:t}, e_{t+1})$
- $= \alpha\, P(e_{t+1} | X_{t+1}, e_{1:t})\, P(X_{t+1} | e_{1:t})$
- $= \alpha\, P(e_{t+1} | X_{t+1})\, P(X_{t+1} | e_{1:t})$
- $= \alpha\, P(e_{t+1} | X_{t+1}) \sum_{x_t} P(x_t \mid e_{1:t})\, P(X_{t+1} | x_t, e_{1:t})$
- $= \alpha\, \underline{P(e_{t+1} | X_{t+1})} \sum_{x_t} \underline{P(x_t \mid e_{1:t})}\, \underline{P(X_{t+1} | x_t)}$

Given by HMM | Pre-computed | Given by HMM

Filtering algorithm

- Aim: devise a ***recursive filtering*** algorithm of the form
  - $P(X_{t+1} | e_{1:t+1}) = g(e_{t+1}, P(X_t | e_{1:t}))$



- $P(X_{t+1} | e_{1:t+1}) = P(X_{t+1} | e_{1:t}, e_{t+1})$
- $= \alpha P(e_{t+1} | X_{t+1}, e_{1:t}) P(X_{t+1} | e_{1:t})$

LHS: $P(X_{t+1}, e_{1:t}, e_{t+1}) / P(e_{1:t}, e_{t+1})$

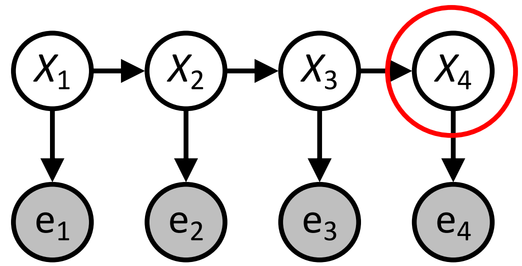
RHS: $\alpha P(e_{t+1}, X_{t+1}, e_{1:t}) / \cancel{P(X_{t+1}, e_{1:t})} * \cancel{P(X_{t+1}, e_{1:t})} / P(e_{1:t})$

RHS: $\alpha P(e_{t+1}, X_{t+1}, e_{1:t}) / P(e_{1:t})$

$\alpha = P(e_{1:t}) / P(e_{1:t}, e_{t+1})$ which is the same for all x_{t+1}

Filtering algorithm

- Aim: devise a ***recursive filtering*** algorithm of the form
  - $P(X_{t+1}|e_{1:t+1}) = g(e_{t+1}, P(X_t|e_{1:t}))$

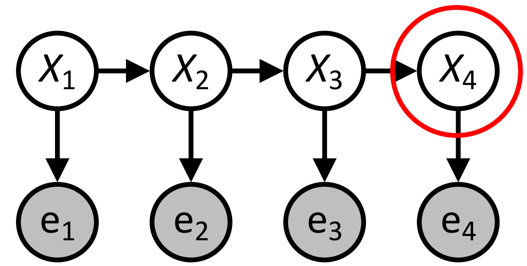


- $P(X_{t+1}|e_{1:t+1}) = P(X_{t+1}|e_{1:t}, e_{t+1})$
- $= \alpha\, P(e_{t+1}|X_{t+1}, e_{1:t})\, P(X_{t+1}|\, e_{1:t})$
- $= \alpha\, P(e_{t+1}|X_{t+1})\, P(X_{t+1}|\, e_{1:t})$

Why does $P(e_{t+1}|X_{t+1}, e_{1:t}) = P(e_{t+1}|X_{t+1})$?
Variables are independent of non-descendants given parents
If I know X_4, nothing else will help be better predict e_4

Filtering algorithm

- Aim: devise a ***recursive filtering*** algorithm of the form
  - $P(X_{t+1}|e_{1:t+1}) = g(e_{t+1}, P(X_t|e_{1:t}))$



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

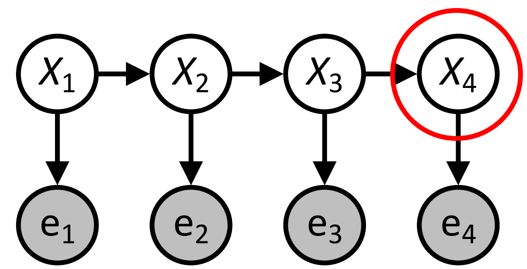
P(A|B)P(B) = P(A,B)

Marginalization over x_t

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

Filtering algorithm

- Aim: devise a ***recursive filtering*** algorithm of the form
  - $P(X_{t+1} | e_{1:t+1}) = g(e_{t+1}, P(X_t | e_{1:t}))$



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

Given by HMM — Pre-computed — Given by HMM

Variables are independent of non-descendants given parents

"Forward" algorithm

Given by HMM *(vector)*

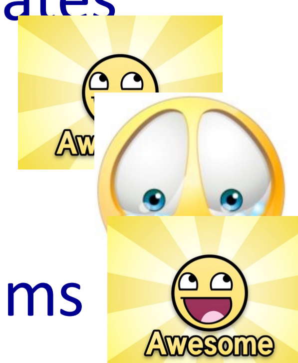
Pre-computed *(scalar for each term in sum)*

Given by HMM *(vector for each term in sum)*

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

Normalize (α) — Update ($P(e_{t+1} | X_{t+1})$) — Predict ($\sum_{x_t} P(x_t \mid e_{1:t})\, P(X_{t+1} \mid x_t)$)

- $\boldsymbol{f}_{1:t+1}$ = FORWARD($\boldsymbol{f}_{1:t}$, e_{t+1}) ; $\boldsymbol{f}_{1:t}$ is $P(X_t | e_{1:t})$ *for t=0, note $e_{1:0}$ is empty
- Cost per time step: $O(|X|^2)$ where $|X|$ is the number of states
- Time and space costs are ***constant***, independent of t
- $O(|X|^2)$ is infeasible for models with many state variables
- We get to invent really cool approximate filtering algorithms



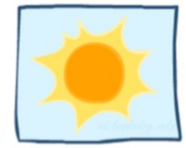
And the same thing in linear algebra

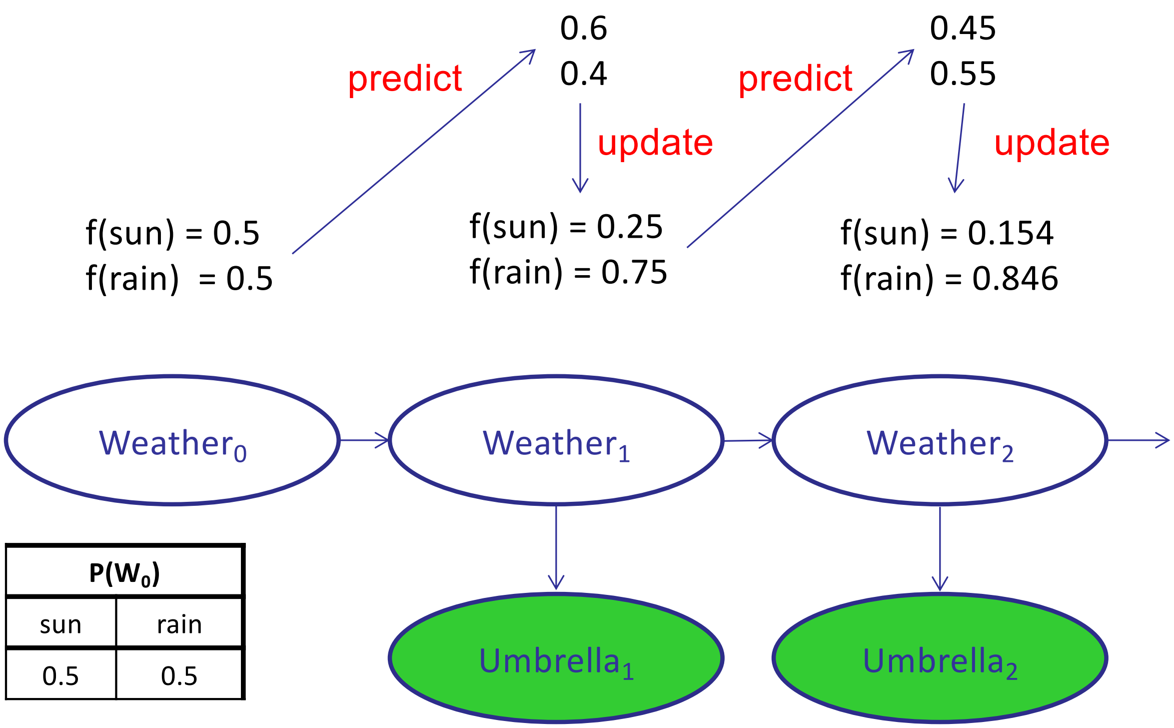
- Transition matrix T, observation matrix O_t
  - Observation matrix has state likelihoods for E_t along diagonal
  - E.g., for U_1 = true, $O_1 = \begin{pmatrix} 0.2 & 0 \\ 0 & 0.9 \end{pmatrix}$
- Filtering algorithm becomes
  - $\boldsymbol{f}_{1:t+1} = \alpha\, O_{t+1} T^{\mathsf{T}} \boldsymbol{f}_{1:t}$

X_{t-1}	$P(X_t \mid X_{t-1})$	
	sun	rain
sun	0.9	0.1
rain	0.3	0.7

W_t	$P(U_t \mid W_t)$	
	true	false
sun	0.2	0.8
rain	0.9	0.1

Example: Weather HMM



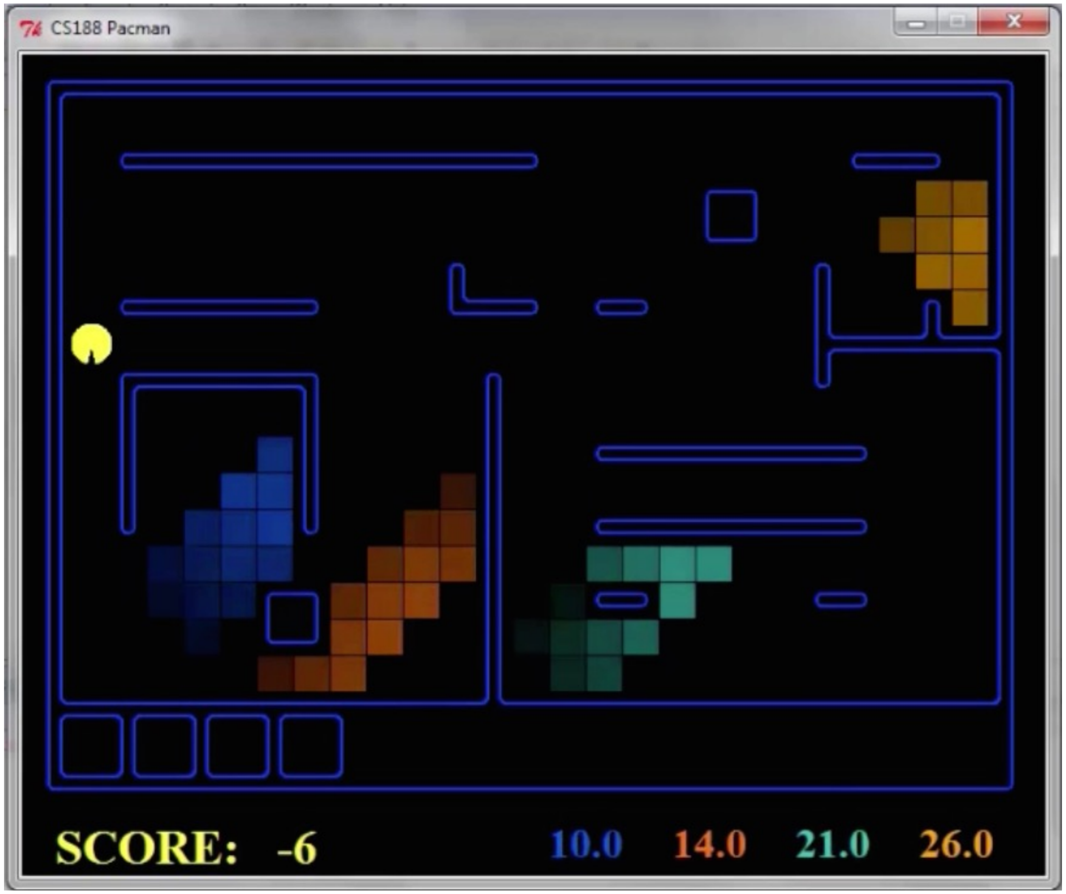


P(W_0)	
sun	rain
0.5	0.5

W_{t-1}	P(W_t|W_{t-1})	
	sun	rain
sun	0.9	0.1
rain	0.3	0.7

W_t	P(U_t|W_t)	
	true	false
sun	0.2	0.8
rain	0.9	0.1

Pacman – Hunting Invisible Ghosts with Sonar



[Demo: Pacman – Sonar – No Beliefs(L14D1)]

Video of Demo Pacman – Sonar

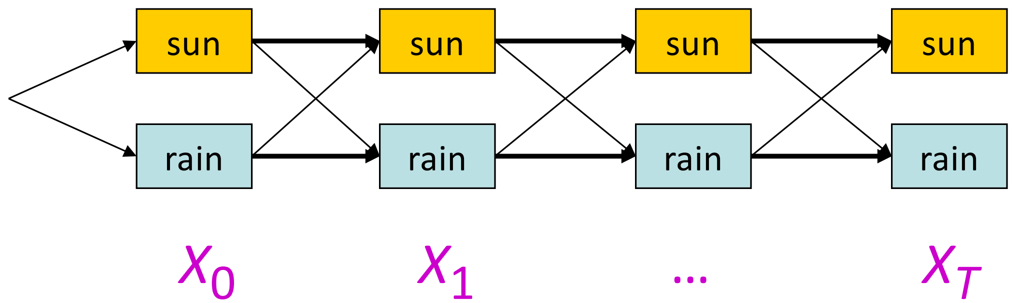
Most Likely Explanation

Inference tasks

- ***Filtering***: $P(X_t | e_{1:t})$
  - ***belief state***—input to the decision process of a rational agent
- ***Prediction***: $P(X_{t+k} | e_{1:t})$ for $k > 0$
  - evaluation of possible action sequences; like filtering without the evidence
- ***Smoothing***: $P(X_k | e_{1:t})$ for $0 \leq k < t$
  - better estimate of past states, essential for learning
- ***Most likely explanation***: $\arg\max_{x_{1:t}} P(x_{1:t} \mid e_{1:t})$
  - speech recognition, decoding with a noisy channel

Most likely explanation = most probable path

- ***State trellis***: graph of states and transitions over time



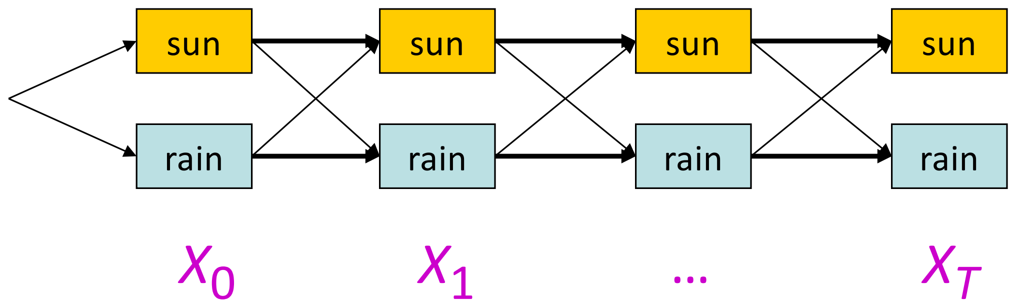
- arg $\max_{x_{1:t}} P(x_{1:t} \mid e_{1:t})$
- = arg $\max_{x_{1:t}} \alpha\, P(x_{1:t}, e_{1:t})$
- = arg $\max_{x_{1:t}} P(x_{1:t}, e_{1:t})$
- = arg $\max_{x_{1:t}} P(x_0) \prod_t P(x_t \mid x_{t-1}) P(e_t \mid x_t)$
- = arg $\max_{x_{1:t}} \log [\, P(x_0) \prod_t P(x_t \mid x_{t-1}) P(e_t \mid x_t) \,]$
- = arg $\max_{x_{1:t}} \log P(x_0) + \sum_t \log P(x_t \mid x_{t-1}) + \log P(e_t \mid x_t)$

All given by HMM

Alternative form

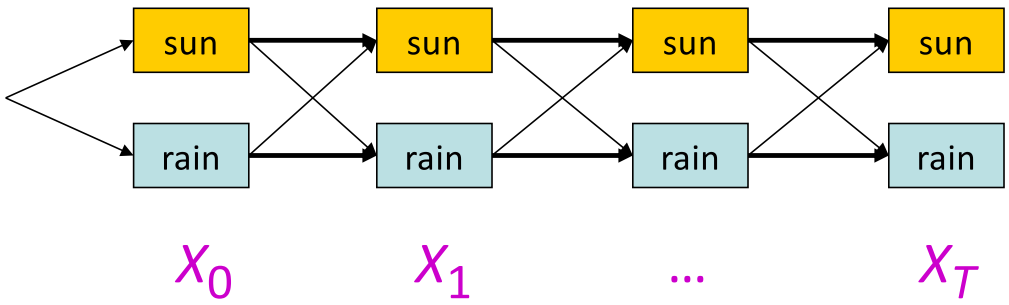
Most likely explanation = most probable path

- ***State trellis***: graph of states and transitions over time



- Each arc represents some transition $x_{t-1} \rightarrow x_t$
- Each arc has weight $P(x_t \mid x_{t-1})\ P(e_t \mid x_t)$ (arcs to initial states have weight $P(x_0)$)
- The ***product*** of weights on a path is proportional to that state sequence's probability
- Forward algorithm computes sums of paths, ***Viterbi algorithm*** computes best paths

Forward / Viterbi algorithms



Forward Algorithm (sum)

For each state at time t, keep track of the ***total probability of all paths*** to it

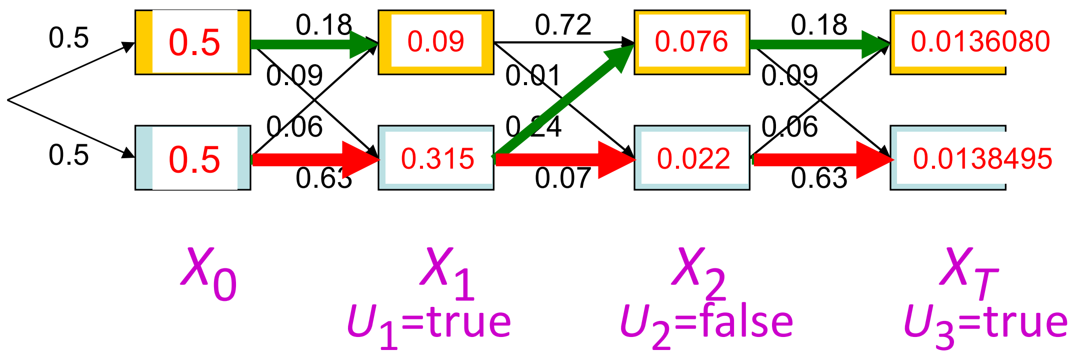
$$\mathbf{f}_{1:t+1} = \text{FORWARD}(\mathbf{f}_{1:t}, e_{t+1}) = \alpha P(e_{t+1}|X_{t+1}) \sum_{x_t} P(X_{t+1} | x_t)\, \mathbf{f}_{1:t}$$

Viterbi Algorithm (max)

For each state at time t, keep track of the ***maximum probability of any path*** to it

$$\mathbf{m}_{1:t+1} = \text{VITERBI}(\mathbf{m}_{1:t}, e_{t+1}) = P(e_{t+1}|X_{t+1}) \max_{x_t} P(X_{t+1} | x_t)\, \mathbf{m}_{1:t}$$

Viterbi algorithm contd.



W_{t-1}	$P(W_t \mid W_{t-1})$	
	sun	rain
sun	0.9	0.1
rain	0.3	0.7

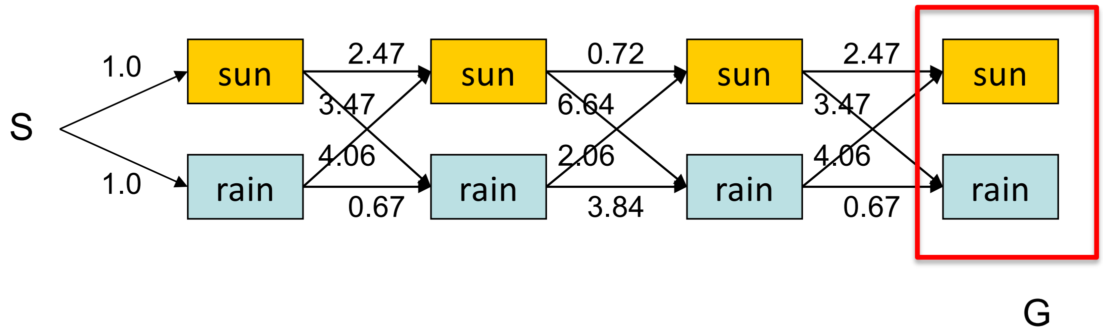
W_t	$P(U_t \mid W_t)$	
	true	false
sun	0.2	0.8
rain	0.9	0.1

Time complexity?
$O(|X|^2 T)$

Space complexity?
$O(|X| T)$

Number of paths?
$O(|X|^T)$

Viterbi in negative log space



W_{t-1}	$P(W_t \mid W_{t-1})$	
	sun	rain
sun	0.9	0.1
rain	0.3	0.7

W_t	$P(U_t \mid W_t)$	
	true	false
sun	0.2	0.8
rain	0.9	0.1

argmax of product of probabilities
= argmin of sum of negative log probabilities
= minimum-cost path

Viterbi is essentially breadth-first graph search
What about A*?