flashtpx: Simulation Run 2

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Contents

Overview

This is the second simulation run of *flashtpx* without the non-negative constraint. The main idea is to try and replicate the results for the `FitGoM()` in CountClust or `topics()` model in the maptpx package due to Matt Taddy.

Without the non-negative constraint, *flashtpx* is basically applying *flash* with the covariance matrix for the data estimated from the GoM or topic model fitting on the counts data. Here we apply *flashtpx* on the counts data generated from a chosen simulation design and then interpret the results and compare the results to the PMA model fitting.

Simulation Design

We load the packages and the functions we need to perform the model.

```
library(ashr)
library(irlba)
library(PMA)
source("../R/flash.R")
```

Next we determine the `omega` matrix with 2 clusters with cluster membership in cluster 1 varying from 0.8 to 0.2 linearly.

```
n.out <- 600
omega_sim <- cbind(seq(0.6, 0.4, length.out = n.out),
    1 - seq(0.6, 0.4, length.out = n.out))
dim(omega_sim)
```

```
## [1] 600   2
```

```
K <- dim(omega_sim)[2]

par(mar = c(2, 2, 2, 2))
barplot(t(omega_sim), col = 2:(K + 1), axisnames = F,
    space = 0, border = NA, main = paste("No. of clusters=",
        K), las = 1, ylim = c(0, 1), cex.axis = 1.5,
    cex.main = 1.4)
```

So we have two clusters. How do these clusters look? Assume we have 100 genes.

```
freq <- rbind(c(0.1, 0.2, rep(0.7/98, 98)), c(rep(0.7/98,
    98), 0.1, 0.2))
str(freq)
```

```
##  num [1:2, 1:100] 0.1 0.00714 0.2 0.00714 0.00714 ...
```

So the first cluster has high expression at first 2 genes and low expression at the other 98 genes.

```
counts <- t(do.call(cbind, lapply(1:dim(omega_sim)[1],
    function(x) rmultinom(1, 1000, prob = omega_sim[x,
        ] %*% freq))))
dim(counts)
```

```
## [1] 600 100
```

We next fit a standard topic model with $K = 2$.

```
topic.fit <- maptpx::topics(counts, K = 2)
```

```
##
## Estimating on a 600 document collection.
## Fitting the 2 topic model.
## log posterior increase: 81.2, 2.1, 1, 1, 1, 1, 1.1, 1.1, 1.2, 1.4, 1.6, 1.9, 2.3, 2.9, 3.7, 4.7, 6, 7.5
```

```
omega <- topic.fit$omega
theta <- topic.fit$theta
```

Brief methods overview

Under the standard topic model, we have

$$c_{ng} \sim Poi(c_{n+} \sum_{k=1}^{K} \omega_{nk}\theta_{kg})$$

Let us define

$$\lambda_{ng} = c_{n+} \sum_{k=1}^{K} \omega_{nk}\theta_{kg}$$

Under the normal model, if λ_{ng} is large, we can assume

$$c_{ng} \sim N(\lambda_{ng}, \lambda_{ng})$$

which is equivalent to saying

$$c_{ng} = \lambda_{ng} + e_{ng} \qquad e_{ng} \sim N(0, \lambda_{ng})$$

For applying *flash*, we first estimate the λ in the variance using topic model estimate (we call this λ to be $\lambda^{\star}$).

to guard against the odd possibility that for some n and g, this estimate $\lambda^{\star}$ could be 0, we replace such cases as of now with a small value 0.0001.

In this example model we have considered $c_{n+} = 1000$.

```
lambda_star <- 1000 * (omega_sim %*% freq)
lambda_star[lambda_star == 0] <- 1e-04
dim(lambda_star)
```

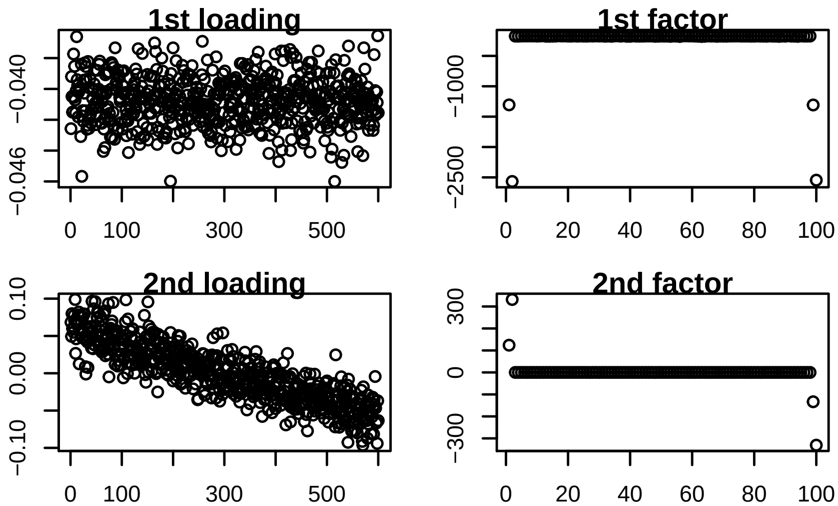
```
## [1] 600 100
```

FLASH model fitting

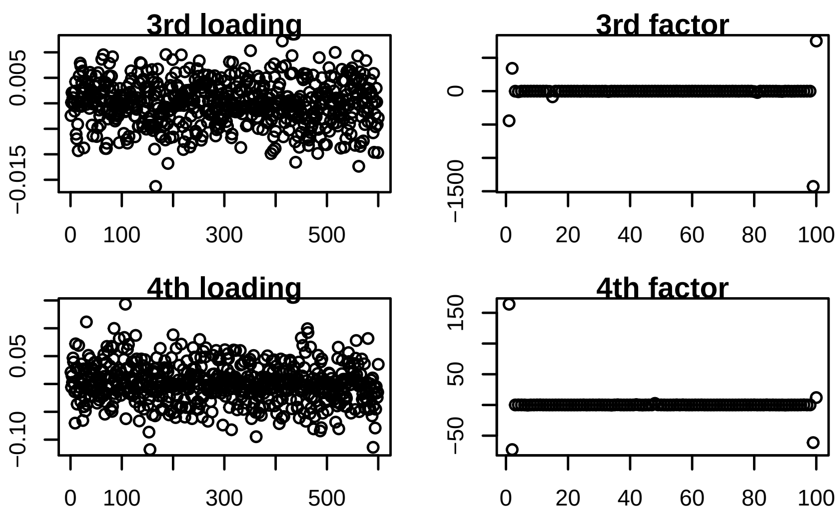
flash then fits the model

$$c_{ng} = \sum_{k=1}^{K} l_{nk} f_{kg} + e_{ng} \qquad e_{ng} \sim N(0, \lambda^{\star}_{ng})$$

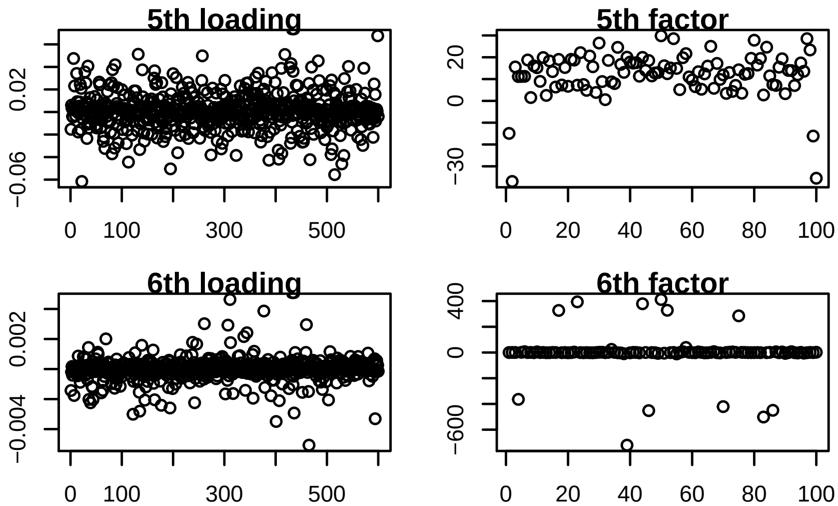
```
g1 = suppressMessages(flash(counts, sigmae2_true = lambda_star))
f = g1$f
l = g1$l
res = counts - l %*% t(f)
# g_new = flash(res,nonnegative =
# TRUE,sigmae2_true = lambda)
g2 = suppressMessages(flash(res, sigmae2_true = lambda_star))
l = g2$l
f = g2$f
res = res - l %*% t(f)
g3 = suppressMessages(flash(res, sigmae2_true = lambda_star))
l = g3$l
f = g3$f
res = res - l %*% t(f)
g4 = suppressMessages(flash(res, sigmae2_true = lambda_star))
l = g4$l
f = g4$f
res = res - l %*% t(f)
g5 = suppressMessages(flash(res, sigmae2_true = lambda_star))
l = g5$l
f = g5$f
res = res - l %*% t(f)
g6 = suppressMessages(flash(res, sigmae2_true = lambda_star))
l = g6$l
f = g6$f
par(mfrow = c(2, 2))
par(cex = 0.6)
par(mar = c(3, 3, 0.8, 0.8), oma = c(1, 1, 1,
    1))
plot(g1$l, main = "1st loading")
plot(g1$f, main = "1st factor")
plot(g2$l, main = "2nd loading")
plot(g2$f, main = "2nd factor")
```




```r
plot(g3$l, main = "3rd loading")
plot(g3$f, main = "3rd factor")
plot(g4$l, main = "4th loading")
plot(g4$f, main = "4th factor")
```




```r
plot(g5$l, main = "5th loading")
plot(g5$f, main = "5th factor")
plot(g6$l, main = "6th loading")
plot(g6$f, main = "6th factor")
```



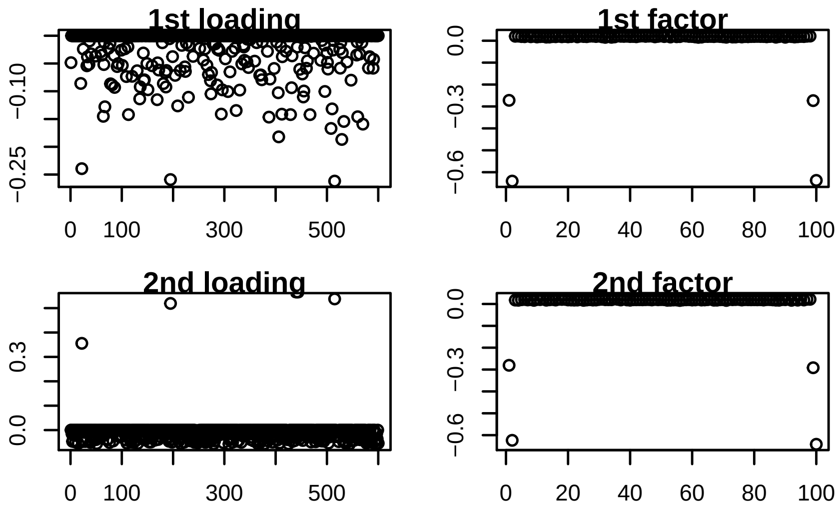
PMA model fitting

We compare the output of *flash* with that of the `PMD()` function of the package PMA. We use their default settings for shrinkage.

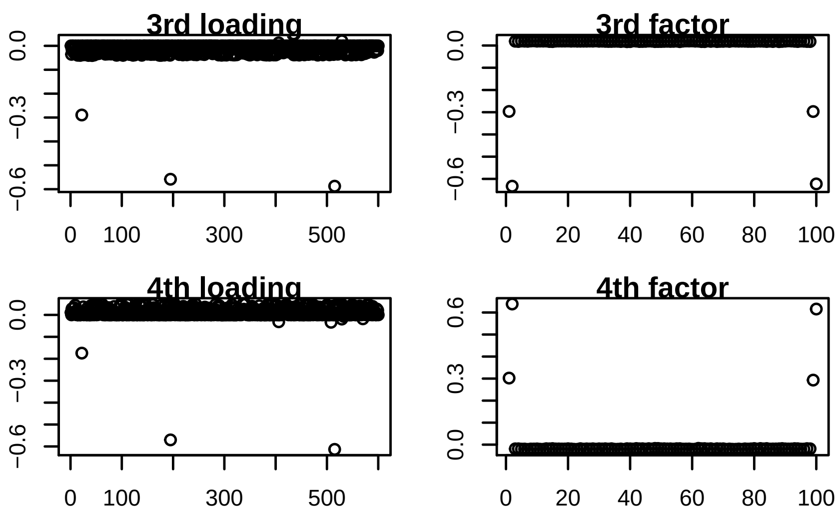
```
out <- PMD(counts, K = 6)
```

```
## 123456789101112131415161718
## 1234567891011121314151617181920
## 12345678
## 123456789
## 1234567891011121314151617
## 1234567891011121314151617181920
```

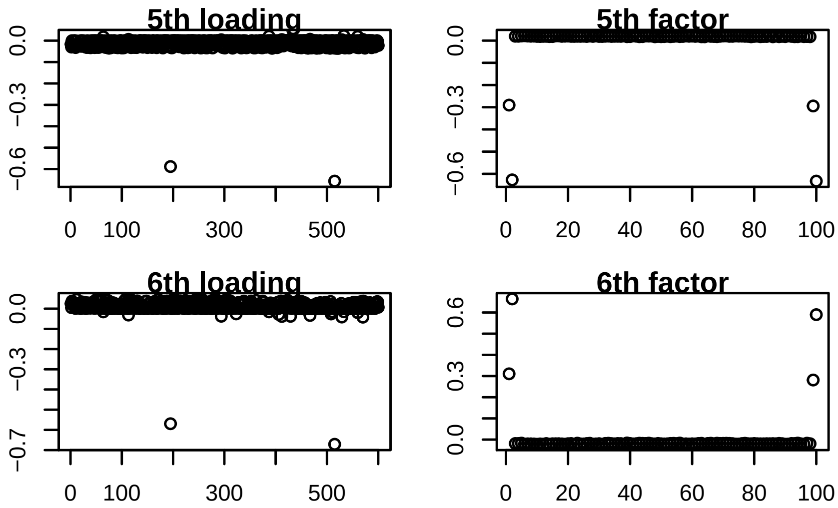
```
par(mfrow = c(2, 2))
par(cex = 0.6)
par(mar = c(3, 3, 0.8, 0.8), oma = c(1, 1, 1,
    1))
plot(out$u[, 1], main = "1st loading")
plot(out$v[, 1], main = "1st factor")
plot(out$u[, 2], main = "2nd loading")
plot(out$v[, 2], main = "2nd factor")
```




```r
plot(out$u[, 3], main = "3rd loading")
plot(out$v[, 3], main = "3rd factor")
plot(out$u[, 4], main = "4th loading")
plot(out$v[, 4], main = "4th factor")
```




```r
plot(out$u[, 5], main = "5th loading")
plot(out$v[, 5], main = "5th factor")
plot(out$u[, 6], main = "6th loading")
plot(out$v[, 6], main = "6th factor")
```




```r
sessionInfo()
```

```
## R version 3.2.4 (2016-03-10)
## Platform: x86_64-apple-darwin13.4.0 (64-bit)
## Running under: OS X 10.10.5 (Yosemite)
##
## locale:
## [1] en_US.UTF-8/en_US.UTF-8/en_US.UTF-8/C/en_US.UTF-8/en_US.UTF-8
##
## attached base packages:
## [1] stats     graphics  grDevices utils
## [5] datasets  methods   base
##
## other attached packages:
## [1] Rcpp_0.12.4   PMA_1.0.9     impute_1.44.0
## [4] plyr_1.8.3    irlba_2.0.0   Matrix_1.2-4
## [7] ashr_1.0.8
##
## loaded via a namespace (and not attached):
##  [1] knitr_1.12.3      magrittr_1.5
##  [3] MASS_7.3-43       doParallel_1.0.10
##  [5] pscl_1.4.9        SQUAREM_2014.8-1
##  [7] lattice_0.20-33   foreach_1.4.3
##  [9] stringr_1.0.0     tools_3.2.4
## [11] parallel_3.2.4    grid_3.2.4
## [13] maptpx_1.9-2      htmltools_0.3
## [15] iterators_1.0.8   assertthat_0.1
## [17] yaml_2.1.13       digest_0.6.9
## [19] formatR_1.2.1     codetools_0.2-14
## [21] slam_0.1-32       evaluate_0.8
```

```
## [23] rmarkdown_0.9.2   stringi_1.0-1
## [25] truncnorm_1.0-7   tufte_0.2
```