Testing different imputation methods on PUMS (MAR) - DPMPM

```
# load dataset: df
load('../../Datasets/ordinalPUMS.Rdata')

# take 10,000 samples: df
set.seed(0)
n = 10000
sample <- sample(nrow(df), size = 10000)
df <- df[sample,]

# create MCAR scneario with 30% chance of missing: df_observed
missing_prob = 0.3
df_observed <- df
missing_col = c(1,3,7,9,10,11)

# Make VEH and WKL MCAR
missing_col_MCAR = c(1,10)
for (col in missing_col_MCAR) {
  missing_ind <- rbernoulli(n,p = missing_prob)
  df_observed[missing_ind, col] <- NA
}

# Make the rest MAR
numeric_df = sapply(df, as.numeric)
normalized_df = t(t(numeric_df-1)/(apply(numeric_df, MARGIN = 2, FUN = max)-1))
missing_col_MAR = c(3,7,9,11)
fully_observed_col = c(2,4,5,6,8)
beta_NP = c(-0.05, -1.5, 0.6, -2, -0.05)
beta0_NP = -0.05
beta_SCHL = c(-3, 3, -0.75, 0.05, -0.2)
beta0_SCHL = 0.05
beta_AGEP = c(0.05, -0.2, 0.05, -1.25, 1)
beta0_AGEP = -0.05
beta_PINCP = c(3, -0.05, -2.5, 0.05, -1)
beta0_PINCP = -0.05

# missing probability for NP
prob_NP = apply(t(t(normalized_df[, fully_observed_col])*beta_NP)+beta0_NP, MARGIN = 1, sum)
prob_NP = exp(prob_NP)/(exp(prob_NP)+1)
indicator = rbernoulli(n, p = prob_NP)
df_observed[indicator, missing_col_MAR[1]] <- NA

# missing probability for SCHL
prob_SCHL = apply(t(t(normalized_df[, fully_observed_col])*beta_SCHL)+beta0_SCHL, MARGIN = 1, sum)
prob_SCHL = exp(prob_SCHL)/(exp(prob_SCHL)+1)
indicator = rbernoulli(n, p = prob_SCHL)
df_observed[indicator, missing_col_MAR[2]] <- NA
```

```r
# missing probability for AGEP
prob_AGEP = apply(t(t(normalized_df[, fully_observed_col])*beta_AGEP)+beta0_AGEP, MARGIN = 1, sum)
prob_AGEP = exp(prob_AGEP)/(exp(prob_AGEP)+1)
indicator = rbernoulli(n, p = prob_AGEP)
df_observed[indicator, missing_col_MAR[3]] <- NA

# missing probability for PINCP
prob_PINCP = apply(t(t(normalized_df[, fully_observed_col])*beta_PINCP)+beta0_PINCP, MARGIN = 1, sum)
prob_PINCP = exp(prob_PINCP)/(exp(prob_PINCP)+1)
indicator = rbernoulli(n, p = prob_PINCP)
df_observed[indicator, missing_col_MAR[4]] <- NA

# 30.58% missing
apply(is.na(df_observed), MARGIN = 2, mean)
```

```
##    VEH     MV     NP   RMSP    ENG  MARHT   SCHL RACNUM   AGEP    WKL  PINCP
## 0.3030 0.0000 0.3121 0.0000 0.0000 0.0000 0.2814 0.0000 0.3355 0.3017 0.3011
```

DPMPM

Multiple imputation using NPBayesImputeCat package

Ref: https://cran.r-project.org/web/packages/NPBayesImputeCat/NPBayesImputeCat.pdf

1. Create and initialize the Rcpp_Lcm model object using CreateModel with the following arguments:

- X: dataframe to be imptuted = df
- MCZ: dataframe with the definition of structural zero = NULL
- K: the maximum number of mixture components = 40
- Nmax: An upper truncation limit for the augmented sample size = 0
- aalpha: the hyper parameter alpha in stick-breaking prior = 0.25
- balpha: the hyper parameter beta in stick-breaking prior = 0.25
- seed = 0

2. Set the tracer for the sampling process

- k_star: the effective cluster number
- psi: conditional multinomial probabilties
- ImputedX: imputation result

3. Run the model using the method Run of Rcpp_Lcm class with the following arguments:

- burnin = 10000
- iter = 10000
- thinning = 5

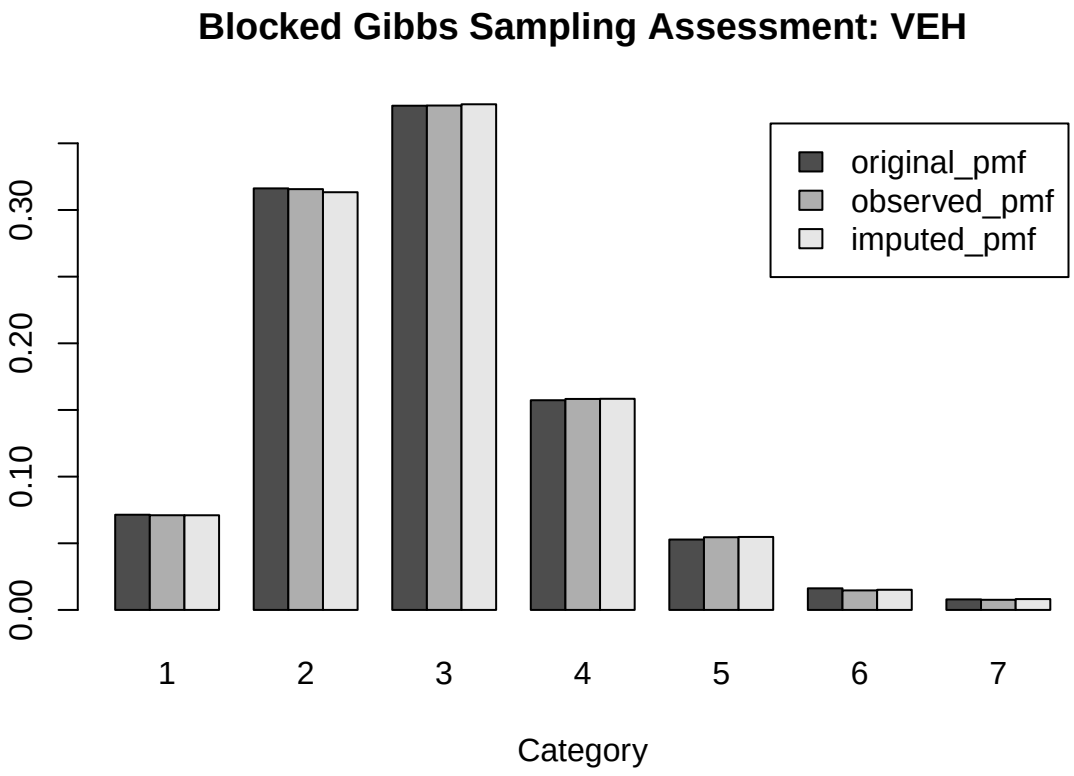
4. Obtain result

```r
N = 40
Mon = 10000
B = 10000
thin.int = 5

# 1. Create and initialize the Rcpp_Lcm model object
model = CreateModel(X = df_observed, MCZ = NULL, K = N, Nmax = 0,
                    aalpha = 0.25, balpha = 0.25, seed = 0)
# 2. Set tracer
model$SetTrace(c('k_star', 'psi', 'ImputedX', 'alpha'),Mon)
```

```
# 3. Run model using Run(burnin, iter, thinning)
model$Run(B,Mon,thin.int)
```

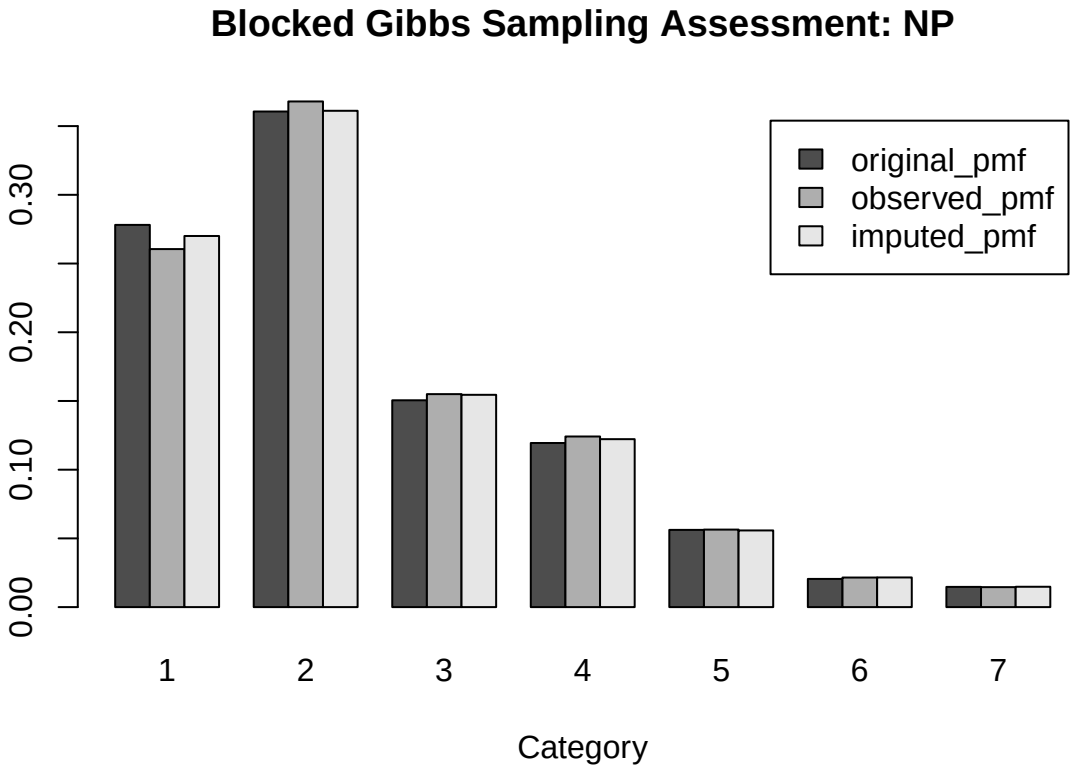
```
# Extract results
output <- model$GetTrace()
k_star <- output$k_star
psi <- output$psi
imputed_df <- output$ImputedX
alpha <- output$alpha

#retrieve parameters from the final iteration
result <- model$snapshot

#convert ImputedX matrix to dataframe, using proper factors/names etc.
ImputedX <- GetDataFrame(result$ImputedX,df)
```

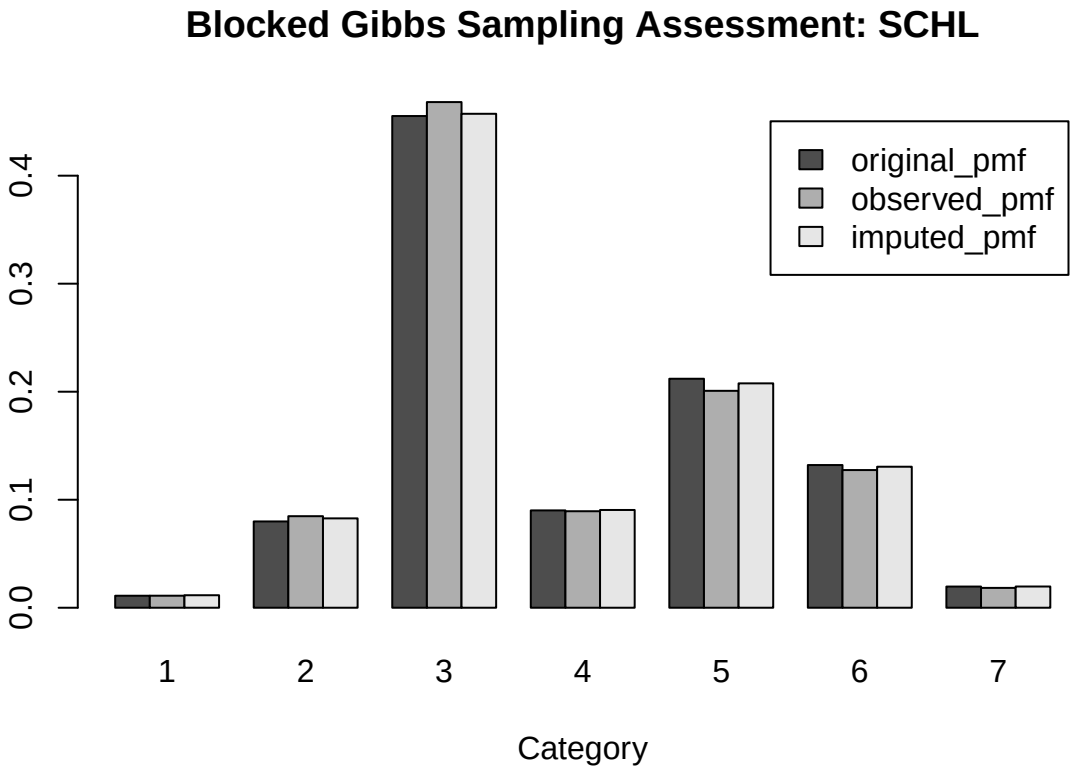
Diagnostics

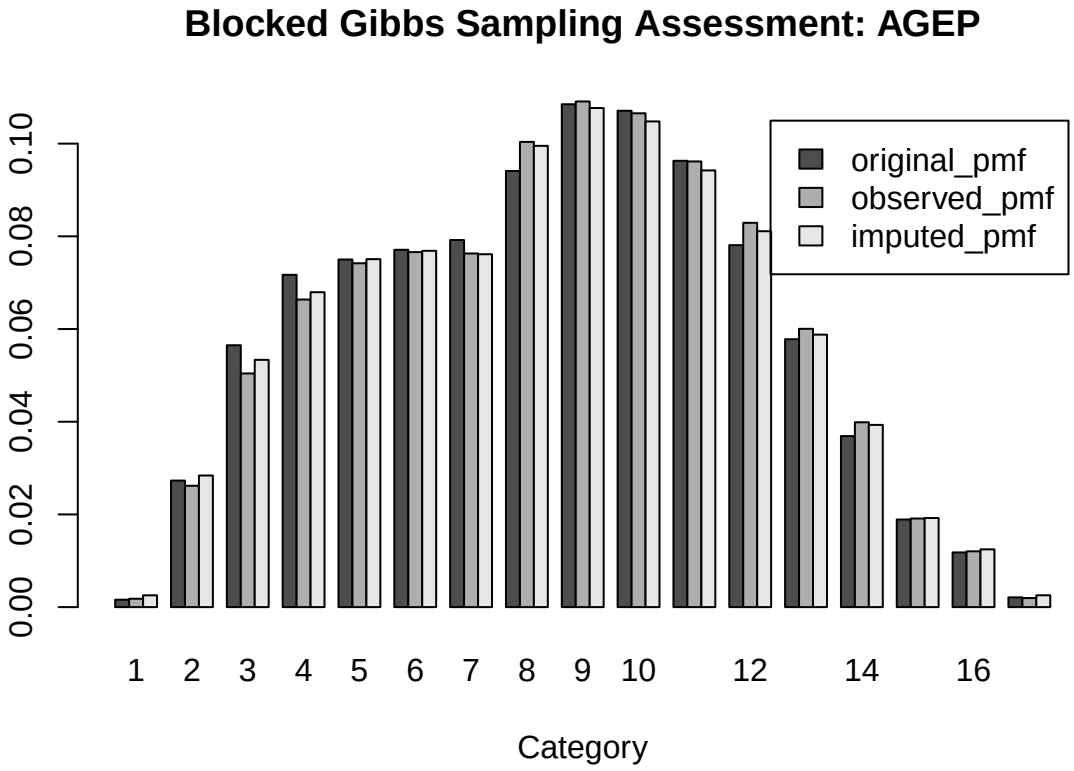


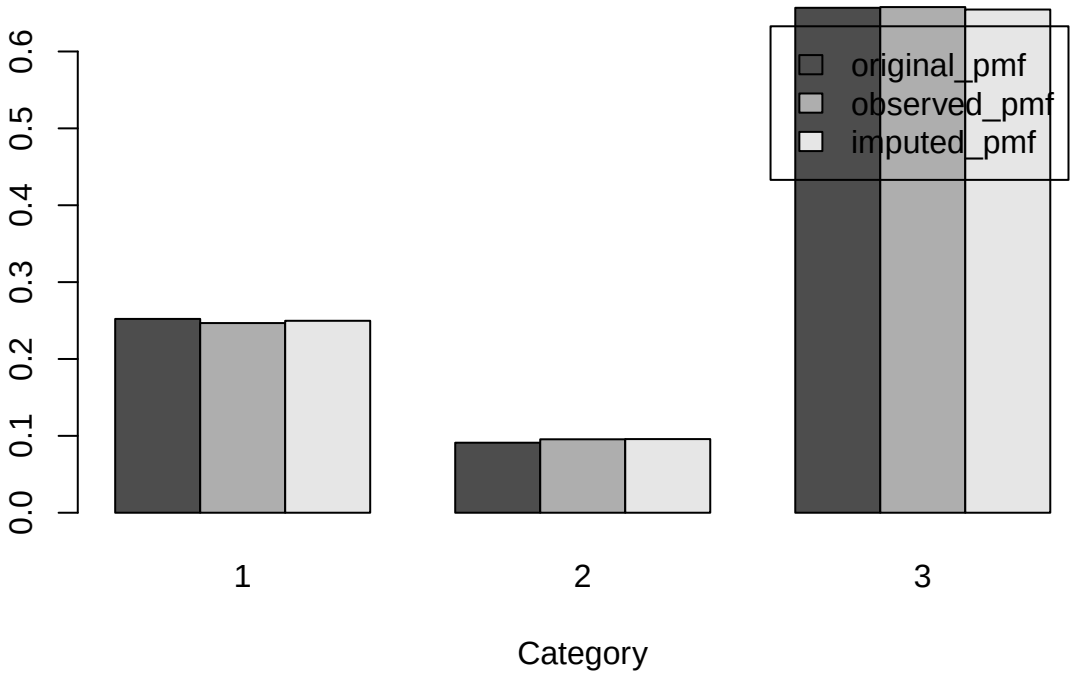
Assess bivariate joint distribution

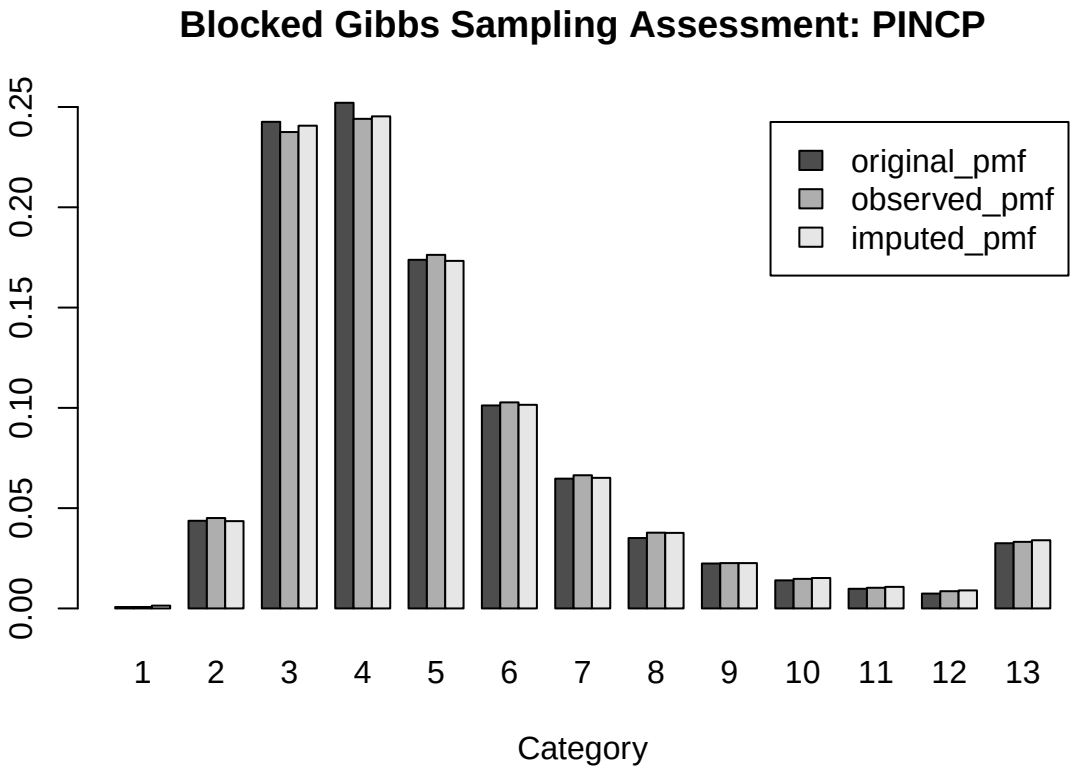
Assess trivariate joint distribution

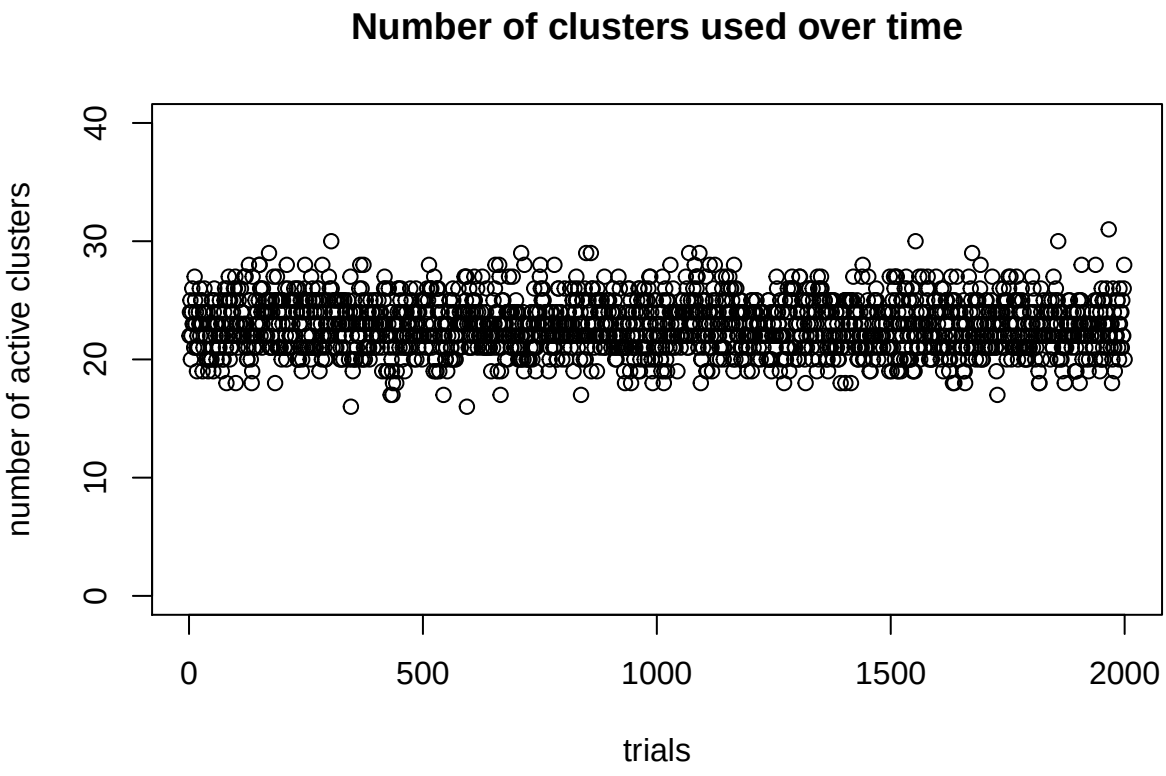

Blocked Gibbs Sampling Assessment: NP
original_pmf
observed_pmf
imputed_pmf
0.00
0.10
0.20
0.30
1
2
3
4
5
6
7
Category

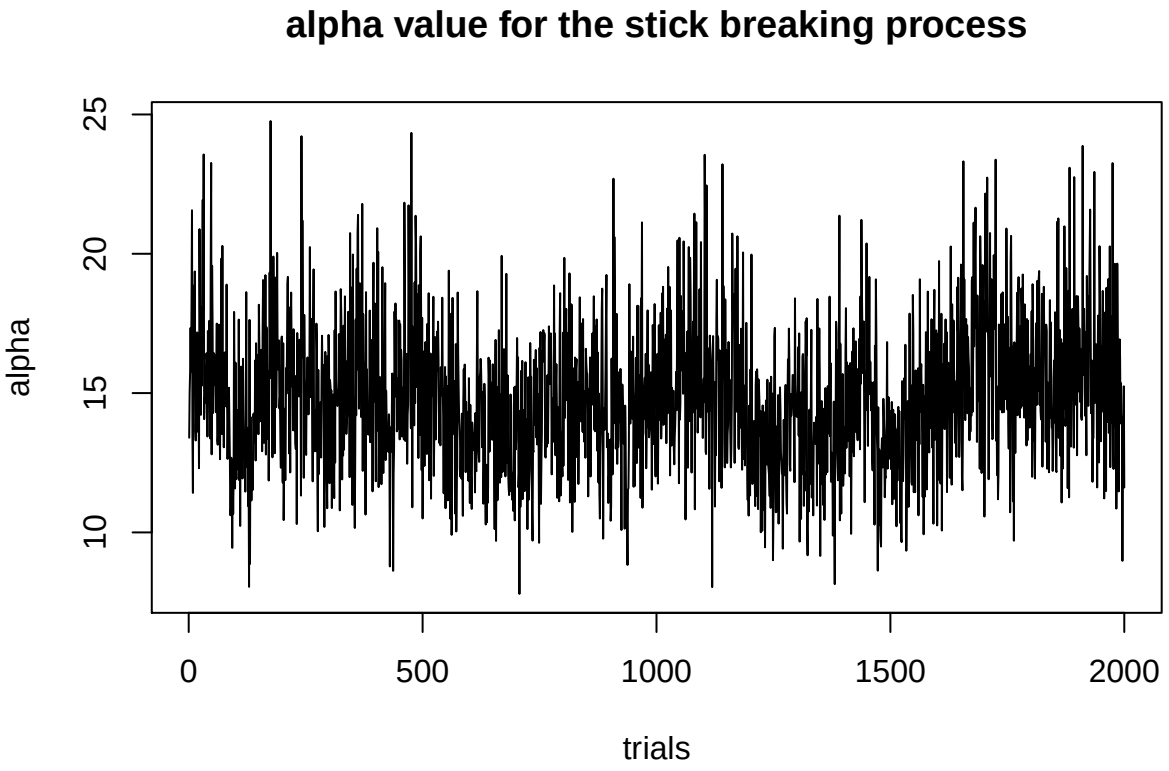

Blocked Gibbs Sampling Assessment: SCHL
original_pmf
observed_pmf
imputed_pmf
0.0
0.1
0.2
0.3
0.4
1
2
3
4
5
6
7
Category

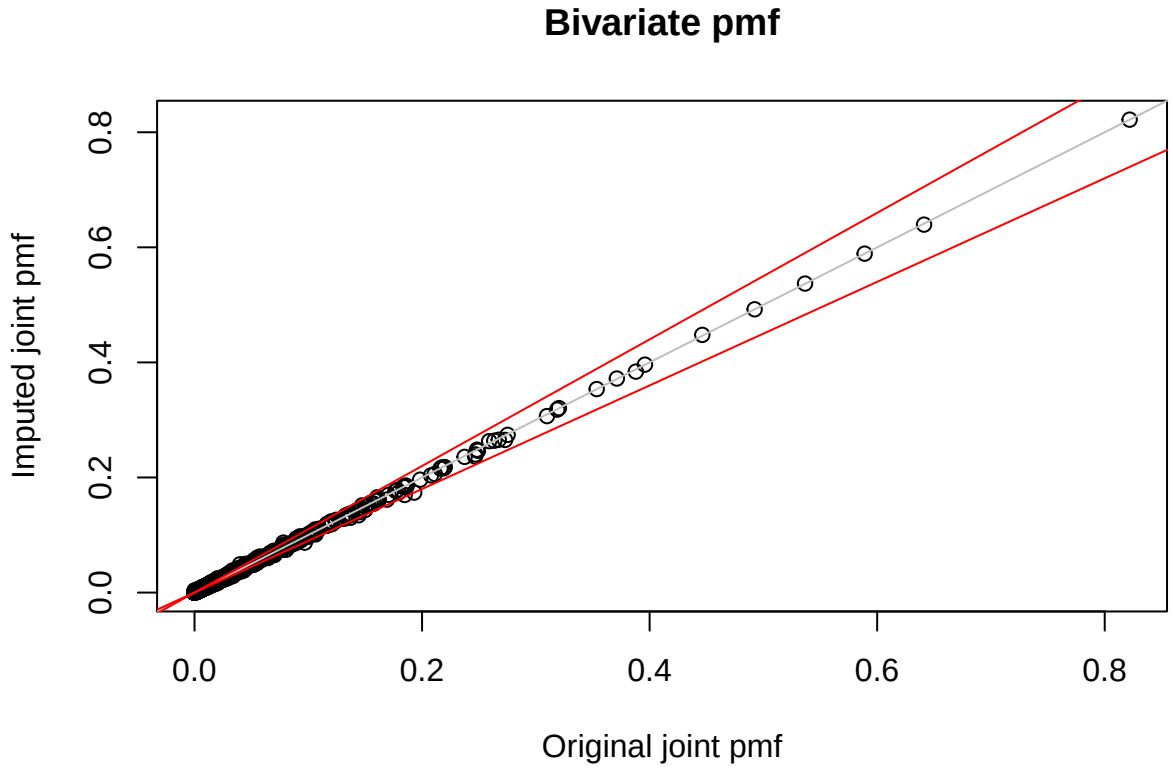

Blocked Gibbs Sampling Assessment: AGEP
0.00
0.02
0.04
0.06
0.08
0.10
1
2
3
4
5
6
7
8
9
10
12
14
16
Category
original_pmf
observed_pmf
imputed_pmf

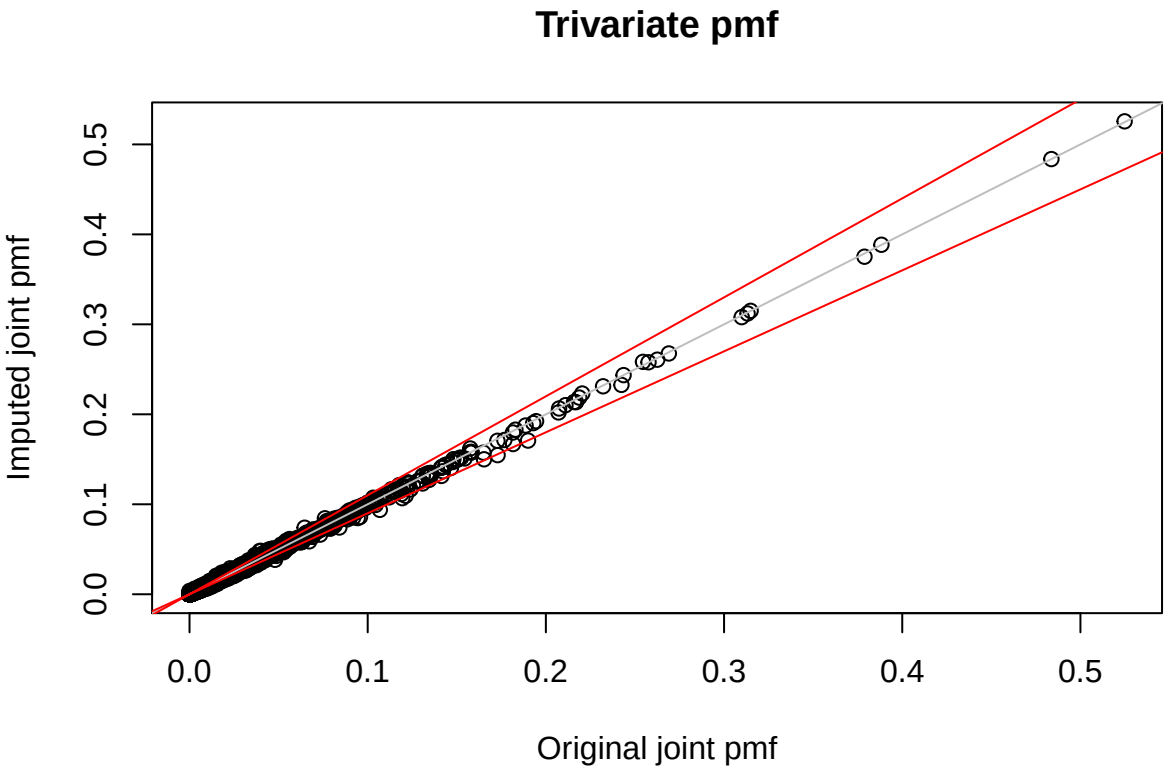

Blocked Gibbs Sampling Assessment: WKL
0.0
0.1
0.2
0.3
0.4
0.5
0.6
1
2
3
Category
original_pmf
observed_pmf
imputed_pmf


Blocked Gibbs Sampling Assessment: PINCP
original_pmf
observed_pmf
imputed_pmf
0.00
0.05
0.10
0.15
0.20
0.25
1
2
3
4
5
6
7
8
9
10
11
12
13
Category


Number of clusters used over time
number of active clusters
0
10
20
30
40
0
500
1000
1500
2000
trials


alpha value for the stick breaking process
alpha
10
15
20
25
0
500
1000
1500
2000
trials


Bivariate pmf
Imputed joint pmf
0.0
0.2
0.4
0.6
0.8
Original joint pmf


Trivariate pmf
Imputed joint pmf
Original joint pmf
0.0
0.1
0.2
0.3
0.4
0.5