

MBV4410/9410 Fall 2016

Dec. 6 - Analysing transcriptome data (using R) – part 2



### **Outline**

### **Monday**

### Before lunch:

- Transcriptomics (lectures/practical)
  - Sequencing technologies
  - Transcriptome assembly
  - Gene expression

### After lunch:

- Basic R/RStudio (lecture)
- Installing/setting up R/RStudio
- Basic R (practical)

### **Tuesday**

Continue the transcriptomics pipeline (lectures/practical)

- Count gene expression
- Experimental design
- Quality assessment
- Differential gene expression

### After lunch:

- Bioconductor (lecture)
- Transcriptomics/DE-test (lecture/practical)

#### Reference Sequence Software genome data setup Sequence quality checks Steps 1 and 2 Collect metadata for Steps 3-6 experiment Mapping reads, Alternative organize files, alignment Steps 7-12 Transcript SAM/BAM files) inspect mapping annotation Alternative Feature counting counting Step 13 (count table) Data structures, Step 14 normalization. edgeR DESeg fitness checks 2-group differential GLM-based differential comparison comparisons Inspect and save results

Additional sanity

checks

Step 15

### **Summary**

**FastQC** – *view* fastq files (fastq.gz / fq.gz)

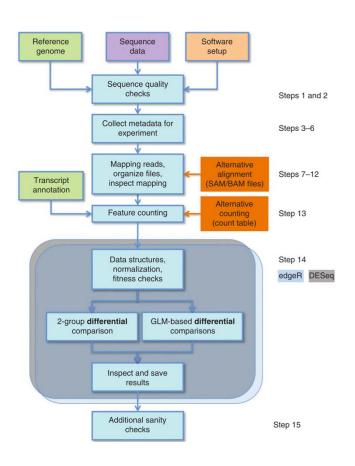
**trim-galore** – *trims* the fastq files on quality and/or adapters

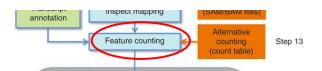
**TopHat2** – *maps* the trimmed reads to the genome

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### **Counting gene expression**





### Counting gene expression

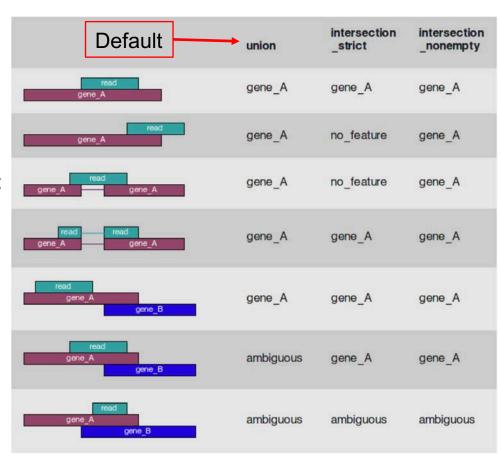
### **HTSeq-counts**

http://www-huber.embl.de/HTSeq/doc/count.html

### HTSeq gives "raw counts"

Many programs to count/estimate expression:

- HTSeq (python) gives raw counts
- Cufflinks (tuxedo pipeline) fpkm values
- RSEM (de novo transcriptomes) expected counts
- summarizeOverlaps (R) similar to HTSeq
- ...





### **Counting gene expression**

### Raw counts

The number of reads (pairs counting as one) mapping to a feature.

Not scaled by length (i.e. longer fragments = higher count) or sequencing depth (i.e. more sequences = higher count).

### Counts per million (cpm)

Scaled by sequencing depth, not length.

### **TPM**

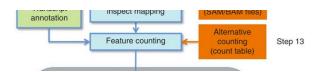
Transcripts per million. Scaled by sequencing depth and length

### fpkm/rpkm

Reads/fragments per kilobase of exon per million reads mapped. Similar to TPM. Scaled by sequencing depth and length

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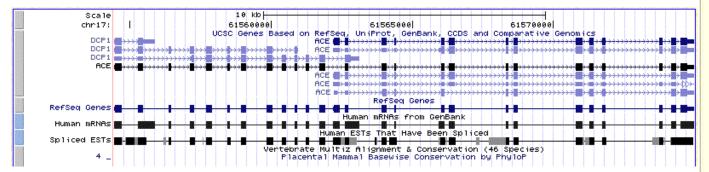
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### **Annotation files**

.gtf .gff .wig .gtf2 .gff3 .bed .vcf

- Like "Tracks" in a genome browser
- Specify coordinates in a genome
- A multitude of formats...



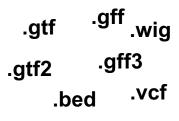


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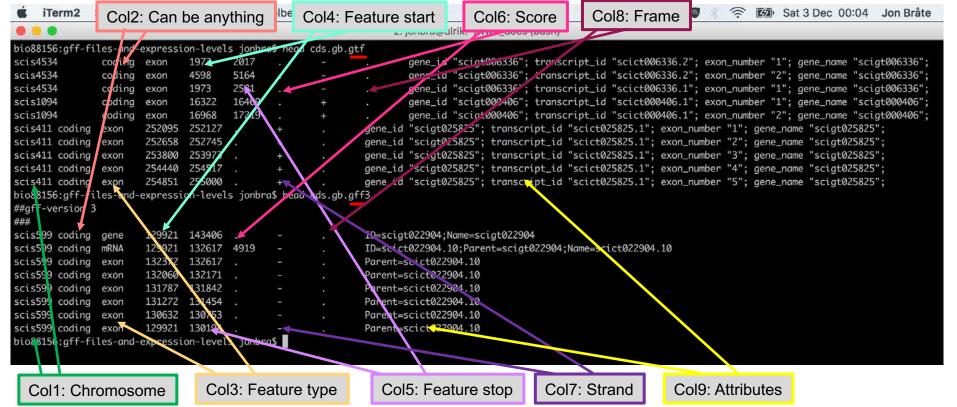
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### **Annotation files**



### .gtf and .gff3 most common (perhaps...). 9 tab-separated columns



## **Exercise 3 – Counting gene expression**

#### Experimental design Reference Sequence Software genome data setup Sequence quality checks Steps 1 and 2 Collect metadata for Steps 3-6 experiment Mapping reads, Alternative organize files. alignment Steps 7-12 Transcript inspect mapping (SAM/BAM files) annotation Alternative Feature counting counting Step 13 (count table) Data structures, Step 14 normalization, edgeR DESeq fitness checks 2-group differential GLM-based differential comparison comparisons Inspect and save results Additional sanity Step 15 checks

### **Experimental design**

#### Experimental design Sequence Reference Software data genome setup Sequence quality checks Steps 1 and 2 Collect metadata for Steps 3-6 experiment Mapping reads, Alternative organize files. alignment Steps 7-12 Transcript inspect mapping SAM/BAM files) annotation Alternative Feature counting counting Step 13 (count table) Data structures. Step 14 normalization. edgeR DESeg fitness checks 2-group differential **GLM-based differential** comparison comparisons Inspect and save results Additional sanity Step 15 checks

### **Experimental design**

### **Experimental design**

A crucial prerequisite for a successful RNA-seq study is that the data generated have the potential to answer the biological questions of interest. This is achieved by first defining a good experimental design, that is, by choosing the library type, sequencing depth and number of replicates appropriate for the biological system under study,

Conesa et al. Genome Biology (2016) 17:13 DOI 10.1186/s13059-016-0881-8

Genome Biology

### REVIEW

#### **Open Access**

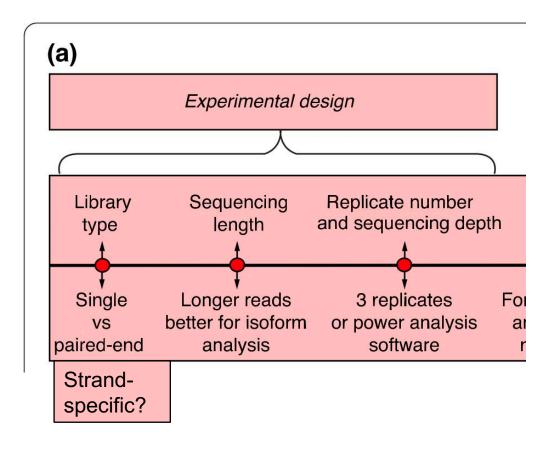
## A survey of best practices for RNA-seq data analysis



Ana Conesa<sup>1,2\*</sup>, Pedro Madrigal<sup>3,4\*</sup>, Sonia Tarazona<sup>2,5</sup>, David Gomez-Cabrero<sup>6,7,8,9</sup>, Alejandra Cervera<sup>10</sup>, Andrew McPherson<sup>11</sup>, Michał Wojciech Szcześniak<sup>12</sup>, Daniel J. Gaffney<sup>3</sup>, Laura L. Elo<sup>13</sup>, Xuegong Zhang<sup>14,15</sup> and Ali Mortazavi<sup>16,17\*</sup>

#### Experimental design Reference Sequence Software setup genome data Sequence quality checks Steps 1 and 2 Collect metadata for Steps 3-6 experiment Mapping reads, Alternative organize files, alignment Steps 7-12 Transcript SAM/BAM files) inspect mapping annotation Alternative Feature counting counting Step 13 (count table) Data structures. Step 14 normalization, edgeR DESeq fitness checks 2-group differential GLM-based differential comparison comparisons Inspect and save results Additional sanity Step 15 checks

### **Experimental design**



### **Experimental design**

## Goal

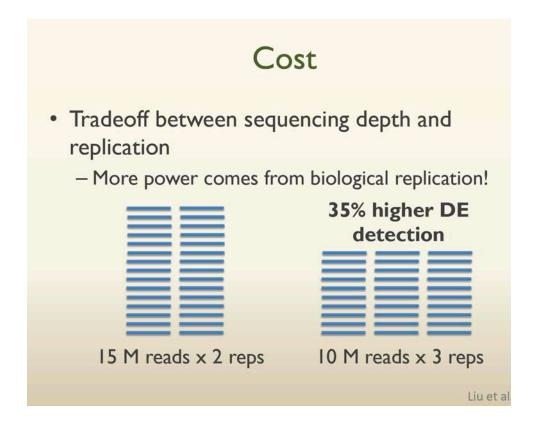
- To answer your research question, given logistical constraints.
- You can't do it all!

### **Experimental design - replicates**

## Differential expression analysis

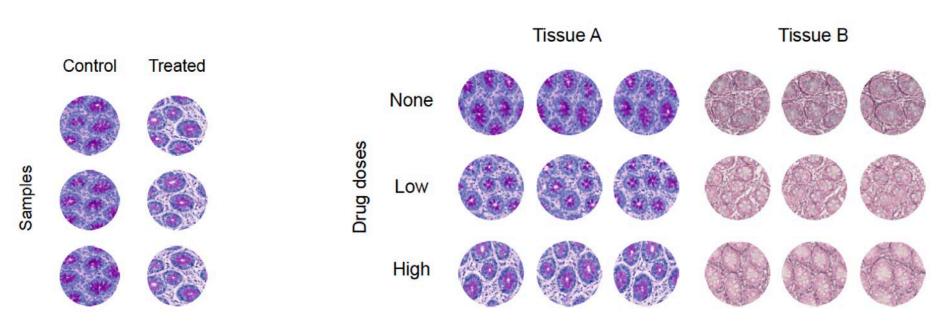
- Statistical power
  - The ability to distinguish differential expression due to treatment effect from background noise

### **Experimental design - replicates**



## **Experimental design - replicates**

Quickly becomes many samples!



Simple design: control vs. treated

Complex design: Two factors, *tissue* in two levels (A and B) and *drug* in three levels.

### Experimental design – systematic bias

- Ensure that you will not have any systematic biases:
  - Distribute the biological groups in a balanced way.
  - Divide into batches of the same sizes, limited by the capacity on each step.
  - Tip: in excel (or similar program) color code sample name according to biological group, and in next column color code by batch.
- Randomize and balance according to the biology your are interested in.

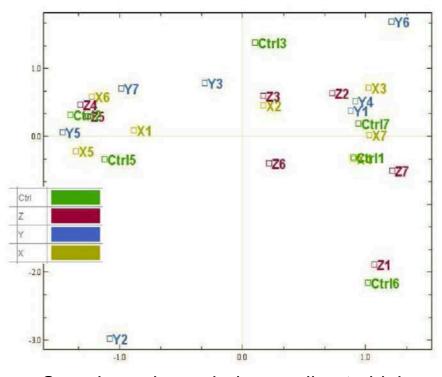
## Experimental design: an example

Biology	
A1	
A2	
А3	
A4	
A5	
A6	
B1	
B2	
В3	
B4	
B5	
B6	
C1 (	
C2	
СЗ	
C4	
C5	
C6	

Biology	Sample preparation order
A1	1
B4	2
C2	3
А3	4
B6	5
C4	6
A5	7
B2	8
C6	9
A2	10
В3	11
C1	12
A4	13
B5	14
C3	15
A6	16
B1	17
C5	18

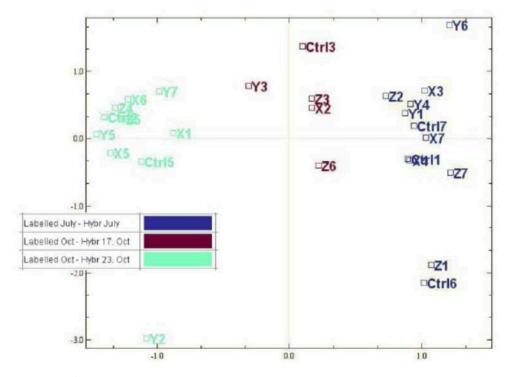
Biology	Sample preparation order	Extraction order		
A2	10	1		
В6	5	2		
C1	12	3		
A5	7	4		
B5	14	5		
C6	9	6		
A6	16	7		
B4	2	- 8		
C5	18	9		
A3	4	10		
C3	15	11		
B2	8	12		
A4	13	13		
C4	6	14		
B1	17	15		
A1	1	16		
В3	11	17		
C2	3	18		

## **Experimental design: batch effect**

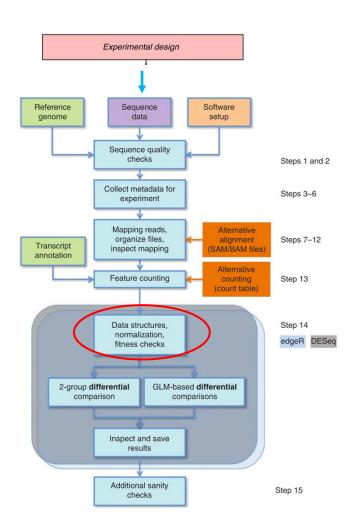


Samples color coded according to biology

### **Experimental design: batch effect**

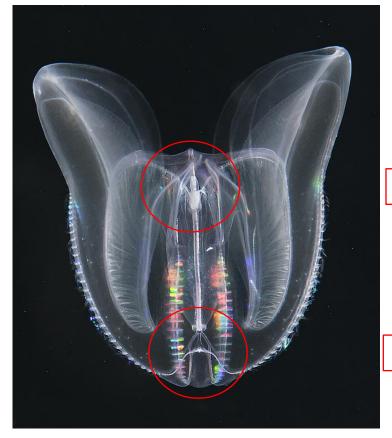


Samples color coded according to labeling date



# Data exploration and quality assessment

Mnemiopsis leidyi



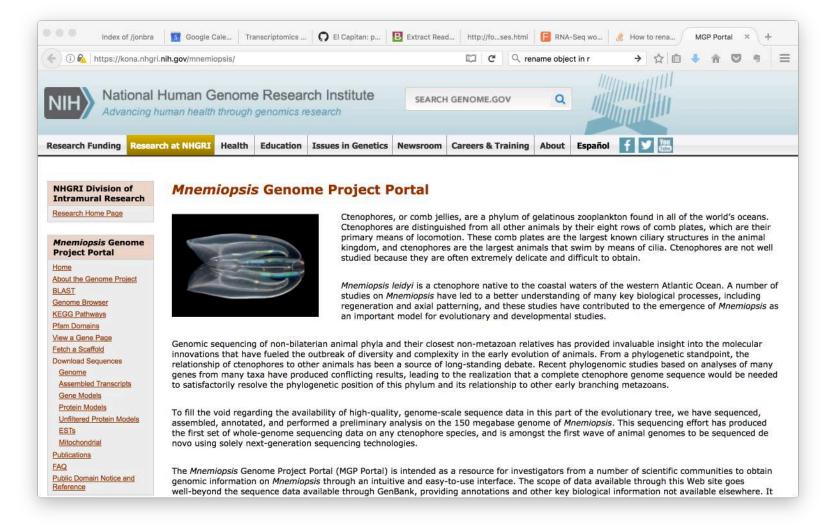
Oral organ X 4 replicates

Goal: Find genes upregulated in the aboral organ

Aboral organ X 4 replicates

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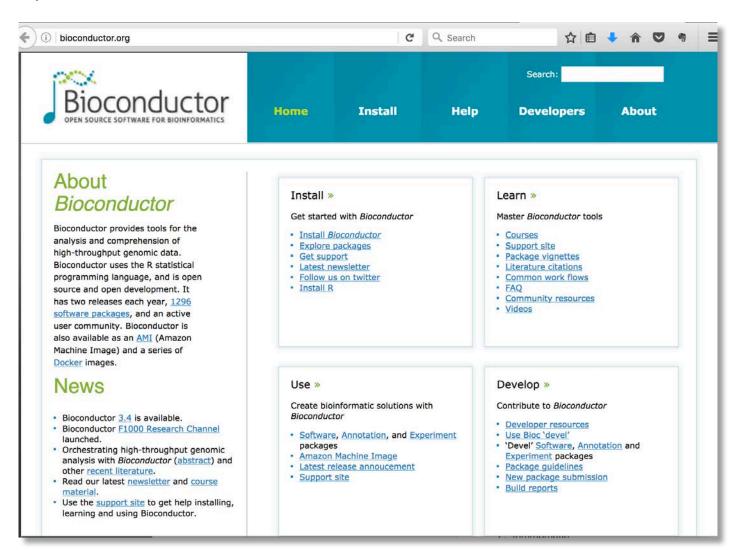
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	aboral1 <sup>‡</sup>	aboral2 <sup>‡</sup>	aboral3	aboral4 <sup>‡</sup>	oral1	oral2	oral3 ‡	oral4 <sup>‡</sup>
ML000110a	69	175	141	139	108	146	133	63
ML000111a	0	0	0	0	0	1	0	0
ML000112a	1	10	8	3	2	13	6	1
ML000113a	383	546	402	471	290	190	282	317
ML000114a	188	214	257	230	289	215	162	128
ML000115a	493	455	540	501	413	403	419	452
ML000116a	404	462	464	362	516	336	285	336
ML000117a	266	361	301	273	396	277	239	277
ML000118a	177	158	162	153	164	131	107	136
ML000119a	382	339	362	295	254	310	259	308
ML00011a	37	26	33	29	24	46	34	26
ML000120a	227	225	250	141	333	241	130	169
ML000121a	385	294	398	213	385	351	188	270
ML000122a	352	336	336	283	442	300	245	276
ML000123a	1353	1232	1534	1162	1919	1272	976	1130
ML000124a	882	1694	1025	1001	979	834	655	849

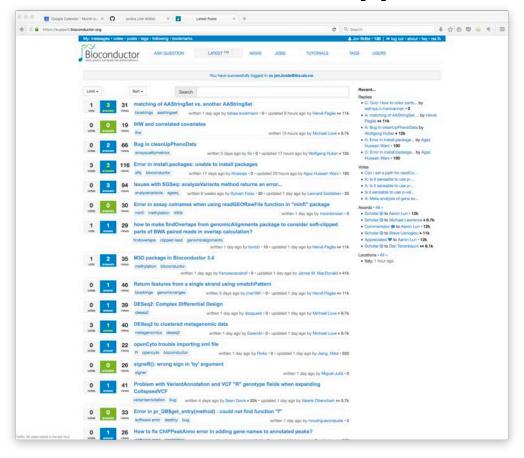
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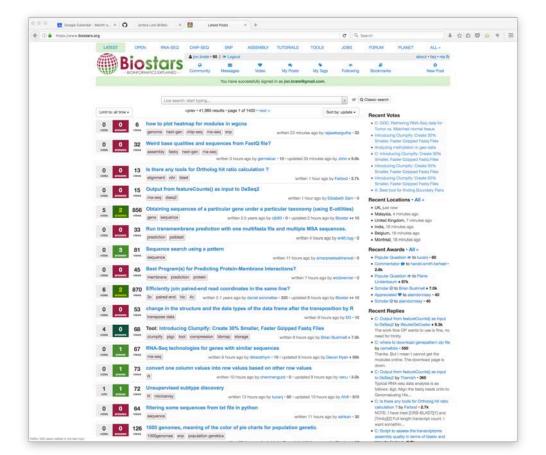


- **DESeq2 and edgeR** two of the most common pacakges for RNA-seq analysis (differential expression).
- DESeq2 and edgeR based on "raw counts" such as from HTSeq
- Tuxedo pipeline (TopHat+Cufflinks+Cuffdiff) also very common – fpkm-based. –
- Often people run all three procedures and compare

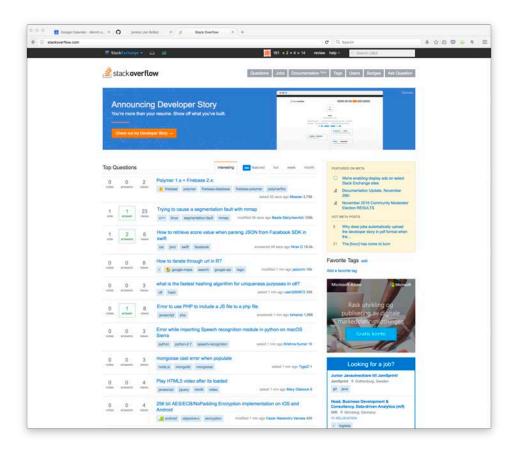
### **Useful sites – Bioconductor support**



### Useful sites – Biostars.org



### Useful sites – Stackoverflow.com



### **Useful literature on RNA-seq analysis**

### **PROTOCOL**

## Count-based differential expression analysis of RNA sequencing data using R and Bioconductor

Simon Anders<sup>1</sup>, Davis J McCarthy<sup>2,3</sup>, Yunshun Chen<sup>4,5</sup>, Michal Okoniewski<sup>6</sup>, Gordon K Smyth<sup>4,7</sup>, Wolfgang Huber<sup>1</sup> & Mark D Robinson<sup>8,9</sup>

<sup>1</sup>Genome Biology Unit, European Molecular Biology Laboratory, Heidelberg, C Centre for Human Genetics, University of Oxford, Oxford, UK. <sup>4</sup>Bioinformatic Medical Biology, University of Melbourne, Melbourne, Victoria, Australia. <sup>6</sup>Fus Statistics, University of Melbourne, Melbourne, Victoria, Australia. <sup>8</sup>Institute o Bioinformatics, University of Zurich, Zurich, Switzerland. Correspondence shc

Published online 22 August 2013; doi:10.1038/nprot.2013.099

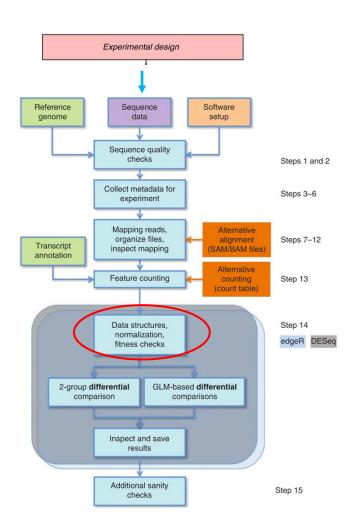
### **PROTOCOL**

## Differential gene and transcript expression analysis of RNA-seq experiments with TopHat and Cufflinks

Cole Trapnell<sup>1,2</sup>, Adam Roberts<sup>3</sup>, Loyal Goff<sup>1,2,4</sup>, Geo Pertea<sup>5,6</sup>, Daehwan Kim<sup>5,7</sup>, David R Kelley<sup>1,2</sup>, Harold Pimentel<sup>3</sup>, Steven L Salzberg<sup>5,6</sup>, John L Rinn<sup>1,2</sup> & Lior Pachter<sup>3,8,9</sup>

Broad Institute of MIT and Harvard, Cambridge, Massachusetts, USA. Department of Stem Cell and Regenerative Biology, Harvard University, Cambridge, Massachusetts, USA. Department of Computer Science, University of California, Berkeley, California, USA. Computer Science and Artificial Intelligence Lab, Department of Electrical Engineering and Computer Science, Massachusetts Institute of Technology, Cambridge, Massachusetts, USA. Department of Medicine, McKusick-Nathans Institute of Genetic Medicine, Johns Hopkins University School of Medicine, Baltimore, Maryland, USA. Department of Biostatistics, Johns Hopkins University, Baltimore, Maryland, USA. Correspondence, Maryland, USA. Department of Mathematics, University of California, Berkeley, California, USA. Department of Molecular and Cell Biology, University of California, Berkeley, California, USA. Correspondence should be addressed to C.T. (cole@broadinstitute.org).

Published online 1 March 2012; doi:10.1038/nprot.2012.016

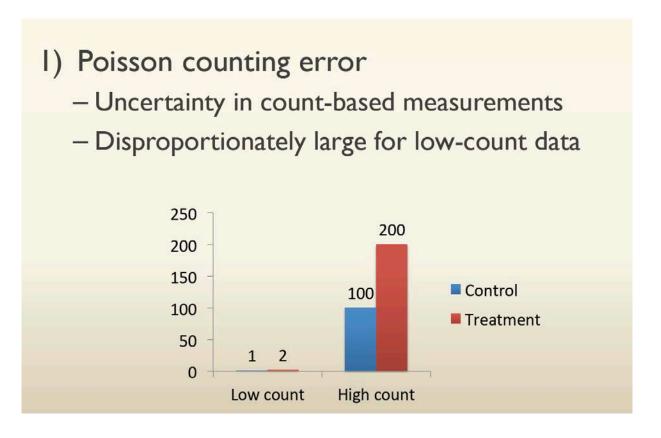


# Data exploration and quality assessment

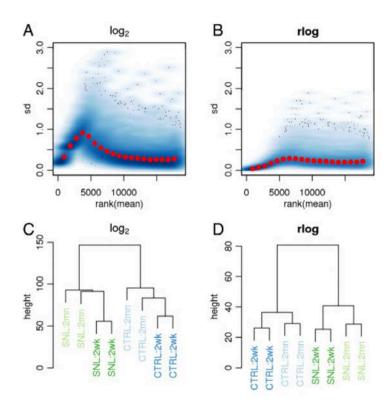
### **Transformation**

- For visualization
- Homoskedastic data the variance is the same across the means.
- For RNA-seq raw counts, however, the variance grows with the mean. => Higher counts, more variance.
- E.g. PCA plot dominated by highly expressed genes.
- log2-transform common but now then, small numbers tend to dominate due to strong poisson noise

### Strong poisson noise for low count values



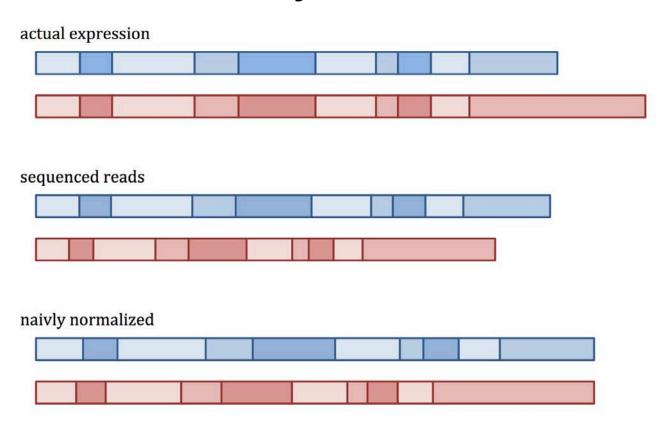
### **DESeq2 – variance stabilizing transformation (rlog)**



## Normalization for library size

- If sample A has been sampled deeper than sample B, we expect counts to be higher.
- Naive approach: Divide by the total number of reads per sample
- Problem: Genes that are strongly and differentially expressed may distort the ratio of total reads.

## **Normalization for library size**



## Normalization for library size

- To compare more than two samples:
- Form a "virtual reference sample" by taking, for each gene, the geometric mean of counts over all samples
- **DESeq2:** Normalize each sample to this reference, to get one scaling factor ("size factor") per sample.

### Differential expression analysis - distributions

### Variation summary, intuitively

Total  $CV^2$  = Technical  $CV^2$  + Biological  $CV^2$ 

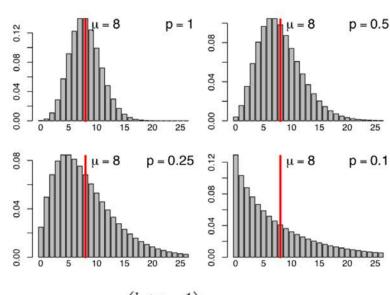
For **low counts**, the Poisson (technical) variation or the measurement error is dominant.

For **higher counts**, the Poisson variation gets smaller, and another source of variation becomes dominant, the **dispersion** or the **biological variation**. Biological variation does not get smaller with higher counts.



## Differential expression analysis

- DESeq2 uses the negative binomial distribution.
- In pairwise DE tests performs a Wald test
- Many genes have zero counts
- Some genes have high counts



$$\Pr(Y = k) = {k + r - 1 \choose r - 1} p^r (1 - p)^k \text{ for } k = 0, 1, 2, \dots$$

### DE testing— adjusted p-values

## Multiple hypothesis testing

- Thousands of genes = thousands of hypothesis tests (simultaneously)
- Increased chance of false positives! (Type I error)
  - e.g. you test for differential expression in 1000 genes
     that are not differentially expressed
  - You would expect  $1000 \times 0.05 = 50$  of them to have a P-value < 0.05
- Individual P-values not useful
  - Need multiple testing statistic instead

### DE testing— adjusted p-values

## False discovery rate

(Benjamini & Hochberg 1995)

- The expected proportion of Type I errors among the rejected hypotheses
  - i.e. the proportion of false positives
- Tends to be conservative if many genes are DE
  - FDR = 0.05 common for exploratory/broad scope studies
  - FDR < 0.05 common for medical applications and hunts for candidate genes

## Try Bioconductor (DESeq2 and edgeR) yourself

http://folk.uio.no/jonbra/R\_DESeq2\_exercises.html