

# SCnorm: robust normalization of single-cell RNA-seq data

*Rhonda Bacher and Christina Kendzierski*

February 18, 2019

## Contents

1	Introduction . . . . .	1
2	Run SCnorm . . . . .	2
2.1	Required inputs . . . . .	2
2.2	SCnorm: Check count-depth relationship . . . . .	3
2.3	SCnorm: Normalization . . . . .	5
2.4	Evaluate choice of $K$ . . . . .	7
3	SCnorm: Multiple Conditions . . . . .	8
4	SCnorm: UMI data . . . . .	9
5	Spike-ins . . . . .	10
6	Within-sample normalization . . . . .	10
7	Session info . . . . .	12
8	Frequently Asked Questions . . . . .	13

## 1 Introduction

---

Normalization is an important first step in analyzing RNA-seq expression data to allow for accurate comparisons of a gene’s expression across samples. Typically, normalization methods estimate a scale factor per sample to adjust for differences in the amount of sequencing each sample receives. This is because increases in sequencing typically lead to proportional increases in gene counts. However, in scRNA-seq data sequencing depth does not affect gene counts equally. SCnorm (as detailed in Bacher\* and Chu\* *et al.*, 2017) is a normalization approach we developed for single-cell RNA-seq data (scRNA-seq). SCnorm groups genes based on their count-depth relationship and within each group applies a quantile regression to estimate scaling factors to remove the effect of sequencing depth from the counts.

If you use SCnorm in published research, please cite:

## SCnorm: robust normalization of single-cell RNA-seq data

Bacher R, Chu LF, Leng N, Gasch AP, Thomson J, Stewart R, Newton M, Kendzierski C. SCnorm: robust normalization of single-cell RNA-seq data. Nature Methods. 14 (6), 584-586

(<http://www.nature.com/nmeth/journal/v14/n6/full/nmeth.4263.html>)

If after reading through this vignette and the FAQ section you have questions or problems using SCnorm, please post them to <https://support.bioconductor.org> and tag "SCnorm". This will notify the package maintainers and benefit other users.

## 2 Run SCnorm

Before analysis can proceed, the SCnorm package must be installed.

The easiest way to install SCnorm is through Bioconductor (<https://bioconductor.org/packages/SCnorm>):

```
if (!requireNamespace("BiocManager", quietly=TRUE))
  install.packages("BiocManager")
BiocManager::install("SCnorm")
```

There are two additional ways to download SCnorm.

The first option is most useful if using a previous version of SCnorm (which can be found at <https://github.com/rhondabacher/SCnorm/releases>).

The second option is to download the most recent development version of SCnorm. This version may be used with versions of R below 3.4. This version includes use of summarized-Experiment, but parallel computation is maintained using the parallel package.

```
install.packages("SCnorm_x.x.x.tar.gz", repos=NULL, type="source")
#OR
library(devtools)
devtools::install_github("rhondabacher/SCnorm", ref="devel")
```

After successful installation, the package must be loaded into the working space:

```
library(SCnorm)
```

### 2.1 Required inputs

**Data:** Input to SCnorm may be either of class SummarizedExperiment or a matrix. The expression matrix should be a  $G \times by \times S$  matrix containing the expression values for each gene and each cell, where  $G$  is the number of genes and  $S$  is the number of cells/samples. Gene names should be assigned as rownames and not a column in the matrix. Estimates of gene expression are typically obtained using RSEM, HTSeq, Cufflinks, Salmon or similar approaches.

The object `ExampleSimSCData` is a simulated single-cell data matrix containing 5,000 rows of genes and 90 columns of cells.

```
data(ExampleSimSCData)
ExampleSimSCData[1:5,1:5]
```

## SCnorm: robust normalization of single-cell RNA-seq data

```
##           Cell_1      Cell_2      Cell_3      Cell_4      Cell_5
## Gene_1  3.809447  0.5891684  6.505612  33.052416  0.000000
## Gene_2  21.703998  3.9118515  0.000000  0.000000  5.651665
## Gene_3   2.128070  0.0000000  11.587132  11.352172  5.402953
## Gene_4  22.681505  0.0000000  27.495737  2.571482  8.248906
## Gene_5   0.000000  23.9983434  38.810055  1.244605  12.693561

str(ExampleSimSCData)

##  num [1:5000, 1:90] 3.81 21.7 2.13 22.68 0 ...
##   - attr(*, "dimnames")=List of 2
##     ..$ : chr [1:5000] "Gene_1" "Gene_2" "Gene_3" "Gene_4" ...
##     ..$ : chr [1:90] "Cell_1" "Cell_2" "Cell_3" "Cell_4" ...
```

SCnorm now implements the *SingleCellExperiment* class. The input data should be formatted as following, where *ExampleSimSCData* is the expression matrix:

```
ExampleSimSCData <- SingleCellExperiment::SingleCellExperiment(assays = list('counts' = ExampleSimSCData))
```

If the data was originally formatted as a *SummarizedExperiment*, then it can be coerced using:

```
ExampleSimSCData <- as(ExampleSimSCData, "SingleCellExperiment")
```

**Conditions:** The object *Conditions* should be a vector of length *S* indicating which condition/group each cell belongs to. The order of this vector MUST match the order of the columns in the *Data* matrix.

```
Conditions = rep(c(1), each= 90)
head(Conditions)

## [1] 1 1 1 1 1 1
```

## 2.2 SCnorm: Check count-depth relationship

Before normalizing using SCnorm it is advised to check the relationship between expression counts and sequencing depth (referred to as the count-depth relationship) for your data. If all genes have a similar relationship then a global normalization strategy such as median-by-ratio in the DESeq package or TMM in edgeR will also be adequate. However, we find that when the count-depth relationship varies among genes using global scaling strategies leads to poor normalization. In these cases we strongly recommend proceeding with the normalization provided by SCnorm.

The *plotCountDepth* function will estimate the count-depth relationship for all genes. The genes are first divided into ten equally sized groups based on their non-zero median expression. The function will generate a plot of the distribution of slopes for each group. We also recommend checking a variety of filter options in case you find that only genes expressed in very few cells or very low expressors are the main concern.

The function *plotCountDepth* produces a plot as output which may be wrapped around a call to *pdf()* or *png()* to save it for future reference. The function also returns the information used for plotting which may be utilized if a user would like to generate a more customized

## SCnorm: robust normalization of single-cell RNA-seq data

figure. The returned object is a list with length equal to the number of conditions and each element of the list is a matrix containing each gene's assigned group (based on non-zero median expression) and its' estimated count-depth relationship (Slope).

```
pdf("check_exampleData_count-depth_evaluation.pdf", height=5, width=7)
countDeptEst <- plotCountDepth(Data = ExampleSimSCData, Conditions = Conditions,
                              FilterCellProportion = .1, NCores=3)
dev.off()

## pdf
## 2

str(countDeptEst)

## List of 1
## $ 1:'data.frame': 5000 obs. of 3 variables:
## ..$ Gene : chr [1:5000] "Gene_1" "Gene_10" "Gene_100" "Gene_1000" ...
## ..$ Group: int [1:5000] 4 1 3 3 3 4 1 1 2 2 ...
## ..$ Slope: num [1:5000] 0.07683 -0.00465 0.038 -0.01725 -0.04196 ...

head(countDeptEst[[1]])

##      Gene Group      Slope
## 1   Gene_1     4 0.076832005
## 2   Gene_10     1 -0.004653532
## 3   Gene_100    3 0.038000496
## 4 Gene_1000    3 -0.017253843
## 5 Gene_1001    3 -0.041956519
## 6 Gene_1002    4 -0.673548775
```

Since gene expression increases proportionally with sequencing depth, we expect to find the estimated count-depth relationships near 1 for all genes. This is typically true for bulk RNA-seq datasets. However, it does not hold in most single-cell RNA-seq datasets. In this example data, the relationship is quite variable across genes.

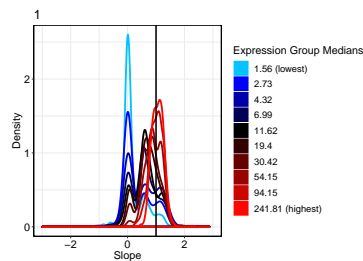


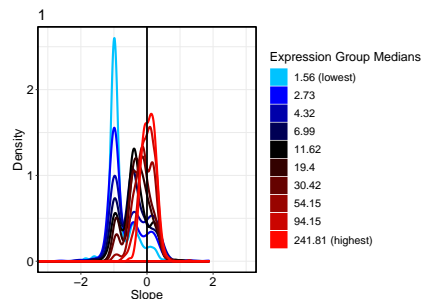
Figure 1: Evaluation of count-depth relationship in un-normalized data

After normalization the count-depth relationship can be estimated on the normalized data, where slopes near zero indicate successful normalization. We can use the function `plotCountDepth` to evaluate normalized data:

```
ExampleSimSCData = SingleCellExperiment::counts(ExampleSimSCData)
# Total Count normalization, Counts Per Million, CPM.
ExampleSimSCData.CPM <- t((t(ExampleSimSCData) / colSums(ExampleSimSCData)) *
                        mean(colSums(ExampleSimSCData)))
```

## SCnorm: robust normalization of single-cell RNA-seq data

```
countDeptEst.CPM <- plotCountDepth(Data = ExampleSimSCData,  
                                   NormalizedData = ExampleSimSCData.CPM,  
                                   Conditions = Conditions,  
                                   FilterCellProportion = .1, NCores=3)
```



```
str(countDeptEst.CPM)  
  
## List of 1  
## $ 1:'data.frame': 5000 obs. of 3 variables:  
## ..$ Gene : chr [1:5000] "Gene_1" "Gene_10" "Gene_100" "Gene_1000" ...  
## ..$ Group: int [1:5000] 4 1 3 3 3 4 1 1 2 2 ...  
## ..$ Slope: num [1:5000] -0.923 -1.005 -0.962 -1.017 -1.042 ...  
  
head(countDeptEst.CPM[[1]])  
  
##      Gene Group      Slope  
## 1   Gene_1      4 -0.9231680  
## 2   Gene_10     1 -1.0046535  
## 3   Gene_100    3 -0.9619995  
## 4 Gene_1000    3 -1.0172538  
## 5 Gene_1001    3 -1.0419565  
## 6 Gene_1002    4 -1.6735488
```

If normalization is successful the estimated count-depth relationship should be near zero for all genes. Here the highly expressed genes appear well normalized, while moderate and low expressors have been over-normalized and have negative slopes.

## 2.3 SCnorm: Normalization

SCnorm will normalize across cells to remove the effect of sequencing depth on the counts. The function `SCnorm` returns: the normalized expression counts, a list of genes which were not considered in the normalization due to filter options, and optionally a matrix of scale factors (if `reportSF = TRUE`).

The default filter for SCnorm only considers genes having at least 10 non-zero expression values. The user may wish to adjust the filter and may do so by changing the value of `FilterCellNum`. The user may also wish to not normalize very low expressed genes. The parameter `FilterExpression` can be used to exclude genes which have non-zero medians lower than a threshold specified by `FilterExpression` (`FilterExpression=0` is default).

## SCnorm: robust normalization of single-cell RNA-seq data

SCnorm starts at  $K = 1$ , which normalizes the data assuming all genes should be normalized in one group. The sufficiency of  $K = 1$  is evaluated by estimating the normalized count-depth relationships. This is done by splitting genes into 10 groups based on their non-zero unnormalized median expression (equally sized groups) and estimating the mode for each group. If all 10 modes are within .1 of zero, then  $K = 1$  is sufficient. If any mode is large than .1 or less than -.1, SCnorm will attempt to normalize assuming  $K = 2$  and repeat the group normalizations and evaluation. This continues until all modes are within .1 of zero. (Simulation studies have shown .1 generally works well and is default, but may be adjusted using the parameter `Thresh` in the `SCnorm` function). If `PrintProgressPlots = TRUE` is specified, the progress plots of SCnorm will be created for each value of  $K$  tried (default is `FALSE`).

Normalized data can be accessed using the `results()` function.

```
Conditions = rep(c(1), each= 90)
pdf("MyNormalizedData_k_evaluation.pdf")
par(mfrow=c(2,2))
DataNorm <- SCnorm(Data = ExampleSimSCData,
                   Conditions = Conditions,
                   PrintProgressPlots = TRUE,
                   FilterCellNum = 10, K = 1,
                   NCores=3, reportSF = TRUE)

## Setting up parallel computation using 3 cores

## SCnorm will normalize assuming 1 is the optimal number of groups. It is not
## advised to set this.

## Gene filter is applied within each condition.

## 0 genes in condition 1 will not be included in the normalization due to
## the specified filter criteria.

## A list of these genes can be accessed in output,
## see vignette for example.

## Done!

dev.off()

## pdf
## 2

DataNorm

## class: SingleCellExperiment
## dim: 5000 90
## metadata(2): ScaleFactors GenesFilteredOut
## assays(2): counts normcounts
## rownames(5000): Gene_1 Gene_2 ... Gene_4999 Gene_5000
## rowData names(0):
## colnames(90): Cell_1 Cell_2 ... Cell_89 Cell_90
## colData names(0):
## reducedDimNames(0):
## spikeNames(0):

NormalizedData <- SingleCellExperiment::normcounts(DataNorm)
NormalizedData[1:5,1:5]
```

## SCnorm: robust normalization of single-cell RNA-seq data

```
##           Cell_1    Cell_2    Cell_3    Cell_4    Cell_5
## Gene_1  4.927704  0.4627998  5.239220  26.2840393  0.000000
## Gene_2  28.075171  3.0728125  0.000000  0.0000000  5.782488
## Gene_3   2.752762  0.0000000  9.331563  9.0275072  5.528019
## Gene_4  29.339624  0.0000000  22.143373  2.0449014  8.439849
## Gene_5   0.000000  18.8510249  31.255229  0.9897386  12.987387
```

The list of genes not normalized according to the filter specifications may be obtained by:

```
GenesNotNormalized <- results(DataNorm, type="GenesFilteredOut")
str(GenesNotNormalized)

## List of 1
## $ GenesFilteredOutGroup1: chr(0)
```

If scale factors should be returned, then they can be accessed using:

```
ScaleFactors <- results(DataNorm, type="ScaleFactors")
str(ScaleFactors)

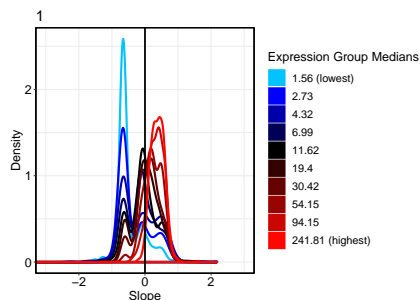
## num [1:5000, 1:90] 0.773 0.773 0.773 0.773 0.773 ...
## - attr(*, "dimnames")=List of 2
## ..$ : chr [1:5000] "Gene_1" "Gene_2" "Gene_3" "Gene_4" ...
## ..$ : chr [1:90] "Cell_1" "Cell_2" "Cell_3" "Cell_4" ...
```

## 2.4 Evaluate choice of $K$

SCnorm first fits the model for  $K = 1$ , and sequentially increases  $K$  until a satisfactory stopping point is reached. In the example run above,  $K = 4$  is chosen, once all 10 slope densities have an absolute slope mode  $< .1$ .

We can also use the function `plotCountDepth` to make the final plot of the normalized count-depth relationship:

```
countDeptEst.SCNorm <- plotCountDepth(Data = ExampleSimSCData,
                                       NormalizedData = NormalizedData,
                                       Conditions = Conditions,
                                       FilterCellProportion = .1, NCores=3)
```



```
str(countDeptEst.SCNorm)

## List of 1
```

## SCnorm: robust normalization of single-cell RNA-seq data

```
## $ 1:'data.frame': 5000 obs. of 3 variables:
## ..$ Gene : chr [1:5000] "Gene_1" "Gene_10" "Gene_100" "Gene_1000" ...
## ..$ Group: int [1:5000] 4 1 3 3 3 4 1 1 2 2 ...
## ..$ Slope: num [1:5000] -0.593 -0.675 -0.597 -0.692 -0.684 ...

head(countDeptEst.SCNorm[[1]])

##      Gene Group      Slope
## 1   Gene_1      4 -0.5927619
## 2   Gene_10     1 -0.6748594
## 3   Gene_100    3 -0.5970708
## 4 Gene_1000    3 -0.6915538
## 5 Gene_1001    3 -0.6835126
## 6 Gene_1002    4 -1.3863016
```

### 3 SCnorm: Multiple Conditions

When more than one condition is present SCnorm will first normalize each condition independently then apply a scaling procedure between the conditions. In this step the assumption is that most genes are not differentially expressed (DE) between conditions and that any systematic differences in expression across the majority of genes is due to technical biases and should be removed.

Zeros are not included in the estimations of scaling factors across conditions by default, this will make the means across conditions equal when zeros are not considered (which can then be used for downstream differential expression analyses with [MAST](#), for example). However, if the proportion of zeros is very unequal between conditions and the user plans to use a downstream tool which includes zeros in the model (such as [DESeq](#) or [edgeR](#)), then the scaling should be estimated with zeros included in this calculation by using the `useZerosToScale=TRUE` option:

```
Conditions = rep(c(1, 2), each= 90)
DataNorm <- SCnorm(Data = MultiCondData,
                  Conditions = Conditions,
                  PrintProgressPlots = TRUE,
                  FilterCellNum = 10,
                  NCores=3,
                  useZerosToScale=TRUE)
```

Generally the definition of condition will be obvious given the experimental setup. If the data are very heterogeneous within an experimental setup it may be beneficial to first cluster more similar cells into groups and define these as conditions in SCnorm.

For very large datasets, it might be more reasonable to normalize each condition separately. To do this, first normalize each Condition separately:

```
DataNorm1 <- SCnorm(Data = ExampleSimSCData[,1:45],
                  Conditions = rep("1", 45),
                  PrintProgressPlots = TRUE,
                  FilterCellNum = 10,
                  NCores=3, reportSF = TRUE)
```



## SCnorm: robust normalization of single-cell RNA-seq data

```
DataNorm2 <- SCnorm(Data = ExampleSimSCData[,46:90],
  Conditions = rep("2", 45),
  PrintProgressPlots = TRUE,
  FilterCellNum = 10,
  NCores=3, reportSF = TRUE)
```

Then the final scaling step can be performed as follows:

```
normalizedDataSet1 <- results(DataNorm1, type = "NormalizedData")
normalizedDataSet2 <- results(DataNorm2, type = "NormalizedData")

NormList <- list(list(NormData = normalizedDataSet1),
  list(NormData = normalizedDataSet2))
OrigData <- ExampleSimSCData
Genes <- rownames(ExampleSimSCData)
useSpikes = FALSE
useZerosToScale = FALSE

DataNorm <- scaleNormMultCont(NormData = NormList,
  OrigData = OrigData,
  Genes = Genes, useSpikes = useSpikes,
  useZerosToScale = useZerosToScale)

str(DataNorm$ScaledData)
myNormalizedData <- DataNorm$ScaledData
```

## 4 SCnorm: UMI data

If the single-cell expression matrix is very sparse (having a lot of zeros) then SCnorm may not be appropriate. Currently, SCnorm will issue a warning if at least one cell/sample has less than 100 non-zero values or total counts below 10,000. SCnorm will fail if the filtering criteria or quality of data leaves less than 100 genes for normalization.

If the data have many tied count values consider setting the option `ditherCounts=TRUE` (default is `FALSE`) which will help in estimating the count-depth relationships. This introduces some randomness but results will not change if the command is rerun.

It is highly recommended to check the count-depth relationship before and after normalization. In some cases, it might be desired to adjust the threshold used to decide K. Lowering the threshold may improve results for some datasets (default `Thresh = .1`).

For larger datasets, it may also be desired to increase the speed. One way to do this is to change the parameter `PropToUse`. `PropToUse` controls the proportion of genes nearest to the overall group mode to use for the group fitting (default is `.25`).

```
checkCountDepth(Data = umiData, Conditions = Conditions,
  FilterCellProportion = .1, FilterExpression = 2)
```

## SCnorm: robust normalization of single-cell RNA-seq data

```
DataNorm <- SCnorm(Data = umiData, Conditions= Conditions,  
  PrintProgressPlots = TRUE,  
  FilterCellNum = 10,  
  PropToUse = .1,  
  Thresh = .1,  
  ditherCounts = TRUE)
```

## 5 Spike-ins

---

SCnorm does not require spike-ins, however if high quality spike-ins are available then they may be used to perform the between condition scaling step. If `useSpikes=TRUE` then only the spike-ins will be used to estimate the scaling factors. If the spike-ins do not span the full range of expression, SCnorm will issue a warning and will use all genes to scale. SCnorm also assumes the spike-ins are named with the prefix "ERCC-".

```
DataNorm <- SCnorm(Data = MultiCondData, Conditions = Conditions,  
  PrintProgressPlots = TRUE,  
  FilterCellNum = 10, useSpikes=TRUE)
```

## 6 Within-sample normalization

---

SCnorm allows correction of gene-specific features prior to the between-sample normalization. We implement the regression based procedure from

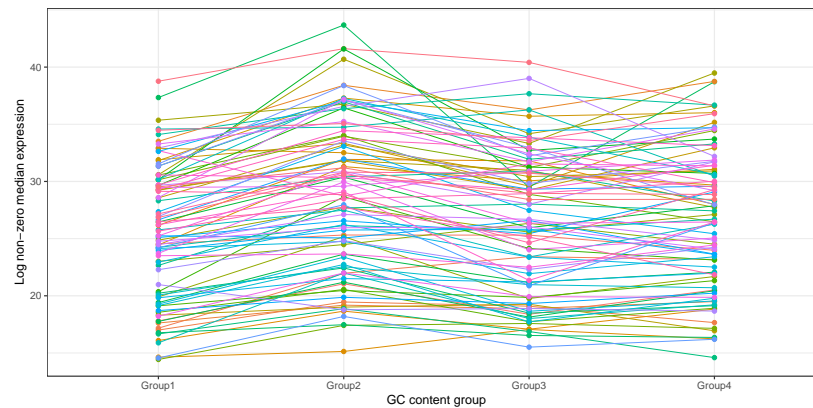
Risso et al., 2011 in [EDASeq](#). To use this feature you must set `withinSample` equal to a vector of gene-specific features, one per gene. This could be anything, but is often GC-content or gene length.

A function to evaluate the extent of bias in expression related to the gene-specific feature is `plotWithinFactor()`. Genes are split into 4 (`NumExpressionGroups = 4` is default) equally sized groups based on the gene-specific factor provided. For each cell the median expression of genes in each group is estimated and plotted. The function `plotWithinFactor` returns the information used for plotting as a matrix of the expression medians for each group for all cells.

In this example I generate a random vector of gene specific features, this may be the proportion of GC content for example. Each cell receives a different color

```
#Colors each sample:  
exampleGC <- runif(dim(ExampleSimSCData)[1], 0, 1)  
names(exampleGC) <- rownames(ExampleSimSCData)  
withinFactorMatrix <- plotWithinFactor(ExampleSimSCData, withinSample = exampleGC)
```

## SCnorm: robust normalization of single-cell RNA-seq data

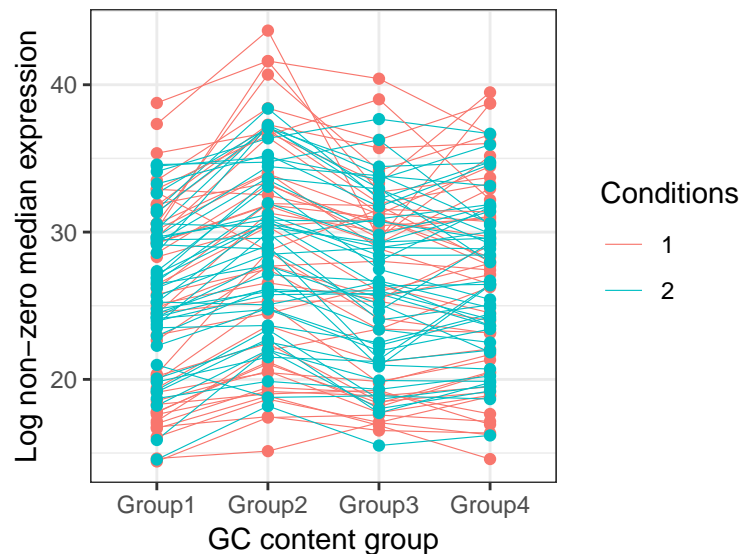


```
head(withinFactorMatrix)
```

```
##      Sample Condition  Group1  Group2  Group3  Group4
## Cell_1 Cell_1         1 17.79670 21.04748 18.38047 20.50711
## Cell_2 Cell_2         1 31.82260 37.29122 35.70271 36.01684
## Cell_3 Cell_3         1 30.14701 33.95080 31.22077 34.45334
## Cell_4 Cell_4         1 37.33889 43.67944 29.50058 38.72606
## Cell_5 Cell_5         1 25.76602 27.48973 23.39817 26.26570
## Cell_6 Cell_6         1 25.09586 26.56063 25.43633 29.08342
```

Specifying a Conditions vector will color each cell according to its associated condition:

```
#Colors samples by Condition:
Conditions <- rep(c(1,2), each=45)
withinFactorMatrix <- plotWithinFactor(ExampleSimSCData, withinSample = exampleGC,
                                       Conditions=Conditions)
```



```
head(withinFactorMatrix)
```

```
##      Sample Condition  Group1  Group2  Group3  Group4
## Cell_1 Cell_1         1 17.79670 21.04748 18.38047 20.50711
```

## SCnorm: robust normalization of single-cell RNA-seq data

```
## Cell_2 Cell_2      1 31.82260 37.29122 35.70271 36.01684
## Cell_3 Cell_3      1 30.14701 33.95080 31.22077 34.45334
## Cell_4 Cell_4      1 37.33889 43.67944 29.50058 38.72606
## Cell_5 Cell_5      1 25.76602 27.48973 23.39817 26.26570
## Cell_6 Cell_6      1 25.09586 26.56063 25.43633 29.08342
```

```
# To run correction use:
DataNorm <- SCnorm(ExampleSimSCData, Conditions,
                   PrintProgressPlots = TRUE,
                   FilterCellNum = 10, withinSample = exampleGC)
```

For additional evaluation on whether to correct for these features or other options for correction, see: Risso, D., Schwartz, K., Sherlock, G. & Dudoit, S. GC-content normalization for RNA-Seq data. BMC Bioinformatics 12, 480 (2011).

## 7 Session info

Here is the output of sessionInfo on the system on which this document was compiled:

```
print(sessionInfo())

## R version 3.5.2 (2018-12-20)
## Platform: x86_64-w64-mingw32/x64 (64-bit)
## Running under: Windows Server 2012 R2 x64 (build 9600)
##
## Matrix products: default
##
## locale:
## [1] LC_COLLATE=C
## [2] LC_CTYPE=English_United States.1252
## [3] LC_MONETARY=English_United States.1252
## [4] LC_NUMERIC=C
## [5] LC_TIME=English_United States.1252
##
## attached base packages:
## [1] stats      graphics  grDevices  utils      datasets  methods   base
##
## other attached packages:
## [1] SCnorm_1.4.7
##
## loaded via a namespace (and not attached):
## [1] SummarizedExperiment_1.12.0 tidyselect_0.2.5
## [3] xfun_0.4 reshape2_1.4.3
## [5] purrr_0.3.0 lattice_0.20-38
## [7] colorspace_1.4-0 snow_0.4-3
## [9] htmltools_0.3.6 stats4_3.5.2
## [11] yaml_2.2.0 rlang_0.3.1
## [13] pillar_1.3.1 glue_1.3.0
## [15] BiocParallel_1.16.6 SingleCellExperiment_1.4.1
## [17] BiocGenerics_0.28.0 matrixStats_0.54.0
```

```
## [19] GenomeInfoDbData_1.2.0      plyr_1.8.4
## [21] stringr_1.4.0               zlibbioc_1.28.0
## [23] MatrixModels_0.4-1          munsell_0.5.0
## [25] gtable_0.2.0                moments_0.14
## [27] evaluate_0.13               forcats_0.4.0
## [29] labeling_0.3                 Biobase_2.42.0
## [31] knitr_1.21                   SparseM_1.77
## [33] IRanges_2.16.0              GenomeInfoDb_1.18.2
## [35] quantreg_5.38               parallel_3.5.2
## [37] highr_0.7                   Rcpp_1.0.0
## [39] scales_1.0.0                BiocManager_1.30.4
## [41] DelayedArray_0.8.0          S4Vectors_0.20.1
## [43] XVector_0.22.0              BiocStyle_2.10.0
## [45] ggplot2_3.1.0               digest_0.6.18
## [47] stringi_1.3.1               dplyr_0.8.0.1
## [49] GenomicRanges_1.34.0        grid_3.5.2
## [51] tools_3.5.2                 bitops_1.0-6
## [53] magrittr_1.5                 lazyeval_0.2.1
## [55] RCurl_1.95-4.11             tibble_2.0.1
## [57] cluster_2.0.7-1             crayon_1.3.4
## [59] pkgconfig_2.0.2             Matrix_1.2-15
## [61] data.table_1.12.0           assertthat_0.2.0
## [63] rmarkdown_1.11              R6_2.4.0
## [65] compiler_3.5.2
```

## 8 Frequently Asked Questions

---

### Does SCnorm work for all datasets?

No, while SCnorm has proven useful in normalizing many single-cell RNA-seq datasets, it will not be appropriate in every setting. It is important to evaluate normalized data for selected genes as well as overall (e.g. using `plotCountDepth`).

### Can I use SCnorm on your 10X (or very sparse) dataset?

SCnorm is not intended for datasets with more than ~80% zero counts, often K will not converge in these situations. Setting the `FilterExpression` parameter to 1 or 2 may help, but is not a guarantee. It may also be helpful to use the `ditherCounts = TRUE` parameter for sparse UMI based data which may contain numerous tied counts (counts of 1 and 2 for example).

### Can/Should I use SCnorm on my bulk RNA-seq data?

SCnorm can normalize bulk data. However, SCnorm should not be used to normalize data containing less than 10 cells/samples. Consideration must also be given to what downstream analysis methods will be used. Methods such as DESeq2 or edgeR typically expect a matrix of scaling factors to be supplied, these can be obtained in SCnorm by setting `reportSF=TRUE` in the SCnorm function.

The count-depth relationship of both unnormalized and normalized bulk RNA-seq data can be evaluated using the `plotCountDepth` function.

### How can I speedup SCnorm if I have thousands of cells?

Utilizing multiple cores via the `NCores` parameter is the most effective way.

Splitting the data into smaller clusters may also improve speed. Here is one example on how to cluster and the appropriate way to run `SCnorm`: (This method of clustering single-cells was originally suggested by Lun et al., 2016 in [scrn](#).)

```
library(dynamicTreeCut)
distM <- as.dist( 1 - cor(BigData, method = 'spearman'))
htree <- hclust(distM, method='ward.D')
clusters <- factor(unname(cutreeDynamic(htree, minClusterSize = 50,
                                     method="tree", respectSmallClusters = FALSE)))
names(clusters) <- colnames(BigData)
Conditions = clusters

DataNorm <- SCnorm(Data = BigData,
                  Conditions = Conditions,
                  PrintProgressPlots = TRUE,
                  FilterCellNum = 10,
                  NCores=3, useZerosToScale=TRUE)
```

### When should I set the parameter `useZerosToScale=TRUE` ?

This parameter is only used when specifying multiple conditions in `SCnorm`. The `useZerosToScale` parameter will determine whether zeros are used in estimating the condition based scaling factors.

Use the default, `useZerosToScale=FALSE`, when planning to use single-cell specific methods such as MAST that separately model continuous and discrete measurements.

If you plan on using an analysis method that explicitly uses zeros in the model like DESeq2, then `useZerosToScale=TRUE` should be used.

### SCnorm was unable to converge.

`SCnorm` will fail if  $K$  exceeds 25 groups. It is unlikely that such a large number of groups is appropriate. This might happen if a large proportion of your genes have estimated count-depth relationships very close to zero. Typically this error can be resolved by removing genes with very small counts from the normalization using the parameter `FilterExpression`. Genes having non-zero median expression less than `FilterExpression` will not be scaled during normalization. An appropriate value for `FilterExpression` will be data dependent and decided based on exploring the data. One way that might help decide is to see if there are any natural cutoffs in the non-zero medians:

```
MedExpr <- apply(Data, 1, function(c) median(c[c != 0]))
plot(density(log(MedExpr), na.rm=T))
abline(v=log(c(1,2,3,4,5)))
# might set FilterExpression equal to one of these values.
```