Data Mining and Machine Learning

HMMs fo peech
Recogniti MMs

Peter Jančovič

UNIVERSITY OF BIRMINGHAM

Objectives

To understand

- Differences between types of HMMs

UNIVERSITY OF BIRMINGHAM

HMM taxonomy

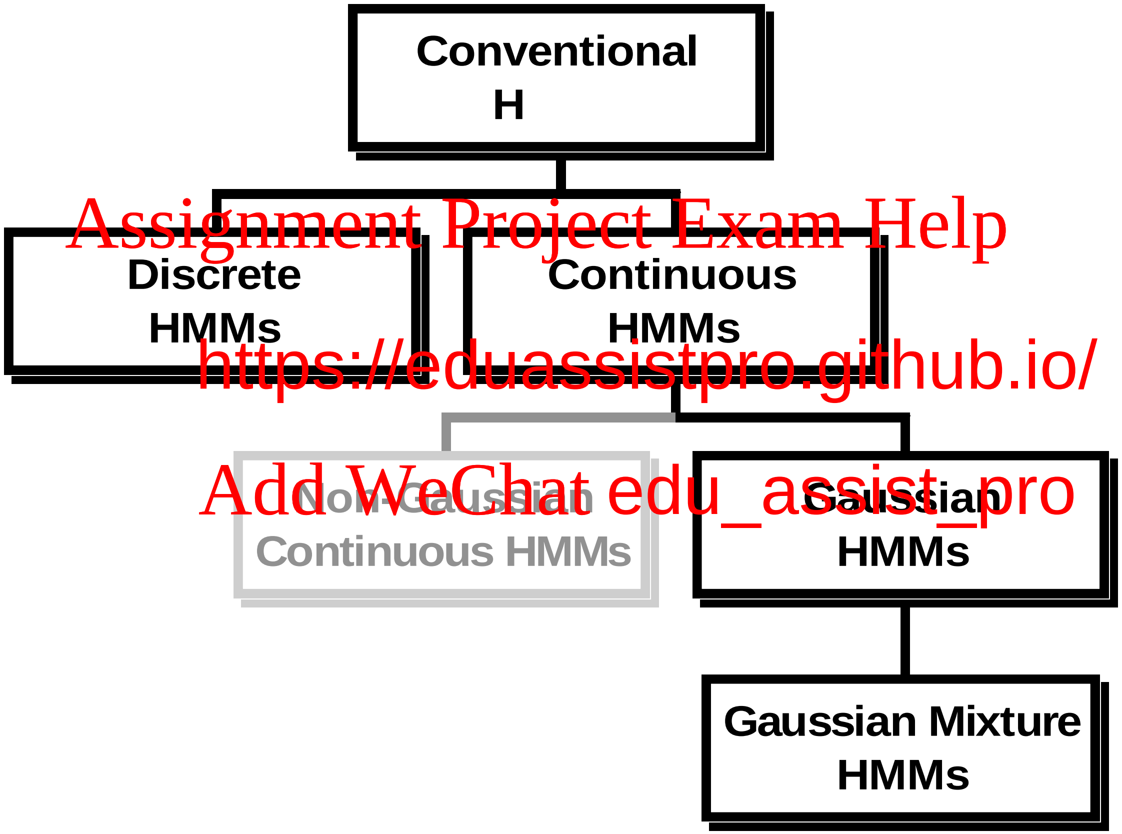
Hidden
***semi*-Markov models**
Improved duration modelling

Conventional HMMs

/ NN 'Hybrids'
Best of both Worlds?

Segmental HMMs
Improved segment modelling

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

Discrete HMMs

- If VQ is used, then a state output PDF b_i is defined by a **list** of probabilities

  $b_i(m) = \text{Prob}(y_t = z_m \mid x_t = s_i)$

- The resulting HMM is a **discrete HMM**

- Common in m

- Computationa
- Disadvantages

  – VQ may introduce non-recoverable errors

  – Choice of metric d for VQ?

- Outperformed by Continuous HMM

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 PD ... al tractability and computational usefulness (see ... ning & recognition" later)
- Most people begin with Gaussian PDFs
- Resulting HMMs called **Gaussian HMMs**

Gaussian HMMs

- State output PDFs are multivariate Gaussian

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

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

Gaussian HMMs - Issues

- Significant computational savings if covariance matrix can be assumed to be diagonal
- In general, Gaussian PDFs are **not** flexible enough to model spe accurately
  - In many a lling speech from multiple speakers) a un F is inadequate
  - Even if unimodal PDF is basically OK there may be more subtle inadequacies

UNIVERSITY OF BIRMINGHAM

Gaussian Mixture HMMs

- Any PDF can be approximated arbitrarily closely by a Gaussian mixture PDF with sufficient components
- But...
  - More mix re more data for robust mo on
  - Parameter smoothing a 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 goo

- **But** ‘classica with time-varying data

- Research interest in ‘hybrid’ systems which use NNs to relate the observations to the states of the underlying Markov model

- More recently, recurrent NNs also replacing HMMs

UNIVERSITY OF BIRMINGHAM

Summary

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

UNIVERSITY OF BIRMINGHAM