L14: Refinements for HMMs

Types of HMM structures

Implementation issues

Continuous and semi-continuous HMMs

Robustness to environment and channel effects

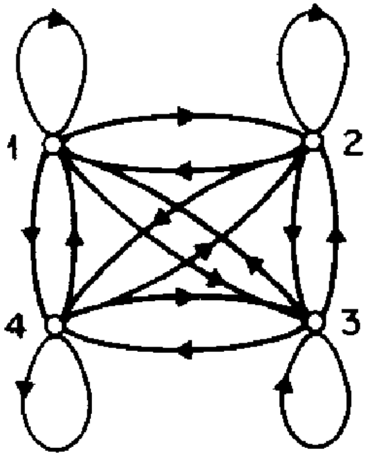
Speaker independent recognition

Model adaptation

Discriminative training

This lecture is based on [Rabiner and Juang, 1993; Holmes, 2001, ch11; Gold and Morgan, 200, ch.27]

Types of HMM structure

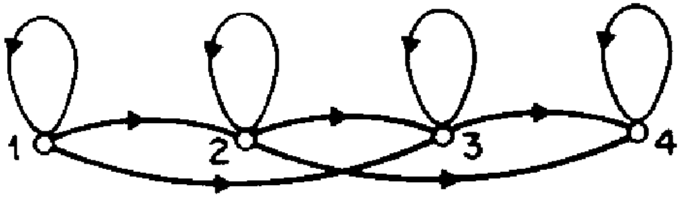


Ergodic

- An ergodic HMM is a fully connected model, where each state can be reached in one step from every other state
  - This is the most general type of HMM, and the one that had been implicitly assumed earlier

Left-right

- A left-right or Bakis model is one where no transitions are allowed to states whose indices are lower than the current state $(a_{ij} = 0;\ \forall j < i)$
  - Left-right models are best suited to model signals whose properties change over time, such as speech
  - When using left-right models, some additional constraints are commonly placed, such as preventing large transitions $a_{ij} = 0\ \ \forall j > i + \Delta$



[Rabiner, 1989]

Implementation issues

Scaling

- Since $\alpha_t(i)$ is the product of a large number of terms that are less than one, machine precision is likely to be exceeded sooner or later
- To solve this problem, the $\alpha's$ are re-scaled periodically to avoid underflow, and a similar scaling is done to the $\beta's$ so that the scaling coefficients cancel out exactly

Multiple observation sequences

- Our HMM derivations were based on a single observation sequence
  - This becomes a problem in left-right models, since the transient nature of the states only allows a few observations to be used for each state
- For this reason, one has to use multiple observation sequences
  - Re-estimation formulas for multiple sequences can be found in [Rabiner and Juang, 1993]

Initial parameter estimates

- How are the initial HMM parameters chosen so that Baum-Welch is more likely to converge to a global maximum?
- Random or uniform initial values for π and A have experimentally been found to work well in most cases
- Careful selection of initial values for B, however, has been found to be helpful in the discrete case and essential in the continuous case
  - These initial estimates may be found by segmenting the sequences with k-means clustering

Continuous and semi-continuous HMMs

Discrete HMMs

- Our discussion of HMMs thus far has focused on discrete HMMs
- Discrete HMMs assume that the observations are defined by a set of discrete symbols from a finite alphabet
- In speech, however, observations are inherently multidimensional and have continuous features

There are two alternatives to handle continuous vectors

- Convert the continuous multivariate observations into discrete univariate observations via a codebook (e.g., with k-means)
  - This approach, however, may lead to degraded performance as a result of the discretization of the continuous signals
- Employ HMM states that have continuous observation densities $b_j(\quad)$
  - This is, in general, a much better alternative, which we explore next

Continuous HMMs

- C-HMMs model the observation probabilities with a continuous density function, as opposed to a multinomial
  - To ensure that the model parameters can be re-estimated in a consistent manner, some restrictions are applied to the form of the observation pdf
  - The most common form is the Gaussian mixture model

$$b_j(o) = \sum_{k=1}^{M} c_{jk} N\left(o, \mu_{jk}, \Sigma_{jk}\right)$$

  - where o is the observation vector, and $\left(c_{jk}, \mu_{jk}, \Sigma_{jk}\right)$ are the mixture coefficient, mean and covariance for the k-th Gaussian component at state S_j, respectively

- The re-estimation formulas for the continuous case generalize very gracefully from the discrete HMM
  - The term $\gamma_t(j)$ generalizes to $\gamma_t(j,k)$, which represents the probability of being in state S_j at time t with k-mixture component accounting for observation o_t

$$\gamma_t(j,k) = \left[\frac{\alpha_t(j)\beta_t(j)}{\sum_{j=1}^{N} \alpha_t(j)\beta_t(j)}\right]\left[\frac{c_{jk}N\left(o_t,\mu_{jk},\Sigma_{jk}\right)}{\sum_{m=1}^{M} c_{jm}N\left(o_t,\mu_{jm},\Sigma_{jm}\right)}\right]$$

  - Note how the first fraction is the same as in the discrete HMM case, whereas the second fraction is due to the k-th Gaussian component

- The re-estimation formulas for the continuous HMM are
  - The new $\hat{c}_{jk}$is the ratio between the expected number of times the system is in state S_j using the k-th mixture component, and the expected number of times the system is in state S_j

$$\hat{c}_{jk} = \frac{\sum_{t=1}^{T} \gamma_t(j,k)}{\sum_{t=1}^{T} \sum_{k=1}^{M} \gamma_t(j,k)}$$

  - The new $\hat{\mu}_{jk}$ weights the numerator in the equation for $\hat{c}_{jk}$ by the observation, to produce the portion of the observation that can be accounted by that mixture component

$$\hat{\mu}_{jk} = \frac{\sum_{t=1}^{T} \gamma_t(j,k) o_t}{\sum_{t=1}^{T} \gamma_t(j,k)}$$

  - The re-estimation formula for the covariance term can be interpreted similarly

$$\hat{\Sigma}_{jk} = \frac{\sum_{t=1}^{T} \gamma_t(j,k)(o_t - \mu_{jk})(o_t - \mu_{jk})^T}{\sum_{t=1}^{T} \gamma_t(j,k)}$$

  - The re-estimation formula for transition probabilities a_{ij} is the same as in the discrete HMM

Issues with C-HMMs

- C-HMMs avoid the distortions introduced by a discrete codebook, but
  - A large number of mixtures are generally required to improve the recognition accuracy as compared to D-HMMs [Huang, 1992]
  - As a result, the computational complexity of C-HMMs increases considerably with respect to D-HMMs
  - The number of free parameters increases significantly, which means that a larger training set is required to train the model properly

Semi-continuous HMMs

- SC-HMMs represent a compromise between D-HMMs and C-HMMs
- In SC-HMMs, the observation space is modeled with a Gaussian mixture whose components (μ, Σ) are shared by all states in the HMM
- Each state in the HMM, though, is allowed to have a different mixing coefficient c_{jk} for each of the k Gaussian components in the "common" mixture
- SC-HMMs are also referred to as tied-mixture HMMs

Robustness to environmental & channel effects

ASR in real environments

- Ideally, speech signals for ASR would be recorded in a quiet environment, with a good-quality close-talking microphone
- In practice, the speech signal will have been corrupted in some way
  - Even if the recorded signal isn't corrupted, speakers tend to modify their speech (e.g., increased vocal effort) as the environment worsens; this is known as the Lombard effect

Types of noise

- Additive noise
  - Examples: environmental noise (electronics, machinery, vehicles, other speakers), noise introduced by poor-quality microphones or noisy transmission channels
  - Additive noise is best dealt within the linear spectral domain
- Convolutional noise
  - Examples: room reverberation, differences in microphone handsets (channel bandwidth limitations, spectral shaping)
  - Convolutional noise is best dealt within the log spectral or cepstral domain, since it becomes additive

- These and other sources of distortion create a mismatch between the conditions in which the recognizer is used, and those under which is was initially trained
  - One possible solution to this issue is to train the recognizer under similar conditions as those that will occur operationally
  - However, it is not always possible to predict operational conditions in advance, and these conditions change over time
- Thus, techniques are needed to deal with corrupted speech signals, which can be grouped into two categories
  - Feature-based methods
    - Applied directly at the level of speech features
  - Model-based methods
    - Built into the recognition process itself

Feature-based methods

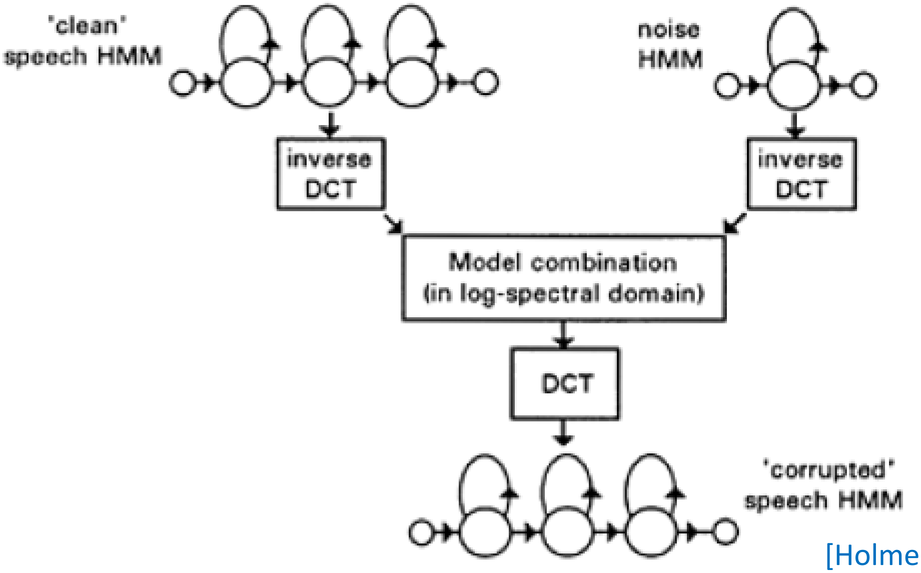
- Spectral subtraction
  - Used to remove additive noise
  - An average of the noise spectrum is obtained from silent segments
  - This average noise spectrum is subtracted from the speech spectrum
  - Negative values in the resulting spectrum are set to zero
- Cepstral mean subtraction/normalization
  - Used to remove convolutional noise
  - Noise spectra must be estimated in speech regions, since speech must be present for convolutional distortions to appear
  - Assuming these distortions remain constant over an utterance, one can then remove them by subtracting the (cepstral or log) mean feature vector computed over a long window
- Relative spectral processing (RASTA)
  - Removes slowly varying components in the spectrum, to which human listeners do not pay much attention
  - Generally performed with Perceptual Linear Prediction (PLP), a variant of LPC that is more consistent with psychoacoustics

Model-based methods

- Noise masking
  - A simple technique that replaces any channel levels below noise levels with an estimate of the noise signal
  - By applying this to both observed signals and to the stored model, noisy channels do not contribute to the model's predictions
- Decomposition
  - A separate HMM is built to model noise characteristics
    - A one-state HMM may suffice for stationary noise, multi-state may be needed for more complex noise sources
  - For each possible state pairing (one state from the noise HMM, another from the speech HMM), estimate probability that signal belongs either to noise or to speech
    - As a result, the method can be used to decompose a noisy speech signal into its constituent parts

– Parallel Model Combination

- Separate HMMs are built for both clean speech and pure noise, using standard cepstral methods
- State parameters are then converted into linear spectra (i.e., by means of an inverse DCT) and added for different levels of noise
- The added parameters are converted back to the cepstral domain to obtain an HMM that handles ‘corrupted’ speech



[Holmes, 2001]

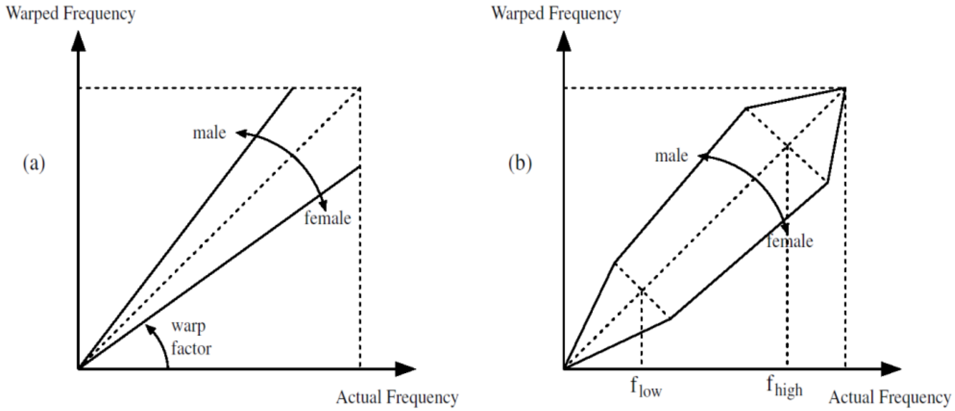
Speaker-independent recognition

Speaker differences

- Acoustic realizations of a word may be highly variable across speakers due to physical differences, accent/dialect, speaking style, etc.
- One alternative is to train the recognizer on multiple speakers
  - The underlying Gaussians become broader to accommodate for multiple speakers and therefore will have a greater degree of overlap across different phonemes, which impacts performance
- A second option is to train a separate recognizer for each type of speaker (e.g., males vs. females)
  - With this option, however, we either need to identify the type of the speaker (which cannot be done with perfect accuracy) or run multiple recognizers in parallel (which increases computational load)
- Other alternatives, which we review next, include
  - Speaker normalization
  - Model adaptation

Speaker normalization

- Individuals differ in the physical dimensions of their vocal tract
- Vocal tract length influences formant frequencies
  - Shorter VTL implies higher formant frequencies
  - Female formants are 10-20% higher than male formants
- Solution: Warp the frequency axis
- Approaches
  - Calculate average formant frequencies, and do a piece-wise linear warp
  - Define a warping function, and optimize its parameters from data



[Gales and Young, 2008]

Model adaptation

Objective

- Adapts model parameters to provide a better match to data from other speaker, channel effects or recording conditions
- The amount of calibration data needed to adapt model parameters is only a fraction of that required to train a recognizer from scratch
- Thus, adaptation provides a trade-off between two types of recognizer
  - Speaker-dependent (SD) recognizers: trained on data from a single speaker, easier to train and more accurate
  - Speaker-independent (SI) recognizers, trained on data from multiple speakers, longer training time, lower recognition accuracy

Types of model adaptation

- Supervised: the text of the adaptation is known
- Unsupervised: the text of the adaptation is unknown
  - In this case, the initial model is used to recognize the calibration data, and the recognized transcription is then used to adapt the models
  - As would be expected, this method requires that the initial recognition be sufficiently accurate

Maximum likelihood linear regression (MLLR)

- The most widely used of speaker adaptation
- Applies a linear transformation to the mean of the Gaussians

$$\hat{\mu}_{jm}=A_c\mu_{jm} + b_c$$

  - where A_c and b_c are a regression matrix and bias vector associated with a broad class c, which are learned using an EM procedure
- When the amount of adaptation data is very small, a single transform $(c = 1)$ can be shared across all the Gaussians in the model; as the amount of data increases, the number of transforms can be increased accordingly
- Using a small amount of adaptation data (15 sec), MLLR can improve recognition performance by 7-10%
  - MLLR can also be applied to the covariance matrices, though the additional gains in performance are modest (less than 2%)
- A variant of MLLR known as constrained MLLR (CMLLR) applies a common linear transform to the mean and covariance

$$\hat{\mu}_{jm}=A_c\mu_{jm} + b_c$$
$$\hat{\Sigma}_{jm} = A_c\Sigma_{jm}A_c^T$$

Bayesian/MAP adaptation

- Uses parameters from an existing SI recognizer as priors, and attempts to maximize the parameter's posterior given the new calibration data

$$\theta_{MAP} = \arg\max_{\theta} P(X|\theta)P(\theta)$$

- Using various assumptions, MAP adaptation reduces to simple expressions for updating the Gaussian means (j: state; m: mixture)

$$\hat{\mu}_{jm} = \frac{N_{jm}}{N_{jm} + \tau}\bar{\mu}_{jm} + \frac{\tau}{N_{jm} + \tau}\mu_{jm}$$

  - where μ_{jm} and $\bar{\mu}_{jm}$ are the mean of the SI model and the mean of the adaptation data, respectively, N_{jm} is the occupation likelihood of the adaptation data and τ is a weighting for the a-priori knowledge
  - Similar equations can be derived for the covariance parameters Σ_{jm}

- Thus, the MAP remains close to the SI estimate when N_{jm} is small, and departs as the amount of adaptation data increases
- MAP has more degrees of freedom than MLLR but also requires significantly more adaptation data

Speaker adaptive training (SAT)

- MLLR can be incorporated into the training procedure of speaker-independent recognizers
- Procedure
  - Start off with a default SI recognizer
  - Estimate a transform for each speaker
  - Re-estimate the model given each of the speakers transformed data
  - Repeat until convergence or termination condition is met
- As a result, the final SI recognizer is less influenced by speaker-specific characteristics, since these are captured by the transforms
- SAT can reduce error rates by an additional 5-10% w.r.t. to MLLR

Discriminative training

Drawbacks of MLE estimation

- MLE maximizes the likelihood of the data given the correct model ω_i, and only data from class ω_i is used to train the parameters θ_i
  - However, there is no guarantee that if $x \in \omega_i$, the likelihood $P(x|\omega_i)$ will be higher than that of the wrong classes $P\left(x|\omega_j\right)_{j \neq i}$
- In contrast, discriminative training techniques aim to maximize the ability of the model to distinguish among the different classes
  - This is achieved by estimating model parameters in a way that improves the likelihood of the correct model relative to the likelihood of the incorrect models
- Three discriminative training techniques will be reviewed here
  - Maximum mutual information (MMI) training
  - Corrective training
  - Generalized probabilistic descent (GPD)

Relation to the MAP criterion

- The MAP criterion seeks to find parameters θ that maximize

$$P(\omega_i|x,\theta)=\frac{p(x|\omega_i,\theta)P(\omega_i|\theta)}{p(x|\theta)}$$

  - where $p(x|\theta)$ is typically ignored since it is independent of ω_i

- During training, however, $p(x|\theta)$ does change and we cannot be assured that the quotient $P(\omega_i|x,\theta)$ will increase
- Expanding the denominator

$$p(x)=\sum_{c=1}^{C}p(x|\omega_c)P(\omega_c)=p(x|\omega_i)P(\omega_i)+\sum_{j\neq i}p\left(x|\omega_j\right)P\left(\omega_j\right)$$

  - and plugging it into the posterior yields

$$P(\omega_i|x\ )=\frac{p(x|\omega_i)P(\omega_i)}{p(x|\omega_i)P(\omega_i)+\sum_{j\neq i}p\left(x|\omega_j\right)P\left(\omega_j\right)}=\frac{1}{1+\frac{\sum_{j\neq i}p\left(x|\omega_j\right)P\left(\omega_j\right)}{p(x|\omega_i)P(\omega_i)}}$$

  - Thus, to increase $P(\omega_i|x,\theta)$ during training, we must increase the likelihood of the correct model $p(x|\omega_i)$ while decreasing the likelihood of the incorrect models $p\left(x|\omega_{j\neq i}\right)$

- Training procedures that attempt to do this are known as discriminative

Maximum mutual information (MMI) training

- The goal of MMI training is to maximize the mutual information between the observations x and the class labels ω

$$I(x,\omega|\theta) = E\left[\log \frac{p(x,\omega|\theta)}{p(x|\theta)P(\omega|\theta)}\right]$$

  - Which, for a particular choice of model and acoustic pair, becomes

$$I(x,\omega_i|\theta) = \log \frac{p(x,\omega_i|\theta)}{p(x|\theta)P(\omega_i|\theta)}$$

- To see that this criterion is discriminative, note that

$$p(x,\omega_i|\theta) = p(x|\omega_i,\theta)P(\omega_i|\theta)$$

  - Thus, substituting back into the earlier expression yields

$$I(x,\omega_i|\theta) = \log \frac{p(x|\omega_i,\theta)}{p(x|\theta)}$$

  - Assuming that we have a total of C models, then

$$I(x,\omega_i|\theta) = \log \frac{p(x|\omega_i,\theta)}{\sum_{c=1}^{C} p(x|\omega_c,\theta)P(\omega_c|\theta)}$$

  - Note that this equation differs from the one in the previous page in that it lacks a prior in the numerator and there is a log function

- Gradient descent techniques are used to update parameters in the direction that most increases the mutual information

Corrective training

- A pragmatic discriminative training procedure, in which the parameters are modified only for those utterances in which the correct model had a lower likelihood than the best model
- For these cases, the acoustic probabilities are adapted upward (towards the example) for the correct model ω_c and downwards for the incorrect models ω_i:
  - if $p(x|\omega_i, \theta) \geq p(x|\omega_c, \theta) + \Delta$
  - then $\theta \rightarrow \theta^*$
  - such that $p(x|\omega_c, \theta^*) \geq p(x|\omega_c, \theta)$ and $p(x|\omega_i, \theta^*) \leq p(x|\omega_i, \theta)$
- where Δ is a margin that must be exceeded before an utterance is considered to be recognized so poorly as to suggest correction of the models
  - For more details, see [LR Bahl, PF Brown, PV de Souza, and RL Mercer, "A New Algorithm for the Estimation of Hidden Markov Model Parameters," ICASSP, 1988, p. 493-496]

Generalized probabilistic descent

- GPD is a generalization of corrective training, MMI as well as several other discriminative procedures
- Consider a discriminant function $g_i(x;\theta)$ for each class ω_i

$$g_i(x|\theta) = -\log p(x|\omega_i,\theta)$$

- In GDP, we define the following miss-classification measure

$$d_j(x|\theta) = g_j(x|\theta) - \log\left\{\frac{1}{C-1}\sum_{k\neq j} e^{\eta g_k(x|\theta)}\right\}^{1/\eta}$$

  - where the term η allows us to control the effect of the competing classes
    - For $\eta = 1$, the competing term is the average of all competing discriminant functions, whereas for $\eta \rightarrow \infty$ the competing term is the maximum of them
    - Note that, for $\eta = 1$ and $P(\omega_i) = 1/C$, this measure reduces to that of MMI
- This measure can be used to minimize the misclassification rate
  - This is done by passing $d_i(x;\theta)$ through a sigmoidal function $S(\quad)$ and minimizing the following expression through gradient descent

$$E(\theta) = \sum_j \sum_{x\in\omega_j} S(d_i(x;\theta))$$

Discussion

- MMI and GPD are much more computationally intensive than MLE due to the inefficiency of gradient descent and the fact that every model parameter must be updated for each training example
- As a result, these procedures are generally used only for tasks containing few classes or data samples
- For all other cases, corrective training provides a more pragmatic approach to discriminative training