

[Return to Main](#)

[Objectives](#)

Review:

[The EM Algorithm](#)

[Reestimation Equations](#)

Mixtures:

[Continuous Densities](#)

[Mixture Densities](#)

[Probability Calculations](#)

[Application of EM](#)

[Reestimation Equations](#)

On-Line Resources:

[Mixture Modeling](#)

[Semicontinuous HMMs](#)

[Ten Years of HMMs](#)

LECTURE 25: CONTINUOUS MIXTURE DENSITIES

- Objectives:
 - Review the EM algorithm
 - Introduce continuous mixture densities
 - Understand why they are useful in speech recognition
 - Develop reestimation equations for the parameters of a mixture density

This lecture combines material from the course textbook:

X. Huang, A. Acero, and H.W. Hon, *Spoken Language Processing - A Guide to Theory, Algorithm, and System Development*, Prentice Hall, Upper Saddle River, New Jersey, USA, ISBN: 0-13-022616-5, 2001.

and information found in most standard speech textbooks:

J. Deller, et. al., *Discrete-Time Processing of Speech Signals*, MacMillan Publishing Co., ISBN: 0-7803-5386-2, 2000.

[Return to Main](#)**Introduction:**

01: Organization
[\(html\)](#), [\(pdf\)](#)

Speech Signals:

02: Production
[\(html\)](#), [\(pdf\)](#)

03: Digital Models
[\(html\)](#), [\(pdf\)](#)

04: Perception
[\(html\)](#), [\(pdf\)](#)

05: Masking
[\(html\)](#), [\(pdf\)](#)

06: Phonetics and Phonology
[\(html\)](#), [\(pdf\)](#)

07: Syntax and Semantics
[\(html\)](#), [\(pdf\)](#)

Signal Processing:

08: Sampling
[\(html\)](#), [\(pdf\)](#)

09: Resampling
[\(html\)](#), [\(pdf\)](#)

10: Acoustic Transducers
[\(html\)](#), [\(pdf\)](#)

11: Temporal Analysis
[\(html\)](#), [\(pdf\)](#)

12: Frequency Domain Analysis
[\(html\)](#), [\(pdf\)](#)

13: Cepstral Analysis
[\(html\)](#), [\(pdf\)](#)

14: **Exam No. 1**
[\(html\)](#), [\(pdf\)](#)

15: Linear Prediction
[\(html\)](#), [\(pdf\)](#)

16: LP-Based Representations

ECE 8463: FUNDAMENTALS OF SPEECH RECOGNITION

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 URL: http://www.isip.msstate.edu/resources/courses/ece_8463

Modern speech understanding systems merge interdisciplinary technologies from Signal Processing, Pattern Recognition, Natural Language, and Linguistics into a unified statistical framework. These systems, which have applications in a wide range of signal processing problems, represent a revolution in Digital Signal Processing (DSP). Once a field dominated by vector-oriented processors and linear algebra-based mathematics, the current generation of DSP-based systems rely on sophisticated statistical models implemented using a complex software paradigm. Such systems are now capable of understanding continuous speech input for vocabularies of hundreds of thousands of words in operational environments.

In this course, we will explore the core components of modern statistically-based speech recognition systems. We will view speech recognition problem in terms of three tasks: signal modeling, network searching, and language understanding. We will conclude our discussion with an overview of state-of-the-art systems, and a review of available resources to support further research and technology development.

Tar files containing a compilation of all the notes are available. However, these files are large and will require a substantial amount of time to download. A tar file of the html version of the notes is available [here](#). These were generated using wget:

```
wget -np -k -m
http://www.isip.msstate.edu/publications/courses/ece_8463/lectures/current
```

A pdf file containing the entire set of lecture notes is available [here](#). These were generated using Adobe Acrobat.

Questions or comments about the material presented here can be directed to help@isip.msstate.edu.

([html](#), [pdf](#))

17: Spectral Normalization

([html](#), [pdf](#))

Parameterization:

18: Differentiation

([html](#), [pdf](#))

19: Principal Components

([html](#), [pdf](#))

20: Linear Discriminant Analysis

([html](#), [pdf](#))

Acoustic Modeling:

21: Dynamic Programming

([html](#), [pdf](#))

22: Markov Models

([html](#), [pdf](#))

23: Parameter Estimation

([html](#), [pdf](#))

24: HMM Training

([html](#), [pdf](#))

25: Continuous Mixtures

([html](#), [pdf](#))

26: Practical Issues

([html](#), [pdf](#))

27: Decision Trees

([html](#), [pdf](#))

28: Limitations of HMMs

([html](#), [pdf](#))

Language Modeling:

LECTURE 25: CONTINUOUS MIXTURE DENSITIES

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and information found in most standard speech textbooks:

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THE EXPECTATION MAXIMIZATION (EM) ALGORITHM

- The Expectation Maximization (EM) algorithm can be viewed as a generalization of maximum likelihood parameter estimation (MLE) when the data observed is incomplete. We observe some data y , and seek to maximize $P(Y = y|\lambda)$. However, in order to do this, we need to know some hidden data x .
- We assume a parameter vector λ and estimate the probability that each x occurred in the generation of y . In this way, we can assume we observed the pair (x, y) with probability $P(X = x, Y = y|\lambda)$.
- To compute the new $\bar{\lambda}$, we use the maximum likelihood estimate of λ .
- Does this process converge?

According to Bayes' rule:

$$P(X = x, Y = y|\bar{\lambda}) = P(X = x|Y = y, \bar{\lambda})P(Y = y|\bar{\lambda})$$

The log likelihood can be expressed as:

$$\log P(Y = y|\bar{\lambda}) = \log P(X = x, Y = y|\bar{\lambda}) - \log P(X = x|Y = y, \bar{\lambda})$$

We take the conditional expectation of $\log P(Y = y|\bar{\lambda})$ over X :

$$\begin{aligned} E_{\lambda}[\log P(Y = y|\bar{\lambda})]_{X|Y=y} &= \sum_x (P(X = x|Y = y, \lambda)) \log P(Y = y|\bar{\lambda}) \\ &= \log P(Y = y|\bar{\lambda}) \end{aligned}$$

Combining the previous two expressions:

$$\begin{aligned} \log P(Y = y|\bar{\lambda}) &= E_{\lambda}[\log P(X, Y = y|\bar{\lambda})]_{X|Y=y} - E_{\lambda}[\log P(X|Y = y, \bar{\lambda})]_{X|Y=y} \\ &= Q(\lambda, \bar{\lambda}) - H(\lambda, \bar{\lambda}) \end{aligned}$$

The convergence of the EM algorithm lies in the fact that if we choose $\bar{\lambda}$ such that $Q(\lambda, \bar{\lambda}) \geq Q(\lambda, \lambda)$, then $\log P(Y = y|\bar{\lambda}) \geq \log P(Y = y|\lambda)$.

This follows because we can show that $H(\lambda, \bar{\lambda}) \leq H(\lambda, \lambda)$ using a special case

of Jensen's inequality ($\sum_x p(x) \log p(x) \geq \sum_x p(x) \log q(x)$).

A summary of the procedure is:

The EM Algorithm

Step 1: Choose an initial estimate λ .

Step 2: **E-step**: Compute auxiliary Q -function $Q(\lambda, \bar{\lambda})$ (which is also the expectation of the log likelihood of the data) based on λ .

Step 3: **M-step**: Compute $\hat{\lambda} = \arg \max Q(\lambda, \bar{\lambda})$ to maximize the auxiliary Q -function.

Step 4: Iteration: Set $\lambda = \bar{\lambda}$, and repeat from Step 2 until convergence.

ESTIMATION EQUATIONS

The functions in our auxiliary functions Q are of the form $F(x) = \sum_i y_i \log x_i$,

where $\sum_i x_i = 1$. Using Lagrange multipliers, this function can be shown to

have a maximum value at $x_i = y_i / \sum_i y_i$. The model reestimation equations that result from this optimization are:

$$\hat{a}(j|i) = \frac{\frac{1}{P(y_1^T|\lambda)} \sum_{t=1}^T P(y_1^T, s_{t-1} = i, s_t = j|\lambda)}{\frac{1}{P(y_1^T|\lambda)} \sum_{t=1}^T P(y_1^T, s_{t-1} = i|\lambda)} = \frac{\sum_{t=1}^T \gamma_t(j|i)}{\sum_{t=1}^T \sum_{k=1}^N \gamma_t(k|i)}$$

This is just the ratio of the expected number of transitions from state i to state j and the expected number of transitions from state i .

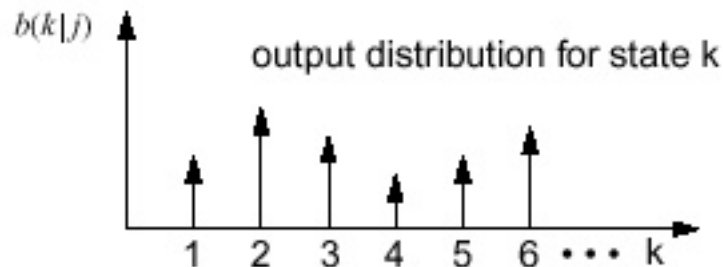
Similarly,

$$\hat{b}_j(k) = \frac{\frac{1}{P(y_1^T|\lambda)} \sum_{t=1}^T P(y_1^T, s_t = j|\lambda) \delta(y^t, o^t)}{\frac{1}{P(y_1^T|\lambda)} \sum_{t=1}^T P(y_1^T, s_t = j|\lambda)} = \frac{\sum_{t \in (y^t = o^t)} \sum_{i=1}^M \gamma_t(j|i)}{\sum_{t=1}^T \sum_{i=1}^M \gamma_t(j|i)}$$

This is the ratio of the number of times the k^{th} observation vector was emitted from state j and the number of times any observation vector was emitted from state j .

CONTINUOUS PROBABILITY DENSITY FUNCTIONS

The discrete HMM incorporates a discrete probability density function, captured in the matrix B , to describe the probability of outputting a symbol:



Signal measurements, or feature vectors, are continuous-valued N-dimensional vectors. In order to use our discrete HMM technology, we must vector quantize (VQ) this data — reduce the continuous-valued vectors to discrete values chosen from a set of M codebook vectors. Initially, most HMMs were based on VQ front-ends. However, for the past 15 years or so, the continuous density model has become widely accepted.

The likelihood of generating observation $y(t)$ in state j is defined as:

$$b(y(t)|j) \equiv f_{y|x}(y(t)|j)$$

Note that taking the negative logarithm of $b(\cdot)$ will produce a log-likelihood, or a Mahalanobis-like distance. But what form should we choose for $f(\cdot)$?

Let's assume a Gaussian model, of course:

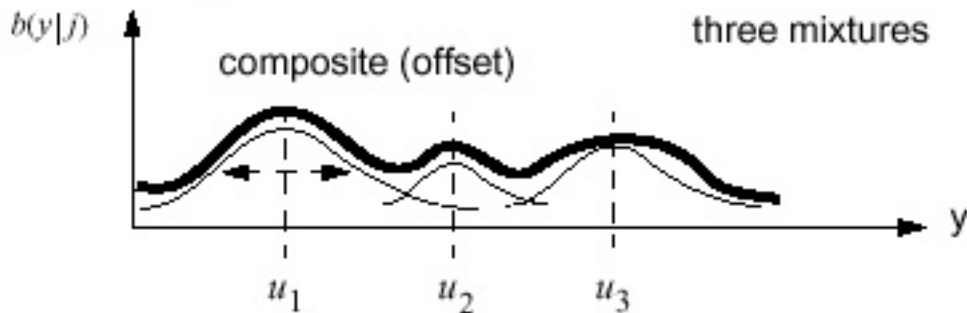
$$f_{y|x}(y|i) = \frac{1}{\sqrt{2\pi|\Sigma_i|}} \exp\left\{-\frac{1}{2}(y - \mu_i)^T \Sigma_i^{-1} (y - \mu_i)\right\}$$

Note that this amounts to assigning a mean and covariance matrix to each state — a significant increase in complexity. However, shortcuts such as variance-weighting can help reduce complexity.

Also, note that the log of the output probability at each state becomes precisely the Mahalanobis distance (principal components) we studied at the beginning of the course.

MIXTURE DENSITIES: A POWERFUL MODELING TOOL

Of course, the output distribution need not be Gaussian, or can be multimodal to reflect the fact that several contexts are being encoded into a single state (male/female, allophonic variations of a phoneme, etc.). Much like a VQ approach can model any discrete distribution, we can use a weighted linear combination of Gaussians, or a mixture distribution, to achieve a more complex statistical model.



Mathematically, this is expressed as:

$$f_{\underline{y}|\underline{x}}(\underline{y}|i) = \sum_{m=1}^M c_{im} \mathfrak{N}(\underline{y}; \underline{\mu}_{im}, \underline{\Sigma}_{im})$$

In order for this to be a valid pdf, the mixture coefficients must be nonnegative and satisfy the constraint:

$$\sum_{m=1}^M c_{im} = 1, \quad 1 \leq i \leq S$$

Note that mixture distributions add significant complexity to the system: m means and covariances at each state.

PROBABILITY CALCULATIONS

Consider a Gaussian mixture density function

$$b_j(\mathbf{y}) = \sum_{k=1}^M c_{jk} b_{jk}(\mathbf{y}) = \sum_{k=1}^M c_{jk} \mathfrak{N}(\mathbf{y}, \boldsymbol{\mu}_{jk}, \boldsymbol{\Sigma}_{jk})$$

Recall that the mixture weights are constrained to sum to 1: $\sum_{k=1}^M c_{jk} = 1$.

We can write the joint probability of the data and states given the model as:

$$p(\mathbf{Y}, \mathbf{S} | \boldsymbol{\lambda}) = \prod_{t=1}^T a_{s_{t-1}, s_t} b_{s_t}(\mathbf{y}_t) = \sum_{k_1=1}^M \sum_{k_2=1}^M \dots \sum_{k_T=1}^M \left\{ \prod_{t=1}^T a_{s_{t-1}, s_t} b_{s_t k_t}(\mathbf{y}_{s_t}) c_{s_t k_t} \right\}$$

This can be considered the sum of the product of all densities with all possible state sequences, \mathbf{S} , and all possible mixture components, \mathbf{K} :

$$p(\mathbf{Y}, \mathbf{S}, \mathbf{K} | \boldsymbol{\lambda}) = a_{s_{t-1}, s_t} b_{s_t k_t}(\mathbf{y}_{s_t}) c_{s_t k_t}$$

and

$$p(\mathbf{X} | \boldsymbol{\lambda}) = \sum_{\mathbf{S}} \sum_{\mathbf{K} \in \Omega^T} p(\mathbf{Y}, \mathbf{S}, \mathbf{K} | \boldsymbol{\lambda})$$

APPLICATION OF EM: OPTIMIZATION

We can write the auxiliary function:

$$Q(\lambda|\bar{\lambda}) = \sum_{\mathcal{S}} \sum_{\mathbf{K} \in \Omega^T} \frac{p(\mathbf{Y}, \mathcal{S}, \mathbf{K}|\lambda)}{p(\mathbf{Y}, \lambda)} \log(p(\mathbf{Y}, \mathcal{S}, \mathbf{K}|\lambda))$$

which has the expected decomposition:

$$\log(p(\mathbf{Y}, \mathcal{S}, \mathbf{K}|\lambda)) = \sum_{t=1}^T \log \hat{a}_{s_{t-1}s_t} + \sum_{t=1}^T \log \hat{b}_{s_t k_t}(\mathbf{y}_t) + \sum_{t=1}^T \log \hat{c}_{s_t k_t}$$

The auxiliary function has three components:

$$Q(\lambda|\bar{\lambda}) = \sum_{i=1}^N Q_{a_i}(\lambda, \hat{a}_i) + \sum_{j=1}^N \sum_{k=1}^M Q_{b_{jk}}(\lambda, \hat{b}_{jk}) + \sum_{j=1}^N \sum_{k=1}^M Q_{c_{jk}}(\lambda, \hat{c}_{jk})$$

The first resembles the term we had for discrete distributions. The remaining two terms are new:

$$Q_{b_{jk}}(\lambda, \hat{b}_{jk}) = \sum_{t=1}^T p(s_t = j, k_t = k | \mathbf{Y}, \lambda) \log \hat{b}_{jk}(\mathbf{y}_t)$$

and

$$Q_{c_{jk}}(\lambda, \hat{c}_{jk}) = \sum_{t=1}^T p(s_t = j, k_t = k | \mathbf{Y}, \lambda) \log \hat{c}_{jk}$$

REESTIMATION EQUATIONS

Maximization of $Q_{b_{jk}}(\lambda, \hat{b}_{jk})$ requires differentiation with respect to the parameters of the Gaussian: $[\mu_{jk}, \Sigma_{jk}]$. This results in the following equations:

$$\hat{\mu}_{jk} = \frac{\frac{1}{p(\mathbf{Y}|\lambda)} \sum_{t=1}^T p(\mathbf{Y}, s_t = j, k_t = k | \lambda) \mathbf{y}_t}{\frac{1}{p(\mathbf{Y}|\lambda)} \sum_{t=1}^T p(\mathbf{Y}, s_t = j, k_t = k | \lambda) \mathbf{y}_t}} = \frac{\sum_{t=1}^T \zeta_t(j, k) \mathbf{y}_t}{\sum_{t=1}^T \zeta_t(j, k)}$$

$$\hat{\Sigma}_{jk} = \frac{\frac{1}{p(\mathbf{Y}|\lambda)} \sum_{t=1}^T p(\mathbf{Y}, s_t = j, k_t = k | \lambda) (\mathbf{y}_t - \hat{\mu}_{jk})(\mathbf{y}_t - \hat{\mu}_{jk})^\dagger}{\frac{1}{p(\mathbf{Y}|\lambda)} \sum_{t=1}^T p(\mathbf{Y}, s_t = j, k_t = k | \lambda) \mathbf{y}_t}}$$

$$= \frac{\sum_{t=1}^T \zeta_t(j, k) (\mathbf{y}_t - \hat{\mu}_{jk})(\mathbf{y}_t - \hat{\mu}_{jk})^\dagger}{\sum_{t=1}^T \zeta_t(j, k)}$$

where $\zeta_t(j, k)$ is computed as:

$$\zeta_t(j, k) = \frac{p(\mathbf{Y}, s_t = j, k_t = k | \lambda)}{p(\mathbf{Y}|\lambda)} = \frac{\sum_{i=1}^N \alpha_{t-1}(i) a(j|i) c_{jk} b_{jk}(\mathbf{y}_t) \beta_t(j)}{\sum_{i=1}^N \alpha_T(i)}$$

Similarly, we can reestimate the mixture coefficients using a similar equation:

T

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

Mixture Modelling page

Welcome to [David Dowe](#)'s clustering and mixture modelling page. Mixture modelling (or mixture modeling) concerns modelling a statistical distribution by a mixture (or weighted sum) of other distributions. Mixture modelling is also known as

- unsupervised concept learning (in Artificial Intelligence)
- intrinsic classification (in Philosophy), or, classification
- clustering
- numerical taxonomy In 1995, an [International Workshop on Mixtures](#) (also [here](#)) was held. Also, an e-mailing list exists for "Classification, clustering, and phylogeny estimation", namely (CLASS-L@CCVM.SUNYSB.EDU or) owner-class-1@CCVM.SUNYSB.EDU, as does a WWW site for the [International Federation of Classification Societies \(IFCS\)](#), a WWW site for the [Classification Society of North America \(CSNA\)](#), a WWW site for the [Societe Francophone de Classification \(SFC\)](#), a WWW site for the (Polish) [Sekcja Klasyfikacji i Analizy Danych PTS \(SKAD\)](#) and a WWW site for the (Dutch) [Vereniging voor Ordinatie en Classificatie \(VOC\)](#).

In 2001, there will be: [Mixtures 2001](#), Recent Developments in Mixture Modelling, 23 - 28 July 2001, [Universität der Bundeswehr, Hamburg](#), Germany. *Deadline* December 31, 2000. Most mixture modelling is done for mixtures of

- Normal (or Gaussian) distributions.
- However, other distributions for which mixture modelling has been done include (e.g.) :
- the multinomial (Bernoulli or multi-category) distribution,
 - the Poisson distribution and
 - the von Mises circular distribution. **Bibliographies**

[Chris Fraley](#)'s [Classification Bibliography](#).

[Peter Macdonald](#)'s [mixture distribution bibliography](#).

[Fionn Murtagh](#) (and [CSNA](#))'s [Classification Bibliographies](#).

Warren S. Sarle's selected [Bibliography on Cluster Analysis](#).

[Luis Talavera](#)'s [Bibliography of Conceptual Clustering](#).

[John Uebersax](#)'s Latent Class Analysis [bibliography](#). Below we give lists of some available mixture modellers of various distributions: [On-Line Software for Clustering and Multivariate Analysis](#) listed by the [CSNA](#).

[Fionn Murtagh](#)'s list of [Multivariate Data Analysis Software](#) and

[Fionn Murtagh](#)'s [pointers to, and addresses of, lots of multivariate data analysis code](#).

[S*i*ftware](#)'s [links to clustering software](#).

Mixture modellers of Binomial distributions

See "Mixture modellers of Multinomial (or Bernoulli or multi-category) distributions" below. **Mixture modellers of Gamma distributions**

"MIX". Commercial (see below). **Mixture modellers of Gaussian distributions**

[AutoClass](#) (and [Peter Cheeseman](#)). *Method*: Bayesian.

[Clustan](#): www.clustan.com.

[COBWEB](#), by [Doug H. Fisher](#).

[ECOBWEB](#) concept formation program.

[John Wolfe](#)'s Normix (was [here](#)).

"[MIX](#)" [Software Home Page](#) (and [About MIX](#)) and [mixture distribution bibliography](#). Commercial.

[Snob software](#) & [ReadMe](#) & [documentation](#) files), and [latest paper](#); by [C Wallace](#) and [D. Dowe](#).

Snob Method: Bayesian, [Minimum Message Length \(MML\)](#), information theory and [Kolmogorov complexity](#) - see "[Minimum Message Length and Kolmogorov complexity](#)", *Comp. J.*, 42:4. *Snob*

Features: Deals with missing data.

[S. Akaho's EM algorithm](#) with link to paper. *Features*: scale and shift parameters, JAVA demo'.

S. Akaho's program also does "line mixing".

[Mike Alder](#) (from [CIIPS](#), [U.W.A.](#))'s [book](#) (including some examples of the EM algorithm used for Gaussian mixture modelling).

C. Ambroise et al.'s [Constrained clustering and the EM algorithm](#) software for spatial clustering (was [Constrained clustering and the EM algorithm](#)).

[S. Aylward](#)'s [Mixture Modeling for Medical Image Segmentation](#). *Method*: Permits mixture models comprising infinitely many Gaussian components with continuous collective parameterizations.

[Kaye Basford](#) (co-author of mixture modelling book with (below) [Geoff McLachlan](#))'s home page and

[The Biometrics Unit](#) (University of Queensland)'s [publications](#).

R. A. Baxter and J. J. Oliver, [Finding overlapping components with MML](#).

[Hamparsum Bozdogan](#)'s home page.

[Dr Carroll](#)'s [Quasilikelihood estimation in measurement error models with correlated replicates](#) paper. [Dr](#)

[Carroll](#)'s *Method*: quasilikelihood estimations.

[Complex Systems Computation group \(CoSCo\)](#), U. of Helsinki. Home page and research projects.

[D. Dacunha-Castelle](#) and [E. Gassiat](#)'s work, papers nos. 25 and 44. *Method*: Maximum Likelihood.

[Petros Dellaportas](#) (and [Dimitris Karlis](#))'s (mixture modelling) [papers](#). Dellaportas-Karlis mixture modelling *Method*: Hierarchical, empirical Bayes, method of moments and simulation techniques.

[David Dowe](#): See [Snob](#) by [C. Wallace](#) and D. Dowe. See also R. Edwards and D. Dowe.

Russell Edwards and [David Dowe](#) have extended [Snob](#) to deal with single Gaussian factor analysis (assuming total assignment) using [MML](#).

[Peter Green](#).

Cem Hocaoglu.

[HTK Book](#) (and links to chapters). Commercial. Entropic Cambridge Research Laboratory Ltd.

[Michael Jordan](#)'s [projects](#).

[Murray Jorgensen](#)'s home page (link to [MULTIMIX](#)).

[Geoff McLachlan](#) is the author of several articles and a joint book on mixture modelling (with (above)

[Kaye Basford](#)) and is currently completing [EMMIX](#) (MIXFIT) software, suitable for Max L'hood fitting of Gaussians in discriminant and cluster analyses and many experimental situations. Permits

re-sampling-based tests and bootstrap-based standard error assessment. [Some of G. McLachlan](#) and David Peel's [data sets](#).

[Radford Neal's Bayesian Mixture Modeling by Monte Carlo Simulation](#) and [Markov Chain Sampling Methods for Dirichlet Process Mixture Models](#). R. Neal's *Method*: Exhibits the true Bayesian predictive distribution, not needing to decide on a "correct" no. of components.

Adrian Raftery's and [Chris Fraley's Model-Based Clustering Software \(MCLUST\)](#).

[Christian Robert's ftp site](#).

Arthur C. Sanderson.

[Rob Tibshirani's research](#), and T. Hastie & [R. Tibshirani](#) Gaussian [mixture paper](#). T. Hastie

& R. Tibshirani's *Method(s)*: Linear discriminant analysis, Maximum Likelihood, non-parametric.

[Chris Wallace](#) and [David Dowe's Snob](#) work (and [software](#) and [ReadMe](#)), and [latest paper](#) - see [Snob](#) above. Uses [MML](#).

[Mike West's publications](#). **Mixture modellers of logistic distributions**

[Dr Carroll's A nonparametric mixture approach to case-control studies with errors in covariables](#) paper.

[Dr Carroll's Method](#): nonparametric.

[Dr Carroll's Segmented regression with errors in predictors](#) paper. [Dr Carroll's Method](#): semiparametric & parametric. Linear and logistic distributions. **Mixture modellers of log-Normal distributions**

See "Mixture modellers of Gaussian distributions" above. **Mixture modellers of Multinomial (or Bernoulli or multi-category) distributions**

[Snob](#), by [Chris Wallace](#) and [David Dowe](#) - see [Snob](#) above, under "Gaussian". Uses [MML](#).

[Murray Jorgensen's](#) home page (see above, or link to [MULTIMIX](#)).

[Martin Puterman's](#) home page, with several of his papers, data and codes. M. Puterman has worked on mixture models for discrete data. *Method*: Maximum Likelihood and penalised likelihood.

[John Uebersax's Latent Class Analysis](#) page has [FAQs](#), [bibliographies](#), [software links](#), examples, and some of his [papers and programs](#) (including [MIXBIN](#), which estimates a mixture of binomials). **Mixture modellers of Normal distributions**

See "Mixture modellers of Gaussian distributions" above. **Mixture modellers of Poisson distributions**

[Snob](#), by [Chris Wallace](#) and [David Dowe](#) - see [Snob](#) above, under "Gaussian". Uses [MML](#).

[Petros Dellaportas's](#) home page. **Mixture modellers of von Mises circular distributions**

[Snob](#), by [Chris Wallace](#) and [David Dowe](#) - see [Snob](#) above, under "Gaussian". Uses [MML](#). **Mixture modellers of Weibull distributions**

"MIX". Commercial (see above).

Mixture modellers of Other distributions and Miscellaneous

[Shotaro Akaho's EM algorithm](#) (with link to paper) for "line mixing" (see above).

M. Black and [A. Jepson's Mixture Models for Optical Flow Computation](#). Explores use of mixture models to represent optical flow in image regions containing multiple motions due to occlusion and transparency.

[Sara van de Geer's](#) Home page. *Method*: General mixing models, maximum likelihood, asymptotic normality of linear functionals of the mixing distribution.

[IBM's CViz](#).

[D. Laidlaw, K. Fleischer + A. Barr, Class'n of MRI Data for Geometric Modeling and Visualization](#).

Laidlaw, Fleischer and Barr's *Method*: Bayesian Mixture Classification.

[Christian Lenart's \(fuzzy\) clustering page](#) and [description of software](#).

[MEME software](#) for finding patterns in DNA and protein sequences.

[MIT \(Germany\)'s DataEngine Product Family page](#). *Method*: Fuzzy clustering. Commercial.

[NSWC Advanced Computational Technology Group's pattern recognition and classification](#), including work on mixtures based density estimation applied to statistical pattern recognition and image processing, e.g. J. Solka and W. Poston's [Visualization of Finite and Adaptive Mixtures Models - Univariate Examples](#).

[Adrian Raftery's clustering and spatial point pattern research](#) and [group on clustering and Bayesian model selection](#).

[SPIDER](#) is a large image processing system for electron microscopy, including multivariate statistical classification and cluster analysis. Commercial.

[SUBDUE](#), by [Diane J. Cook](#) and [Lawrence B. Holder](#). *Method*: Hierarchical clustering using a [MDL](#) heuristic to iteratively identify subgraphs within a graph that minimally compress the input graph.

[M. Afzal Upal's publications](#) on comparison(s) of non-hierarchical unsupervised classification algorithms.

Data links

[Some data links](#); and [Geoff McLachlan](#) and David Peel's "[Finite Mixture Models](#)" and [data sets](#).

Of possible interest

[Statistical Society of Canada Case Studies in Data Analysis for 2000](#) and [Mixtures Plus - Case Studies](#). [StatLib Index](#) (from the [Carnegie Mellon University Statistics Department](#)).

[Tjen-Sien Lim's "Tree-Structured & Rules Induction Programs Homepage"](#)

[Kevin Murphy's list of free Bayes net software](#).

[Data Mining Information](#), maintained by [Graham Williams](#).

[Online Machine Learning Resources](#), maintained by the [ML Group](#) at the [Austrian Research Institute for Artificial Intelligence \(OFAI\)](#), Vienna, Austria.

[Artificial Intelligence Resources](#), maintained by NRC-CNRC Institute for Information Technology.

[A Guide to the Web for Statisticians](#) (was [A Guide to the Web for Statisticians](#)), maintained by [Gordon Smyth](#).

[Autonomous Agents '97 Related Sites](#).

[AI Intelligence](#) (and [here](#))'s [AI Information Bank](#). Commercial.

[International Rough Set Soc'y](#), U. Regina's [Electronic Bulletin of the Rough Set Community](#) pages.

[Bayesian Knowledge Discoverer \(BKD\)](#), by [Marco Ramoni](#) and [Paola Sebastiani](#): A program for model selection with missing data using directed graphical models and discrete variables.

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[NASA Data Archive and Distribution Service](#).

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This (mixture modelling, clustering, unsupervised concept learning, intrinsic classification and numerical taxonomy) page <http://www.csse.monash.edu.au/~dld/mixture.modelling.page.html> was put together by Dr. [David Dowe](#), Dept. of Computer Science, Monash University, Clayton, Vic. 3168, Australia

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The Sphinx3 trainer can be used to train both semi-continuous and continuous HMMs.

THE DIFFERENCE BETWEEN DISCRETE, SEMI-CONTINUOUS AND CONTINUOUS MODELS

Discrete models

The vector space is partitioned into N regions and every vector is replaced by the numerical identifier (id) of the region it belongs to. In the discrete HMM for a phone, each state distribution is a histogram (with N bins) of the occurrence-frequency of each region. Here we are essentially assuming that all data within a region are equally probable.

The process of partitioning a vector space into regions and replacing each vector by a representative from the region it belongs to is referred to as "vector quantization".

Semi-continuous models

The essential conceptual difference between discrete and semi-continuous models is that all data within a bin are not assumed to be equi-probable in semi-continuous models. Instead, we assign a probability density to all data within a bin.

In semi-continuous models the vector space is partitioned into N regions as in the case of discrete models. However there are several differences. Partitions are not rigid, and do not have clear boundaries. Instead, the data vectors are used to compute a mixture of N parametric distributions, usually Gaussians, and each of these N distributions are visualized as representing the distribution of data within a particular partition. It is important to note that the partitioning itself is not explicitly done. It is assumed that the data belonging to any state of any HMM come from these various partitions in proportions that are characteristic of that state. However, within any partition, the distribution of data is dependent only on the partition and not on the state. The state distribution of any state is thus simply a sum of the N distributions (representing each of the partitions) weighted by the true fraction of data points from that state which came from the partitions.

Here, the underlying "truth" about the distribution associated with any state of an HMM is that, had one had all possible examples of the realization of that state, and explicit knowledge of which partition each of these vectors came from, then the true distribution of the state could be approximated as a sum of the N partitions weighted by the fraction of vectors from that state belonging to each partition. This "true" fraction is what we are trying to estimate from the limited data that we see, using the limited knowledge that we have of the data belonging to that state.

From the point of view of each vector, we do not associate a unique partition with any vector. Instead, we assign to the vector a probability of belonging to any partition. Thus every vector has a probability distribution associated with it, composed of the probabilities of belonging to each of the N partitions. During the training process these probability distributions associated with the vectors belonging to any state of any HMM are aggregated to give a single histogram, which is normalized to give the "mixture weight" distribution for that state. The probability distributions are also used simultaneously to update the parameters of the distribution associated with each partition of the vector space.

For a vector, the notion of "belonging to a state" is not absolute. It can only be absolute if the process of generation of the vectors were known at every stage to an observer. This is further compounded by the

fact that the assumed model itself may be inaccurate. In other words, we cannot assign any vector exclusively to a particular state of an HMM. Instead, we can associate a probability of it having being generated by distribution of any state. A simple example to clarify this is as follows: If we took a mixture of 3 Gaussians and used one of them to generate a vector, we could assign an absolute probability to that vector of belonging to its generating Gaussian. This assignment comes merely because we know which Gaussian generated the vector. Once the vector was generated, and that underlying knowledge obscured from an observer, the observer could at best assign probabilities of the vector having been generated from each of the 3 Gaussians. The observer's assignments could never be more specific than this in the absence of any other knowledge. However, the fact remains that the vector did indeed come from one of the 3 Gaussians, we simply cannot exploit the fact. We have to make guesses.

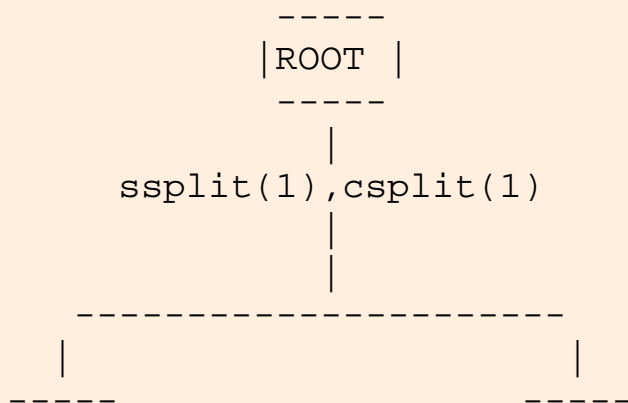
Here is a good practical approximation to Semi-continuous HMMs. It is not theoretically completely accurate (and not what the Sphinx does), but if you implemented this it would work too (though not as well as the theoretically correct version discussed above). In this approximation the vector space is explicitly partitioned into N parts and a histogram is constructed for every state of every hmm. This histogram is based on the counts of vectors that correspond to each partition. The vectors themselves are not replaced. Once all histograms are computed, the hmms are used to re-estimate the boundaries of the N partitions of the vector space. In order to do this, each partition is associated with a parametric distribution with its parameters computed from the vectors in that partition. The final models are in the form of parameters of the final distributions of the partitions (which form the final codebook) and the histograms or "mixture-weights" corresponding to each model. Also associated with each "base" acoustic unit modeled is a transition probabilities matrix. All "higher-level" acoustic units which may have been formed by some combination of the "base" acoustic units use the transition matrix of the base acoustic unit they are chiefly associated with. Triphones, quinphones, diphones etc. fall into the "higher-level" units category. A triphone, for example, is chiefly associated with its central phone.

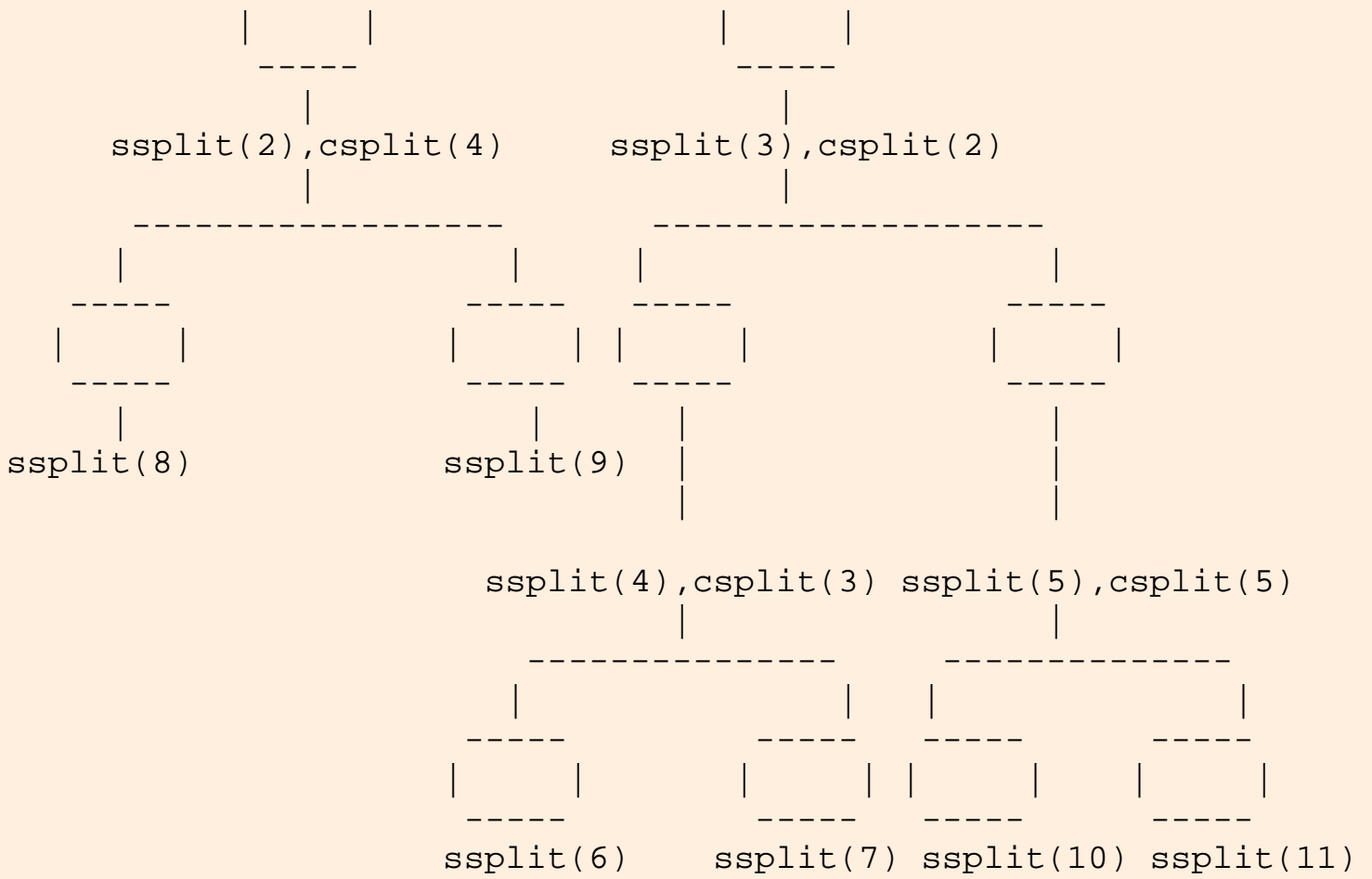
Continuous models

In continuous HMMs the partitioning of the vector space is itself state-specific, unlike semi-continuous models where the partitioning is unique and shared by all states. More about this later...

THE ALGORITHM USED FOR BUILDING TREES

simple split (ssplit) (sequence in which this step is done),
 compound split (csplit) (sequence in which this step is done)





Ten years of HMMs

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Contents

- [Contents](#)
- [About this document](#)
- [1 General](#)
- [2 Applications](#)
 - [2.1 Acoustics](#)
 - [2.2 Biosciences](#)
 - [2.3 Climatology](#)
 - [2.4 Control](#)
 - [2.5 Communications](#)
 - [2.6 Econometrics](#)
 - [2.7 Handwriting and text recognition](#)
 - [2.8 Image processing and computer vision](#)
 - [2.9 Other applications](#)
 - [2.10 Signal processing](#)
 - [2.11 Speech processing](#)

About this document

This list of references has been obtained by searching in a large bibliographic database for entries which featured the words *Hidden* and *Markov* (or the acronym *HMM*) in their title. Only the reference corresponding to review papers **published after 1989 and before the end of 2000** have been retained here. Basically, the list contains all the references matching the above criteria. I however had to revise somehow this policy for references concerning speech processing since there were too many of them (which means that I pruned approximately 20% of the speech references, usually older and/or hard to find ones).

Because there are quite a number of references (about 360), I have tried to sort them according to some categories. **General** is for anything that is about the model in general and does not appear to be connected to a particular application. **Applications** is the other main category. Some of the sub-categories overlap to some extent (Signal and Communications, or Image and Text recognition, for instance). **Other applications** is the sub-category for "unusual" applications (those that appear only rarely). In each category, the references are sorted in reversed time order (the more recent coming first).

This is the third (and, presumably, final) version of this document: The one dated 1997 does not contain any reference for the period 1997-2000 (!) - about one hundred references have been added since then; The other one, dated February 2001, is almost identical to this final version.

This document is available at address <http://www-sig.enst.fr/~cappe/> in [HTML](#), [gz-compressed postscript](#) and [pdf](#) formats.

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