MCLUST: Software for Model-Based Clustering, Density Estimation and Discriminant Analysis

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MCLUST is a software package for model-based clustering, density estimation and discriminant analysis interfaced to the S-PLUS commercial software.¹ ² It implements parameterized Gaussian hierarchical clustering algorithms and the EM algorithm for parameterized Gaussian mixture models with the possible addition of a Poisson noise term. Also included are functions that combine hierarchical clustering, EM and the Bayesian Information Criterion (BIC) in comprehensive strategies for clustering, density estimation, and discriminant analysis. MCLUST provides functionality for displaying and visualizing clustering and classification results. A web page with related links can be found at

http://www.stat.washington.edu/mclust

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²Thanks go to Ron Wehrens for comments and suggestions leading to improvements in the MCLUST documentation and software.

¹Insightful Corp., Seattle, WA USA — http://www.insightful.com/splus

²A version of MCLUST is also available with an R language interface instead of S-PLUS (ported by Ron Wehrens http://www-cac.sci.kun.nl/people/rwehrens). R is freely available for noncommercial use — see http://lib.stat.cmu.edu/R/CRAN.
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The MCLUST software, with offerings originally limited to model-based hierarchical clustering, was extended to include EM for parameterized Gaussian mixture models, as well as a clustering strategy in which the model and number of clusters are simultaneously selected via the Bayesian Information Criterion (BIC) [10]. This manuscript describes a substantial upgrade to MCLUST, which includes the following among its new features:

- EM for four diagonal covariance mixture models.
- Density estimation via parameterized Gaussian mixtures.
- Simulation from parameterized Gaussian mixtures.
- Discriminant analysis via MclustDA.
- Methods for one dimensional data.
- Enhanced displays, including uncertainty plots and random projections.

A comprehensive treatment of the methods used in MCLUST can be found in [11].

1 Models

In MCLUST, each cluster is represented by a Gaussian model

\[ \phi_k(x | \mu_k, \Sigma_k) = (2\pi)^{-\frac{d}{2}}|\Sigma_k|^{-\frac{1}{2}} \exp \left\{ -\frac{1}{2} (x_i - \mu_k)^T \Sigma_k^{-1} (x_i - \mu_k) \right\}, \]

where \( x \) represents the data, and \( k \) is an integer subscript specifying a particular cluster. Clusters are ellipsoidal, centered at the means \( \mu_k \). The covariances \( \Sigma_k \) determine their other geometric features.

Each covariance matrix is parameterized by eigenvalue decomposition in the form

\[ \Sigma_k = \lambda_k D_k A_k D_k^T, \]

where \( D_k \) is the orthogonal matrix of eigenvectors, \( A_k \) is a diagonal matrix whose elements are proportional to the eigenvalues of \( \Sigma_k \), and \( \lambda_k \) is a scalar. The orientation of the principal components of \( \Sigma_k \) is determined by \( D_k \), while \( A_k \) determines the shape of the density contours; \( \lambda_k \) specifies the volume of the corresponding ellipsoid, which is proportional to \( \lambda_k^d |A_k| \), where \( d \) is the data dimension. Characteristics (orientation, volume and shape) of distributions are usually estimated from the data, and can be allowed to vary between clusters, or constrained to be the same for all clusters [17, 2, 7]. This parameterization includes but is not restricted to well-known models such as equal-volume spherical variance (\( \Sigma_k = \lambda I \)) which gives the sum of squares criterion [21], constant variance [12], and unconstrained variance [20].

In one dimension, there are just two models: E for equal variance and V for varying variance. In more than one dimension, the model identifiers code geometric characteristics of the model. For example, EVI denotes a model in which the volumes of all clusters are equal (E), the shapes of the clusters may vary (V), and the orientation is the identity (I).
Clusters in this model have diagonal covariances with orientation parallel to the coordinate axes. Parameters associated with characteristics designated by E or V are determined from the data. Table 1 shows the various multivariate model options currently available in MCLUST for hierarchical clustering (denoted HC) and EM.

Table 1: Parameterizations of the covariance matrix \( \Sigma_k \) currently available in MCLUST for hierarchical clustering (HC) and/or EM for multidimensional data. ('\*' in the appropriate column indicates availability).

<table>
<thead>
<tr>
<th>Identifier</th>
<th>Model</th>
<th>HC</th>
<th>EM</th>
<th>Distribution</th>
<th>Volume</th>
<th>Shape</th>
<th>Orientation</th>
</tr>
</thead>
<tbody>
<tr>
<td>EII</td>
<td>( \lambda I )</td>
<td>*</td>
<td>*</td>
<td>Spherical</td>
<td>equal</td>
<td>equal</td>
<td>NA</td>
</tr>
<tr>
<td>VII</td>
<td>( \lambda_k I )</td>
<td>*</td>
<td>*</td>
<td>Spherical</td>
<td>variable</td>
<td>equal</td>
<td>NA</td>
</tr>
<tr>
<td>EEI</td>
<td>( \lambda A )</td>
<td>*</td>
<td>*</td>
<td>Diagonal</td>
<td>equal</td>
<td>equal</td>
<td>coordinate axes</td>
</tr>
<tr>
<td>VEI</td>
<td>( \lambda_k A )</td>
<td>*</td>
<td>*</td>
<td>Diagonal</td>
<td>variable</td>
<td>equal</td>
<td>coordinate axes</td>
</tr>
<tr>
<td>EVI</td>
<td>( \lambda A_k )</td>
<td>*</td>
<td>*</td>
<td>Diagonal</td>
<td>equal</td>
<td>variable</td>
<td>coordinate axes</td>
</tr>
<tr>
<td>WI</td>
<td>( \lambda_k A_k )</td>
<td>*</td>
<td>*</td>
<td>Diagonal</td>
<td>variable</td>
<td>equal</td>
<td>coordinate axes</td>
</tr>
<tr>
<td>EEE</td>
<td>( \lambda DAD^T )</td>
<td>*</td>
<td>*</td>
<td>Ellipsoidal</td>
<td>equal</td>
<td>equal</td>
<td>equal</td>
</tr>
<tr>
<td>VVV</td>
<td>( \lambda_k D_k A_k D_k^T )</td>
<td>*</td>
<td>*</td>
<td>Ellipsoidal</td>
<td>variable</td>
<td>variable</td>
<td>variable</td>
</tr>
<tr>
<td>EEV</td>
<td>( \lambda D_k A D_k^T )</td>
<td>*</td>
<td>*</td>
<td>Ellipsoidal</td>
<td>equal</td>
<td>equal</td>
<td>variable</td>
</tr>
<tr>
<td>VEV</td>
<td>( \lambda_k D_k A D_k^T )</td>
<td>*</td>
<td>*</td>
<td>Ellipsoidal</td>
<td>variable</td>
<td>equal</td>
<td>variable</td>
</tr>
</tbody>
</table>

2 Obtaining and Installing MCLUST

MCLUST can be obtained in one of several ways:

- via the world wide web at http://www.stat.washington.edu/mclust
- via anonymous ftp from ftp.u.washington.edu in the directory public/mclust
- from Statlib; see http://lib.stat.cmu.edu/S/mclust

Note: The S-PLUS density function has been changed to add a method = "mclust" option (see Section 11.3). In both UNIX/Linux and Windows, there will be a warning that density has been masked. However, the default behavior of density remains unaltered.

2.1 Using MCLUST with S-PLUS 6 for UNIX/Linux

The file MCLUST.tar.gz is a packed version of a directory containing all the necessary files for incorporating MCLUST into S-PLUS on UNIX systems. The commands to unpack it (and remove the tar file) are:

gunzip MCLUST.tar.gz
tar xvf MCLUST.tar
tar zcvf MCLUST.tar
rm MCLUST.tar
This creates a directory called MCLUST. To run the software in this directory, do the following.

```bash
  cd MCLUST
  Splus CHAPTER
  Splus make
  Splus TRUNC_AUDIT 0
```

The `Splus make` command

- compiles the Fortran code, which will automatically loaded when S-PLUS is invoked in this directory.
- sources the S-PLUS functions in mclust.q into the .Data directory
- compiles and loads the help files (file extension .sgml)

The software can now be used by running S-PLUS in directory MCLUST. They can also be run in a different working directory, using the following S-PLUS commands

```r
  > dyn.open(".../MCLUST/S.so")
  > attach(".../MCLUST/.Data")
```

where `.../` indicates the path to the directory MCLUST.

### 2.2 Using MCLUST with S-PLUS 6 for Windows

The file Mclust.zip contains the necessary files for running MCLUST with S-PLUS 6 for Windows. To install MCLUST on Windows, extract the contents of Mclust.zip to a directory called mclust. That directory needs to be attached in S-PLUS in order to access the MCLUST functions. To use the MCLUST help files, either click on the file mclust.chm included in the folder, or else execute it as a command from a DOS prompt.

### 3 Hierarchical Clustering

MCLUST provides functions hc for model-based hierarchical agglomeration, and hclass for determining the resulting classifications. As an example of the use of hc and hclass, consider Fisher’s iris data [9], which is available as a data set in S-PLUS. Figure 1 is a pairs plot of the iris data in which the three species are differentiated by symbol.

We first transform the data from a three-dimensional array to a matrix in which the species information is lost, then apply the hierarchical clustering algorithm for variable volume spherical variances (VII):

```r
  > irisMatrix <- matrix(aperm(iris[,c(1,3,2)],150,4),dimnames(iris)[1:2])
  > hcVIIiris <- hc(modelName = "VII", data = irisMatrix)
```

---

A description of this data set is available in S-PLUS from the command line via `help(iris)` or from the S-PLUS help window under ‘datasets’.
Figure 1: Pairs plot of Fisher’s iris data showing classification into species.

The classification produced by \texttt{hc} for various numbers of clusters can be obtained with \texttt{hclass}. For example, for the classifications corresponding to 2 and 3 clusters:

\begin{verbatim}
> cl <- hclass(hcVIIiris, 2:3)
\end{verbatim}

The classifications can be displayed with the data using \texttt{clPairs}:

\begin{verbatim}
> clPairs(data = irisMatrix, classification = cl[, "2"])
> clPairs(data = irisMatrix, classification = cl[, "3"])
\end{verbatim}

More options for displaying clustering and classification results are discussed in Section 9.

The function \texttt{hc} starts by default with every observation of the data in a cluster by itself, and continues until all observations are merged into a single cluster. Arguments \texttt{partition} and \texttt{minclus} can be used to initialize the process at a chosen nontrivial partition, and to stop it before it reaches the final stage of merging.
4 EM for Mixture Models

\texttt{mclust} provides iterative EM (Expectation-Maximization) methods for maximum likelihood clustering with parameterized Gaussian mixture models. In this application, an iteration of EM consists of an ‘E’-step, which computes a matrix \( z \) such that \( z_{ik} \) is an estimate of the conditional probability that observation \( i \) belongs to group \( k \) given the current parameter estimates, and an ‘M-step’, which computes maximum likelihood parameter estimates given \( z \). In the limit, the parameters usually converge to the maximum likelihood values for the Gaussian mixture model

\[
\prod_{i=1}^{n} \sum_{k=1}^{G} \tau_k \phi_k(x_i \mid \mu_k, \Sigma_k),
\]

and the sums of the columns of \( z \) converge to \( n \) times the mixing proportions \( \tau_k \), where \( n \) is the number of observations in the data. Here \( G \) is the number of groups in the data, which is fixed in the EM algorithm. The parameterizations of \( \Sigma_k \) currently available for EM in \texttt{mclust} are listed in Table 1. They are a subset of the parameterizations discussed in [7], which gives details of the EM algorithm for these models.

\texttt{mclust} functions \texttt{em}, \texttt{me} (iterated M-step followed by E-step), \texttt{estep} and \texttt{mstep} implement EM for the parameterized Gaussian mixtures. Given the data, an initial estimate of \( z \), and the model specification, \texttt{me} produces the values of \( z \) associated with maximum likelihood parameters. Initial estimates of \( z \) may be obtained from a discrete classification, that is, a matrix of indicator variables with exactly one 1 per row. For example, \texttt{me} can be started with a classification produced by \texttt{hc}:

\begin{verbatim}
> hcVVViris <- hc( modelName = "VVV", data = irisMatrix) # unconstrained model
> cl <- hclass(hcVVViris, 3)  # 3-group hc classification
> meVVViris <- me( modelName = "VVV", data = irisMatrix, z = unmap(cl))
\end{verbatim}

The function \texttt{unmap} converts a discrete classification into the corresponding indicator variables. In general, the models used in \texttt{hc} and \texttt{me} need not be the same. It may in some cases be desirable to use one of the faster methods in \texttt{hc} (e.g. spherical or unconstrained models), followed by specification of a more complex model for EM.

For any matrix \( z \) of conditional probabilities, there is a corresponding discrete classification assigning each observation to the group represented by the column in which the \( z \) value for that observation (row) is maximized. \texttt{mclust} provides a function \texttt{map} for converting \( z \) to this ‘nearest’ classification. The following call to \texttt{clPairs} plots the iris data along with its classification obtained from \texttt{me} in the above example:

\begin{verbatim}
> clPairs( irisMatrix, map(meVVViris$z))
\end{verbatim}

Besides initial values, other parameters can influence the outcome of \texttt{em} or \texttt{me}. These include:

- \texttt{tol} Iteration convergence tolerance. The default is \texttt{.Mclust$tol=c(1.e-5, 1.e-5)}, where the first value is the tolerance for relative convergence of the loglikelihood in the EM algorithm, and the second value is the relative parameter convergence tolerance for the M-step for those models that have an iterative M-step ("VEI", "VEE", "VVE", "VEV").
eps A tolerance for terminating iterations due to ill-conditioning, such as near singularity in covariance matrices. The default is \( Mclust\$eps \) which is the relative machine precision \( 2.220446e-16 \) in the release.

Although these are in some sense hidden by the defaults, they may have a significant affect on results and should be taken into consideration in analysis. An example in which \( tol = 1.e-4 \) and \( tol = 1.e-5 \) give quite different results is given in Section 8.

### 4.1 Uncertainty

The uncertainty in the classification associated with \( z \) can be obtained by subtracting the probability of the most likely group for each observation from 1:

\[
> \text{uncer} \leftarrow 1 - \text{apply}( \text{meVWiris}\$z, 1, \text{max})
\]

The S-PLUS function \text{quantile} applied to the uncertainty gives a measure of the quality of the classification.

\[
> \text{quantile(uncer)}
\]

| %     | 0% | 25% | 50% | 75% | 100%
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0</td>
<td>0.949809e-08</td>
<td>0.001384177</td>
<td>0.3378195</td>
<td></td>
</tr>
</tbody>
</table>

In this case the indication is that the majority of observations are well classified. Note, however, that when groups intersect, uncertain classifications would be expected in the overlapping regions.

When a true classification is known, the relative uncertainty of misclassified observations can be displayed by the function \text{uncerPlot}, as is done below for the \text{iris} example (see Figure 2):

\[
> \text{irisClass} \leftarrow \text{rep(dimnames(iris)[[3]], rep(50,3))}
\]

\[
> \text{uncerPlot}(z = \text{meVWiris}\$z, \text{truth = irisClass})
\]

Plotting an uncertainty surface is also possible for two-dimensional data (see Section 9.1).

### 4.2 Individual E and M Steps

\text{MCLUST} includes functions \text{estep} and \text{mstep} implementing the individual steps of the EM iteration. Conditional probabilities \( z \) and the log likelihood can be recovered from parameters via \text{estep}, while parameters can be recovered from conditional probabilities \( z \) using \text{mstep}:

\[
> \text{ms} \leftarrow \text{mstep}( \text{modelName = "VVV", data = irisMatrix, z = meVWiris}\$z)
> \text{ms}
\]

\[
> \text{es} \leftarrow \text{estep}( \text{modelName = "VVV", data = irisMatrix,}
    \mu = \text{ms}\$\mu, \text{sigma = ms}\$\text{sigma, pro = ms}\$\text{pro})
> \text{es}
\]
Figure 2: Uncertainty plot for the 3-cluster classification of Fisher’s iris data via EM based on unconstrained Gaussian mixtures. The plot was created with `uncerPlot`, and shows the relative uncertainty of misclassified observations.

It is often useful in applications to invoke `estep` by an indirect or list call using the S-PLUS function `do.call`, in which the output of e.g. `mstep` is passed as a list without the need to explicitly identify individual parameters.

```r
> es <- do.call("estep", c(list(data = irisMatrix), ms))
> es
```

In Section 10.1, we show how to use `mstep` and `estep` for discriminant analysis.

## 5 Bayesian Information Criterion

`MCLUST` provides a function `bic` to compute the Bayesian Information Criterion (BIC) [19] given the maximized loglikelihood for model and the data dimensions. The BIC is the value of the maximized loglikelihood with a penalty for the number of parameters in the model, and allows comparison of models with differing parameterizations and/or differing numbers of clusters. In general the larger the value of the BIC, the stronger the evidence for the model and number of clusters (see, e.g. [11]). The following shows the BIC calculation in
MCLUST for the 3-cluster classification Fisher's iris data with the varying variance spherical model:

```r
> hcEIiris <- hc(modelName = "EII", data = irisMatrix)
> cl <- hclass(hcEIiris, 3)

> emEst <- me(modelName = "VII", data = irisMatrix, z = unmap(cl))

> n <- nrow(irisMatrix)
> d <- ncol(irisMatrix)

> bic( modelName = "VII", loglik = emEst$loglik, n = n, d = d, G = 3)
[1] -853.8133

> do.call("bic", emEst)
[1] -853.8133
```

The next section describes functions that combine hierarchical clustering, EM, and BIC in a comprehensive model-based clustering strategy.

6 Cluster Analysis

MCLUST provides two functions, Mclust and EMclust, for cluster analysis combining hierarchical clustering, EM, and BIC. In both functions, hierarchical clustering is used to initialize EM for various parameterizations of the Gaussian model. Mclust is intended to be a simplified function for one-step model-based clustering, with reasonable defaults. EMclust has more options and more flexibility, although it may be more complicated to use.

6.1 Mclust

The input to Mclust is the data and the minimum and maximum numbers of groups to consider. Mclust compares BIC values for parameters optimized via EM for the models EII, VII, EEI, VVI, EEE, VV. All models are initialized with the classification from hierarchical clustering based on the unconstrained VVV model. The output includes the parameters of maximum-BIC model, and the corresponding classification and uncertainty. The following is an example of the use of Mclust with Fisher's iris data:

```r
> irisMclust <- Mclust(irisMatrix)

> summary(irisMclust)

best model: ellipsoidal, unconstrained with 2 groups
```

An S-PLUS object produced by Mclust has the following components:
> names(irisMclust)
[1] "BIC"      "bic"      "classification" "uncertainty"
[5] "n"        "d"        "G"          "z"
[9] "mu"       "sigma"   "pro"        "loglik"
[13] "modelName"

Mclust has an associated plot method for displaying its results.

> plot(irisMclust,irisMatrix)

make a plot selection (0 to exit):

1: plot: BIC
2: plot: Pairs
3: plot: Classification (2-D projection)
4: plot: Uncertainty (2-D projection)
5: plot: All
Selection:

Figure 3 shows BIC, classification, and uncertainty plots corresponding to the model fit to the iris data.
Figure 3: Plots associated with the `mclust` function. Top: BIC. Lower Left: Projection of the optimal classification. Lower Right: Projection of the uncertainty of the optimal classification (see Section 9).
6.2 EMclust

EMclust has more flexibility than Mclust for clustering, by allowing choice of hierarchical clustering (which need not be model-based) as input to initialize EM and choice of models for EM. Users can obtain parameters and clustering results through `summary` for any model or number of mixture components specified, rather than just the maximum-BIC model as in Mclust.

The input to EMclust is the data, a list of models to apply in the EM phase, the desired numbers of groups to consider, and as hierarchical clustering tree in the same format as produced by the function hc for model-based hierarchical clustering (the default is to apply hc for the unconstrained model VVV to the data). It returns the BIC values for all of the chosen models and number of clusters, together with auxiliary information that is used by the corresponding `summary` method for recovering parameter values. The following is an example of the use of EMclust with Fisher’s iris data:

```
> irisBIC <- EMclust(irisMatrix)

> irisBIC

BIC:

<table>
<thead>
<tr>
<th></th>
<th>EII</th>
<th>VII</th>
<th>EEI</th>
<th>VEI</th>
<th>EVI</th>
<th>VVI</th>
<th>EEE</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>-1804.0854</td>
<td>-1804.0854</td>
<td>-1527.1308</td>
<td>-1527.1308</td>
<td>-1527.1308</td>
<td>-1527.1308</td>
<td>-829.9782</td>
</tr>
<tr>
<td>2</td>
<td>-1123.4115</td>
<td>-1012.2352</td>
<td>-1047.9786</td>
<td>-961.2929</td>
<td>-1017.3295</td>
<td>-867.5728</td>
<td>-688.0972</td>
</tr>
<tr>
<td>3</td>
<td>-878.7652</td>
<td>-853.8133</td>
<td>-818.0635</td>
<td>-784.1658</td>
<td>-812.8672</td>
<td>-759.6687</td>
<td>-632.9658</td>
</tr>
<tr>
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<td>-784.3098</td>
<td>-783.8263</td>
<td>-740.4955</td>
<td>-721.5350</td>
<td>-752.5491</td>
<td>-725.1132</td>
<td>-591.4097</td>
</tr>
<tr>
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<td>-705.7813</td>
<td>-698.8104</td>
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<td>-752.2155</td>
<td>-726.9666</td>
<td>-621.8183</td>
</tr>
<tr>
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<td>-705.0659</td>
<td>-688.4205</td>
<td>-664.6910</td>
<td>-749.2664</td>
<td>-729.2289</td>
<td>-613.4585</td>
</tr>
<tr>
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<td>-710.5799</td>
<td>-666.0947</td>
<td>-662.2667</td>
<td>-743.7443</td>
<td>-741.9637</td>
<td>-622.4215</td>
</tr>
<tr>
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<td>-703.3490</td>
<td>-683.6092</td>
<td>-672.0079</td>
<td>-782.4605</td>
<td>-772.4925</td>
<td>-638.2063</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>EEV</th>
<th>VEV</th>
<th>VVV</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>-829.9782</td>
<td>-829.9782</td>
<td>-829.9782</td>
</tr>
<tr>
<td></td>
<td>-644.5997</td>
<td>-561.7285</td>
<td>-574.0178</td>
</tr>
<tr>
<td></td>
<td>-617.7022</td>
<td>-562.5519</td>
<td>-580.8400</td>
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<td>-628.9642</td>
</tr>
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<td></td>
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</tr>
<tr>
<td></td>
<td>-669.7087</td>
<td>-681.3057</td>
<td>-711.5716</td>
</tr>
<tr>
<td></td>
<td>-682.3451</td>
<td>-707.9405</td>
<td>-752.7982</td>
</tr>
<tr>
<td></td>
<td>-722.7178</td>
<td>-735.8582</td>
<td>-790.7023</td>
</tr>
<tr>
<td></td>
<td>-772.5045</td>
<td>-790.6323</td>
<td>-824.8824</td>
</tr>
</tbody>
</table>

> plot(irisBIC)

<table>
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<tr>
<th></th>
<th>EII</th>
<th>VII</th>
<th>EEI</th>
<th>VEI</th>
<th>EVI</th>
<th>VVI</th>
<th>EEE</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>A</td>
<td>B</td>
<td>C</td>
<td>D</td>
<td>E</td>
<td>F</td>
<td>G</td>
</tr>
</tbody>
</table>

The BIC values for this example are shown in Figure 4, with the key to symbols returned by
the plot method. Application of the summary function to this result gives a classification as well as model parameters (not printed):

```r
> irisSummary <- summary(irisBIC, irisMatrix)
```

```
> irisSummary

classification table:
  1  2
 50 100

uncertainty (quartiles):
  0% 25% 50% 75% 100%
   0  0  0 8.917533e-12 0.0002025613

best BIC values:
  VEV,2 VEV,3 VVV,2
-561.7285 -562.5519  -574.0178

best model: ellipsoidal, equal shape
```

The best model among those fitted by EMclust is the equal-shape model VEV, with 2 clusters. The same model with 3 clusters has a BIC value that is little different from the maximum; the conclusion is that there are either 2 or 3 clusters in the data under these models. The 2 cluster EMclust result separates one species from the other while the 3 cluster result nearly separates the three species (there are 5 misclassifications out of 150).

Optimal parameter and z values are available through the summary function associated with EMclust objects, which has arguments allowing the summarizing information to be restricted to a subset of the number of clusters and models. The summary function requires the data to be supplied as an argument in addition to the output from EMclust. The best classification (according to the BIC) is recovered from summary by default. The next best classification is the 3 group classification with the unconstrained model VVV. Parameters associated with this classification can be recovered via summary as follows:

```r
> iris3 <- summary(irisBIC, irisMatrix, G = 3, modelNames = "VEV")
```

```
> iris3

classification table:
  1  2  3
 50 45 55

uncertainty (quartiles):
  0% 25% 50% 75% 100%
   0  0 1.048137e-06 0.002528291 0.4058713
```
Figure 4: BIC values from EMclust for the models A - EII, B - VII, C - EEI, D - VEI, E - EVI, F - VVI, G - EEE, H - EEV, I - VEV, J - VVV applied to Fisher’s iris data.

best BIC value:

VEV,3
-562.5519

best model: ellipsoidal, equal shape

For a complete analysis, it may be desirable to try varying models, initialization strategies for EM and values for the convergence tolerance, as well as using permutations or subsets of the observations, and/or perturbations the data, to see if the classification remains stable. Scaling or otherwise transforming the data may also affect the results. It is advisable to examine the data beforehand, in case (for example) the dimensions can be reduced due to highly correlated variables.

Finally, it is important to take into account numerical issues in cluster analysis. The EM computations break down when the covariance corresponding to one or more components becomes ill-conditioned (singular or nearly singular). In general they cannot proceed if clusters contain only a few observations or if the observations they contain are very nearly colinear. If EM for a model having a certain number of components is applied to a mixture in which there are actually fewer groups, then it may fail due to ill-conditioning. For more
information about ill-conditioned matrices and the resulting consequences for computation, see [14]. The EM functions in MCLUST compute and monitor the conditioning of the covariances, and an error condition is issued when the associated covariance appears to be nearly singular, as determined by a threshold with the default value .Mclust$\text{eps}$.

### 6.3 Clustering with Noise and Outliers

MCLUST uses mixture model which has a single term representing noise as a first order Poisson process to handle noisy data:

\[
\prod_{i=1}^{n} \left[ \frac{\tau_0}{V} + \sum_{k=1}^{K} \tau_k \phi_k(x_i \mid \theta_k) \right],
\]

in which \(V\) is the hypervolume of the data region, and \(\tau_k \geq 0; \sum_{k=0}^{C} \tau_k = 1\). This model has been used successfully in a number of applications [2, 8, 5, 6].

The basic model-based clustering method needs to be modified when the data contains noise. First, a good initial noise estimate must be obtained. Some possible methods for denoising include a Voronoi method [1] and a nearest-neighbor method [4]. Next, hierarchical clustering is applied to the denoised data. Finally, EM based on the Gaussian model with the added noise term (2) is applied to the entire data set, with the data removed in the denoising process as the initial noise estimate.

MCLUST provides a function EMclustN for model-based clustering with noise. In the following example, Poisson noise is added to Fisher’s iris data, with a random initial estimate for the noise.

```r
irisMatrix <- matrix(aperm(iris, c(1,3,2)), 150, 4) dimnames(irisMatrix) <- list(NULL, dimnames(iris)[[2]])

b <- apply(irisMatrix, 2, range) n <- 450 set.seed(0) poissonNoise <- apply(b, 2, function(x, n=n) runif(n, min = x[1]-0.1, max = x[2]+.1), n = n) set.seed(0) noiseInit <- sample(c(T,F),size=150+450,replace=T,prob=c(3,1)) Bic <- EMclustN(data=cbind(irisMatrix,poissonNoise),noise=noiseInit)
```

The data and classification are shown in Figure 5.
Figure 5: Cluster analysis of Fisher’s iris data with added Poisson noise. Upper Left: A projection Fisher’s iris data (circles) with 450 Poisson noise points (small dots). Upper Right: EMclustN classification. Lower: BIC from EMclustN.
7 Simulation from Mixture Densities

Because the cluster analysis strategy described in Section 6 is a model-fitting procedure, it has uses other than grouping observations. Given the parameters for a mixture model, data can be simulated from that model for evaluation and verification. The function `sim` allows simulation from mixture models generated by `MCLUST` functions. Besides the model, `sim` allows a seed as input for reproducibility. As an example, below we simulate from the 2 and 3 class equal-shape models produced by `EMclust` in Section 6.2:

```r
> model2 <- summary( irisBIC, irisMatrix, G=2, modelName="VEV")
> sim2 <- do.call("sim", c(list( n=1000, seed=0), model2))

> model3 <- summary( irisBIC, irisMatrix, G=3, modelName="VEV")
> sim3 <- do.call("sim", c(list( n=1000, seed=0), model3))

> par(pty = "s") # square plotting surface

> coordProj(data=sim2, mu = model2$mu, sigma = model2$sigma)

> coordProj(data=sim3, mu = model3$mu, sigma = model3$sigma)

A projection of each of these simulations is shown in Figure 6, along with the same projection of Fisher’s iris data.
Figure 6: A projection of data simulated from EMclust models for Fisher’s iris data. Upper Left: 1000 data points simulated from the 2-component VEV model. Upper Right: 1000 data points simulated from the 3-component VEV model. Lower: Fisher’s iris data showing classification.
8 Density Estimation

The clustering capabilities of \texttt{MCLUST} can also be viewed as a general strategy for multivariate density estimation.

As an example, we focus on density estimation for the location of maple trees in the Lansing Woods [13, 15] (see Figure 7).

![Lansing Woods Maple Trees](image)

Figure 7: Lansing Woods maple trees.

\texttt{MCLUST} can be used for density estimation as follows: First, use \texttt{EMclust} to get a model for the Lansing Woods maples:

\begin{verbatim}
> maples <- lansing[,"species"] == "maple", -3
> maplesBIC <- EMclust(maples)
> maplesModel <- summary(maplesBIC, maples)
\end{verbatim}

Next, use \texttt{dens} to get the density of a given point relative to that model. The following computes the density on a $100 \times 100$ grid. The function \texttt{grid1} forms a one dimensional grid of a given size over a given range of values, while \texttt{grid2} forms a two dimensional grid given two sequences of values.
> x <- grid1( 150, range = c(0,1))
> y <- grid1( 100, range = c(0,1))
> xy <- grid2(x,y)
> xyDens <- do.call("dens", c(list(data = xy), maplesModel))

The result can be plotted using S-PLUS functions contour, persp, or image.

> par(pty = "s")
> Z <- matrix(log(xyDens), nrow = length(x), ncol = length(y))
> contour(x = x, y = y, z = Z, nlevels = 20)
> persp(x = x, y = y, z = Z)
> image(x = x, y = y, z = Z)

Figure 8 shows the density estimate for both the default convergence tolerance .Mclust$tol = 1.e-5 and a relaxed convergence tolerance 1.e-4 in EMclust. For information on creating classification and density displays for model-based clustering results, see Section 9.
Figure 8: Density estimation for the Lansing Woods maples. Left: relaxed convergence tolerance $\texttt{tol = 1.e-4}$. Right: default convergence tolerance $\texttt{tol = 1.e-5}$. First Row: BIC from model-based clustering. Second Row: EMclust classification with circles/ellipses indicating the standard deviation of each component. Third Row: Density contours with the location of the maples superimposed.
Standard Gaussian kernel density estimates for this data are shown in Figure 9. The kernel densities and bandwidths were computed using the sm software (Bowman and Azzalini 1997).

![Gaussian kernel / cross-validated bandwidth](image1)

![Gaussian kernel / normal optimal smoothing](image2)

Figure 9: Gaussian kernel density estimates for the Lansing Woods maples. Left: Cross-validated bandwidth. Right: Normal optimal bandwidth.

Probably the most common application for density estimation is discriminant analysis, for which a detailed discussion is given in Section 10.

9 Displays

Once parameters values are available, projections of the data showing the means and standard deviations of the corresponding clusters may be plotted. In the two-dimensional case, density and uncertainty surfaces may also be plotted.

9.1 Plotting Two-Dimensional Results

The function mclust2Dplot may be used for displaying the classification, uncertainty, or classification errors for MCLUST models of two-dimensional data. In the following example, classification and uncertainty plots are produced for the Lansing Woods maples example of Section 8. We have defined a function plotMaples1 that calls mclust2Dplot to facilitate plotting the results already obtained for Fisher’s iris data.

```r
> plotMaples1
function(type)
{
  out <- do.call("mclust2Dplot", c(list(data = maples, type = type),
                                 maplesModel))

  invisible()
}
```
Figure 10: Classification (left) and uncertainty (right) for the EMclust modeling of the Lansing Woods maples created with mclust2Dplot. The circles shown are the standard deviations of each mixture component. In the classification plot, points in different classes are indicated by different symbols. In the uncertainty plot, the symbols have the following meaning: large filled symbols, 95% quantile of uncertainty; smaller open symbols, 75–95% quantile; small dots, first three quartiles of uncertainty.

> par(pty = "s", mfrow = c(1,2)) ## plotting parameters

> plotMaples1(type = "classification")
> title("Classification", cex = 0.75)

> plotMaples1(type = "uncertainty")
> title("Uncertainty", cex = 0.75)

The resulting plots are displayed in Figure 10.

The function surfacePlot may be used for displaying the density or uncertainty for MCLUST models of two-dimensional data. It also returns the grid coordinates and corresponding surface values. The following example shows how to display density and uncertainty surfaces for the Lansing Woods maples models.

> plotMaples2
function(type, what, transformation)
{
  out <- do.call( "surfacePlot", c(maplesModel,
  list(data = maples, type = type, what = what, transformation = transformation))
  invisible()
}

> par(pty = "s", mfrow = c(3,2)) ## plotting parameters

> plotMaples2(type = "contour", what = "density", transformation = "log")

25
> plotMaples2(type = "contour", what = "uncertainty", transformation = "log")
> plotMaples2(type = "persp", what = "density", transformation = "log")
> plotMaples2(type = "persp", what = "uncertainty", transformation = "log")
> plotMaples2(type = "image", what = "density", transformation = "log")
> plotMaples2(type = "image", what = "uncertainty", transformation = "log")

The resulting plots are displayed in Figure 11. Note that a gray scale or color scheme may need to be specified on the display device in order to view the image plots.
Figure 11: Density (left column) and uncertainty (right column) surfaces for the Lansing Woods maples. Contour, perspective, and image plots are displayed in the first, second, and third rows respectively. A logarithmic scale was used for the contour plots.
9.2 Plotting Multidimensional Results

9.2.1 Coordinate Projections

To plot coordinate projections in MCLUST, use the function coordProj. In what follows we have defined a function coordIris that calls coordProj to facilitate plotting the results already obtained for the iris data. Note that truth is used only for the errors plot. If the plot type isn’t specified, coordProj will offer a menu of options if there is more than one possibility.

> coordIris
function(dimens, type)
{
  out <- do.call("coordProj", c(list(data = irisMatrix, truth = irisClass,
                                 dimens = dimens, type = type), meVWViris))
  invisible()
}

> par(pty = "s", mfrow = c(2,3))

> coordIris( dimens = c(1,2), type = "classification")
> title("3 Group Classification, Unconstrained Model")

> coordIris( dimens = c(1,2), type = "uncertainty")
> title("Uncertainty")

> coordIris( dimens = c(1,2), type = "errors")
> title("Classification Errors")

Plots for dimens = c(1,2) and dimens = c(3,4) are displayed in Figure 12.
Figure 12: Coordinate projections of Fisher’s iris data created with \texttt{coordProj}. Plots show the 3-cluster classification with associated uncertainty and classification errors for the unconstrained Gaussian mixture model (VVV).
9.2.2 Random Projections

To plot random projections in MCLUST, use the function randProj. In what follows we have defined a function randIris that calls randProj to facilitate plotting the results already obtained for Fisher’s iris data.

```r
> randIris
function(seed, type)
{
  out <- do.call("randProj", c(list(data = irisMatrix, truth = irisClass,
                                   seed = seed, type = type), meVWViris))
  invisible()
}

> par(pty = "s", mfrow = c(2,3))

> randIris( seed = 646, type = "classification")
> title("3 Group Classification, Unconstrained Model")

> randIris( seed = 646, type = "uncertainty")
> title("Uncertainty")

> randIris( seed = 646, type = "errors")
> title("Classification Errors")

Plots for seed = 646 and seed = 666 are displayed in Figure 13.
Figure 13: Random projections of Fisher's iris data created with `randProj`. Plots show the 3-cluster classification with associated uncertainty and classification errors for the unconstrained Gaussian mixture model (WVW).
10 Discriminant Analysis

In discriminant analysis, observations of known classification are used to classify others. MCLUST provides a number of functions that can be used for discriminant analysis. We demonstrate some possible methods applied to the Lansing Woods data [13, 15], which gives the spatial location of maple and hickory trees (see Figure 14).

![Lansing Woods Hickory and Maple Trees](image)

Figure 14: Location of Hickory and Maple Trees in the Lansing Woods. There are 703 hickories (triangles) and 514 maples (squares) in the data set.
10.1 Discriminant Analysis using mstep and estep

MCLUST functions mstep and estep implementing the individual steps of the EM algorithm for Gaussian mixtures can be used for discriminant analysis. The idea is to produce a density estimate for the training data which is a mixture model, in which each known class is modeled by a single Gaussian term.

First, the parameterization giving the best model fit to the training data must be chosen. Most commonly, this would be done by leave-one-out cross validation. Leaving out one training observation at a time, MCLUST function cv1EMtrain fits each model using mstep, then classifies the observation that was left out using estep. The output of cv1EMtrain measures the error rate for each model; that is, the fraction of left-out observations correctly classified by the model fit to the remaining observations.

Using the odd numbered observations in the Lansing Woods data as a training set, the result is:

```r
gt> odd <- seq(from=1, to=nrow(lansing), by=2)
gt> round(cv1EMtrain(data = lansing[odd,-3], labels = lansing[odd,3]),3)
    EII VII EEI VEI EVI VVI EEE EEV VEV VVV
 0.351 0.355 0.345 0.353 0.34 0.358 0.345 0.333 0.35 0.35
```

The equal shape, equal volume, varying orientation model EEV would be selected as the best model, although the error rates do not vary much among the models. When there are two training classes, the EEE model corresponds to linear discriminant analysis, while the VVV model corresponds to quadratic discriminant analysis (e.g. [16]).

To classify the even data points, we first compute the parameters corresponding to the EEV model for the odd data points using mstep, then use estep to get conditional probabilities z and a classification:

```r
gt> cv1Modd <- mstepEEV(data= lansing[odd,-3], z=unmap(lansing[odd,3]))
gt> cv1Zodd <- do.call("estepEEV", c(cv1Modd, list(data= lansing[odd,-3])))$z
gt> compClass(map(cv1Zodd), lansing[odd,3])$error
[1] 0.3316913
```

```r
gt> even <- seq(from=2, to=nrow(lansing), by=2)
gt> cv1Zeven <- do.call("estepEEV", c(cv1Modd, list(data= lansing[even,-3])))$z
gt> compClass(map(cv1Zeven), lansing[even,3])$error
[1] 0.3125
```

The error rate for the training [odd-numbered] data is 33%, while for the test [even-numbered] data it is 31%. The results for this analysis are displayed in the left hand plot of Figure 15.

Another option for model selection that is quicker to compute than cross-validation is to select the best fitting model via BIC after using mstep to fit each model to the training data. A function bicEMtrain is provided in MCLUST for this purpose. For the Lansing Woods data, BIC for the models fitted to the odd-numbered observations is:

```r
gt> round(bicEMtrain(lansing[odd,-3], labels = lansing[odd,3]),1)
    EII VII EEI VEI EVI VVI EEE EEV VEV VVV
-512.1 -526.5 -520 -533.7 -539.5 -554.7 -519.7 -534.3 -549.7 -553.4
```

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According to BIC, the spherical model with equal volume EII is the best model. The error rate for the training data is about 35%, while for the test data it is 33%:

```r
> bicModd <- mstepEII(data=lansing[odd,-3], z=unmap(lansing[odd,3]))
> bicZodd <- do.call("estepEII", c(bicModd, list(data=lansing[odd,-3])))$z
> compClass(map(bicZodd), lansing[odd,3])$error
[1] 0.3513957

> even <- seq(from = 2, to = nrow(lansing), by = 2)
> bicZeven <- do.call("estepEII", c(bicModd, list(data=lansing[even,-3])))$z
> compClass(map(bicZeven), lansing[even,3])$error
[1] 0.3305921
```

The results for this analysis are displayed in the right hand plot of Figure 15. Although the error rate for the test data is somewhat higher for BIC than for crossvalidation, it should be noted that it took more than 10 minutes to execute cv1EMtrain on this training data, while bicEMtrain executed in about half a second.4

### 10.2 Mixture Discriminant Analysis via MclustDA

In Section 10.1, discriminant analysis was accomplished modeling the training data by a mixture density with a single Gaussian component for each class. That section also showed

---

4This is not a precise algorithmic timing comparison because crossvalidation can be accomplished more efficiently for these models using updating schemes, and because the interpreted language S-PLUS is used for parts of the training code.
how to choose the appropriate cross-cluster constraints to give the lowest training error rate using either leave-one-out crossvalidation or BIC. Better discriminant analysis results can often be obtained by using model-based clustering to fit a Gaussian mixture model as a density estimate for each class in the training set.

10.2.1 mclustDA

If both training and test sets are given in advance, the function mclustDA can be used for discriminant analysis. Its input is the training data and associated class labels, and the test data. Six candidate models are considered in the training phase: EII, VII, EEI, VVI, EEE and VVV. The output of mclustDA includes the mixture models for the training data, the classification of both the test data and training data under the model, posterior probabilities for the test data, and the training error rate.

> discriminant <- mclustDA(trainingData = lansing[odd,-3], labels = lansing[odd,3], testData = lansing[even,-3])

> discriminant

trainClass mclustModel numGroups
hickory    hickory    EII     4
maple      maple      EEE     4

training error rate: 0.228

> confusionMatrix(discriminant$testClassification, lansing[even,3])$error
[1] 0.2450658

The error rates for mclustDA classification of the Lansing Woods data are about 23% and 25% for the training [odd-numbered] and test [even-numbered] data, respectively.

The associated plot method offers a selection of coordinate projection plots.

> par(pty = "s", mfrow = c(2,2)) ## plotting parameters

> plot(discriminant, trainingData = lansing[odd,-3], labels = lansing[odd,3],
       testData = lansing[even,-3], identify = T)

make a plot selection (0 to exit):

1: plot: Training and Test Data
2: plot: Training Data - known classification
3: plot: Test Data - mclustDA classification
4: plot: Training Data - misclassified observations
5: plot: All
Selection: 5

Figure 16 shows the result of selecting All. Figure 17 shows the training models for the two classes, as well as the discriminant curve and the misclassified (training and test) data points.
Figure 16: Plots associated with \texttt{mclustDA}. Upper Left: the training [odd-numbered/circles] and test [even-numbered/crosses] Lansing Woods data. Upper Right: the training data with known classification. Lower Left: the \texttt{mclustDA} classification of the data. Lower Right: the errors (filled symbols) in using the \texttt{mclustDA} model to classify the training data.
Figure 17: mclustDA models and discriminant curve for the Lansing Woods data. Upper Left: Model for the training [odd-numbered] hickories. Upper Right: Model for the training [odd-numbered] maples. Lower: discriminant curve with training and test errors (filled symbols). Note the small piece of the curve in the lower left-hand corner.

10.2.2 mclustDAtrain and mclustDAtest

Often more flexibility is required in discriminant analysis. For example, a suitable training set may need to be chosen and/or it may be desirable to test additional data after a training density has already been established. Since training takes much more time than testing, it can be advantageous to separate training and testing computations. In contrast to mclustDA, mclustDAtrain also allows users to choose training model parameterizations, and selects from among all available models as a default. The output of mclustDAtrain is a list, each element being the model for each class.

In the simplest case, a single Gaussian could be fit to each training class. This is similar to the discriminant analysis procedure of Section 10.1, except that in MclustDA a model in for each class of the training data is chosen separately, instead of choosing a parameterized mixture model (which may have cross-cluster constraints) for the training data. In discrim-
inant analysis via M-step and E-step (Section 10.1) restricted to the unconstrained (VVV) model, the maximum likelihood Gaussian is fitted to each component. MclustDA uses BIC, which adds a penalty term to the maximized loglikelihood that increases with the number of parameters, to select the model.

```r
> train1 <- mclustDAtrain(data=lansing[odd,-3], labels=lansing[odd,3], G=1)
EE EII
   1  1
```

The best model for the hickories has an ellipsoidal covariance, while the best model for the maples has a spherical covariance, with error rates as follows:

```r
> test1odd <- mclustDAtest(data = lansing[odd,-3], models = train1)
> names(summary(test1odd))
[1] "classification" "z"

> compClass(summary(test1odd)$classification, lansing[odd,3])$error
[1] 0.3513957

> test1even <- mclustDAtest(data = lansing[even,-3], models = train1)
> compClass(summary(test1even)$classification, lansing[even,3])$error
[1] 0.3618421
```

Prior probabilities for each class can be supplied to the `summary` function for `mclustDAtest`. For example, the proportions of the known classes in the training set could be used as prior probabilities. In the Lansing Woods example, the error rates are somewhat improved with these prior probabilities:

```r
> Hodd <- as.character(lansing[odd, 3]) == "hickory"
> pr0dd <- length(Hodd[Hodd])/length(odd)
> pr0dd
[1] 0.5779967

> probs <- c(pr0dd, 1-pr0dd)

> compClass(summary(test1odd, pro=probs)$classification, lansing[odd,3])$error
[1] 0.3497537

> compClass(summary(test1even,pro=probs)$classification, lansing[even,3])$error
[1] 0.3388158
```

These discriminant analysis results are displayed in Figure 18. By default, `mclustDAtrain` will fit up to nine components for each possible model. Results for the odd-numbered observations in the Lansing Woods data are as follows:
Figure 18: MclustDA with one component per training class. The plots show one standard deviation of the Gaussians used to fit each class of the training data, as well as the discriminant curve (hatched line) where the two groups have equal posterior density. Filled symbols represent misclassified training [odd-numbered] and test [even-numbered] observations. Left: Assumes equal prior probabilities. Right: Assumes training prior probabilities.

```r
> train <- mclustDAtrain(data = lansing[odd,-3], labels = lansing[odd,3])
  EEE EEE
  7  4

> summary(train)
$hickory:
$hickory$model:
[1] "EEV,7"

$hickory$classification:
  [1] 1 1 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3
[38] 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3
[75] 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3
[112] 3 3 2 2 3 2 3 2 3 2 1 1 6 2 2 2 2 4 2 2 4 2 4 6 6 1 1 5 6 6 6 4 6 4 4 4 3 3 3 1 6 1 2 2 2 4 2 4 6 6 1
[149] 1 2 2 2 2 4 2 2 4 6 6 1 1 5 6 6 4 4 4 3 3 3 3 1 6 1 2 2 2 4 2 4 6 6 1
[186] 5 5 6 6 4 4 4 2 1 1 6 1 2 2 2 2 4 2 4 6 6 6 1 1 5 5 6 6 4 4 4 3 1 1 6 1 2
[223] 2 2 2 4 2 4 6 6 6 1 1 5 5 6 6 4 4 4 5 5 5 7 7 7 7 7 7 7 7 7 7 7 7 7 5 5
[260] 5 5 5 4 5 4 5 5 5 7 7 7 7 7 5 5 5 5 5 5 4 5 5 5 5 5 5 7 7 7 7
[297] 7 7 7 7 7 5 5 5 5 5 5 5 5 5 5 5 7 7 7 7 7 7 7 7 7 5 5 5 5 5 5 5 5 5
[334] 5 5 5 7 7 7 7 7 7 7 7 7 7 7 7 5 5 5 5 5 5 4
```

$\text{maple:}$
$\text{maple$model:}$
$\text{[1] "EEE,4"}$

$\text{maple$classification:}$
$\text{[1] 1 1 1 2 1 1 1 1 1 1 1 1 1 1 2 2 2 2 2 2 2 3 2 2 2 4 2 4 1 1 1 2 1 1 1 1 1 1 2 2 2 2 3 2 2 2 2 4 1 4 1 1}$
$\text{[38] 2 2 2 2 3 2 2 2 4 1 4 1 1 1 2 2 1 1 1 1 1 1 2 2 2 2 3 3 2 2 2 1 4 1 1 2 2 1 1 1 1 1 1 1 2 2 2 2}$
$\text{[75] 2 2 1 1 1 1 1 1 1 2 2 2 2 2 2 3 3 3 3 2 2 2 2 1 4 1 1 2 2 1 1 1 1 1 1 2 2 2 2 2 2 2 2 4 1 4 1 1}$
$\text{[75] 2 2 1 1 1 1 1 1 1 2 2 2 2 2 2 3 3 3 3 2 2 2 2 1 4 1 1 2 2 1 1 1 1 1 1 2 2 2 2 2 2 2 2 4 1 4 1 1}$
$\text{[75] 2 2 1 1 1 1 1 1 1 2 2 2 2 2 2 3 3 3 3 2 2 2 2 1 4 1 1 2 2 1 1 1 1 1 1 2 2 2 2 2 2 2 2 4 1 4 1 1}$
$\text{[75] 4 4 4 2 3 3 3 3 3 3 3 3 4 4 4 4 4 4 4 4 1 1 4 4 4 4 2 3 3 3 3 3 3 3 3 4 4 4 4 4 4 4 4 4 1 1 4 4}$
$\text{[149] 4 4 4 2 3 3 3 3 3 3 3 3 4 4 4 4 4 4 4 4 1 1 4 4 4 4 2 3 3 3 3 3 3 3 3 4 4 4 4 4 4 4 4 4 1 1 4 4}$
$\text{[186] 4 4 4 4 4 4 4 4 4 1 1 4 4 4 4 4 2 3 3 3 3 3 3 3 3 4 4 4 4 4 4 4 4 4 1 1 4 4 4 4 4 4 4 4 1 1 4 4}$
$\text{[223] 4 2 3 3 3 3 3 3 3 3 3 3 3 4 4 4 4 4 4 4 4 4 4 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3}$

In this case $\text{mclustDAt}\text{r}i\text{n}$ chooses the 7-class EEV model for the hickory training class and the 4-class EEE model (the same model chosen by $\text{mclustDA}$) for the maple training class.

The density of the test data under the training models can be obtained using $\text{mclustDA}t\text{est}$, while the classification and posterior probabilities of the test data can be recovered from the summary function for $\text{mclustDA}t\text{est}$:

\begin{verbatim}
> testTrain <- mclustDAtest(models = train, data = lansing[odd,-3])

> names(summary(testTrain))
[1] "classification" "z"

> compClass(summary(testTrain)$classification, lansing[odd,3])$error
[1] 0.2249589

> testTest <- mclustDAtest(models = train, data = lansing[even,-3])

> compClass(summary(testTest)$classification, lansing[even,3])$error
[1] 0.2450658
\end{verbatim}

The error rates are about 23% and 25% for the training [odd-numbered] and test [even-numbered] data, respectively, in this case about the same as $\text{mclustDA}$ which restricts the class of models. Figure 19 shows the 7-group EEV model for the hickory training class, as well as the discriminant curve and the misclassified (training and test) data points.
Figure 19: mclustDAttrain models and discriminant curve for the Lansing Woods data. Left: the hickory training [odd-numbered] class with its 7-group EEV model. Right: discriminant curve with training and test errors (filled symbols).
11 One Dimensional Data

The MCLUST functions for clustering, density estimation and discriminant analysis can be applied to one-dimensional as well as multidimensional data. Analysis is somewhat simplified since there are only two possible models — equal variance (denoted E) or varying variance (denoted V).

11.1 Clustering

As an example, we use simulated data consisting of two clusters with variance 1 centered at −9 and 9, respectively, and one cluster with variance 4 centered at 0:

> set.seed(999)
> x <- c(rnorm(300, -9), rnorm(400, 0, sd = 2), rnorm(300, 9))

Cluster analysis for one-dimensional data can be carried out as for two and higher dimensions, except that there is a special plotting function mclust1Dplot:

> par(mfrow = c(2,2))
> xBIC <- EMclust(x)
> plot(xBIC)
> E V
> "1" "2"

> xModel <- summary(xBIC, x)

> do.call("mclust1Dplot", c(list(data = x), xModel))

 mclust1Dplot: make a plot selection (0 to exit):

1: classification
2: uncertainty
3: density
4: all
Selection:

Figure 20 shows the BIC, classification, uncertainty, and density for this simulated example.

11.2 Discriminant Analysis

To illustrate discriminant analysis on one-dimensional data, we use the simulated data set x from the previous section as a training set, with the group centered at the origin as one class and the remaining groups as another.

> set.seed(999)
> x <- c(rnorm(300, -9), rnorm(400, 0, sd = 2), rnorm(300, 9))
> xClass <- c(rep(1,300),rep(2,400),rep(1,300))

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Figure 20: Model-based clustering of one-dimensional data. Clockwise from upper left: BIC, classification, uncertainty, and density from \texttt{EMclust} applied to the simulated one-dimensional example. In the classification plot, all of the data is displayed at the bottom, with the separated classes shown different levels above.

We use the following simulated data as a test set:

```r
> set.seed(0)
> y <- c(rnorm(100, -9), rnorm(100, 0, sd = 2), rnorm(100, 9))
> yClass <- c(rep(1,100),rep(2,100),rep(1,100))
```

Discriminant analysis via EM (Section 10.1) is possible in one dimension. Both leave-one-out crossvalidation and BIC choose the equal variance model E in the training stage:
> round(cv1EMtrain(x, labels=xClass), 3)
  E V
  0.4 0.057
> round(bicEMtrain(x, labels=xClass), 3)
  E V
  -6785.284 -7046.888

The varying variance model \( V \) is chosen by cross-validation, while the equal-variance model is chosen by BIC. The training and test errors for the data with these models are as follows.

Equal variance:

> xEmstep <- mstep(modelName = "E", data = x, z = unmap(xClass))

> xEz <- do.call("estep", c(list(data = x), xEmstep))$z
> compClass(map(xEz), xClass)$error  ## training error
[1] 0.4

> yEz <- do.call("estep", c(list(data = y), xEmstep))$z
> compClass(map(yEz), yClass)$error  ## testing error
[1] 0.3333333

Varying variance:

> xVmstep <- mstep(modelName = "V", data = x, z = unmap(xClass))

> xVz <- do.call("estep", c(list(data = x), xVmstep))$z
> compClass(map(xVz), xClass)$error  ## training error
[1] 0.057

> yVz <- do.call("estep", c(list(data = y), xVmstep))$z
> compClass(map(yVz), yClass)$error  ## testing error
[1] 0.0433333

For discriminant analysis via MclustDA (Section 10.2):

> xtrain <- mclustDAtain(x, labels = xClass)
  E E
  2 1
> xTest <- summary(mclustDAtest(x, xtrain))
> compClass(xTest$classification, xClass)$error  ## training error
[1] 0

> yTest <- summary(mclustDAtest(y, xtrain))
> compClass(yTest$classification, yClass)$error  ## testing error
[1] 0.003333333
11.3 "mclust" option for S-PLUS density function

MCLUST includes an augmented version of the S-PLUS function density for computing the
density of a one-dimensional data set. A method argument has been added, with the option
to specify method = "mclust" to have the density computed via model-based clustering,
instead of the default kernel estimate.

```r
> xdens.default <- density(x, n = 100)
> xdens.mclust <- density(x, n = 100, method = "mclust")
```

The resulting densities for the simulated data used in the previous two sections are dis-
played in Figure 21. A simulation study [18] showed that mixtures of normals with equal

![Density Comparison](image)

Figure 21: A comparison of method = "mclust" and default kernel options for the augmented
S-PLUS density function on the one-dimensional simulated example. Upper Left: The underlying
density (solid line) and the computed density with method = "mclust" (dotted line). Upper Right:
The underlying density (solid line) and the computed density with default kernel method (dotted
line). Lower: Errors for method = "mclust" (solid line) and the default (dotted line).

variance can give substantially better density estimates than kernel-based methods for one-
dimensional data.
12 Extensions

12.1 Large Data Sets

EMclust includes a provision for using a subsample of the data in the hierarchical clustering phase before applying EM to the full data set. This strategy is often adequate for large data sets, although it may miss small groups. Iterative methods for handling such cases are discussed in section 10.3 of [11]. The following example uses a random sample of size 100 in the initial hierarchical clustering phase of EMclust applied to the iris data:

```r
> n <- nrow(irisMatrix)
> s <- sample(1:n, size = 100)
> irisBIC <- EMclust(irisMatrix, subset = s)
```

For very large data sets, the discrimination capability of MCLUST can be used for classification. First, cluster analysis with the methodology of EMclust can be performed on a subset of the data. Then the remaining data points can then be classified (in reasonable sized blocks) using one of the discriminant analysis techniques described in section 10.

12.2 High Dimensional Data

Models in which the orientation is allowed to vary between clusters (EEV, VEV, EVV, VVV), have $O(d^2)$ parameters per cluster, where $d$ is the dimension of the data. For this reason, MCLUST may not work well or may otherwise be inefficient for these models when applied to high-dimensional data. It may still be possible to analyze such data with MCLUST by restriction to models with fewer parameters (e.g. spherical or diagonal models), or else by applying a dimension-reduction technique such as principal components.

Some of the more parsimonious models (e.g. spherical, diagonal, or fixed covariance) can be applied to datasets in which the number of observations is smaller than the data dimension.

13 Function Summary

13.1 Hierarchical Clustering

```
hc  Merge sequences for model-based hierarchical clustering.
hclass  Classifications corresponding to hc results.
```
13.2 Parameterized Gaussian Mixture Models

em  EM algorithm (starting with E-step).
me  EM algorithm (starting with M-step).
estep  E-step of the EM algorithm.
mstep  M-step of the EM algorithm.
mvn  One-component fit.

13.3 Density Computation for Parameterized Gaussian Mixtures

cdens  Component density (without mixing proportions).
dens  Mixture density.

13.4 Model-based Clustering / Density Estimation

EMclust  BIC computation; clusters and models through summary.
Mclust  Combines EMclust and its summary (fewer options).
density  S-PLUS one-dimensional density function with method = "mclust" option.

13.5 Discriminant Analysis

Class Densities as Mixture Components

cvlEMtrain  Training via leave-one-out crossvalidation.
bicEMtrain  Training via BIC.
estep  E-step of the EM algorithm.
mstep  M-step of the EM algorithm.

Parameterized Gaussian Mixture for Class Densities (MclustDA)
mclustDtrain  MclustDA training.
mclustDtest  MclustDA density; classification via summary.
mclustDA  Combines mclustDtrain and mclustDtest (fewer options).

13.6 Support for Modeling and Classification

.Mclust  vector of default values.
mclustOptions  set MCLUST options.
map  Convert conditional probabilities to a classification.
unmap  Convert a classification to indicator variables.
bic  BIC for parameterized Gaussian mixture models.
sim  Simulate data from a parameterized Gaussian mixture model.
compClass  Compare two classifications with equal numbers of classes.
sigma2decomp  Convert mixture covariances to decomposition form.
decomp2sigma  Convert decomposition form to mixture covariances.
grid1  One-dimensional grid.
grid2  Two-dimensional grid.
13.7 Plotting Functions

13.7.1 One-Dimensional Data
mclust1Dplot Classification, uncertainty, density and/or classification errors.

13.7.2 Two-Dimensional Data
mclust2Dplot Classification, uncertainty, and/or classification errors.
surfacePlot Contour, image, or perspective plot of either density or uncertainty.

13.7.3 More than Two Dimensions
Classification, uncertainty, and/or classification errors.
  coordProj coordinate projections
  randProj random projections
  spinProj random projection followed by reflection or rotation

13.7.4 Other Plotting Functions
clPairs pairs plot showing classifications
uncerPlot relative uncertainty of misclassified observations
plot.Mclust plots associated with Mclust results
plot.mclustDA plots associated with mclustDA results
References


