CS 188 Discussion 10:

Hidden Markov Models, Particle Filtering

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Slides based on Sashrika + Joy

Administrivia

- Project 4 due on Mon, Nov 6
- Homework is due on Tuesdays
- We have office hours pretty much all day every weekday (12-7), come to Soda 341B! (my hours are 1-3 PM on Mondays)
- Discussion slides are on Ed

Happy Halloween!

I am too lazy to get a haircut …

Just pretend this is my costume

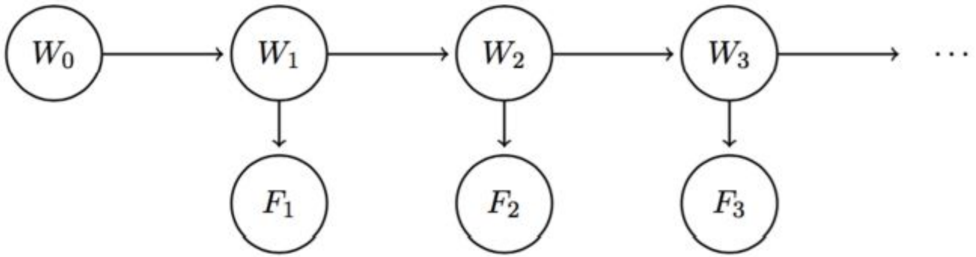
Today's Topics

- Hidden Markov Models (HMMs)
- Exact HMM Inference: Forward Algorithm
- Approximate HMM Inference: Particle Filtering

Hidden Markov Models (HMMs)

This is how we used to do speech recognition!

- **Hidden Markov Model:** model of a Markov process where we can only observe evidence instead of the hidden true states
- **State variables:** random variable, represents true state at a timestep, depends on previous state
- **Evidence variables:** random observations, depends on the true state
- Represent with **initial distribution**, **transition model**, and **sensor model**
- Ex: weather prediction



- State vars $\mathbf{W_i}$ (weather on day i)
- Evid. vars $\mathbf{F_i}$ (forecast on day i)
- Initial dist'n $\mathbf{P(W_0)}$
- Transition model $\mathbf{P(W_{i+1} \mid W_i)}$
- Sensor model $\mathbf{P(F_i \mid W_i)}$

Forward Algorithm

Worksheet Q1

- **Belief distribution** at time *i* given evidence $f_1, \ldots, f_i$

$$B(W_i) = P(W_i | f_1, \ldots, f_i) \qquad B'(W_i) = P(W_i | f_1, \ldots, f_{i-1})$$

- **Forward algorithm** calculates **$B(W_i)$**

$$B(W_{i+1}) \propto P(f_{i+1} | W_{i+1}) \sum_{w_i} P(W_{i+1} | w_i) B(w_i)$$

  - **Time lapse update:** advance model's state by one timestep

$$B'(W_{i+1}) = \sum_{w_i} P(W_{i+1} | w_i) B(w_i)$$

  - **Observation update:** incorporate new evidence

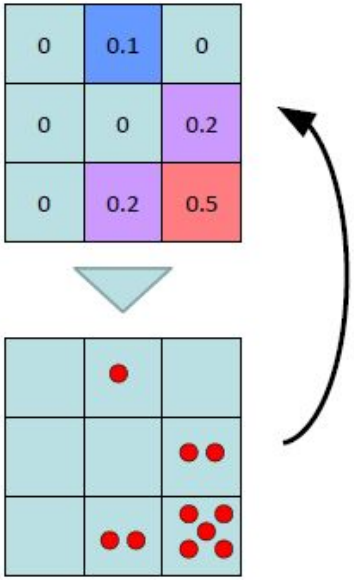
$$B(W_{i+1}) \propto P(f_{i+1} | W_{i+1}) B'(W_{i+1})$$

Particle Filtering

- Hidden Markov Models
- **Particle Filtering**

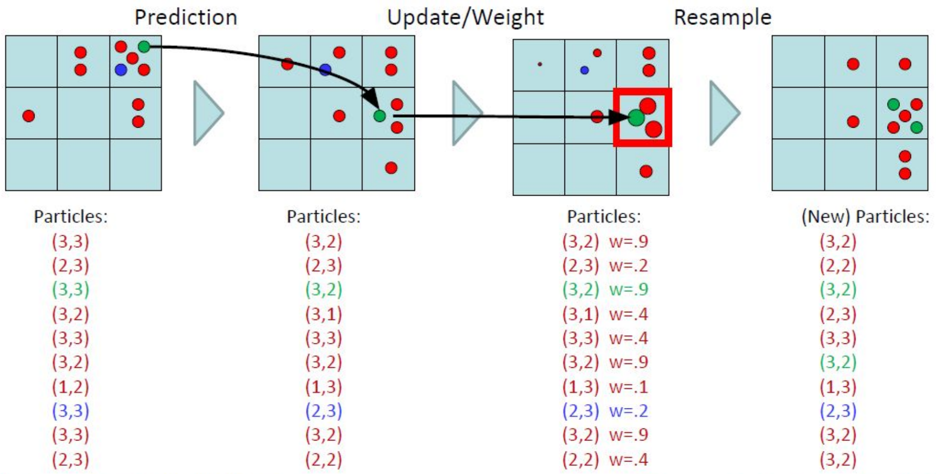
Particle Filtering

- Exact inference might not work if variable domain too large (f/e, continuous)
- **Particle Filtering:** Use set of samples (particles) to represent belief state
  - Store a list of **n** particles. Each particle is in one of d possible states of the hidden variable X.
    - n << d
  - At each timestep, update the positions of each particle by simulating its movement and incorporating evidence
  - To compute the belief distribution at time i for a possible state $P(x_i|e_1,e_2,...e_i)$, simply divide the number of particles in that state by the total number of particles.



Particle Filtering (cont'd) Worksheet Q2

- Prediction
  - Resample particle position (transition model)
  - For every particle, $\mathbf{x_{i+1} \sim P(X_{i+1}|x_i)}$
- Weighting
  - Incorporate new evidence (sensor model)
  - For every particle, **weight** $\mathbf{= P(e_{i+1}|x_{i+1})}$
- Resampling
  - Don't want to track weighted samples
  - Normalize the weights across states and resample **n** times to get new particles.
- Repeat



Rest of the Worksheet

Thank you for attending!

Attendance link:

- https://tinyurl.com/cs188fa23

Discussion No: 10

Remember my name is Kenny

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