Package ‘telescope’

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identifyMixture

Solve label switching and identify mixture.

Description

Clustering of the draws in the point process representation (PPR) using k-means clustering.

Usage

identifyMixture(Func, Mu, Eta, S, centers)

Arguments

**Func**
A numeric array of dimension $M \times d \times K$; data for clustering in the PPR.

**Mu**
A numeric array of dimension $M \times r \times K$; draws of cluster means.

**Eta**
A numeric array of dimension $M \times K$; draws of cluster sizes.

**S**
A numeric matrix of dimension $M \times N$; draws of cluster assignments.

**centers**
An integer or a numeric matrix of dimension $K \times d$; used to initialize `stats::kmeans()`.

Details

The following steps are implemented:

- A functional of the draws of the component-specific parameters (Func) is passed to the function. The functionals of each component and iteration are stacked on top of each other in order to obtain a matrix where each row corresponds to the functional of one component.

- The functionals are clustered into $K_+$ clusters using $k$-means clustering. For each functional a group label is obtained.

- The obtained labels of the functionals are used to construct a classification for each MCMC iteration. Those classifications which are a permutation of $(1, \ldots, K_+)$ are used to reorder the Mu and Eta draws and the assignment matrix S. This results in an identified mixture model.

- Note that only iterations resulting in permutations are used for parameter estimation and deriving the final partition. Those MCMC iterations where the obtained classifications of the functionals are not a permutation of $(1, \ldots, K_+)$ are discarded as no unique assignment of functionals to components can be made. If the non-permutation rate, i.e. the proportion of MCMC iterations where the obtained classifications of the functionals are not a permutation, is high, this is an indication of a poor clustering solution, as the functionals are not clearly separated.
Value

A named list containing:

- "S": reordered assignments.
- "Mu": reordered Mu matrix.
- "Eta": reordered weights.
- "non_perm_rate": proportion of draws where the clustering did not result in a permutation and hence no relabeling could be performed; this is the proportion of draws discarded.

Description

Plots of the level combinations of pairs of variables are created where the size of the circle indicating a level combination is proportional to the frequency of the level combination.

Usage

```r
plotBubble(x, bg = "grey")
```

Arguments

- `x`: A matrix or data.frame; the data consisting of categorical variables.
- `bg`: If specified, the symbols are filled with colour(s), the vector bg is recycled to the number of observations. The default is to fill the symbols with grey color.

Value

`NULL`

Examples

```r
with(chickwts, plotBubble(data.frame(cut(weight, 100 * 1:5), feed)))
```
**plotScatter**

Pairwise scatter plots of the data.

**Description**

Scatter plots of the observations are plotted by selecting pairs of dimensions, potentially colored by a known classification.

**Usage**

\[
\text{plotScatter}(x, z, \text{label} = "", \text{trim} = 0)
\]

**Arguments**

- `x`: A matrix or data.frame; the data consisting of metric variables.
- `z`: A vector; indicating the color to use for the observations.
- `label`: A character string; the text to include in the axes labels.
- `trim`: A scalar numeric in \([0, 0.5]\); trimming to use for quantiles to determine axes.

**Value**

NULL

**Examples**

\[
\text{plotScatter(iris[, 1:4], iris$Species, label = "dim")}
\]

---

**priorOnAlpha_spec**

Specify prior on \(\alpha\).

**Description**

Obtain a function to evaluate the log prior specified for \(\alpha\).

**Usage**

\[
\text{priorOnAlpha_spec}(H = \text{c("alpha_const", "gam_05_05", "gam_1_2", "F_6_3")})
\]

**Arguments**

- `H`: A character indicating which specification should be used.
**Details**

The following prior specifications are supported:

- "alpha_const": \( \alpha \) is fixed at 1.
- "gam_05_05": \( \alpha \sim \text{gamma}(0.5, 0.5) \), i.e., shape = 0.5, rate = 0.5.
- "gam_1_2": \( \alpha \sim \text{gamma}(1, 2) \), i.e., shape = 1, rate = 2.
- "F_6_3": \( \alpha \sim F(6, 3) \), i.e., an F-distribution with degrees of freedom equal to 6 and 3.

**Value**

A named list containing:

- "log_pAlpha": a function of the log prior of \( \alpha \).
- "param": a list with the parameters.

---

**Description**

Obtain a function to evaluate the log prior specified for \( e_0 \).

**Usage**

```r
priorOnE0_spec(E = c("G_1_20", "e0const"), e0)
```

**Arguments**

- **E**
  
  A character indicating which specification should be used.

- **e0**
  
  A numeric scalar giving the fixed value of \( e_0 \).

**Details**

The following prior specifications are supported:

- "G_1_20": \( e_0 \sim \text{gamma}(1, 20) \), i.e., shape = 1, rate = 20.
- "e0const": \( e_0 \) is fixed at \( e_0 \).

**Value**

A named list containing:

- "log_p_e0": a function of the log prior of \( e_0 \).
- "param": a list with the parameters.
priorOnK_spec

Specify prior on $K$.

Description

Obtain a function to evaluate the log prior specified for $K$.

Usage


Arguments

- **P**: A character indicating which specification should be used. See Details for suitable values.
- **K**: A numeric or integer scalar specifying the fixed (if P equals "fixedK") or maximum value (if P equals "Unif") of $K$.

Details

The following prior specifications are supported:

- "fixedK": $K$ has the fixed value $K$ (second argument).
- "Unif": $K \sim \text{Unif}[1, K]$, where the upper limit is given by $K$ (second argument).
- "BNB_111": $K - 1 \sim \text{BNB}(1,1,1)$, i.e., $K - 1$ follows a beta-negative binomial distribution with parameters (1, 1, 1).
- "BNB_121": $K - 1 \sim \text{BNB}(1,2,1)$, i.e., $K - 1$ follows a beta-negative binomial distribution with parameters (1, 2, 1).
- "BNB_143": $K - 1 \sim \text{BNB}(1,4,3)$, i.e., $K - 1$ follows a beta-negative binomial distribution with parameters (1, 4, 3).
- "BNB_443": $K - 1 \sim \text{BNB}(4,4,3)$, i.e., $K - 1$ follows a beta-negative binomial distribution with parameters (4, 4, 3).
- "BNB_943": $K - 1 \sim \text{BNB}(9,4,3)$, i.e., $K - 1$ follows a beta-negative binomial distribution with parameters (9, 4, 3).
- "Pois_1": $K - 1 \sim \text{pois}(1)$, i.e., $K - 1$ follows a Poisson distribution with rate 1.
- "Pois_4": $K - 1 \sim \text{pois}(4)$, i.e., $K - 1$ follows a Poisson distribution with rate 4.
- "Pois_9": $K - 1 \sim \text{pois}(9)$, i.e., $K - 1$ follows a Poisson distribution with rate 9.
- "Geom_05": $K - 1 \sim \text{geom}(0.5)$, i.e., $K - 1$ follows a geometric distribution with success probability $p = 0.5$ and density $f(x) = p(1 - p)^{x}$. 
• "Geom_02": $K - 1 \sim \text{geom}(0.2)$, i.e., $K - 1$ follows a geometric distribution with success probability $p = 0.2$ and density $f(x) = p(1 - p)^x$.
• "Geom_01": $K - 1 \sim \text{geom}(0.1)$, i.e., $K - 1$ follows a geometric distribution with success probability $p = 0.1$ and density $f(x) = p(1 - p)^x$.
• "NB_11": $K - 1 \sim \text{nbinom}(1,0.5)$, i.e., $K - 1$ follows a negative-binomial distribution with $size = 1$ and $p = 0.5$.
• "NB_41": $K - 1 \sim \text{nbinom}(4,0.5)$, i.e., $K - 1$ follows a negative-binomial distribution with $size = 4$ and $p = 0.5$.
• "NB_91": $K - 1 \sim \text{nbinom}(9,0.5)$, i.e., $K - 1$ follows a negative-binomial distribution with $size = 9$ and $p = 0.5$.

Value
A named list containing:
• "log_pK": a function of the log prior of $K$.
• "param": a list with the parameters.

---

```
sampleAlpha(N, Nk, K, alpha, s0_proposal, log_pAlpha)
```

Description
Sample $\alpha$ conditional on the current partition and value of $K$ using an Metropolis-Hastings step with log-normal proposal.

Usage
`sampleAlpha(N, Nk, K, alpha, s0_proposal, log_pAlpha)`

Arguments
- `N` A number; indicating the sample size.
- `Nk` An integer vector; indicating the group sizes in the partition.
- `K` A number; indicating the number of components.
- `alpha` A numeric value; indicating the value for $\alpha$.
- `s0_proposal` A numeric value; indicating the standard deviation of the random walk.
- `log_pAlpha` A function; evaluating the log prior of $\alpha$.

Value
A named list containing:
• "alpha": a numeric, the new $\alpha$ value.
• "acc": logical indicating acceptance.
### sampleE0

*Sample e0 conditional on partition and K using an Metropolis-Hastings step with log-normal proposal.*

**Description**

Sample e0 conditional on the current partition and value of K using an Metropolis-Hastings step with log-normal proposal.

**Usage**

```r
sampleE0(K, Kp, N, Nk, s0_proposal, e0, log_p_e0)
```

**Arguments**

- **K**: A number; indicating the number of components.
- **Kp**: A number; indicating the number of filled components K_\_\_.
- **N**: A number; indicating the sample size.
- **Nk**: An integer vector; indicating the group sizes in the partition.
- **s0_proposal**: A numeric value; indicating the standard deviation of the random walk proposal.
- **e0**: A numeric value; indicating the current value of e0.
- **log_p_e0**: A function; evaluating the log prior of e0.

**Value**

A named list containing:

- "e0": a numeric, the new e0 value.
- "acc": logical indicating acceptance.

### sampleK_alpha

*Sample K conditional on \( \alpha \) where \( e0 = \alpha / K \).*

**Description**

This sampling step only relies on the current partition and is independent of the current component-specific parameters, see Frühwirth-Schnatter et al (2021).

**Usage**

```r
sampleK_alpha(Kp_j, Kmax, Nk_j, alpha, log_pK)
```
Arguments

- **K₀**: A number; indicating the current value of \( K_+ \).
- **Kmax**: A number; indicating the maximum value of \( K \) for which the conditional posterior is evaluated.
- **Nk_j**: A numeric vector; indicating the group sizes in the partition, i.e., the current number of observations in the filled components.
- **alpha**: A number; indicating the value of the parameter \( \alpha \).
- **log_pK**: A function; evaluating the log prior of \( K \).

Value

A number indicating the new value of \( K \).

---

**Description**

This sampling step only relies on the current partition and is independent of the current component-specific parameters, see Frühwirth-Schnatter et al (2021).

**Usage**

\[
sampleK_e0(K_0, Kmax, log_pK, log_p_e0, e0, N)
\]

Arguments

- **K₀**: A number; indicating the current value of \( K_+ \).
- **Kmax**: A number; indicating the maximum value of \( K \), for which the conditional posterior is evaluated.
- **log_pK**: A function; evaluating the prior of \( K \).
- **log_p_e0**: A function; evaluating the log prior of \( e_0 \).
- **e0**: A number; indicating the value of \( e_0 \).
- **N**: A number; indicating the number of observations.

Value

A number indicating the new value of \( K \).
Telescoping sampling of the LCA model where a prior on the number of components \( K \) is specified.

Description

- The MCMC scheme is implemented as suggested in Frühwirth-Schnatter et al (2021).
- The priors on the model parameters are specified as in Frühwirth-Schnatter et al (2021), see the vignette for details and notation.

Usage

```
sampleLCA(
  y,
  S,
  pi,
  eta,
  a0,
  M,
  burnin,
  thin,
  Kmax,
  G = c("MixDynamic", "MixStatic"),
  priorOnK,
  priorOnWeights,
  verbose = FALSE
)
```

Arguments

- `y`: A numeric matrix; containing the data.
- `S`: A numeric matrix; containing the initial cluster assignments.
- `pi`: A numeric vector; containing the initial cluster-specific success probabilities.
- `eta`: A numeric vector; containing the initial cluster sizes.
- `a0`: A numeric vector; containing the parameters of the prior on the cluster-specific success probabilities.
- `M`: A numeric scalar; specifying the number of recorded iterations.
- `burnin`: A numeric scalar; specifying the number of burn-in iterations.
- `thin`: A numeric scalar; specifying the thinning used for the iterations.
- `Kmax`: A numeric scalar; the maximum number of components.
- `G`: A character string; either "MixDynamic" or "MixStatic".
- `priorOnK`: A named list; providing the prior on the number of components \( K \), see `priorOnK_spec()`.
- `priorOnWeights`: A named list; providing the prior on the mixture weights.
- `verbose`: A logical; indicating if some intermediate clustering results should be printed.
sampleLCA

Value

A named list containing:

- "Pi": sampled component-specific success probabilities.
- "Eta": sampled weights.
- "S": sampled assignments.
- "Nk": number of observations assigned to the different components, for each iteration.
- "K": sampled number of components.
- "Kplus": number of filled, i.e., non-empty components, for each iteration.
- "e0": sampled Dirichlet parameter of the prior on the weights (if $e_0$ is random).
- "alpha": sampled Dirichlet parameter of the prior on the weights (if $\alpha$ is random).
- "acc": logical vector indicating acceptance in the Metropolis-Hastings step when sampling either $e_0$ or $\alpha$.

Examples

```r
if (requireNamespace("poLCA", quietly = TRUE)) {
  data("carcinoma", package = "poLCA")
  y <- carcinoma
  N <- nrow(y)
  r <- ncol(y)
  Mmax <- 200
  thin <- 1
  burnin <- 100
  M <- Mmax/thin
  Kmax <- 50
  Kinit <- 10
  G <- "MixDynamic"
  priorOnAlpha <- priorOnAlpha_spec("gam_1_2")
  priorOnK <- priorOnK_spec("Pois_1")
  cat <- apply(y, 2, max)
  a0 <- rep(1, sum(cat))
  cl_y <- kmeans(y, centers = Kinit, iter.max = 20)
  S_0 <- cl_y$cluster
  eta_0 <- cl_y$size/N
  pi_0 <- do.call("cbind", lapply(1:r, function(j) {
    prop.table(table(S_0, y[, j]), 1)
  })),
  result <- sampleLCA(
    y, S_0, pi_0, eta_0, a0,
    M, burnin, thin, Kmax,
    G, priorOnK, priorOnAlpha)
}
sampleMultNormMixture  

Telescoping sampling of a Bayesian finite multivariate Gaussian mixture where a prior on the number of components is specified.

Description

- The MCMC scheme is implemented as suggested in Frühwirth-Schnatter et al (2021).
- The priors on the model parameters are specified as in Frühwirth-Schnatter et al (2021), see the vignette for details and notation.
- The parameterizations of the Wishart and inverse Wishart distribution are used as in Frühwirth-Schnatter et al (2021), see also the vignette.

Usage

```r
sampleMultNormMixture(
  y,
  S,
  mu,
  Sigma,
  eta,
  c0,
  g0,
  G0,
  C0,
  b0,
  B0,
  M,
  burnin,
  thin,
  Kmax,
  G = c("MixDynamic", "MixStatic"),
  priorOnK,
  priorOnWeights,
  verbose = FALSE
)
```
sampleMultNormMixture

Arguments

- **y**: A numeric matrix; containing the data.
- **S**: A numeric matrix; containing the initial cluster assignments.
- **mu**: A numeric matrix; containing the initial cluster-specific mean values.
- **Sigma**: A numeric matrix; containing the initial cluster-specific variance covariance values.
- **eta**: A numeric vector; containing the initial cluster sizes.
- **c0**: A numeric vector; hyperparameter of the prior on \( \Sigma_k \).
- **g0**: A numeric vector; hyperparameter of the prior on \( C_0 \).
- **G0**: A numeric vector; hyperparameter of the prior on \( C_0 \).
- **C0**: A numeric vector; initial value of the hyperparameter \( C_0 \).
- **b0**: A numeric vector; hyperparameter of the prior on \( \mu_k \).
- **B0**: A numeric vector; hyperparameter of the prior on \( \mu_k \).
- **M**: A numeric scalar; specifying the number of recorded iterations.
- **burnin**: A numeric scalar; specifying the number of burn-in iterations.
- **thin**: A numeric scalar; specifying the thinning used for the iterations.
- **Kmax**: A numeric scalar; the maximum number of components.
- **G**: A character string; either "MixDynamic" or "MixStatic".
- **priorOnK**: A named list; providing the prior on the number of components \( K \), see `priorOnK_spec()`.
- **priorOnWeights**: A named list; providing the prior on the mixture weights.
- **verbose**: A logical; indicating if some intermediate clustering results should be printed.

Value

A named list containing:

- "Mu": sampled component means.
- "Eta": sampled weights.
- "S": sampled assignments.
- "Nk": number of observations assigned to the different components, for each iteration.
- "K": sampled number of components.
- "Kplus": number of filled, i.e., non-empty components, for each iteration.
- "e0": sampled Dirichlet parameter of the prior on the weights (if \( e_0 \) is random).
- "alpha": sampled Dirichlet parameter of the prior on the weights (if \( \alpha \) is random).
- "acc": logical vector indicating acceptance in the Metropolis-Hastings step when sampling either \( e_0 \) or \( \alpha \).
Examples

```r
y <- iris[, 1:4]
z <- iris$Species
r <- ncol(y)

Mmax <- 50
thin <- 1
burnin <- 0
M <- Mmax/thin
Kmax <- 40
Kinit <- 10

G <- "MixStatic"
priorOnE0 <- priorOnE0_spec("G_1_20", 1)
priorOnk <- priorOnK_spec("BNB_143")

R <- apply(y, 2, function(x) diff(range(x)))
b0 <- apply(y, 2, median)
B_0 <- rep(1, r)
B0 <- diag((R*2) * B_0)
c0 <- 2.5 + (r-1)/2
g0 <- 0.5 + (r-1)/2
G0 <- 100 * g0/c0 * diag((1/R^2), nrow = r)
C0 <- g0 * chol2inv(chol(G0))

c1_y <- kmeans(y, centers = Kinit, nstart = 100)
S_0 <- c1_y$cluster
mu_0 <- t(c1_y$centers)

eta_0 <- rep(1/Kinit, Kinit)
Sigma_0 <- array(0, dim = c(r, r, Kinit))
Sigma_0[, , 1:Kinit] <- 0.5 * C0

result <- sampleMultNormMixture(
y, S_0, mu_0, Sigma_0, eta_0,
c0, g0, G0, C0, b0, B0,
M, burnin, thin, Kmax, G, priorOnK, priorOnE0)

K <- result$K
Kplus <- result$Kplus

plot(seq_along(K), K, type = "l", ylim = c(0, max(K)),
     xlab = "iteration", main = "",
ylab = expression("K" ~ "/" ~ K["+"]), col = 1)
lines(seq_along(Kplus), Kplus, col = 2)
legend("topright", legend = c("K", expression(K["+"])),
       col = 1:2, lty = 1, box.lwd = 0)
```
samplePoisMixture

Telescoping sampling of a Bayesian finite Poisson mixture with a prior on the number of components $K$.

Description

- The MCMC scheme is implemented as suggested in Frühwirth-Schnatter et al (2021).
- The priors on the model parameters are specified as in Frühwirth-Schnatter et al (2021) and Früwirth-Schnatter and Malsiner-Walli (2019), see the vignette for details and notation.

Usage

```r
samplePoisMixture(
  y,
  S,
  mu,
  eta,
  a0,
  b0,
  h0,
  H0,
  M,
  burnin,
  thin,
  Kmax,
  G = c("MixDynamic", "MixStatic"),
  priorOnK,
  priorOnWeights,
  verbose = FALSE
)
```

Arguments

- `y`: A numeric matrix; containing the data.
- `S`: A numeric matrix; containing the initial cluster assignments.
- `mu`: A numeric matrix; containing the initial cluster-specific rate values.
- `eta`: A numeric vector; containing the initial cluster sizes.
- `a0`: A numeric vector; hyperparameter of the prior on the rate $\mu$.
- `b0`: A numeric vector; hyperparameter of the prior on the rate $\mu$.
- `h0`: A numeric vector; hyperparameter of the prior on the rate $\mu$.
- `H0`: A numeric vector; hyperparameter of the prior on the rate $\mu$.
- `M`: A numeric scalar; specifying the number of recorded iterations.
- `burnin`: A numeric scalar; specifying the number of burn-in iterations.
- `thin`: A numeric scalar; specifying the thinning used for the iterations.
- `Kmax`: A numeric scalar; the maximum number of components.
samplePoisMixture

G  A character string: either "MixDynamic" or "MixStatic".
priorOnK A named list; providing the prior on the number of components K, see priorOnK_spec().
priorOnWeights A named list; providing the prior on the mixture weights.
verbose A logical; indicating if some intermediate clustering results should be printed.

Value

A named list containing:

- "Mu": sampled rate $\mu$.
- "Eta": sampled weights.
- "S": sampled assignments.
- "Nk": number of observations assigned to the different components, for each iteration.
- "K": sampled number of components.
- "Kplus": number of filled, i.e., non-empty components, for each iteration.
- "e0": sampled Dirichlet parameter of the prior on the weights (if $e_0$ is random).
- "alpha": sampled Dirichlet parameter of the prior on the weights (if $\alpha$ is random).
- "acc": logical vector indicating acceptance in the Metropolis-Hastings step when sampling either $e_0$ or $\alpha$.

Examples

```r
N <- 200
z <- sample(1:2, N, prob = c(0.5, 0.5), replace = TRUE)
y <- rpois(N, c(1, 6)[z])

Mmax <- 200
thin <- 1
burnin <- 100
M <- Mmax/thin
Kmax <- 50
Kinit <- 10

G <- "MixDynamic"
priorOnAlpha <- priorOnAlpha_spec("gam_1_2")
priorOnK <- priorOnK_spec("BNB_143")

a0 <- 0.1
h0 <- 0.5
b0 <- a0/mean(y)
H0 <- h0/b0

c1_y <- kmeans(y, centers = Kinit, nstart = 100)
S_0 <- c1_y$cluster
mu_0 <- t(c1_y$centers)
eta_0 <- rep(1/Kinit, Kinit)
```

Telescoping sampling of a Bayesian finite univariate Gaussian mixture where a prior on the number of components $K$ is specified.

Description

- The MCMC scheme is implemented as suggested in Frühwirth-Schnatter et al (2021).
- The priors on the model parameters are specified as in Frühwirth-Schnatter et al (2021), see the vignette for details and notation.
- The parametrizations of the gamma and inverse gamma distribution are used as in Frühwirth-Schnatter et al (2021), see also the vignette.

Usage

```r
sampleUniNormMixture(
  y,
  S,
  mu,
  sigma2,
  eta,
  c0,
  g0,
  G0,
  C0_0,
  b0,
  B0,
  M,
  burnin,
  thin,
  Kmax,
  G = c("MixDynamic", "MixStatic"),
)```

priorOnK,  
priorOnWeights,  
verbose = FALSE
}

Arguments

y  
A numeric matrix; containing the data.
S  
A numeric matrix; containing the initial cluster assignments.
mu  
A numeric matrix; containing the initial cluster-specific mean values.
sigma2  
A numeric matrix; containing the initial cluster-specific variance values.
etta  
A numeric vector; containing the initial cluster sizes.
c0  
A numeric vector; hyperparameter of the prior on $\sigma^2_k$.
g0  
A numeric vector; hyperparameter of the prior on $\sigma^2_k$.
G0  
A numeric vector; hyperparameter of the prior on $\sigma^2_k$.
C0_0  
A numeric vector; initial value of hyperparameter $C_0$.
b0  
A numeric vector; hyperparameter of the prior on $\mu_k$.
B0  
A numeric vector; hyperparameter of the prior on $\mu_k$.
M  
A numeric scalar; specifying the number of recorded iterations.
burnin  
A numeric scalar; specifying the number of burn-in iterations.
thin  
A numeric scalar; specifying the thinning used for the iterations.
Kmax  
A numeric scalar; the maximum number of components.
G  
A character string; either "MixDynamic" or "MixStatic".
priorOnK  
A named list; providing the prior on the number of components K, see priorOnK_spec().
priorOnWeights  
A named list; providing the prior on the mixture weights.
verbose  
A logical; indicating if some intermediate clustering results should be printed.

Value

A named list containing:

- "Mu": sampled component means.
- "Eta": sampled weights.
- "S": sampled assignments.
- "Nk": number of observations assigned to the different components, for each iteration.
- "K": sampled number of components.
- "Kplus": number of filled, i.e., non-empty components, for each iteration.
- "e0": sampled Dirichlet parameter of the prior on the weights (if $e_0$ is random).
- "alpha": sampled Dirichlet parameter of the prior on the weights (if $\alpha$ is random).
- "acc": logical vector indicating acceptance in the Metropolis-Hastings step when sampling either $e_0$ or $\alpha$. 

Examples

```r
if (requireNamespace("mclust", quietly = TRUE)) {
  data("acidity", package = "mclust")
  y <- acidity

  N <- length(y)
  r <- 1

  Mmax <- 200
  thin <- 1
  burnin <- 100
  M <- Mmax/thin
  Kmax <- 50
  Kinit <- 10

  G <- "MixStatic"
  priorOnE0 <- priorOnE0_spec("e0const", 0.01)
  priorOnK <- priorOnK_spec("Pois_1", 50)

  R <- diff(range(y))
  c0 <- 2 + (r-1)/2
  C0 <- diag(c(0.02*(R^2)), nrow = r)
  g0 <- 0.2 + (r-1) / 2
  G0 <- diag(10/(R^2), nrow = r)
  B0 <- diag((R^2), nrow = r)
  b0 <- as.matrix((max(y) + min(y))/2, ncol = 1)

  cl_y <- kmeans(y, centers = Kinit, nstart = 100)
  S_0 <- cl_y$cluster
  mu_0 <- t(cl_y$centers)
  eta_0 <- rep(1/Kinit, Kinit)
  sigma2_0 <- array(0, dim = c(1, 1, Kinit))
  sigma2_0[1, 1, ] <- 0.5 * C0

  result <- sampleUniNormMixture(
    y, S_0, mu_0, sigma2_0, eta_0,
    c0, g0, G0, C0, b0, B0,
    M, burnin, thin, Kmax,
    G, priorOnK, priorOnE0)

  K <- result$K
  Kplus <- result$Kplus

  plot(seq_along(K), K, type = "l", ylim = c(0, max(K)),
       xlab = "iteration", main = "",
       ylab = expression("K" ~ "\(\)" ~ K["+"]), col = 1)
  lines(seq_along(Kplus), Kplus, col = 2)
  legend("topright", legend = c("K", expression(K["+"])),
          col = 1:2, lty = 1, box.lwd = 0)
}
```
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