

# Overview of the scRNAseq dataset collection

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## Contents

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- 1 Raw data availability and accession codes
- 2 Pre-processing and summary
- 3 Data format and metadata
- 4 ERCC spike-ins
- References

## 1 Raw data availability and accession codes

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This package contains a collection of three publicly available single-cell RNA-seq datasets. The data were downloaded from NCBI's SRA or from EBI's ArrayExpress (see below for Accession numbers)

The dataset `fluidigm` contains 65 cells from (Pollen et al. 2014), each sequenced at high and low coverage (SRA: SRP041736).

The dataset `th2` contains 96 T helper cells from (Mahata et al. 2014) (ArrayExpress: E-MTAB-2512).

The dataset `allen` contains 379 cells from the mouse visual cortex. This is a subset of the data published in (Tasic et al. 2016) (SRA: SRP061902).

## 2 Pre-processing and summary

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SRA files were downloaded from the Sequence Read Archive and the SRA Toolkit was used to transform them to FASTQ. FASTQ files were downloaded from EMBL-EBI ArrayExpress.

Reads were aligned with TopHat (v. 2.0.11) (Trapnell, Pachter, and Salzberg 2009) to the appropriate reference genome (GRCh38 for human samples, GRCm38 for mouse). RefSeq mouse gene annotation (GCF\_000001635.23\_GRCm38.p3) was downloaded from NCBI on Dec. 28, 2014. RefSeq human gene annotation (GCF\_000001405.28)

was downloaded from NCBI on Jun. 22, 2015.

featureCounts (v. 1.4.6-p3) (Liao, Smyth, and Shi 2013) was used to compute gene-level read counts and Cufflinks (v. 2.2.0) (Trapnell et al. 2010) was used to compute gene-level FPKM's.

In parallel, reads were mapped to the transcriptome using RSEM (v. 1.3.0) (Li and Dewey 2011) to compute read counts and TPM's.

FastQC (v. 0.10.1) (<http://www.bioinformatics.babraham.ac.uk/projects/fastqc/>) and Picard (v. 1.128) (<http://broadinstitute.github.io/picard/>) were used to compute sample quality control (QC) metrics. (Picard's scripts `CollectRnaSeqMetrics`, `CollectAlignmentSummaryMetrics` and `CollectInsertSizeMetrics`).

Note that all the samples available in GEO and/or ArrayExpress were included in the data object, including the samples that were excluded in the original publication because they did not pass QC.

### 3 Data format and metadata

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The package contains each dataset in the form of `SummarizedExperiment` objects. To illustrate the format of each dataset, we will use the `fluidigm` data.

```
library(scRNAseq)
data(fluidigm)
fluidigm

## class: SummarizedExperiment
## dim: 26255 130
## metadata(3): sample_info clusters which_qc
## assays(4): tophat_counts cufflinks_fpkms rsem_counts rsem_tpm
## rownames(26255): A1BG A1BG-AS1 ... ZZEF1 ZZZ3
## rowData names(0):
## colnames(130): SRR1275356 SRR1274090 ... SRR1275366 SRR127526
1
## colData names(28): NREADS NALIGNED ... Cluster1 Cluster2
```

We can retrieve the gene expression measures by using the `assay` constructor.

```
head(assay(fluidigm)[,1:3])
```

```
##          SRR1275356 SRR1274090 SRR1275251
## A1BG          0          0          0
## A1BG-AS1       0          0          0
## A1CF           0          0          0
## A2M            0          0          0
## A2M-AS1        0          0          0
## A2ML1          0          0          0
```

`assay` will return the gene-level read counts. If we want to access the FPKM values, we need the following

```
head(assay(fluidigm, 2)[,1:3])
```

```
##          SRR1275356 SRR1274090 SRR1275251
## A1BG          0  0.0000000          0
## A1BG-AS1       0  0.3256690          0
## A1CF           0  0.0687904          0
## A2M            0  0.0000000          0
## A2M-AS1        0  0.0000000          0
## A2ML1          0  1.3115300          0
```

Alternatively, we can use the `assays` accessor to get a list with both matrices.

```
names(assays(fluidigm))
```

```
## [1] "tophat_counts" "cufflinks_fpkm" "rsem_counts"  "rsem_
tpm"
```

```
head(assays(fluidigm)$fpkm[,1:3])
```

```
## NULL
```

Note that the all the protein-coding genes are included in the expression matrix, even if they are not expressed in these samples, hence filtering of the non-expressed genes should be performed before any statistical analysis.

```
dim(fluidigm)
```

```
## [1] 26255  130
```

```
table(rowSums(assay(fluidigm))>0)
```

```
##
## FALSE  TRUE
##  9170 17085
```

useful QC information, as well as the available annotation of the samples. This information can be accessed through the `colData` accessor.

```
colData(fluidigm)
```

```
## DataFrame with 130 rows and 28 columns
##           NREADS  NALIGNED  RALIGN TOTAL_DUP  PRIMER
INSERT_SZ
##           <numeric> <numeric> <numeric> <numeric> <numeric>
<numeric>
## SRR1275356 10554900  7555880  71.5862  58.4931 0.0217638
208
## SRR1274090  196162   182494  93.0323  14.5122 0.0366826
247
## SRR1275251  8524470  5858130  68.7213  65.0428 0.0351827
230
## SRR1275287  7229920  5891540  81.4884  49.7609 0.0208685
222
## SRR1275364  5403640  4482910  82.9609  66.5788 0.0298284
228
## ...           ...           ...           ...           ...
...
## SRR1275259  5949930  4181040  70.2705  52.5975 0.0205253
224
## SRR1275253 10319900  7458710  72.2747  54.9637 0.0205342
207
## SRR1275285  5300270  4276650  80.6873  41.6394 0.0227383
222
## SRR1275366  7701320  6373600   82.76  68.9431 0.0266275
233
## SRR1275261 13425000  9554960  71.1727  62.0001 0.0200522
241
##           INSERT_SZ_STD COMPLEXITY  NDUPR PCT_RIBOSOMAL_B
ASES
##           <numeric> <numeric> <numeric>           <nume
ric>
## SRR1275356           63  0.868928  0.343113           2
e-06
## SRR1274090           133  0.997655  0.93573
0
## SRR1275251           89  0.789252  0.201082
0
## SRR1275287           78   0.8981  0.538191
0
## SRR1275364           76  0.890693  0.39166
0
## ...           ...           ...           ...
...
## SRR1275259           80  0.898898  0.399189           5
e-06
## SRR1275253           62  0.863618  0.344744
0
## SRR1275285           76  0.920068  0.638765           2
e-06
## SRR1275366           83  0.860359  0.343122
0
## SRR1275261          105  0.806833  0.234551
0
##           PCT_CODING_BASES PCT_UTR_BASES PCT_INTRONIC_BASES
```

```

##          <numeric>      <numeric>      <numeric>
## SRR1275356      0.125806      0.180954      0.613229
## SRR1274090      0.309822      0.412917      0.205185
## SRR1275251      0.398461      0.473884      0.039886
## SRR1275287      0.19642      0.227592      0.498944
## SRR1275364      0.138617      0.210406      0.543941
## ...          ...          ...          ...
## SRR1275259      0.261384      0.383665      0.26425
## SRR1275253      0.110732      0.190036      0.606814
## SRR1275285      0.143667      0.231103      0.54007
## SRR1275366      0.215696      0.307817      0.409437
## SRR1275261      0.408881      0.391068      0.147748
##          PCT_INTERGENIC_BASES PCT_MRNA_BASES MEDIAN_CV_COVE
RAGE
##          <numeric>      <numeric>      <nume
ric>
## SRR1275356      0.080008      0.30676      1.4
9577
## SRR1274090      0.072076      0.722739      1.0
0758
## SRR1275251      0.08777      0.872345      1.2
4299
## SRR1275287      0.077044      0.424013      0.77
5981
## SRR1275364      0.107035      0.349024      1.4
4137
## ...          ...          ...
...
## SRR1275259      0.090696      0.645049      1.1
0104
## SRR1275253      0.092418      0.300768      1.7
0169
## SRR1275285      0.085158      0.37477      0.71
4087
## SRR1275366      0.06705      0.523513      1.2
5198
## SRR1275261      0.052302      0.799949      0.93
9066
##          MEDIAN_5PRIME_BIAS MEDIAN_3PRIME_BIAS
##          <numeric>      <numeric>
## SRR1275356      0      0.166122
## SRR1274090      0.181742      0.698991
## SRR1275251      0      0.340046
## SRR1275287      0.010251      0.350915
## SRR1275364      0      0.204074
## ...          ...          ...
## SRR1275259      0      0.31555
## SRR1275253      0      0.106902
## SRR1275285      0.019578      0.419987
## SRR1275366      0      0.281554
## SRR1275261      0.000292      0.290117
##          MEDIAN_5PRIME_TO_3PRIME_BIAS sample_id.x
Lane_ID
##          <numeric> <character>      <ch
aracter>

```

```

## SRR1275356      1.03625  SRX534610 D24VYACXX
130502:4
## SRR1274090      0.29351  SRX534823
1
## SRR1275251      0.201518  SRX534623 D24VYACXX
130502:4
## SRR1275287      0.292838  SRX534641 D24VYACXX
130502:1
## SRR1275364      0.619863  SRX534614 D24VYACXX
130502:7
## ...           ...           ...
...
## SRR1275259      0.350391  SRX534627 D24VYACXX
130502:4
## SRR1275253      0.944856  SRX534624 D24VYACXX
130502:3
## SRR1275285      0.194939  SRX534640 D24VYACXX
130502:1
## SRR1275366      0.388272  SRX534615 D24VYACXX
130502:8
## SRR1275261      0.384402  SRX534628 D24VYACXX
130502:3
##           LibraryName avgLength      spots Biological_Conditi
on
##           <character> <integer> <integer>           <characte
r>
## SRR1275356      GW16_2      202    9818076              GW
16
## SRR1274090      NPC_9       60     95454              N
PC
## SRR1275251      GW16_8      202    7935952              GW
16
## SRR1275287      GW21+3_2    202    6531944             GW2
1+3
## SRR1275364      GW16_23     202    4919561              GW
16
## ...           ...           ...           ...
...
## SRR1275259      GW21_3      202    5528916              GW
21
## SRR1275253      GW16_9      202    9562204              GW
16
## SRR1275285      GW21+3_16   202    4860721             GW2
1+3
## SRR1275366      GW16_24     202    7153688              GW
16
## SRR1275261      GW21_4      202    12142387             GW
21
##           Coverage_Type Cluster1 Cluster2
##           <character> <factor> <factor>
## SRR1275356      High      IIIb      III
## SRR1274090      Low       1a       I
## SRR1275251      High      NA       III
## SRR1275287      High      1c       I
## SRR1275364      High      IIIb      III

```

```
## ...      ...      ...      ...
## SRR1275259      High      NA      III
## SRR1275253      High      IIIb     III
## SRR1275285      High      Iva      IV
## SRR1275366      High      NA      III
## SRR1275261      High      II       II
```

The first columns are related to sample quality, while other fields include information on the samples, provided by the original authors in their GEO/SRA submission and/or as Supplementary files in the publication.

Finally, the object contains a list of `metadata` that provide additional information on the experiment.

```
names(metadata(fluidigm))
```

```
## [1] "sample_info" "clusters"      "which_qc"
```

```
metadata(fluidigm)$which_qc
```

```
## [1] "NREADS"      "NALIGNED"
## [3] "RALIGN"      "TOTAL_DUP"
## [5] "PRIMER"      "INSERT_SZ"
## [7] "INSERT_SZ_STD" "COMPLEXITY"
## [9] "NDUPR"      "PCT_RIBOSOMAL_BASES"
## [11] "PCT_CODING_BASES" "PCT_UTR_BASES"
## [13] "PCT_INTRONIC_BASES" "PCT_INTERGENIC_BASES"
## [15] "PCT_MRNA_BASES" "MEDIAN_CV_COVERAGE"
## [17] "MEDIAN_5PRIME_BIAS" "MEDIAN_3PRIME_BIAS"
## [19] "MEDIAN_5PRIME_TO_3PRIME_BIAS"
```

In particular, in all datasets, the `metadata` list includes an element called `which_qc` that contains the names of the `colData` columns that relate to sample QC.

## 4 ERCC spike-ins

The `th2` and `allen` datasets contain the expression of the ERCC spike-ins. Note that these are **included in the same matrices** as the endogenous genes, hence users must use caution to avoid when using the data, to avoid mistreat external spike-ins as endogenous genes. One may wish to split the datasets in two, e.g.:

```
data(th2)
ercc_idx <- grep("^ERCC-", rownames(th2))
th2_endogenous <- th2[-ercc_idx,]
th2_ercc <- th2[ercc_idx,]

head(assay(th2_ercc)[,1:4])
```



##	ERR488983	ERR488967	ERR488989	ERR489021
## ERCC-00002	7775	14356	3868	15478
## ERCC-00003	1	75	1	2114
## ERCC-00004	1167	2468	1960	3914
## ERCC-00009	237	4	1167	1318
## ERCC-00012	0	0	0	0
## ERCC-00013	0	0	0	0

## References

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Liao, Y, GK Smyth, and W Shi. 2013. "featureCounts: An Efficient General Purpose Program for Assigning Sequence Reads to Genomic Features." *Bioinformatics*, btt656.

Mahata, B, X Zhang, AA Kolodziejczyk, V Proserpio, L Haim-Vilmovsky, AE Taylor, D Hebenstreit, et al. 2014. "Single-Cell RNA Sequencing Reveals T Helper Cells Synthesizing Steroids de Novo to Contribute to Immune Homeostasis." *Cell Reports* 7 (4):1130-42.

Pollen, AA, TJ Nowakowski, J Shuga, X Wang, AA Leyrat, JH Lui, N Li, et al. 2014. "Low-Coverage Single-Cell mRNA Sequencing Reveals Cellular Heterogeneity and Activated Signaling Pathways in Developing Cerebral Cortex." *Nature Biotechnology* 32 (10):1053-8.

Tasic, B, V Menon, TN Nguyen, TK Kim, T Jarsky, Z Yao, B Levi, et al. 2016. "Adult Mouse Cortical Cell Taxonomy Revealed by Single Cell Transcriptomics." *Nature Neuroscience* 19:335-46.

Trapnell, C, L Pachter, and SL Salzberg. 2009. "TopHat: Discovering Splice Junctions with RNA-Seq." *Bioinformatics* 25 (9):1105-11.

Trapnell, C, BA Williams, G Pertea, A Mortazavi, G Kwan, MJ Van Baren, SL Salzberg, BJ Wold, and L Pachter. 2010. "Transcript Assembly and Quantification by RNA-Seq Reveals Unannotated Transcripts and Isoform Switching During Cell Differentiation." *Nature Biotechnology* 28 (5):511-15.