Types of HMM

Objectives

- To understand the differences between types of HMM
- *Notes: pp 38-43*

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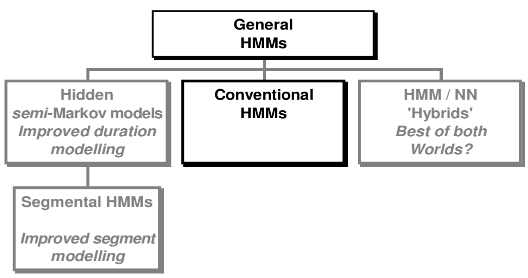
HMM taxonomy



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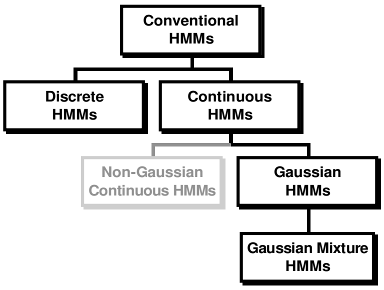
Types of Conventional HMM

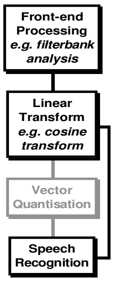


Front-End Processing Re-Visited

Vectors in d-dimensional (continuous) space

Vectors in d-dimensional (continuous) space

Symbols from a **finite** set



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Discrete HMMs

- If VQ is used, then a state output PDF b_i is defined by a **list** of probabilities-
  $b_i(m) = \mathrm{Prob}(y_t = z_m \mid x_t = s_i)$
- The resulting HMM is a **discrete HMM**
- Common in mid-1980/ early-1990s
- Computational advantages
- Disadvantages
  - VQ may introduce non-recoverable errors
  - Choice of metric d for VQ?
- Outperformed by Continuous HMM

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Continuous HMMs

- Without VQ, $b_i(y)$ must be defined for any y in the (continuous) observation set S
- Hence discrete state output PDFs no longer viable
- Use parametric continuous state output PDFs - **Continuous HMMs**
- Choice of PDF restricted by mathematical tractability and computational usefulness (see "HMM training & recognition" later)
- Most people begin with Gaussian PDFs
- Resulting HMMs called **Gaussian HMMs**

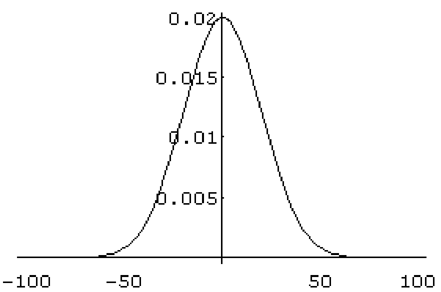
Gaussian HMMs

- State output PDFs are multivariate Gaussian

$$b_i(y) = \frac{1}{\sqrt{(2\pi)^d |C_i|}} \exp\left\{ -\frac{1}{2} \left(y - m_i\right)' C_i^{-1} \left(y - m_i\right) \right\}$$

- m_i and C_i are the mean vector and covariance matrix which define b_i

Gaussian PDF



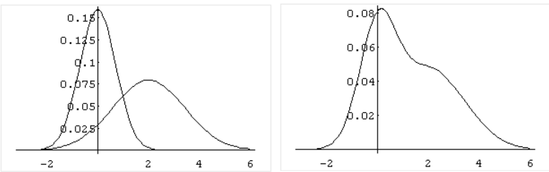
Gaussian PDF with $m_i = 0$ and $C_i = 20$

Gaussian HMMs - Issues

- Significant computational savings if covariance matrix can be assumed to be diagonal
- In general, Gaussian PDFs are **not** flexible enough to model speech pattern variability accurately
  - In many applications (e.g. modelling speech from multiple speakers) a unimodal PDF is inadequate
  - Even if unimodal PDF is basically OK there may be more subtle inadequacies

Gaussian Mixture Densities

Example - 2 component Gaussian mixture



$f(y) = N_{(0,1)}(y)$

$g(y) = N_{(2,2)}(y)$

$m(y)=w.f(y) + (1-w).g(y)$

Gaussian Mixture HMMs

- Any PDF can be approximated arbitrarily closely by a Gaussian mixture PDF with sufficient components
- But...
  - More mixture components require more data for robust model parameter estimation
  - Parameter smoothing and sharing needed (e.g. ‘tied mixtures’, ‘grand variance’,...)
- Gaussian mixture HMMs widely used in systems in research laboratories.

Relationship with Neural Networks

- 'Classical' HMM training methods focus on fitting state output PDFs to data (modelling), rather than minimizing overlap between PDFs (discrimination).
- NNs are good at discrimination
- **But** NNs poor at coping with time-varying data
- Research interest in 'hybrid' systems which use NNs to relate the observations to the states of the underlying Markov model.

Summary

- Types of HMM
- Discrete HMMs
- Continuous HMMs
- Gaussian HMMs
- Gaussian Mixture HMMs