



# Deeper differential expression analysis with shrinkage correction

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# Follow-along preliminaries



## Software:

- R: <https://cran.r-project.org/>
- Rstudio: <https://posit.co/download/rstudio-desktop/>
- R packages:

```
install.packages("BiocManager")  
BiocManager::install(c("DESeq2", "pasilla", "ggplot2"))
```

## Analysis scripts:

- [https://github.com/JBrownBiostat/DifferentialExpressionTraining\\_May2024](https://github.com/JBrownBiostat/DifferentialExpressionTraining_May2024)

# Other resources

From the original developers, Michael Love, Simon Anders, Wolfgang Huber:  
<https://bioconductor.org/packages/release/bioc/vignettes/DESeq2/inst/doc/DESeq2.html>

General (single-cell RNA) pipelines from some greats in the field:  
<https://bioconductor.org/books/3.17/OSCA/>

Carpentry workshop from Bioconductor:  
<https://carpentries-incubator.github.io/bioc-rnaseq/>

# DE definitions: data structure

A  $G \times J$  matrix of abundance measures across:

- $G$  many features: **genes**, transcripts, exons, protein binding peaks, methylation sites, etc.
- $J$  many samples: **experimental libraries**, single cells, spatial spots, binned pixels, etc.
- First few lines from the *pasilla* dataset of pasilla gene knock-down in drosophila melanogaster

	Samp1	Samp2	Samp3	Samp4	Samp5	Samp6	Samp7
FBgn0000003	0	0	0	0	0	0	1
FBgn0000008	92	161	76	70	140	88	70
FBgn0000014	5	1	0	0	4	0	0
FBgn0000015	0	2	1	2	1	0	0
FBgn0000017	4664	8714	3564	3150	6205	3072	3334
FBgn0000018	583	761	245	310	722	299	308
FBgn0000022	0	1	0	0	0	0	0
FBgn0000024	10	11	3	3	10	7	5
FBgn0000028	0	1	0	0	0	1	1
FBgn0000032	1446	1713	615	672	1698	696	767



Switch over to `bulkRNA_AnalysisScript.R`

# DE definitions: what are we testing

Most generally:

- Is the effect size of a given combination of covariates significantly non-zero

In practice:

- Is the abundance of gene  $g$  in condition  $A$  significantly different than in condition  $B$  controlling for appropriate nuisance variation

Implied comparison of interest:

- Ratios measured as log (2) fold-changes

# DE definitions: typical model spec.

DESeq2 (and other models) assume observed expression is effectively modeled as a *Negative Binomial GLM*, i.e.:

$$y_{gj} \sim NB(\mu_{gj}, \phi_g)$$
$$\log(\mu_{gj}) := [X\vec{\beta}]_{gj} + \log(s_j)$$

For observed counts  $y_{gj}$ , design matrix  $X$ , coefficient vector  $\vec{\beta}$ , normalization factor/offset  $s_j$ , and dispersion parameter  $\phi_g$ .

# NB GLM: Comp. to linear regression



Traditional “simple linear regression” can be written as a Normal GLM:

$$y_{gj} = [X\vec{\beta}]_{gj} + \epsilon_{gj} \text{ s.t. } \epsilon_{gj} \sim N(0, \sigma_g^2)$$

is equivalent to:

$$\begin{aligned} y_{gj} &\sim N(\mu_{gj}, \sigma_g^2) \\ \mu_{gj} &:= [X\vec{\beta}]_{gj} \end{aligned}$$



Identity link (Normal):

$$\mu_{gj} = [X\vec{\beta}]_{gj} = x_{g0}\beta_0 + x_{g1}\beta_1 \cdots + x_{gK}\beta_K$$

Log link (Negative Binomial):

$$\begin{aligned}\log(\mu_{gj}) &= [X\vec{\beta}]_{gj} + \log(s_j) \\ \Rightarrow \mu_{gj} &= (e^{x_{g0}\beta_0} e^{x_{g1}\beta_1} \cdots e^{x_{gK}\beta_K}) s_j\end{aligned}$$

Action of log link indicates data  $Y$  should be raw expression and not normalized expression

# (Pre) Calculation of normalization offset



In DESeq2 (and other methods) normalization factors  $s_j$  are offsets:

- $s_j$  are calculated prior to model estimation (fixed)
- $s_j$  have an implicit fixed coefficient  $\beta_s = 1$

Popular norm. factor calculation methods include:

1. Reads-per-kilobase-million (RPKM)
2. Transcripts/Counts-per-million (TPM/CPM)
3. Library-size normalization
4. Trimmed-mean-of-m-values (TMM, default in edgeR)

# DESeq2 normalization default



Method of *Median of Ratios* and *Scran*:

- Median of Ratios (MR) from Anders and Huber 2010
- Scran based on Lun, Bach, and Marioni 2016

Both methods based on the median of ratios relationship:

$$\hat{s}_j := \operatorname{median}_g \left\{ \frac{\widehat{y}_{gj}}{\left( \prod_g^G \widehat{y}_{gj} \right)^{\frac{1}{G}}} \right\} = \operatorname{median}_g \left\{ \frac{\widehat{y}_{gj}}{\exp \left[ \frac{1}{G} \sum_g^G \log(\widehat{y}_{gj}) \right]} \right\}$$

For MR,  $\widehat{y}_{gj} = y_{gj}$  and  $s_j = \hat{s}_j$

For Scran,  $\widehat{y}_{gj}$  is based on a pooling of cells and  $s_j$  is derived from a deconvolution of (multiple) estimates  $\hat{s}_j$  that are based on sample  $j$



Switch over to `bulkRNA_AnalysisScript.R`

# NB GLM: Dispersion estimates



Dispersion is analogous to variance, specifically:

$$y \sim NB(\mu, \phi) \Rightarrow \mathbb{E}[y] = \mu; \mathbb{V}[y] = \mu + \phi\mu^2$$

In typical bulk experiments, replicate counts are low:

- High standard error on fitted  $\phi$
- Reduced power to identify significant  $\beta_{gk}$

So pool information across genes with similar expression levels...

*Note:* MLE of  $\phi$  only exists when sample variance is greater than sample mean...



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