Hidden Markov Models: Decoding & Training

Natural Language Processing

CMSC 35100

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Agenda

- Speech Recognition
  - Hidden Markov Models
    - Uncertain observations
    - Recognition: Viterbi, Stack/A*
    - Training the model: Baum-Welch

Speech Recognition Model

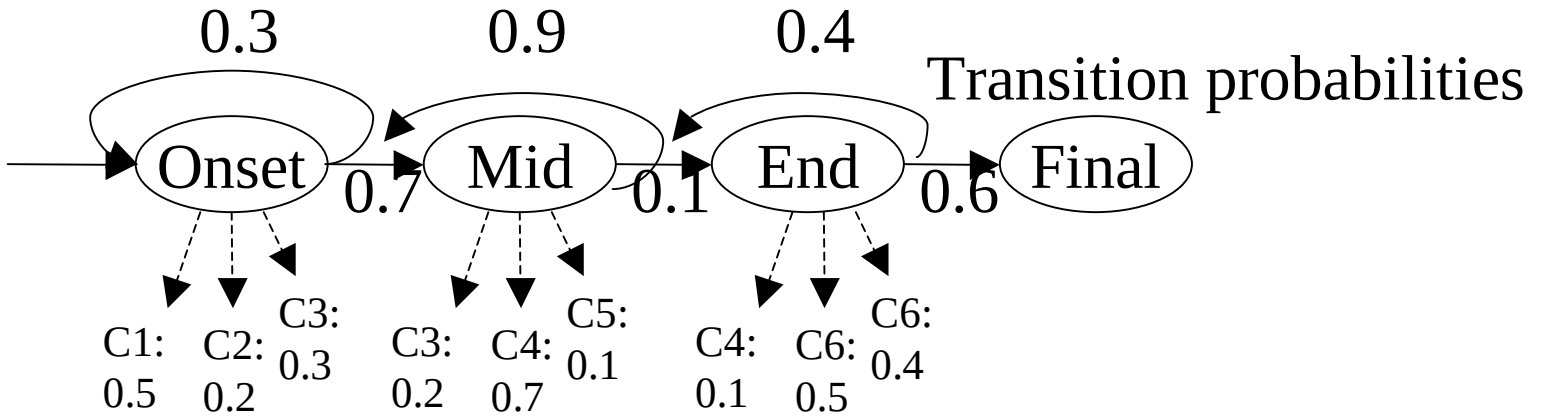
- Question: Given signal, what words?
- Problem: uncertainty
  - Capture of sound by microphone, how phones produce sounds, which words make phones, etc
- Solution: Probabilistic model
  - P(words|signal) =
  - P(signal|words)P(words)/P(signal)
  - Idea: Maximize P(signal|words)*P(words)
    - P(signal|words): acoustic model; P(words): lang model

Hidden Markov Models (HMMs)

- An HMM is:
  - 1) A set of states: $Q = q_o, q_1, ..., q_k$
  - 2) A set of transition probabilities: $A = a_{01}, ..., a_{mn}$
    - Where *aij* is the probability of transition *qi* -> *qj*
  - 3)Observation probabilities: $B = b_i(o_t)$
    - The probability of observing *ot* in state *i*
  - 4) An initial probability dist over states: π_i
    - The probability of starting in state *i*
  - 5) A set of accepting states

Acoustic Model

- 3-state phone model for [m]
  - Use Hidden Markov Model (HMM)



  - Probability of sequence: sum of prob of paths

Viterbi Algorithm

- Find BEST word sequence given signal
  - Best P(words|signal)
  - Take HMM & VQ sequence
    - => word seq (prob)
- Dynamic programming solution
  - Record most probable path ending at a state i
    - Then most probable path from i to end
    - O(bMn)

Viterbi Code

```
Function Viterbi(observations length T, state-graph) returns best-path
Num-states<-num-of-states(state-graph)
Create path prob matrix viterbi[num-states+2,T+2]
Viterbi[0,0]<- 1.0
For each time step t from 0 to T do
   for each state s from 0 to num-states do
      for each transition s' from s in state-graph
          new-score<-viterbi[s,t]*at[s,s']*bs'(ot)
          if ((viterbi[s',t+1]=0) || (viterbi[s',t+1]<new-score))
              then
                 viterbi[s',t+1] <- new-score
                 back-pointer[s',t+1]<-s
Backtrace from highest prob state in final column of viterbi[] & return
```

Enhanced Decoding

- Viterbi problems:
  - Best phone sequence not necessarily most probable word sequence
    - E.g. words with many pronunciations less probable
  - Dynamic programming invariant breaks on trigram
- Solution 1:
  - Multipass decoding:
    - Phone decoding -> n-best lattice -> rescoring (e.g. tri)

Enhanced Decoding: A*

- Search for highest probability path
  - Use forward algorithm to compute acoustic match
  - Perform **fast match** to find next likely words
    - Tree-structured lexicon matching phone sequence
  - Estimate path cost:
    - Current cost + underestimate of total
  - Store in priority queue
  - Search best first

Modeling Sound, Redux

- Discrete VQ codebook values
  - Simple, but inadequate
  - Acoustics highly variable
- Gaussian pdfs over continuous values
  - Assume normally distributed observations
    - Typically sum over multiple shared Gaussians
      - "Gaussian mixture models"
      - Trained with HMM model

$$b_j(o_t) = \frac{1}{\sqrt{(2\pi)\,|\sum j|}} e^{[(o_t-\mu_j)'\sum_j^{-1}(o_t-\mu_j)]}$$

Learning HMMs

- Issue: Where do the probabilities come from?
- Solution: Learn from data
  - Trains transition (aij) and emission (bj) probabilities
    - Typically assume structure
  - Baum-Welch aka forward-backward algorithm
    - Iteratively estimate counts of transitions/emitted
    - Get estimated probabilities by forward comput'n
      - Divide probability mass over contributing paths

Forward Probability

$$\alpha_j(1) = a_{1j} b_j(o_1), 1 < j < N$$

$$\alpha_j(t) = \left[\sum_{i=2}^{N-1} \alpha_i(t-1) a_{ij} \right] b_j(o_t)$$

$$P(O \mid \lambda) = \alpha_N(T) = \sum_{i=2}^{N-1} \alpha_i(T) a_{iN}$$

Where α is the forward probability, t is the time in utterance,
i,j are states in the HMM, aij is the transition probability,
bj(ot) is the probability of observing ot in state bj
N is the final state, T is the last time, and 1 is the start state

Backward Probability

$$\beta_i(T) = a_{iN}$$

$$\beta_i(t) = \sum_{i=2}^{N-1} a_{ij} b_j(o_{t+1}) \beta_j(t+1)$$

$$P(O \mid \lambda) = \alpha_N(T) = \beta_1(T) = \sum_{j=2}^{N-1} a_{1j} b_j(o_1) \beta_j(1)$$

Where β is the backward probability, t is the time in utterance,
i,j are states in the HMM, aij is the transition probability,
bj(ot) is the probability of observing ot in state bj
N is the final state, T is the last time, and 1 is the start state

Re-estimating

- Estimate transitions from i->j

$$\tau_t(i,j) = \frac{\alpha_i(t) a_{ij} b_j(o_t) \beta_j(t+1)}{\alpha_N(T)}$$

$$\hat{a}_{ij} = \frac{\sum_{t=1}^{T-1} \tau_t(i,j)}{\sum_{t=1}^{T-1} \sum_{j=1}^{N} \tau_t(i,j)}$$

- Estimate observations in j

$$\sigma_j(t) = \frac{P(q_t = j, O \mid \lambda)}{P(O \mid \lambda)} = \frac{\alpha_j(t)\beta_j(t)}{P(O \mid \lambda)}$$

$$\hat{b}_j(v_k) = \frac{\sum_{t=1 s.t. o_t = v_k}^{T} \sigma_j(t)}{\sum_{t=1}^{T} \sigma_j(t)}$$

ASR Training

- Models to train:
  - Language model: typically tri-gram
  - Observation likelihoods: B
  - Transition probabilities: A
  - Pronunciation lexicon: sub-phone, word
- Training materials:
  - Speech files – word transcription
  - Large text corpus
  - Small phonetically transcribed speech corpus

Training

- Language model:
  - Uses large text corpus to train n-grams
    - 500 M words
- Pronunciation model:
  - HMM state graph
  - Manual coding from dictionary
    - Expand to triphone context and sub-phone models

HMM Training

- Training the observations:
  - E.g. Gaussian: set uniform initial mean/variance
    - Train based on contents of small (e.g. 4hr) phonetically labeled speech set (e.g. Switchboard)
- Training A&B:
  - Forward-Backward algorithm training

Does it work?

- Yes:
  - 99% on isolate single digits
  - 95% on restricted short utterances (air travel)
  - 80+% professional news broadcast
- No:
  - 55% Conversational English
  - 35% Conversational Mandarin
  - ?? Noisy cocktail parties

Speech Synthesis

- Text to speech produces
  - Sequence of phones, phone duration, phone pitch
- Most common approach:
  - Concatentative synthesis
    - Glue waveforms together
- Issue: Phones depend heavily on context
  - Diphone models: mid-point to mid-point
    - Captures transitions, few enough contexts to collect (1-2K)

Speech Synthesis: Prosody

- Concatenation intelligible but unnatural
- Model duration and pitch variation
  - Could extract pitch contour directly
  - Common approach: TD-PSOLA
    - Time-domain pitch synchronous overlap and add
      - Center frames around pitchmarks to next pitch period
      - Adjust prosody by combining frames at pitchmarks for desired pitch and duration
      - Increase pitch by shrinking distance b/t pitchmarks
      - Can be squeaky

Speech Recognition as Modern AI

- Draws on wide range of AI techniques
  - Knowledge representation & manipulation
    - Optimal search: Viterbi decoding
  - Machine Learning
    - Baum-Welch for HMMs
    - Nearest neighbor & k-means clustering for signal id
  - Probabilistic reasoning/Bayes rule
    - Manage uncertainty in signal, phone, word mapping
- Enables real world application