CS 188: Artificial Intelligence
Spring 2010

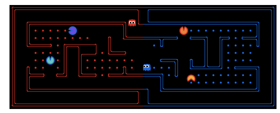
Lecture 21: DBNs, Viterbi, Speech Recognition

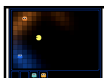
4/8/2010

Pieter Abbeel – UC Berkeley

Announcements

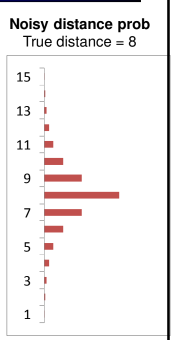
- Written 6 due tonight
- Project 4 up!
  - Due 4/15 – start early!
- Course contest update
  - Planning to post by Friday night





P4: Ghostbusters

- **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

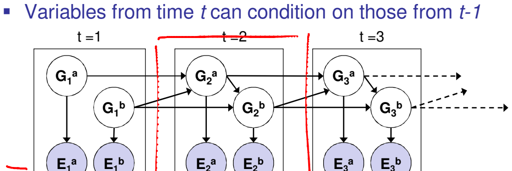


Today

- Dynamic Bayes Nets (DBNs)
  - [sometimes called temporal Bayes nets]
- HMMs: Most likely explanation queries
- Speech recognition
  - A massive HMM!
  - Details of this section not required
- Start machine learning

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*

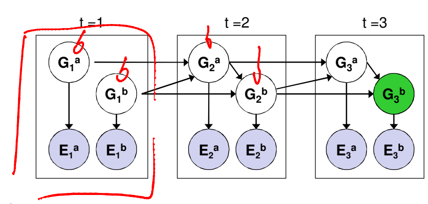


- Discrete valued dynamic Bayes nets are also HMMs

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

? $P(G_3^b \mid e_1^a, e_2^a, e_3^a, e_1^b, e_2^b, e_3^b)$



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

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: $P(\underbrace{\mathbf{E_1}^a}|\mathbf{G_1}^a) * P(\underbrace{\mathbf{E_1}^b}|\mathbf{G_1}^b)$
- **Resample:** Select prior samples (tuples of values) in proportion to their likelihood

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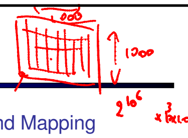
SLAM



- 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]
  - [intel-lab-raw-odo.wmv, intel-lab-scan-matching.wmv, visionSlam_heliOffice.wmv]

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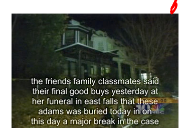
Speech and Language

- Speech technologies
  - Automatic speech recognition (ASR)
  - Text-to-speech synthesis (TTS)
  - Dialog systems



- Language processing technologies
  - Machine translation


"Il est impossible aux journalistes de rentrer dans les régions tibétaines"

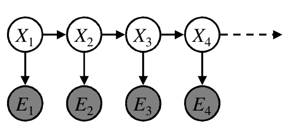

"It is impossible for journalists to enter Tibetan areas"

  - Information extraction
  - Web search, question answering
  - Text classification, spam filtering, etc…

Most likely Explanation

HMMs: MLE Queries

- HMMs defined by
  - States X
  - Observations E
  - Initial distr: $P(X_1)$
  - Transitions: $P(X|X_{-1})$
  - Emissions: $P(E|X)$



- Query: most likely explanation:

2^t

$$\arg\max_{x_{1:t}} P(x_{1:t}|e_{1:t})$$

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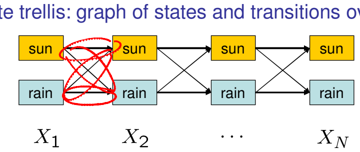
$\arg\max_{x_{1:t}} P(x_{1:t}|e_{1:t})$

State Path Trellis

- State trellis: graph of states and transitions over time



- Each arc represents some transition $x_{t-1} \rightarrow x_t$
- Each arc has weight $\boxed{P(x_t|x_{t-1})P(e_t|x_t)}$ $t=2$
- Each path is a sequence of states
- The product of weights on a path is the seq's probability
- Can think of the Forward (and now Viterbi) algorithms as computing sums of all paths (best paths) in this graph

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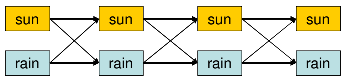
Viterbi Algorithm



$m_t(\text{rain})$
$m_t(\text{sun})$

$$x^*_{1:T} = \arg\max_{x_{1:T}} P(x_{1:T}|e_{1:T}) = \arg\max_{x_{1:T}} P(x_{1:T}, e_{1:T})$$

$$m_t[x_t] = \max_{x_{1:t-1}} P(x_{1:t-1}, x_t, e_{1:t})$$

$$= \max_{x_{1:t-1}} P(x_{1:t-1}, e_{1:t-1}) P(x_t|x_{t-1}) P(e_t|x_t)$$

$$= P(e_t|x_t) \max_{x_{t-1}} P(x_t|x_{t-1}) \max_{x_{1:t-2}} P(x_{1:t-1}, e_{1:t-1})$$

$$= P(e_t|x_t) \max_{x_{t-1}} P(x_t|x_{t-1}) m_{t-1}[x_{t-1}]$$

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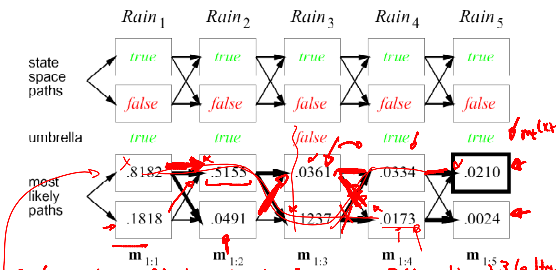
Example



$P_1(\text{rain}=\text{true}) \cdot P(e_1|\text{rain}=\text{true})$ .5155 = .8182 * P(true|true) * P(e_2|true)

.5155 > .1818 * P(true|false) * P(e_2|true)

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- *Speech recognition*
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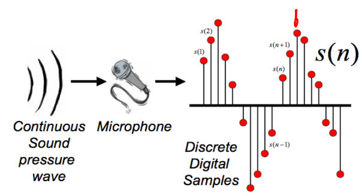
Digitizing Speech



Thanks to Bryan Pellom for this slide!

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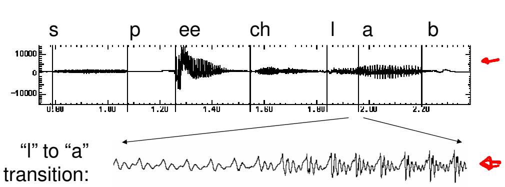
Speech in an Hour

- Speech input is an acoustic wave form



Graphs from Simon Arnfield's web tutorial on speech, Sheffield:
http://www.psyc.leeds.ac.uk/research/cogn/speech/tutorial/

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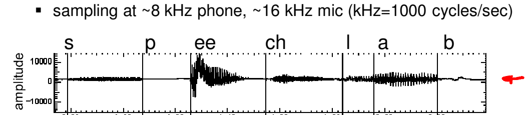
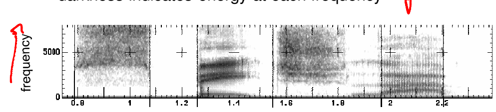
Spectral Analysis

- Frequency gives pitch; amplitude gives volume
  - sampling at ~8 kHz phone, ~16 kHz mic (kHz=1000 cycles/sec)



- Fourier transform of wave displayed as a spectrogram
  - darkness indicates energy at each frequency



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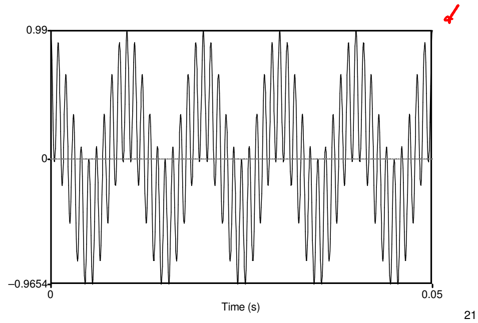
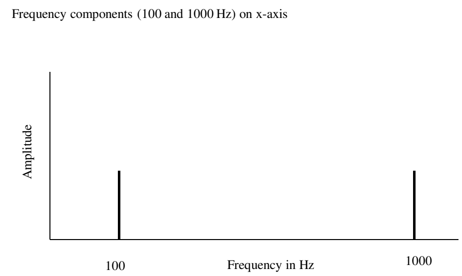
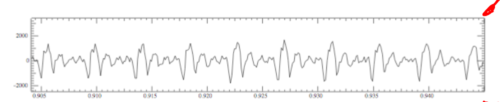
Adding 100 Hz + 1000 Hz Waves



Spectrum



Part of [ae] from "lab"



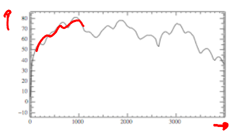
- Note complex wave repeating nine times in figure
- Plus smaller waves which repeats 4 times for every large pattern
- Large wave has frequency of 250 Hz (9 times in .036 seconds)
- Small wave roughly 4 times this, or roughly 1000 Hz
- Two little tiny waves on top of peak of 1000 Hz waves

$f(t) = \sum_f a_f \sin(f \cdot 2\pi t) + b_f \cos(f 2\pi t)$

Back to Spectra

energy for f $= a_f^2 + b_f^2$

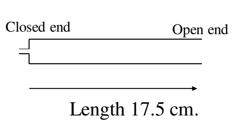
- Spectrum represents these freq components
- Computed by Fourier transform, algorithm which separates out each frequency component of wave.



- x-axis shows frequency, y-axis shows magnitude (in decibels, a log measure of amplitude)
- Peaks at 930 Hz, 1860 Hz, and 3020 Hz.

Resonances of the vocal tract

- The human vocal tract as an open tube



- Air in a tube of a given length will tend to vibrate at resonance frequency of tube.
- Constraint: Pressure differential should be maximal at (closed) glottal end and minimal at (open) lip end.

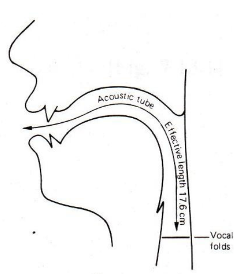
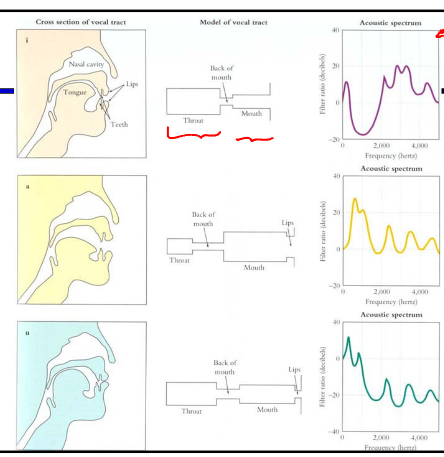


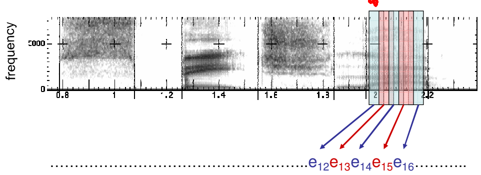
Figure from W. Barry Speech Science slides



From Mark Liberman's website

Acoustic Feature Sequence

- Time slices are translated into acoustic feature vectors (~39 real numbers per slice)



- These are the observations, now we need the hidden states X

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State Space

- P(E|X) encodes which acoustic vectors are appropriate for each phoneme (each kind of sound)
- P(X|X') encodes how sounds can be strung together
- We will have one state for each sound in each word
- From some state x, can only:
  - Stay in the same state (e.g. speaking slowly)
  - Move to the next position in the word
  - At the end of the word, move to the start of the next word
- We build a little state graph for each word and chain them together to form our state space X

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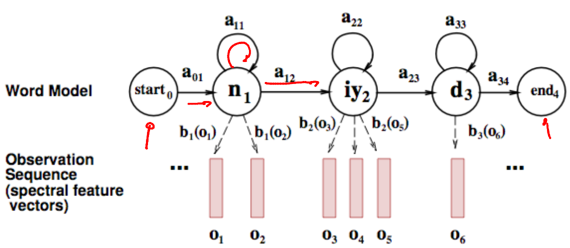
HMMs for Speech



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Decoding

- While there are some practical issues, finding the words given the acoustics is an HMM inference problem
- We want to know which state sequence $x_{1:T}$ is most likely given the evidence $e_{1:T}$:

phoneme sequence   spectrogram data

$$x^*_{1:T} = \underset{x_{1:T}}{\arg\max}\, P(x_{1:T}|e_{1:T})$$

$$= \underset{x_{1:T}}{\arg\max}\, P(x_{1:T}, e_{1:T})$$

- From the sequence x, we can simply read off the words

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End of Part II!

- Now we're done with our unit on probabilistic reasoning
- Last part of class: machine learning

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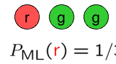
Parameter Estimation

- Estimating the distribution of a random variable
- *Elicitation:* ask a human!
  - Usually need domain experts, and sophisticated ways of eliciting probabilities (e.g. betting games)
  - Trouble calibrating
- *Empirically:* use training data
  - 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*

$\theta = P(\text{red})$ $\theta \in (0,1)$

$$\underbrace{L(x,\theta) = \prod_i P_\theta(x_i)}_{\text{find } \theta \text{ which maximizes } L(x;\theta)}$$

$\theta * (1-\theta) * (1-\theta)$

$\frac{1}{3} * \frac{2}{3} * \frac{2}{3}$