# CS 188: Artificial Intelligence
## Spring 2011

Lecture 19: Dynamic Bayes Nets, Naïve Bayes

4/6/2011

Pieter Abbeel – UC Berkeley

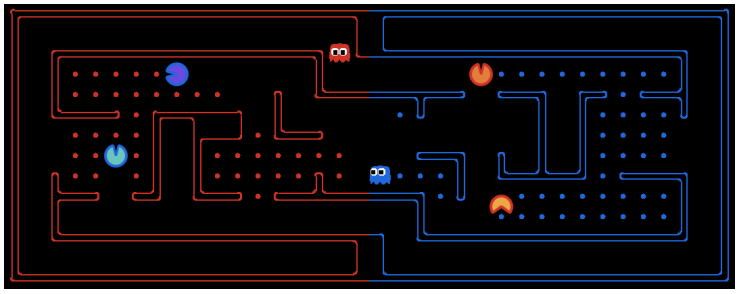
Slides adapted from Dan Klein.

# Announcements

- W4 out, due next week Monday
- P4 out, due next week Friday
- Mid-semester survey

# Announcements II

- Course contest

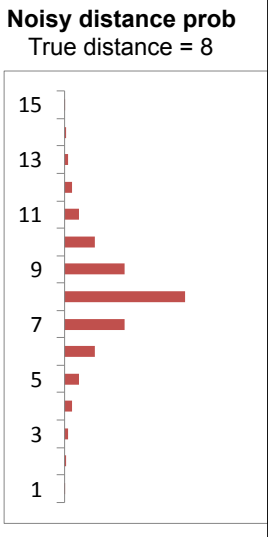


  - Regular tournaments. Instructions have been posted!
  - First week extra credit for top 20, next week top 10, then top 5, then top 3.
  - First nightly tournament: tentatively Monday night

3

# P4: Ghostbusters 2.0

- **Plot:** Pacman's grandfather, Grandpac, learned to hunt ghosts for sport.
- He was blinded by his power, but could hear the ghosts' banging and clanging.
- **Transition Model:** All ghosts move randomly, but are sometimes biased
- **Emission Model:** Pacman knows a "noisy" distance to each ghost



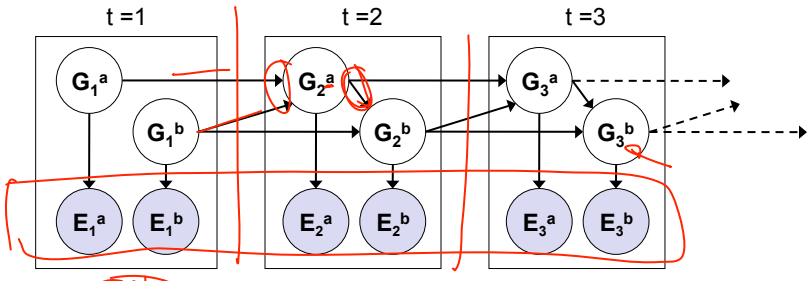
# Today

- Dynamic Bayes Nets (DBNs)
  - [sometimes called temporal Bayes nets]
- Demos:
  - Localization
  - Simultaneous Localization And Mapping (SLAM)
- Start machine learning

5

# Dynamic Bayes Nets (DBNs)

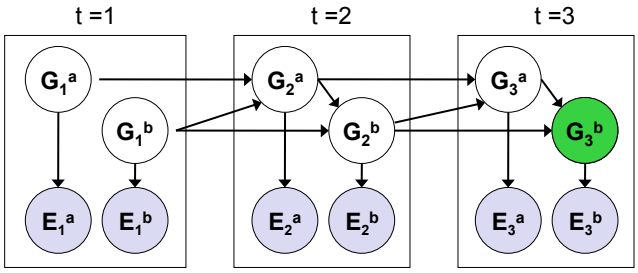
- We want to track multiple variables over time, using multiple sources of evidence
- Idea: Repeat a fixed Bayes net structure at each time
- Variables from time *t* can condition on those from *t-1*




- Discrete valued dynamic Bayes nets are also HMMs

# Exact Inference in DBNs

- Variable elimination applies to dynamic Bayes nets
- Procedure: "unroll" the network for T time steps, then eliminate variables until $P(X_T|e_{1:T})$ is computed




- Online belief updates: Eliminate all variables from the previous time step; store factors for current time only

7

# DBN Particle Filters

- A particle is a complete sample for a time step
- **Initialize**: Generate prior samples for the t=1 Bayes net
  - Example particle: $\mathbf{G_1^a} = (3,3)$ $\mathbf{G_1^b} = (5,3)$
- **Elapse time**: Sample a successor for each particle
  - Example successor: $\mathbf{G_2^a} = (2,3)$ $\mathbf{G_2^b} = (6,3)$
- **Observe**: Weight each entire sample by the likelihood of the evidence conditioned on the sample
  - Likelihood: $P(\mathbf{E_1^a}|\mathbf{G_1^a}) * P(\mathbf{E_1^b}|\mathbf{G_1^b})$
- **Resample:** Select prior samples (tuples of values) in proportion to their likelihood

[Demo]

8

# DBN Particle Filters

- A particle is a complete sample for a time step
- **Initialize**: Generate prior samples for the t=1 Bayes net
  - Example particle: $\mathbf{G}_1^a = (3,3)$ $\mathbf{G}_1^b = (5,3)$
- **Elapse time**: Sample a successor for each particle
  - Example successor: $\mathbf{G}_2^a = (2,3)$ $\mathbf{G}_2^b = (6,3)$
- **Observe**: Weight each entire sample by the likelihood of the evidence conditioned on the sample
  - Likelihood: $P(\mathbf{E}_1^a | \mathbf{G}_1^a) * P(\mathbf{E}_1^b | \mathbf{G}_1^b)$
- **Resample:** Select prior samples (tuples of values) in proportion to their likelihood

9

# Trick I to Improve Particle Filtering Performance: Low Variance Resampling

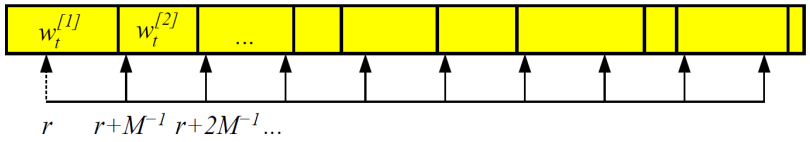



**Figure 4.7** Principle of the low variance resampling procedure. We choose a random number $r$ and then select those particles that correspond to $u = r + (m-1) \cdot M^{-1}$ where $m = 1, \ldots, M$.

- Advantages:
  - More systematic coverage of space of samples
  - If all samples have same importance weight, no samples are lost
  - Lower computational complexity

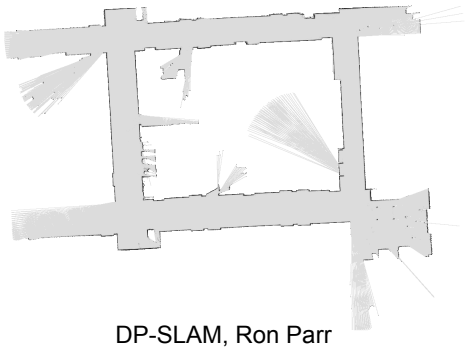
# Trick II to Improve Particle Filtering Performance: Regularization

- If no or little noise in transitions model, all particles will start to coincide

→ regularization: introduce additional (artificial) noise into the transition model

# SLAM

- SLAM = Simultaneous Localization And Mapping
  - We do not know the map or our location
  - Our belief state is over maps and positions!
  - Main techniques: Kalman filtering (Gaussian HMMs) and particle methods
- [DEMOS]



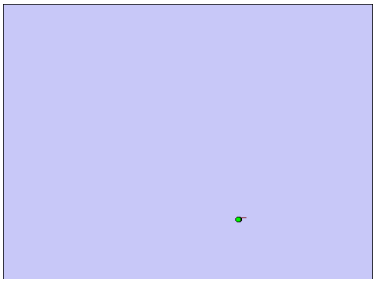
DP-SLAM, Ron Parr

# Robot Localization

- In robot localization:
  - We know the map, but not the robot's position
  - Observations may be vectors of range finder readings
  - State space and readings are typically continuous (works basically like a very fine grid) and so we cannot store B(X)
  - Particle filtering is a main technique

- [Demos]

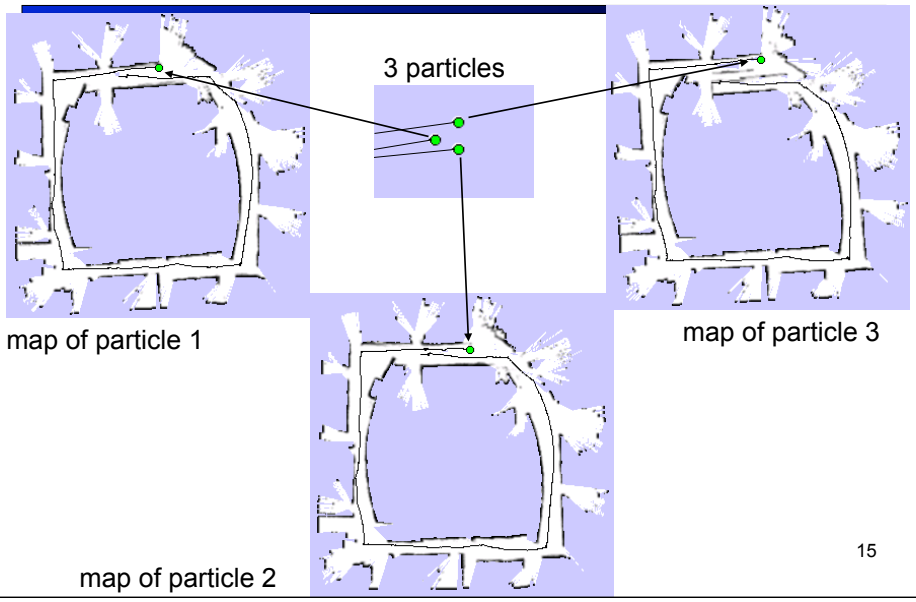
Global-floor



# SLAM

- SLAM = Simultaneous Localization And Mapping
  - We do not know the map or our location
  - State consists of position AND map!
  - Main techniques: Kalman filtering (Gaussian HMMs) and particle methods

# Particle Filter Example




# SLAM

- DEMOS
  - fastslam.avi, visionSlam_heliOffice.wmv

## Further readings

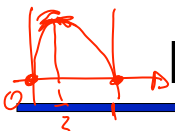
- We are done with Part II Probabilistic Reasoning
- To learn more (beyond scope of 188):
  - Koller and Friedman, Probabilistic Graphical Models (CS281A)
  - Thrun, Burgard and Fox, Probabilistic Robotics (CS287)

## Part III: Machine Learning

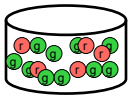
- Up until now: how to reason in a model and how to make optimal decisions
- Machine learning: how to acquire a model on the basis of data / experience
  - Learning parameters (e.g. probabilities)
  - Learning structure (e.g. BN graphs)
  - Learning hidden concepts (e.g. clustering)

# Machine Learning Today

- An ML Example: Parameter Estimation
  - Maximum likelihood
  - Smoothing
- Applications
- Main concepts
- Naïve Bayes



# Parameter Estimation



- Estimating the distribution of a random variable
- *Elicitation:* ask a human (why is this hard?)
- *Empirically:* use training data (learning!)
  - E.g.: for each outcome x, look at the *empirical rate* of that value:

$$P_{\text{ML}}(x) = \frac{\text{count}(x)}{\text{total samples}}$$

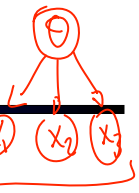

$P_{\text{ML}}(\text{r}) = 1/3$

  - This is the estimate that maximizes the *likelihood of the data*

$$L(x,\theta) = \prod_i P_\theta(x_i)$$

- *Issue: overfitting. E.g., what if only observed 1 jelly bean?*

# Estimation: Smoothing



- Relative frequencies are the maximum likelihood estimates

$$\theta_{ML} = \arg\max_{\theta} P(\mathbf{X}|\theta)$$
$$= \arg\max_{\theta} \prod_i P_\theta(X_i)$$

$$\Rightarrow \quad P_{\text{ML}}(x) = \frac{\text{count}(x)}{\text{total samples}}$$

- In Bayesian statistics, we think of the parameters as just another random variable, with its own distribution

$$\theta_{MAP} = \arg\max_{\theta} P(\theta|\mathbf{X})$$
$$= \arg\max_{\theta} P(\mathbf{X}|\theta)P(\theta)/P(\mathbf{X}) \quad \Rightarrow \quad ????$$
$$= \arg\max_{\theta} P(\mathbf{X}|\theta)P(\theta)$$

# Estimation: Laplace Smoothing

- Laplace's estimate:
  - Pretend you saw every outcome once more than you actually did


$$P_{LAP}(x) = \frac{c(x)+1}{\sum_x [c(x)+1]}$$
$$= \frac{c(x)+1}{N+|X|}$$

$$P_{ML}(X) = \frac{2}{3} \text{ for } H$$

$$P_{LAP}(X) = \frac{2+1}{3+2} = \frac{3}{5} \text{ for } H$$

  - Can derive this as a MAP estimate with *Dirichlet priors* (see cs281a)

$P(\theta) \propto \theta^{\alpha}(1-\theta)^{\beta}$ $\quad \alpha = 1$ $\quad \beta = 1$

# Estimation: Laplace Smoothing

- Laplace's estimate (extended):
  - Pretend you saw every outcome k extra times

$$P_{LAP,k}(x) = \frac{c(x) + k}{N + k|X|}$$

  - What's Laplace with k = 0?
  - k is the strength of the prior

- Laplace for conditionals:
  - Smooth each condition ir

$$P_{LAP,k}(x|y) = \frac{c(x,y) + k}{c(y) + k|X|}$$

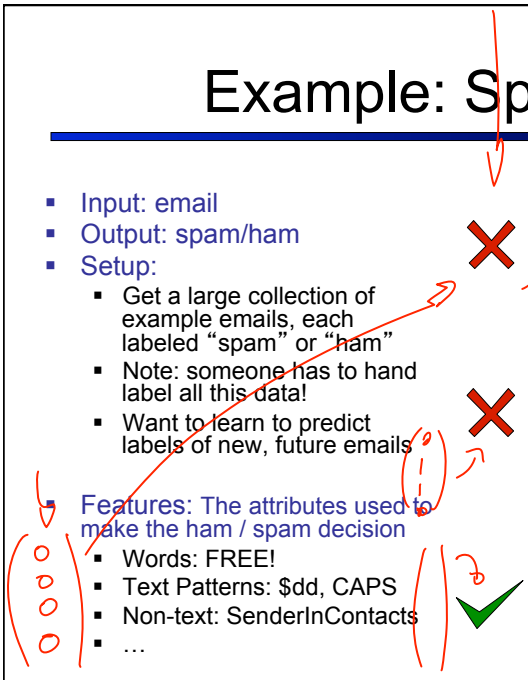

$$P_{LAP,0}(X) = \left(\frac{2}{3}, \frac{1}{3}\right)$$

$$P_{LAP,1}(X) = \left(\frac{3}{5}, \frac{2}{5}\right)$$

$$P_{LAP,100}(X) = \left(\frac{2+100}{3+100\cdot 2}, \frac{1+100}{3+100\cdot 2}\right)$$

# Example: Spam Filter

- Input: email
- Output: spam/ham
- Setup:
  - Get a large collection of example emails, each labeled "spam" or "ham"
  - Note: someone has to hand label all this data!
  - Want to learn to predict labels of new, future emails
- Features: The attributes used to make the ham / spam decision
  - Words: FREE!
  - Text Patterns: $dd, CAPS
  - Non-text: SenderInContacts
  - …



Dear Sir.

First, I must solicit your confidence in this transaction, this is by virture of its nature as being utterly confidencial and top secret. …

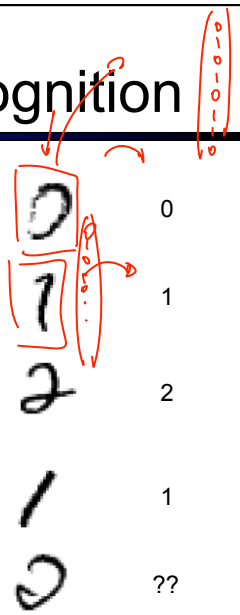
TO BE REMOVED FROM FUTURE MAILINGS, SIMPLY REPLY TO THIS MESSAGE AND PUT "REMOVE" IN THE SUBJECT.

99 MILLION EMAIL ADDRESSES FOR ONLY $99

Ok, Iknow this is blatantly OT but I'm beginning to go insane. Had an old Dell Dimension XPS sitting in the corner and decided to put it to use, I know it was working pre being stuck in the corner, but when I plugged it in, hit the power nothing happened.

# Example: Digit Recognition

- Input: images / pixel grids
- Output: a digit 0-9
- Setup:
  - Get a large collection of example images, each labeled with a digit
  - Note: someone has to hand label all this data!
  - Want to learn to predict labels of new, future digit images
- Features: The attributes used to make the digit decision
  - Pixels: (6,8)=ON
  - Shape Patterns: NumComponents, AspectRatio, NumLoops
  - …




# Other Classification Tasks

- In classification, we predict labels y (classes) for inputs x
- Examples:
  - Spam detection (input: document, classes: spam / ham)
  - OCR (input: images, classes: characters)
  - Medical diagnosis (input: symptoms, classes: diseases)
  - Automatic essay grader (input: document, classes: grades)
  - Fraud detection (input: account activity, classes: fraud / no fraud)
  - Customer service email routing
  - … many more
- Classification is an important commercial technology!

# Important Concepts

- Data: labeled instances, e.g. emails marked spam/ham
  - Training set
  - Held out set
  - Test set
- Features: attribute-value pairs which characterize each x
- Experimentation cycle
  - Learn parameters (e.g. model probabilities) on training set
  - (Tune hyperparameters on held-out set)
  - Compute accuracy of test set
  - Very important: never "peek" at the test set!
- Evaluation
  - Accuracy: fraction of instances predicted correctly
- Overfitting and generalization
  - Want a classifier which does well on *test* data
  - Overfitting: fitting the training data very closely, but not generalizing well
  - We'll investigate overfitting and generalization formally in a few lectures