Part 3: Uncertainty, Probability, and Probabilistic reasoning

Speech recognition with (Hidden) Markov Models

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Dynamic and Distributed Information Systems

Note:
A significant part of these slides where contributed by Andrew W. Moore at CMU
You can find some more interesting info on his home page.
The Rest is based on AIMA 2e

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**: $\mathrm{argmax}_{x_{1:t}} P(x_{1:t}|e_{1:t})$
  - speech recognition, decoding with a noisy channel

Speech recognition

- Speech as probabilistic inference
- Speech sounds
- Word pronunciation
- Word sequences

Speech as probabilistic inference

- *It's not easy to wreck a nice beach*
- Speech signals are noisy, variable, ambiguous
- What is the *most likely* word sequence, given the speech signal?
  I.e., choose *Words* to maximize $P(Words|signal)$
- Use Bayes' rule:
  $$P(Words|signal) = \alpha P(signal|Words)\, \mathrm{P}(Words)$$
- I.e., decomposes into
  acoustic model + **language model**
- *Words* are the hidden state sequence, *signal* is the observation sequence

Phones

- All human speech is composed from 40-50 **phones**, determined by the configuration of **articulators** (lips, teeth, tongue, vocal cords, air flow)
- Form an intermediate level of hidden states between words and signal
  ⇨acoustic model = pronunciation model + phone model
- ARPAbet designed for American English

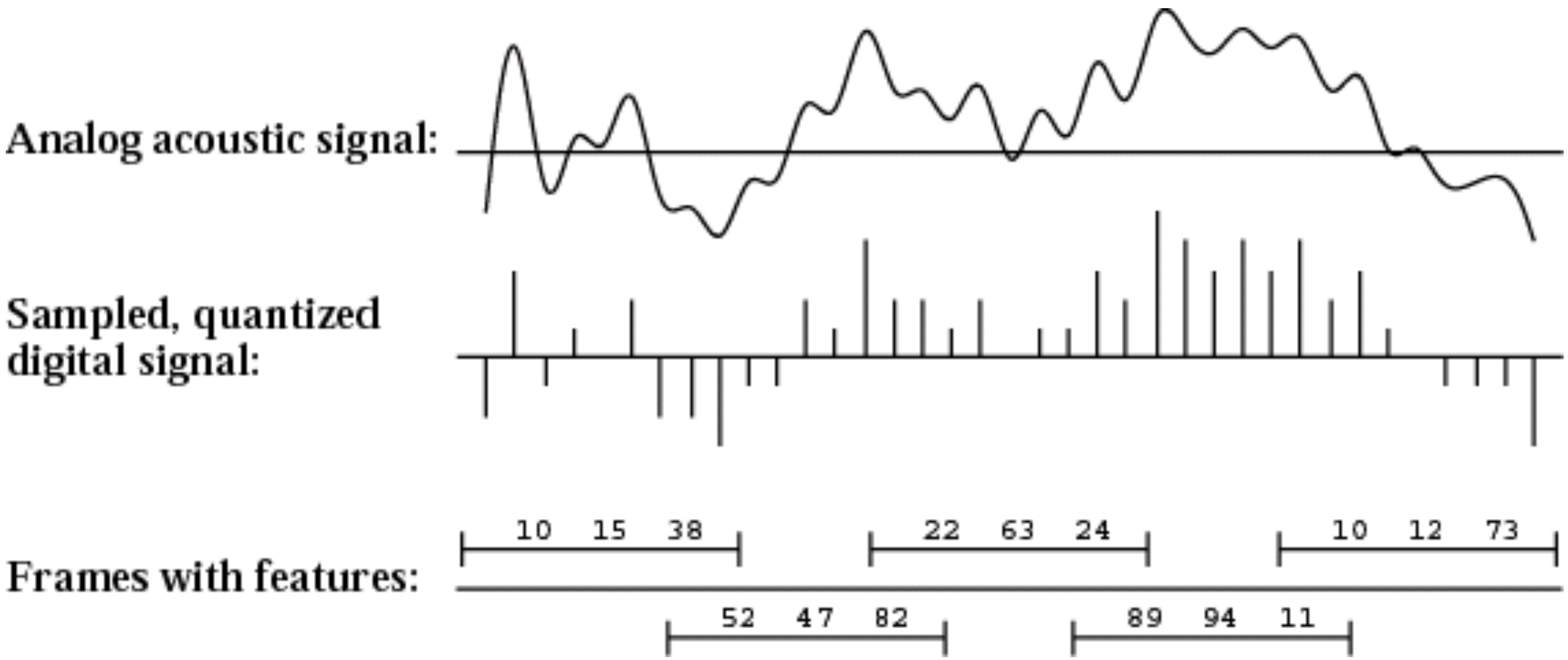
[iy]	beat	[b]	bet	[p]	pet
[ih]	bit	[ch]	Chet	[r]	rat
[ey]	bet	[d]	debt	[s]	set
[ao]	bought	[hh]	hat	[th]	thick
[ow]	boat	[hv]	high	[dh]	that
[er]	Bert	[l]	let	[w]	wet
[ix]	roses	[ng]	sing	[en]	button
⋮	⋮	⋮	⋮	⋮	⋮

- E.g., “ceiling” is [s iy l ih ng] / [s iy l ix ng] / [s iy l en]

Speech sounds

Raw signal is the microphone displacement as a function of time;

processed into overlapping 30ms **frames**, each described by **features**



Frame features are typically **formants -** peaks in the power spectrum

Phone models

- Frame features in *P*(*features*|*phone*) summarized by
  - an integer in [0 … 255] (using **vector quantization**); or
  - the parameters of a mixture of Gaussians

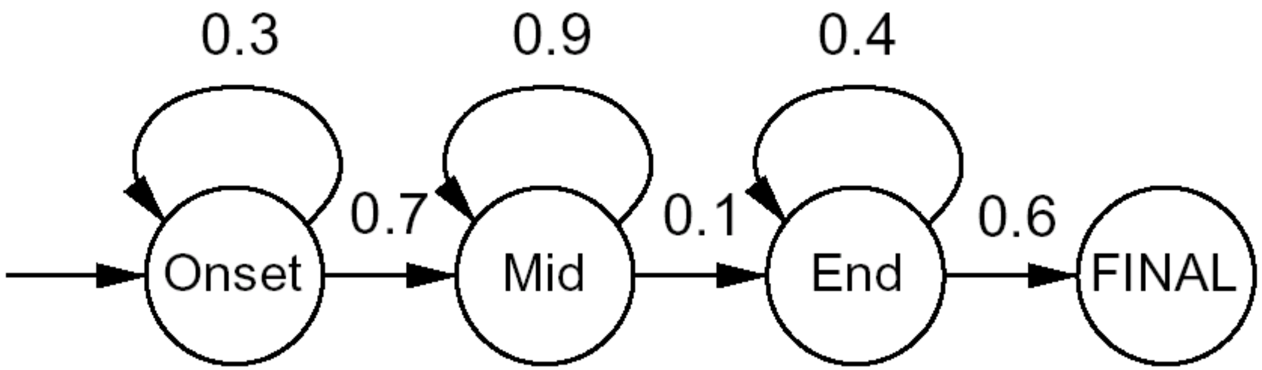
- **Three-state phones**: each phone has three phases (Onset, Mid, End)
  E.g., [t] has silent Onset, explosive Mid, hissing End
  ⇨*P*(*features*|*phone*,*phase*)

- **Triphone context**: each phone becomes n^2 distinct phones, depending on the phones to its left and right
  - E.g., [t] in "star" is written [t(s,aa)] (different from "tar"!)

- Triphones useful for handling **coarticulation** effects: the articulators have inertia and cannot switch instantaneously between positions
  - E.g., [t] in "eighth" has tongue against front teeth

Phone model example

Phone HMM for [m]:

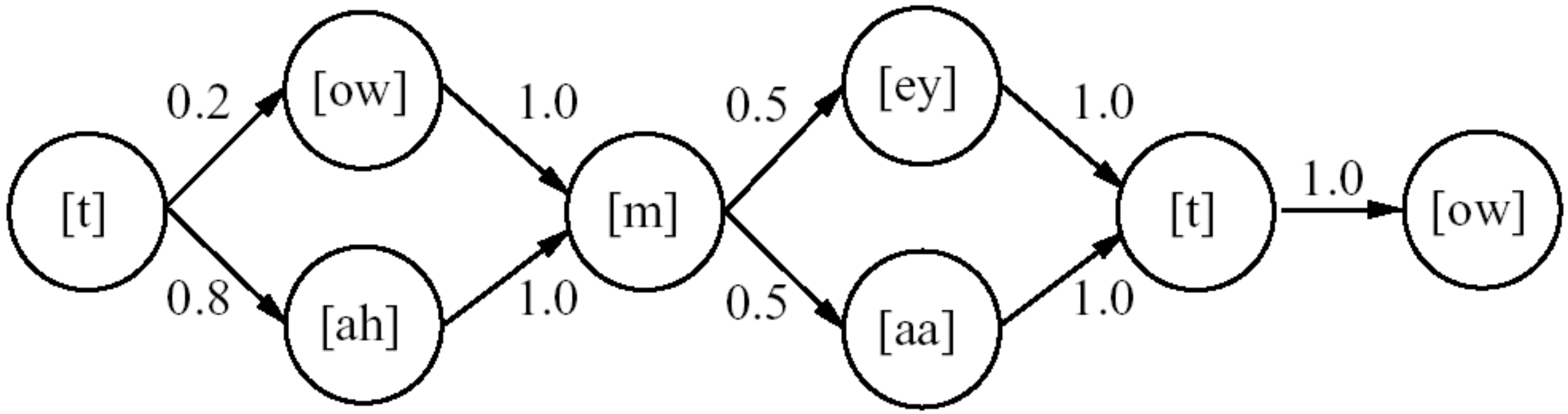


Output probabilities for the phone HMM:

Onset:	Mid:	End:
C1: 0.5	C3: 0.2	C4: 0.1
C2: 0.2	C4: 0.7	C6: 0.5
C3: 0.3	C5: 0.1	C7: 0.4

Word pronunciation models

- Each word is described as a distribution over phone sequences
- Distribution represented as an HMM transition model



P([*towmeytow*]| “tomato”}) = P([*towmaatow*]| “tomato”) = 0.1
P([*tahmeytow*]| “tomato”) = P([*tahmaatow*]| “tomato”) = 0.4

- Structure is created manually, transition probabilities learned from data

Isolated words

- Phone models + word models fix likelihood $P(e_{1:t}|word)$ for any **isolated word**

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

- Prior probability $P(word)$ obtained simply by counting word frequencies

- $P(e_{1:t}|word)$ can be computed recursively: define

  $$\ell_{1:t} = P(X_t, e_{1:t})$$

  and use the recursive update

  $$\ell_{1:t+1} = \text{Forward}(\ell_{1:t}, e_{t+1})$$

  and then $P(e_{1:t}|word) = \sum_{x_t} \ell_{1:t}(x_t)$

- Isolated-word dictation systems with training reach 95-99% accuracy

Continuous speech

- Not just a sequence of isolated-word recognition problems!
  - Adjacent words highly correlated
  - Sequence of most likely words $\neq$ most likely sequence of words
  - Segmentation: there are few gaps in speech
  - Cross-word coarticulation - e.g., “next thing”
- Continuous speech systems manage 60-90% accuracy on a good day

Language model

- Prior probability of a word sequence is given by chain rule:

$$P(w_1 \cdots w_n) = \prod_{i=1}^{n} P(w_i | w_1 \cdots w_{i-1})$$

- **Bigram model**:

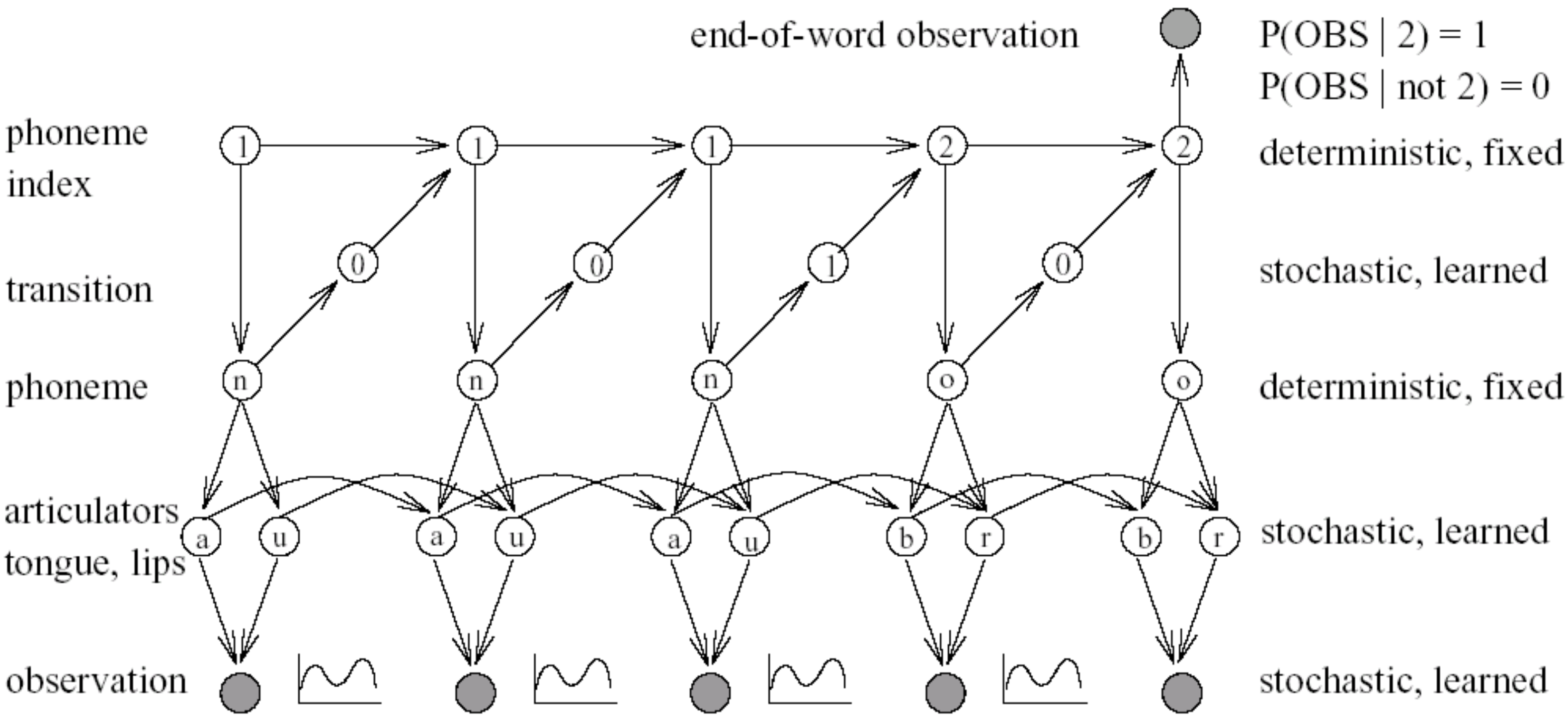
$$P(w_i | w_1 \cdots w_{i-1}) = P(w_i | w_{i-1})$$

- Train by counting all word pairs in a large text corpus
- More sophisticated models (trigrams, grammars, etc.) help a little bit

Combined HMM

- States of the combined language+word+phone model are labeled by the word we're in + the phone in that word + the phone state in that phone
- Viterbi algorithm finds the most likely **phone state** sequence
- Does segmentation by considering all possible word sequences and boundaries
- Doesn't always give the most likely word sequence because each word sequence is the sum over many state sequences
- Jelinek invented A^* in 1969 a way to find most likely word sequence where "step cost" is $-\log P(w_i|w_{i-1})$

DBNs for speech recognition



- Also easy to add variables for, e.g., gender, accent, speed.
- Zweig and Russell (1998) show up to 40% error reduction over HMMs