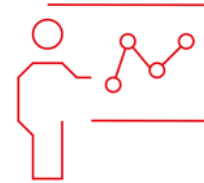




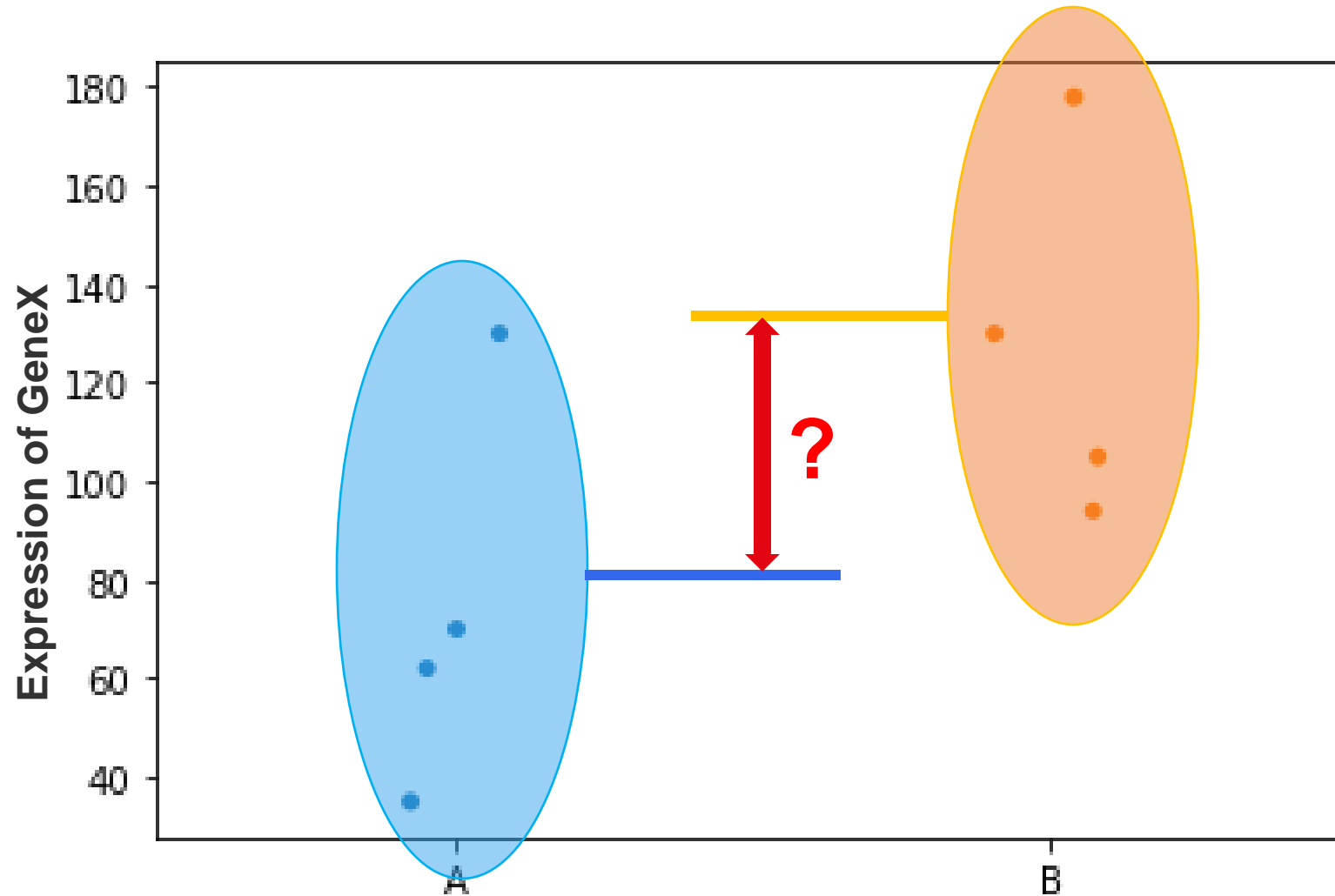
Swiss Institute of
Bioinformatics

Introduction to RNA-Seq: Differential Expression



Wandrille Duchemin

Differential Expression : the goal

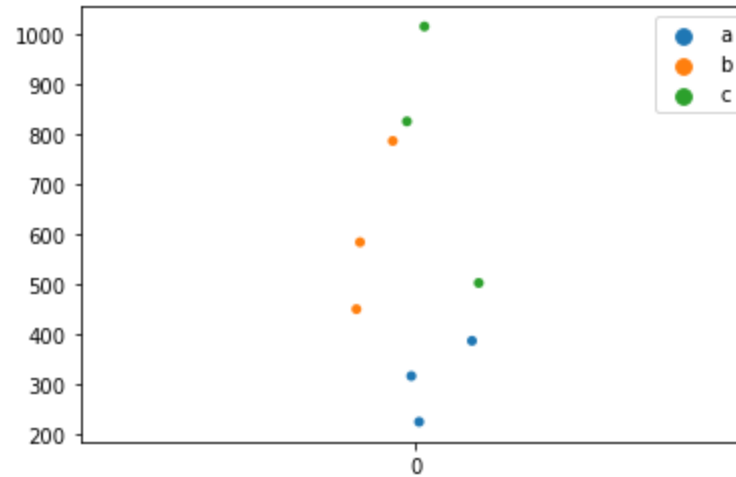
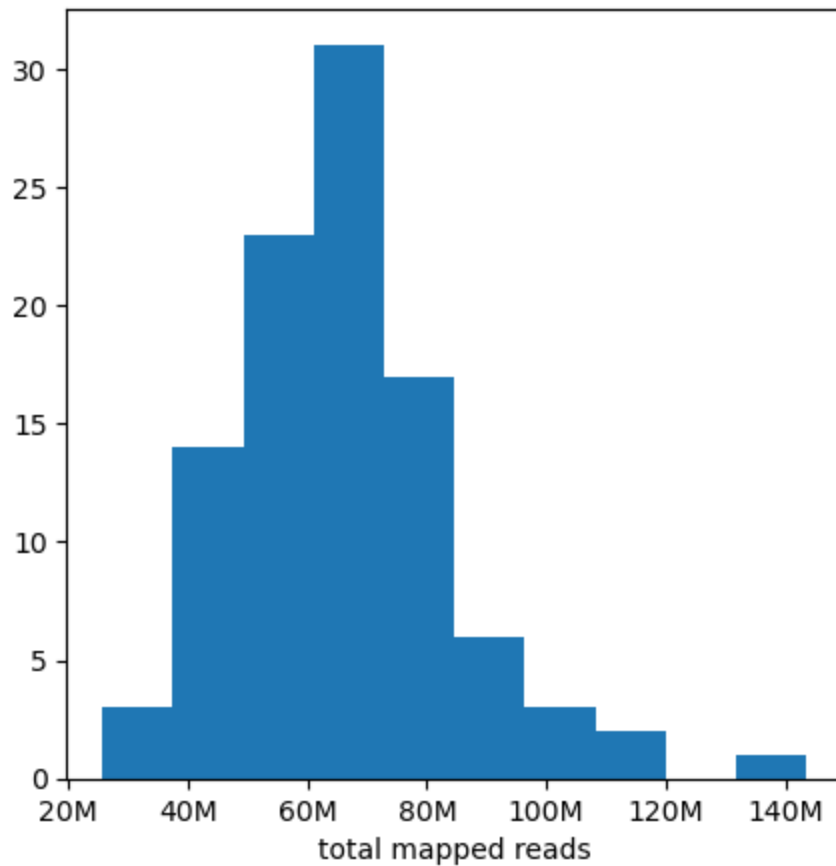


Differential Expression : challenges for RNAseq

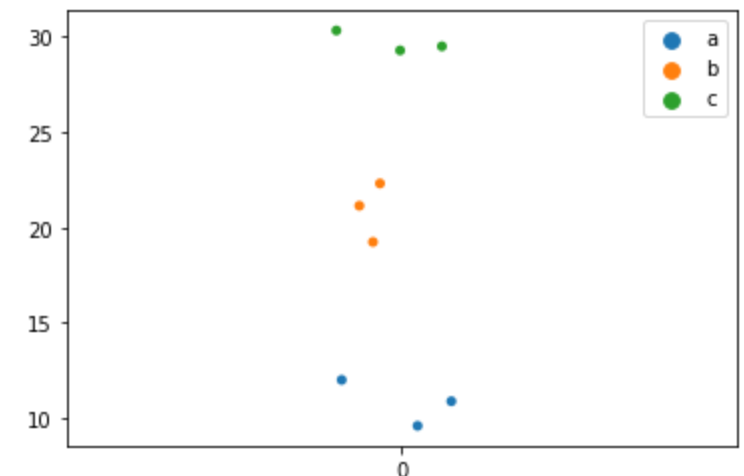
- Sequencing depth varies across libraries
- High dynamic range of expression
- Limited number of samples
- Large number of genes

Differential Expression : challenges for RNAseq

- Sequencing depth varies across libraries

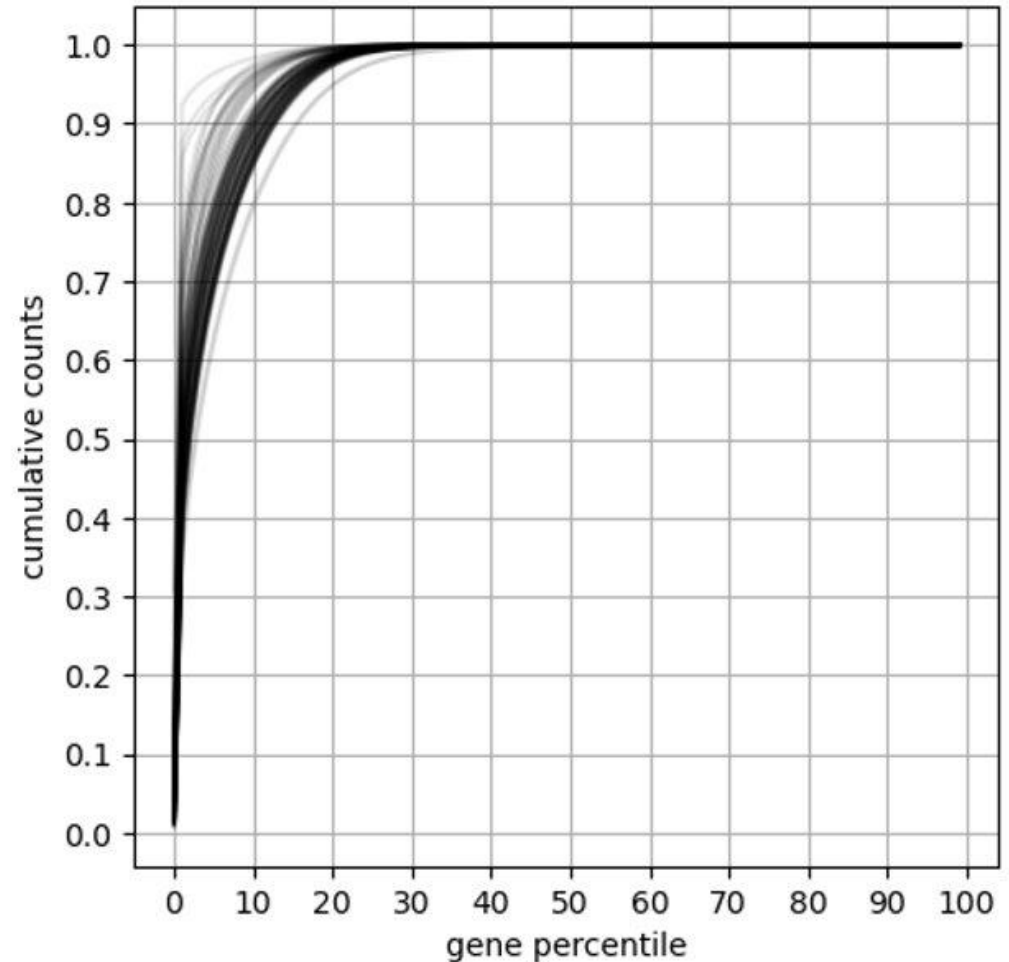
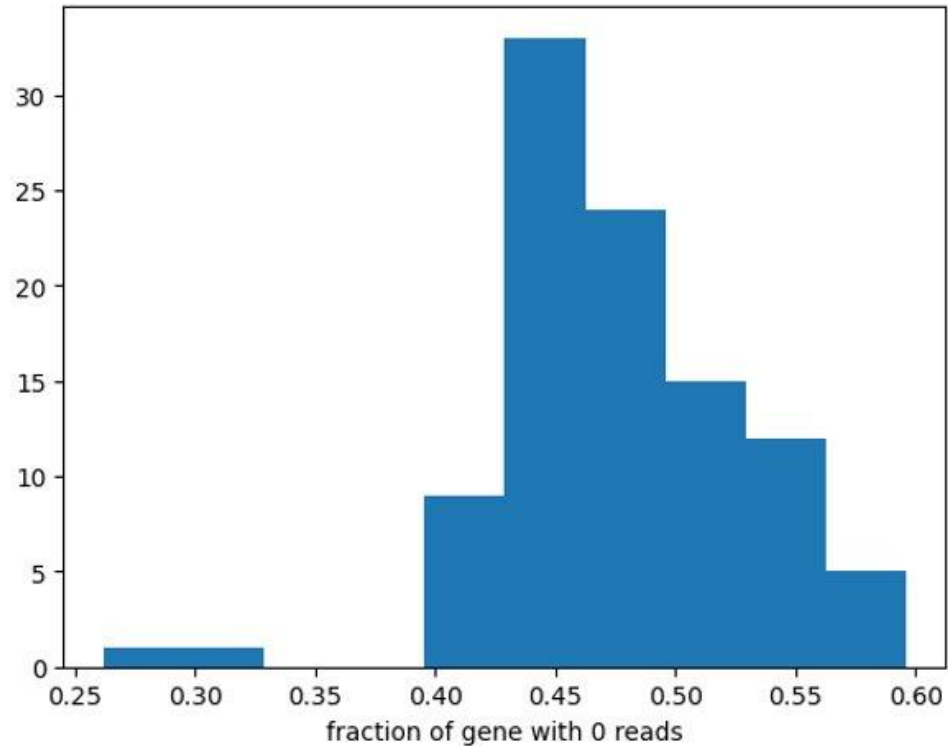


Normalization



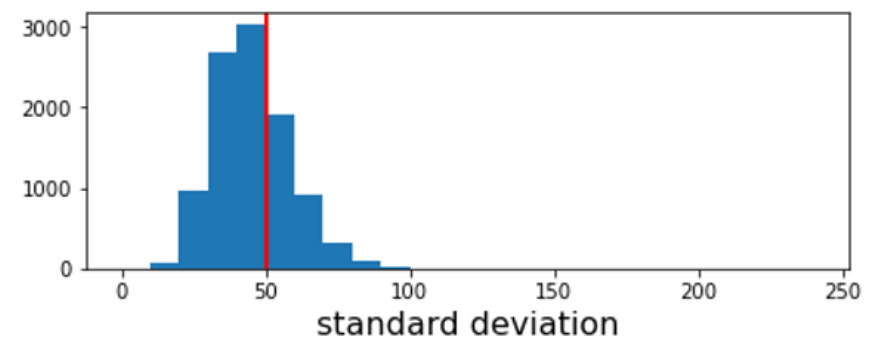
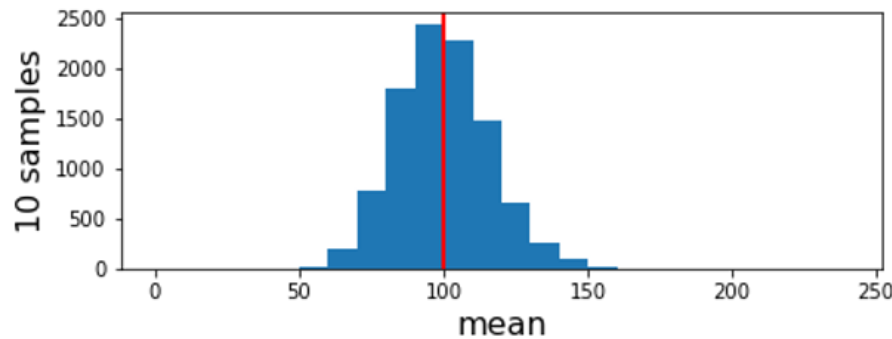
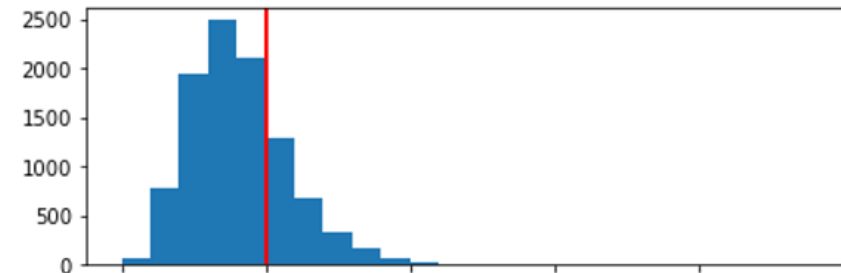
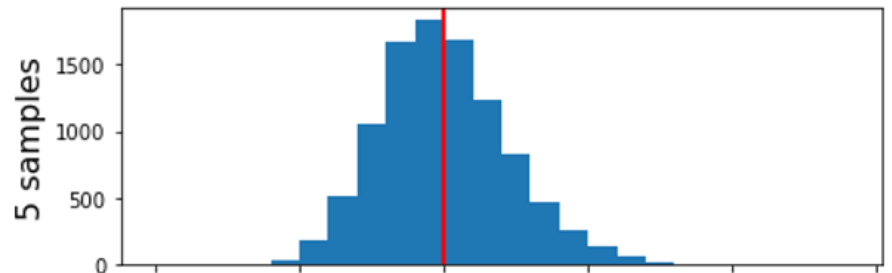
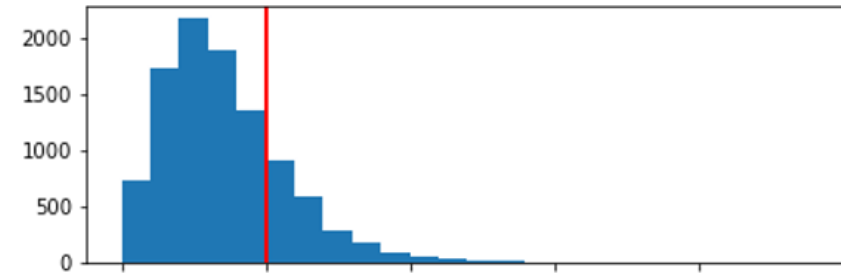
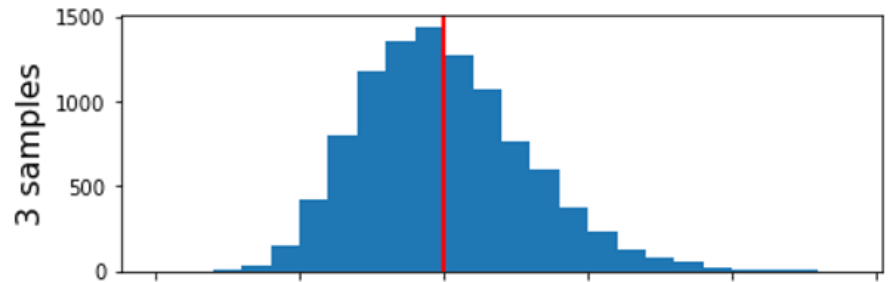
Differential Expression : challenges for RNAseq

- High dynamic range of expression



Differential Expression : challenges for RNAseq

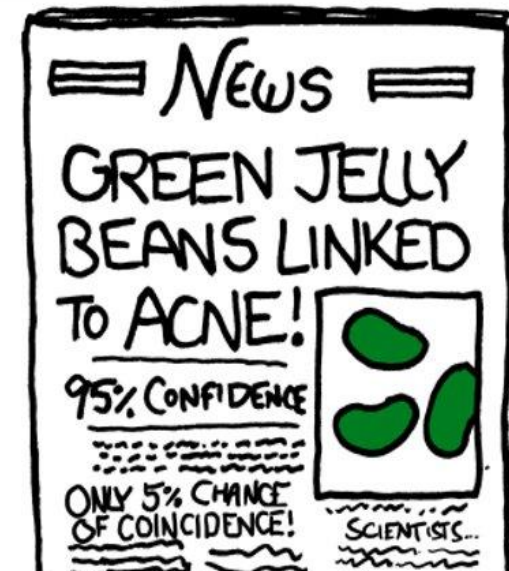
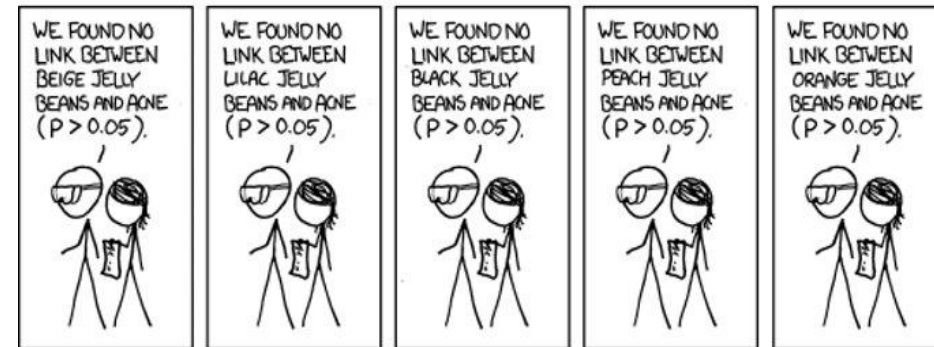
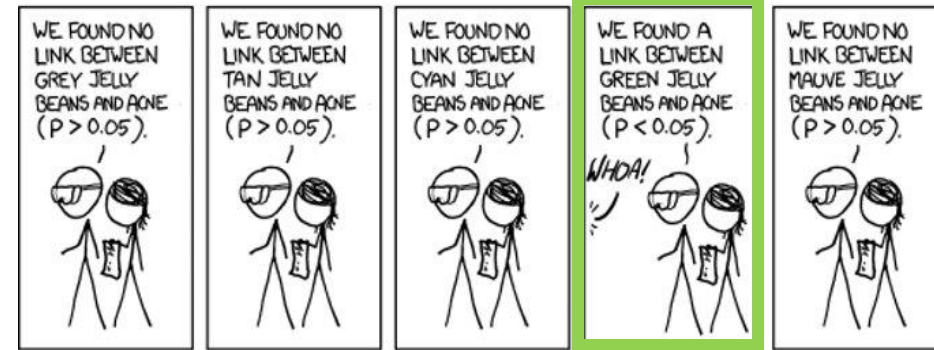
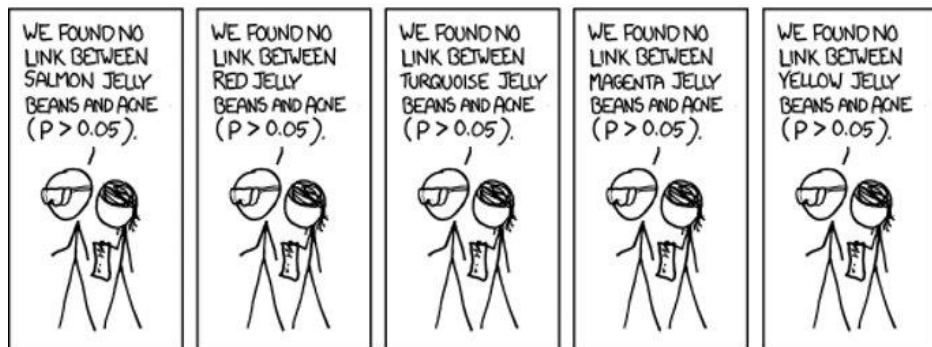
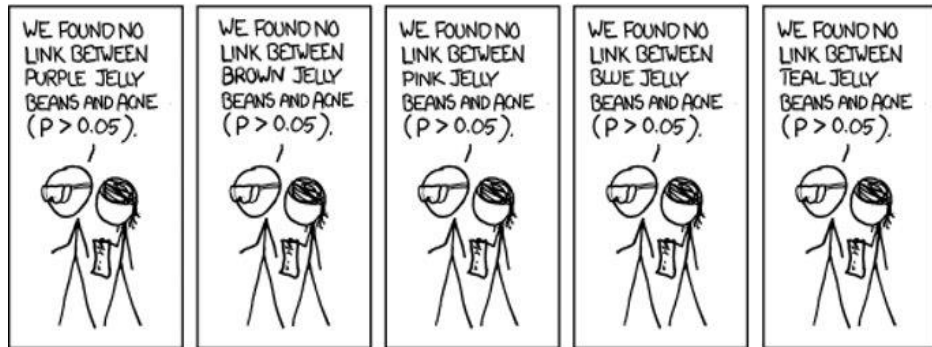
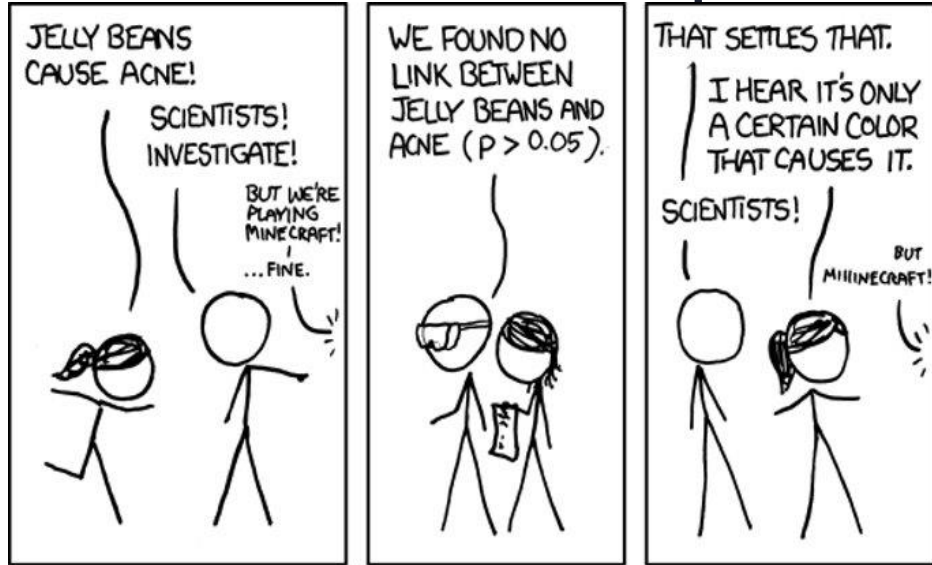
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Differential Expression : challenges for RNAseq

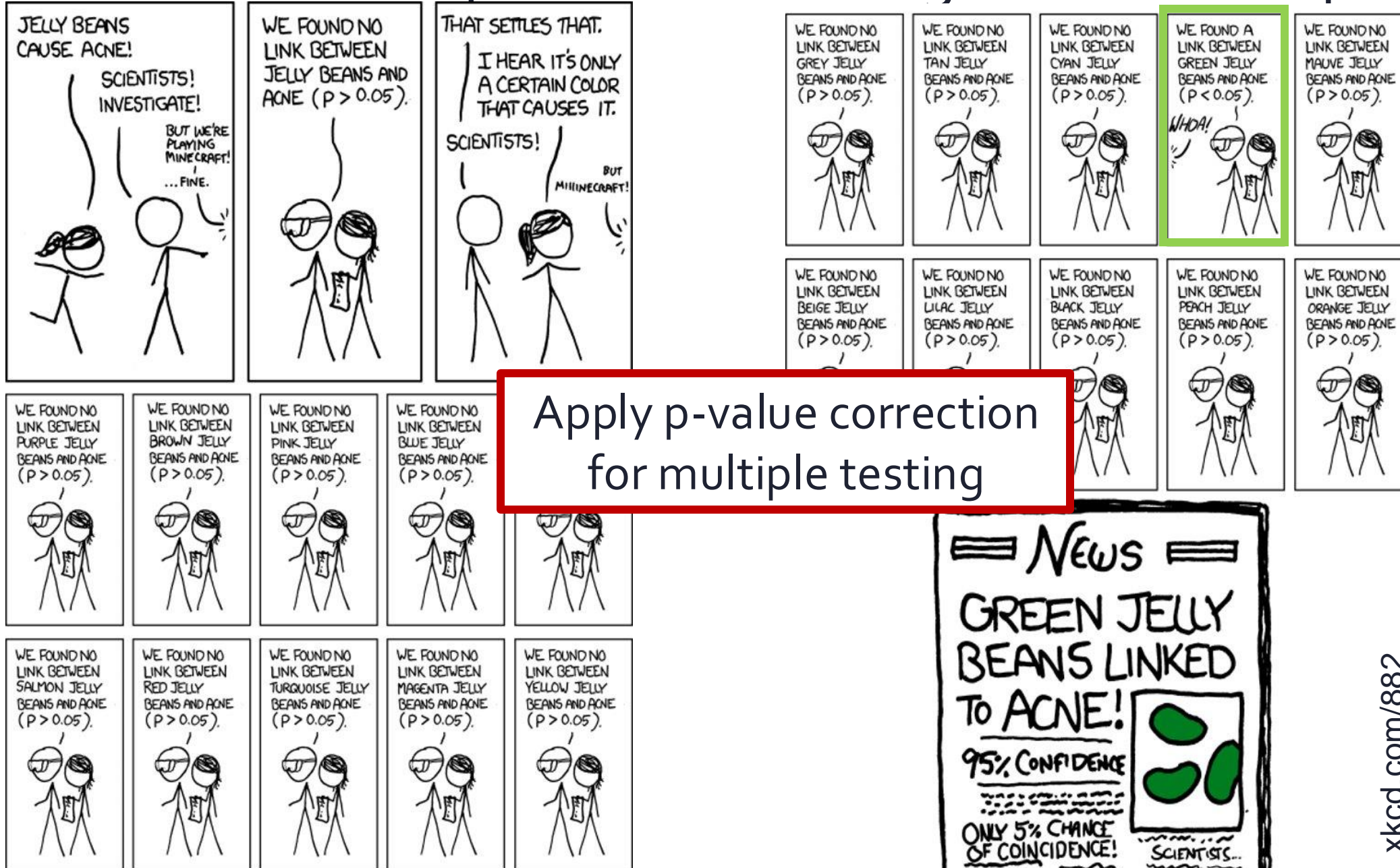
- Large number of genes

Differential Expression : challenges for RNAseq



xkcd.com/882

Differential Expression : challenges for RNAseq



Input for Differential Expression

Counts from mapping

- Affected by library size

TPM from pseudo-aligners

- The R library tximport aggregates counts at the gene-level

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EdgeR and DESeq2 expect raw counts

Digression : "naïve" normalization

CPM (Count Per Million): $\text{count} / \text{library size} * 10^6$

RPKM (Read Per Kilobase per Million): $\text{CPM} / \text{gene length (kb)}$

TPM (Transcript Per Million):

- RPK : $\text{count} / \text{gene length (kb)}$
- TPM : $\text{RPK} / \text{sum(RPK)} * 10^6$

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**The sum of RPKM
is different between
samples**

**The sum of TPM is
constant between samples**

Digression : "naïve" normalization

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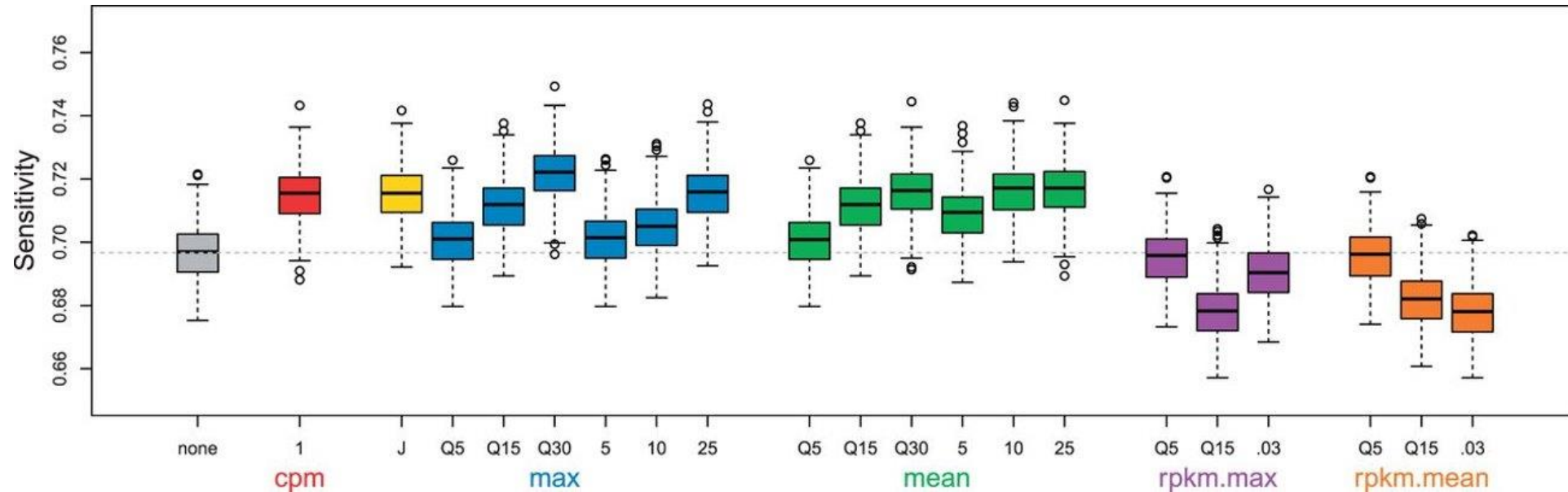
- RPK : $\text{count} / \text{gene length (kb)}$
- TPM : $\text{RPK} / \text{sum(RPK)} * 10^6$

**How do you compute
"gene length" ?**

Differential Expression : filtering low count genes

Very low counts genes:

- Very little information. No chance of DE
- Filtering them out = less test = less p-value correction



EdgeR: $CPM > 10 / (\text{min lib size})$ in at least N samples

DESeq2: mean normalized count optimizing # of DEG

Differential Expression : normalization

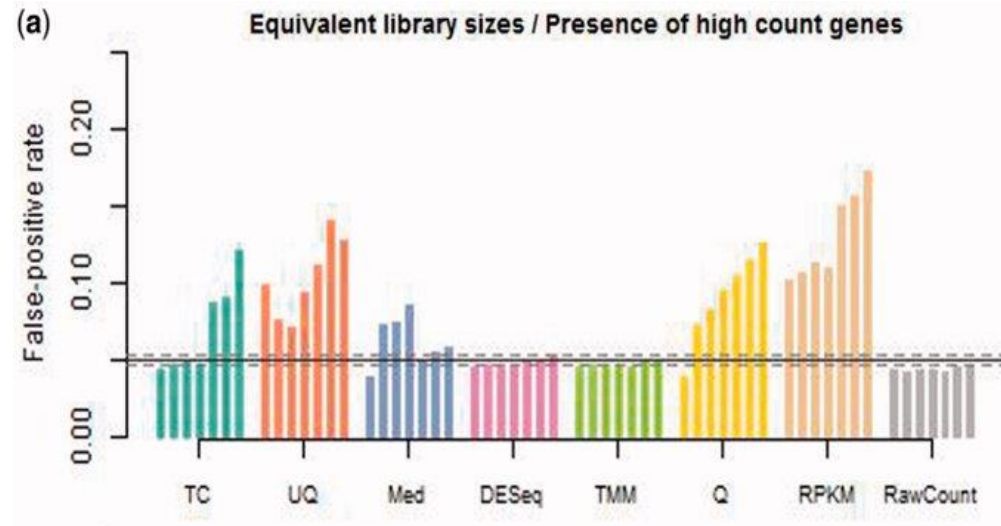
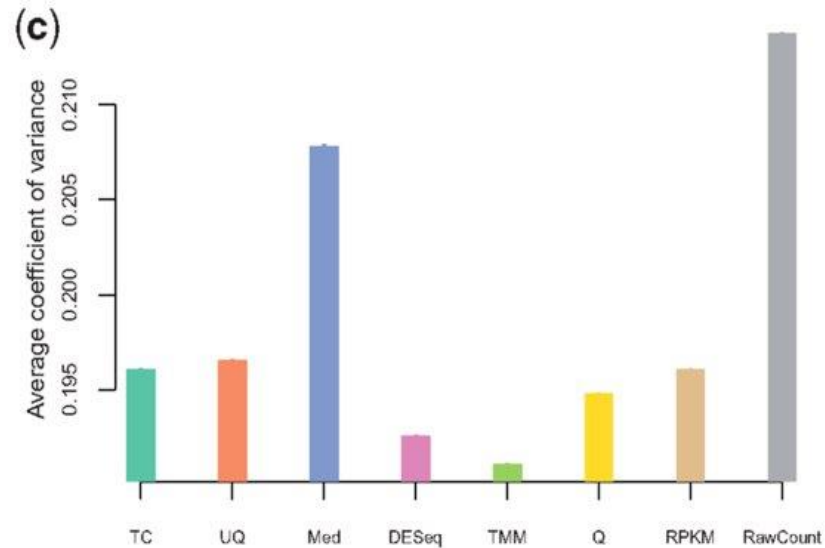


Table 3: Summary of comparison results for the seven normalization methods under consideration

Method	Distribution	Intra-Variance	Housekeeping	Clustering	False-positive rate
TC	-	+	+	-	-
UQ	++	++	+	++	-
Med	++	++	-	++	-
DESeq	++	++	++	++	++
TMM	++	++	++	++	++
Q	++	-	+	++	-
RPKM	-	+	+	-	-

A '-' indicates that the method provided unsatisfactory results for the given criterion, while a '+' and '++' indicate satisfactory and very satisfactory results for the given criterion.

Differential Expression : normalization

EdgeR: "Trimmed Mean of M-Values" (TMM)

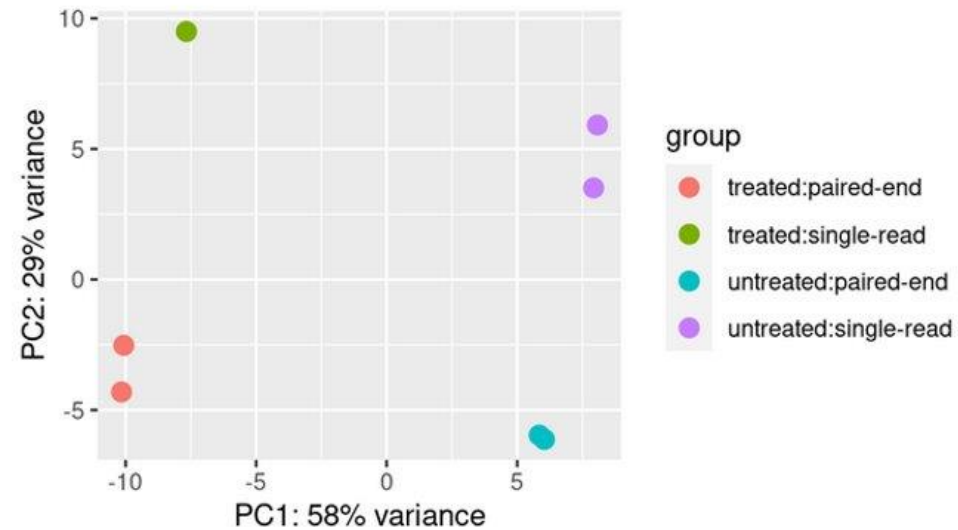
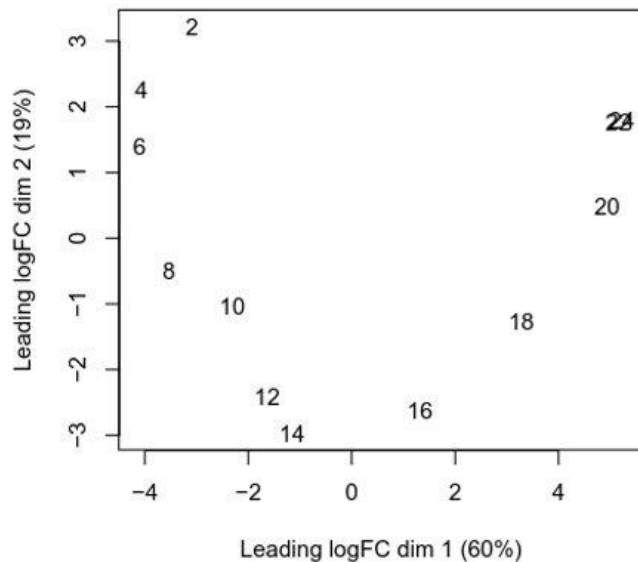
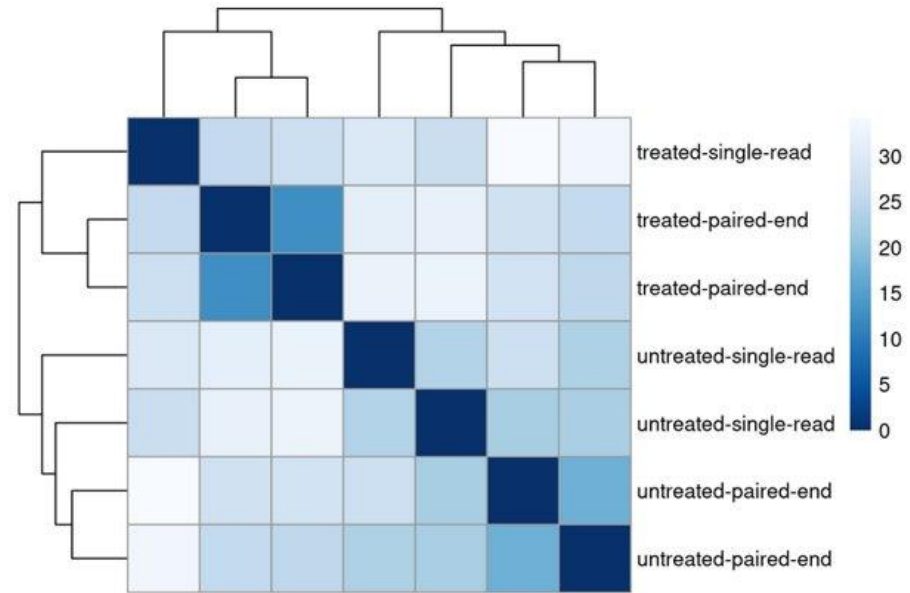
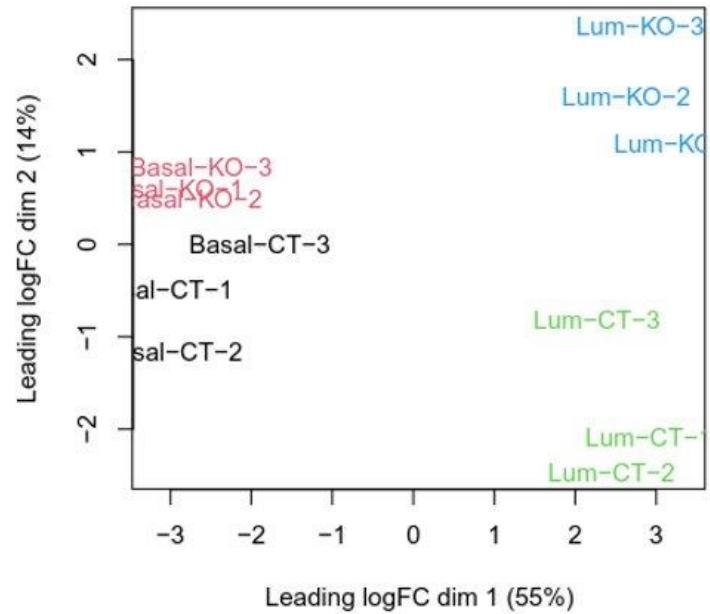
- Set one sample as reference
- For each sample, the TMM is computed as the weighted mean of log ratios between this test and the reference, after exclusion of the most expressed genes and the genes with the largest log ratios.
- Compute the correction factor to get all TMMs to 1

DESeq2: "Relative Log Expression" (RLE)

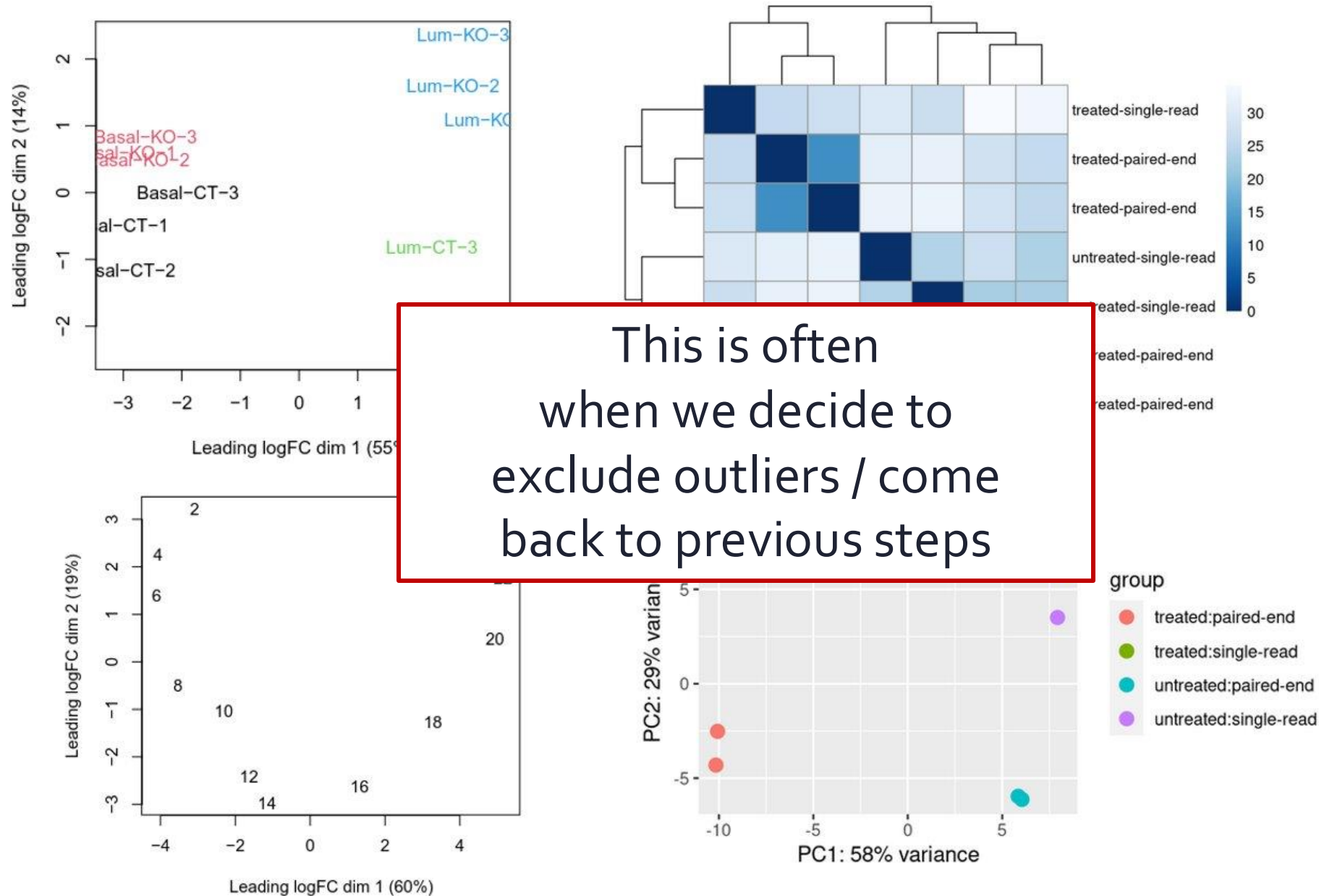
- For each sample: compute the median of the ratio of each gene read count over its geometric mean across all lanes.
- This provides the correction factor that should be applied to all read counts

Both presume that most gene are not DE

Quality Control: PDS or PCA of the samples



Quality Control: PDS or PCA of the samples



Differential Expression : statistical model

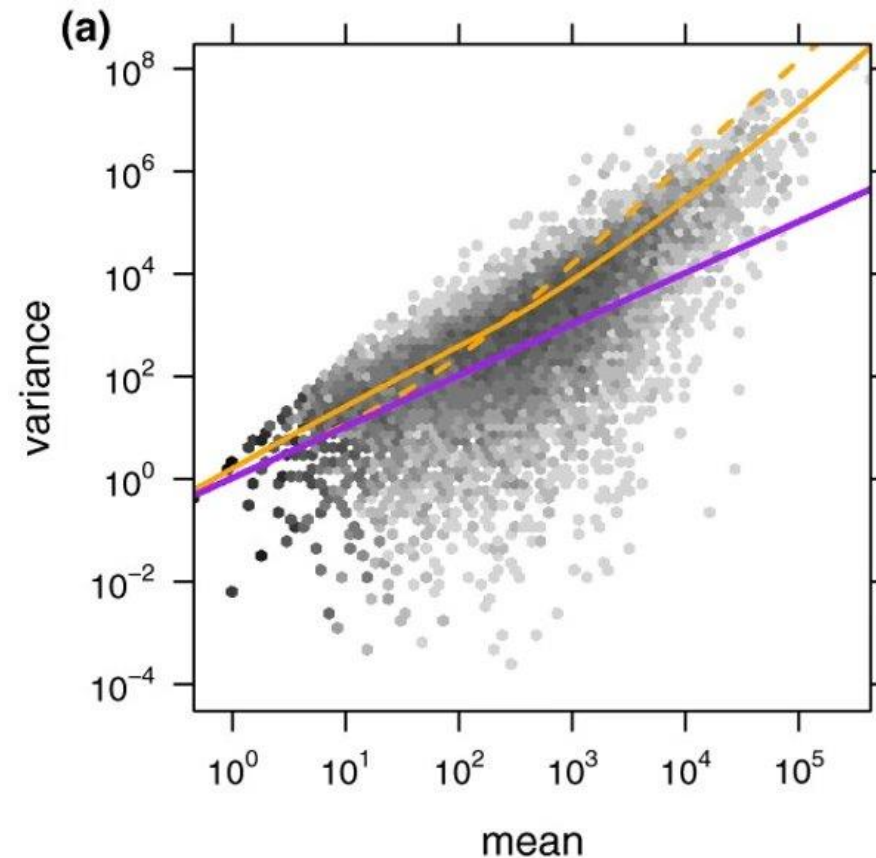
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- Idea: expression corresponds to a number of transcripts, captured and sequenced independently from a given "space" (the sample) --> Poisson model

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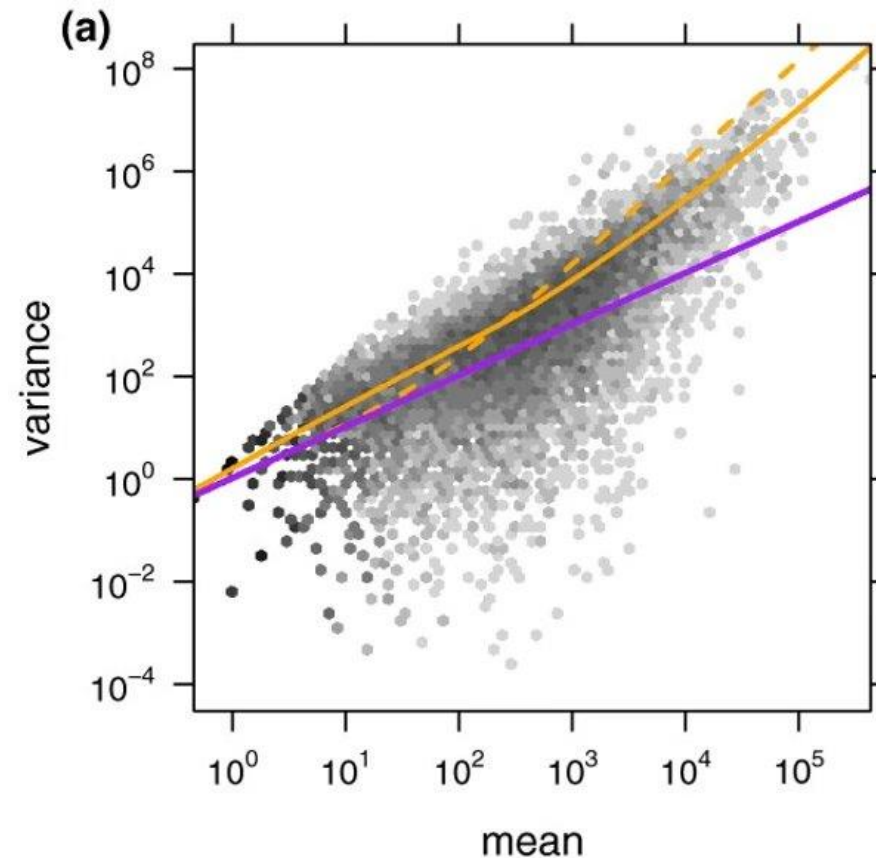
Differential Expression : statistical model

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--> Negative Binomial model

$$\text{Variance} = \mu + \theta\mu^2$$

θ : dispersion parameter
 μ : (expected) expression



Differential Expression : statistical model

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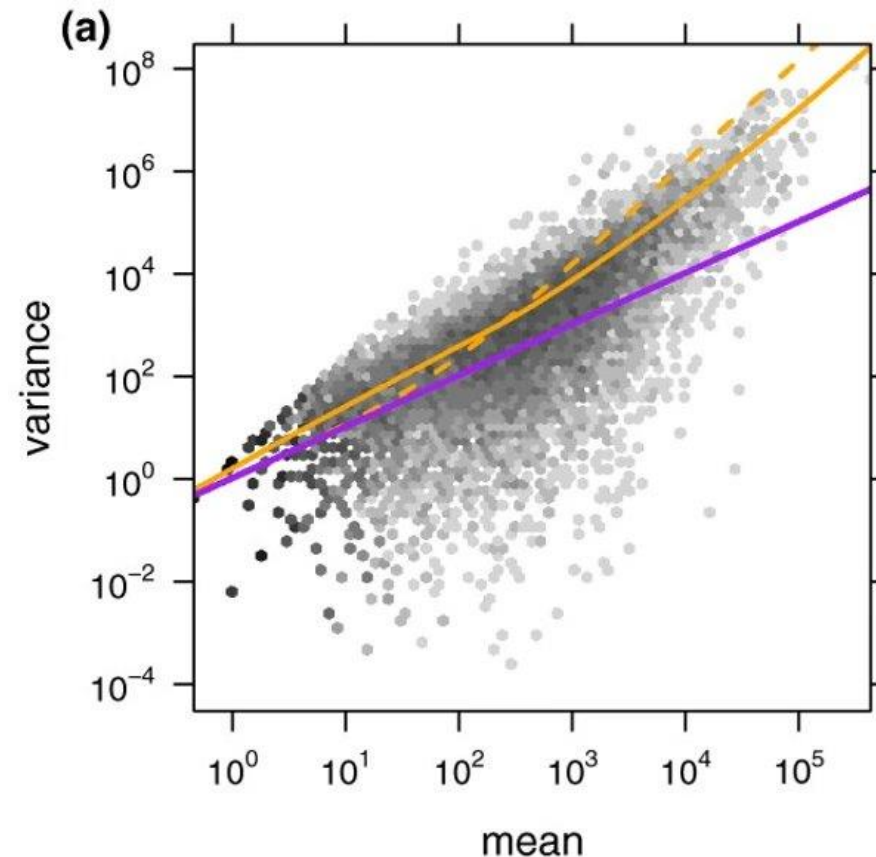
$$\text{Variance} = \mu + \theta\mu^2$$

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Often modelled with a linear model:

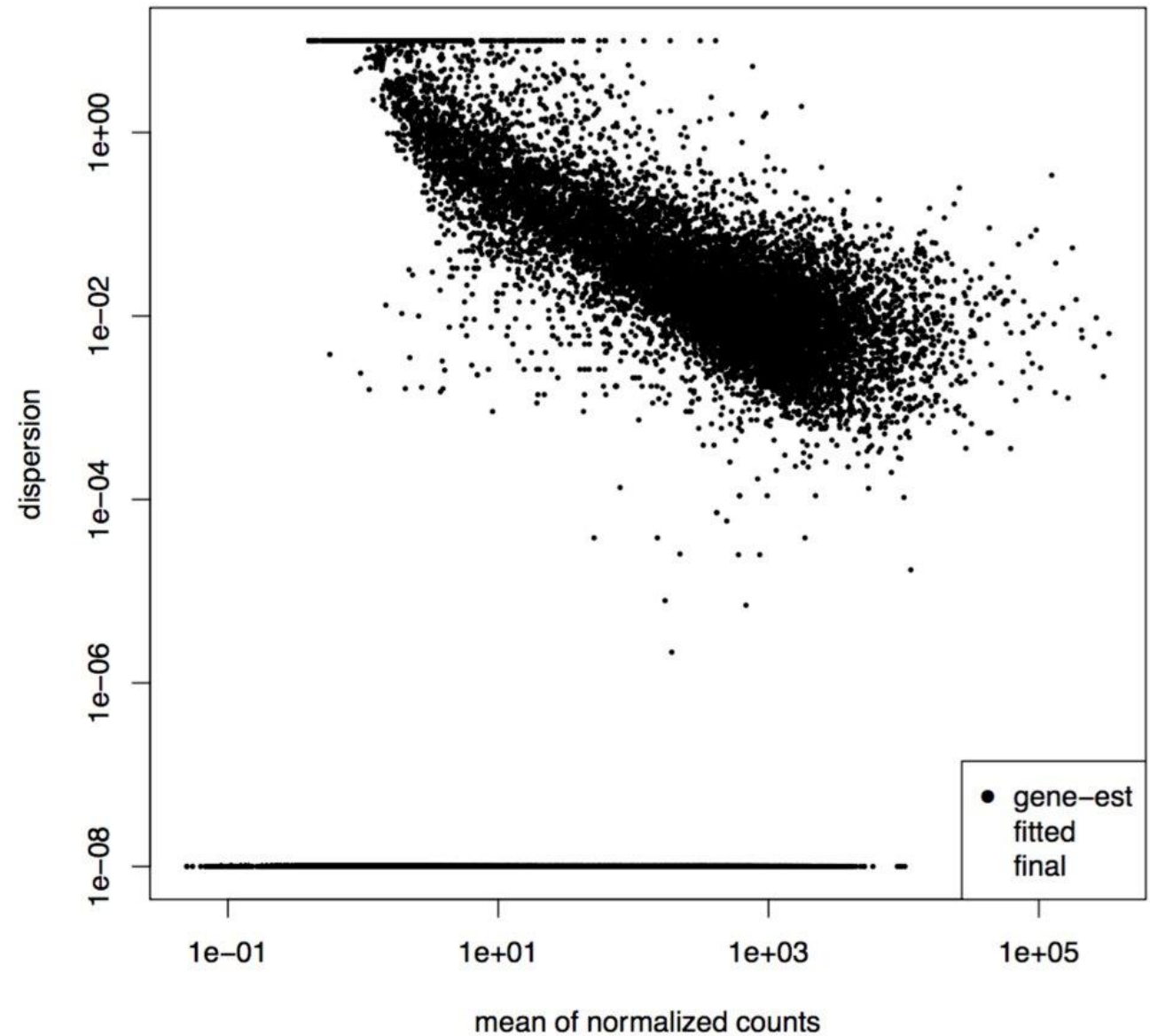
$\mu = \text{base level} + \text{genotype effect} + \text{batch effect} + \text{treatment effect} \dots$



Estimating dispersion

Problem:

we often have very few replicates



Estimating dispersion

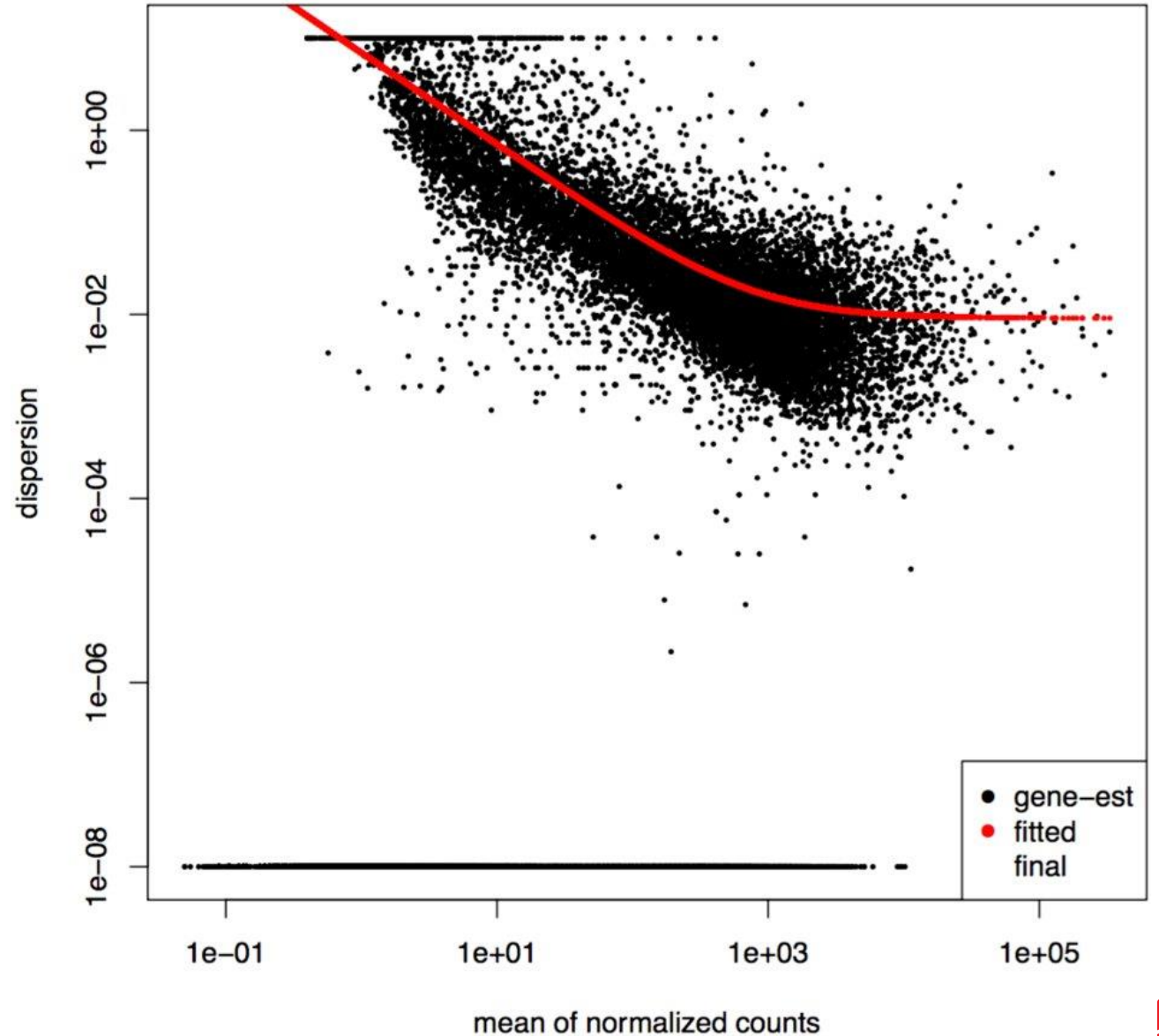
Problem:

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Solution:

take advantage of the large number of genes

Shrink gene-wise estimates toward the center value observed of dispersion across **genes with similar expression**.



Estimating dispersion

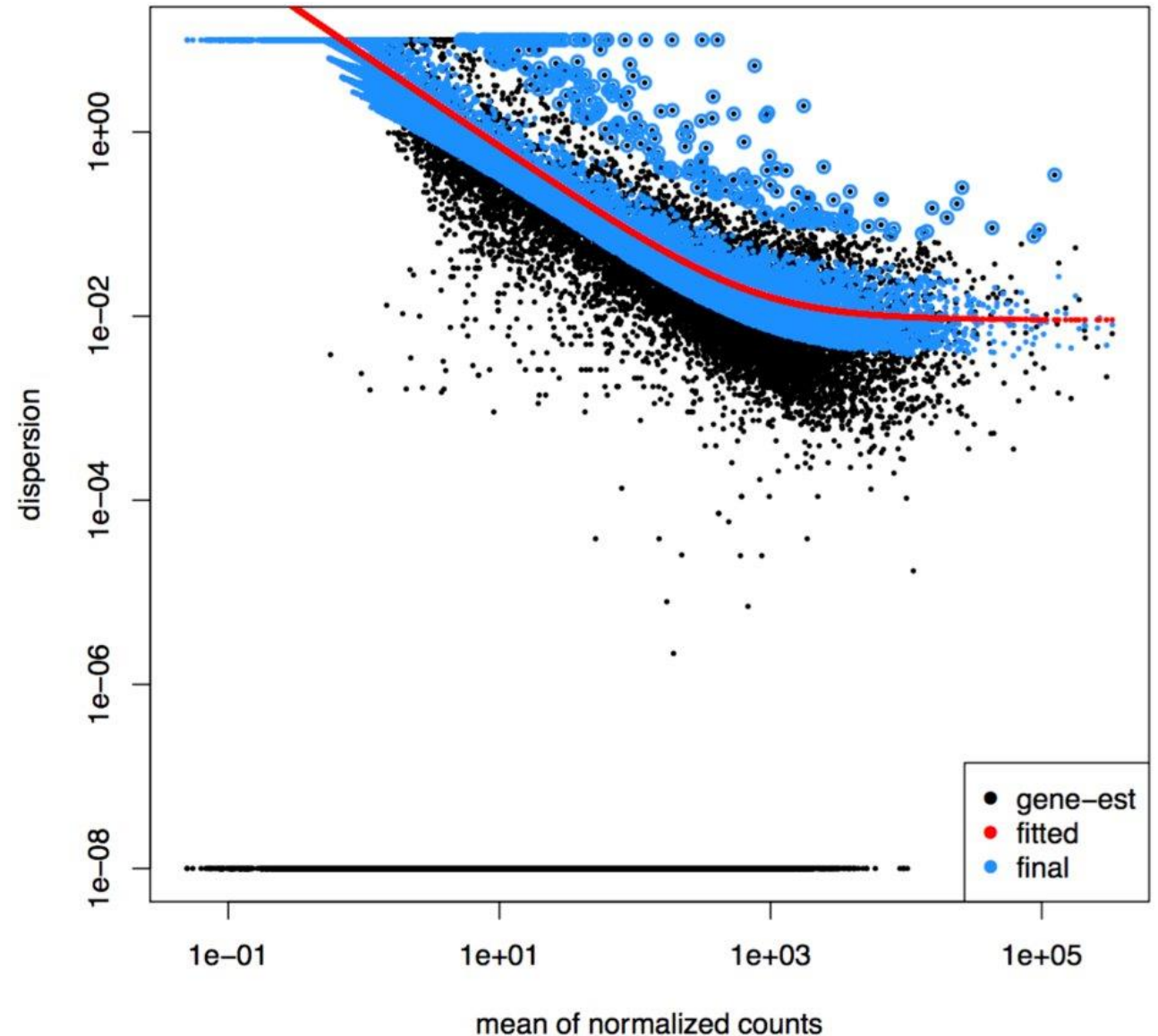
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Testing for differential expression: DESeq2

For each gene:

Z-score = shrunken LFC / estimated standard error

Wald test:

Compare Z-score to a standard normal distribution to compute a **p-value**

Benjamini-Hochberg procedure to **adjust p-values**

Testing for differential expression: edgeR

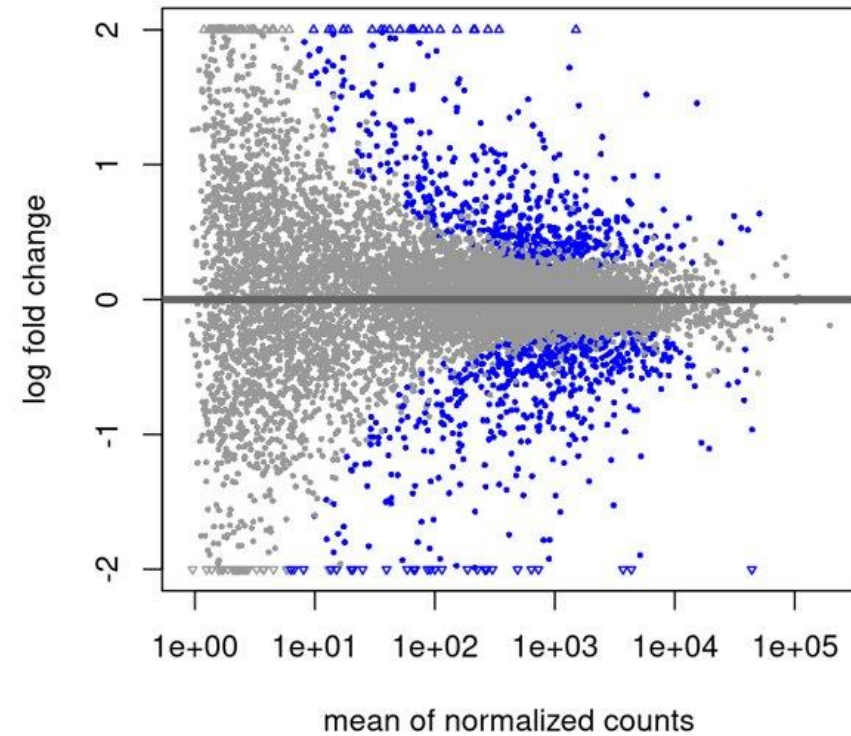
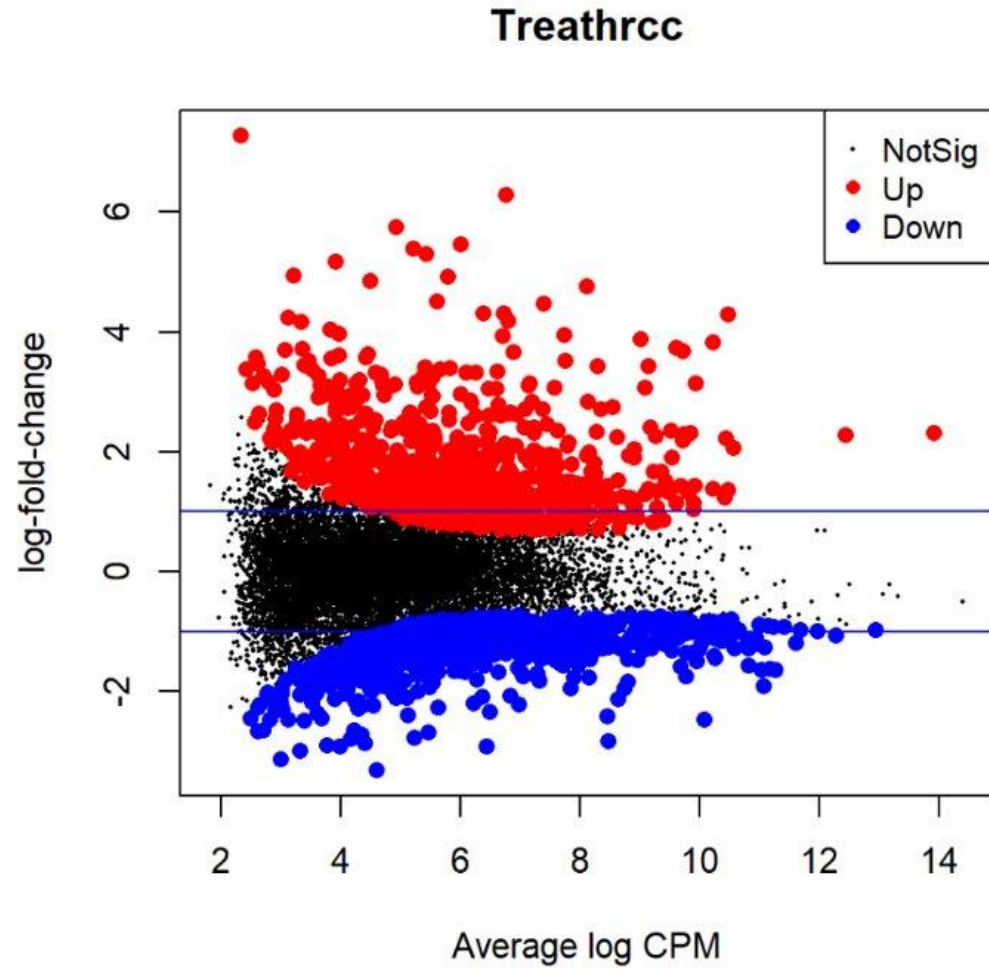
"simple": 1 factor : `exactTest()`

using the computed conditional distribution for the sum of counts in a group

Otherwise: GLM framework

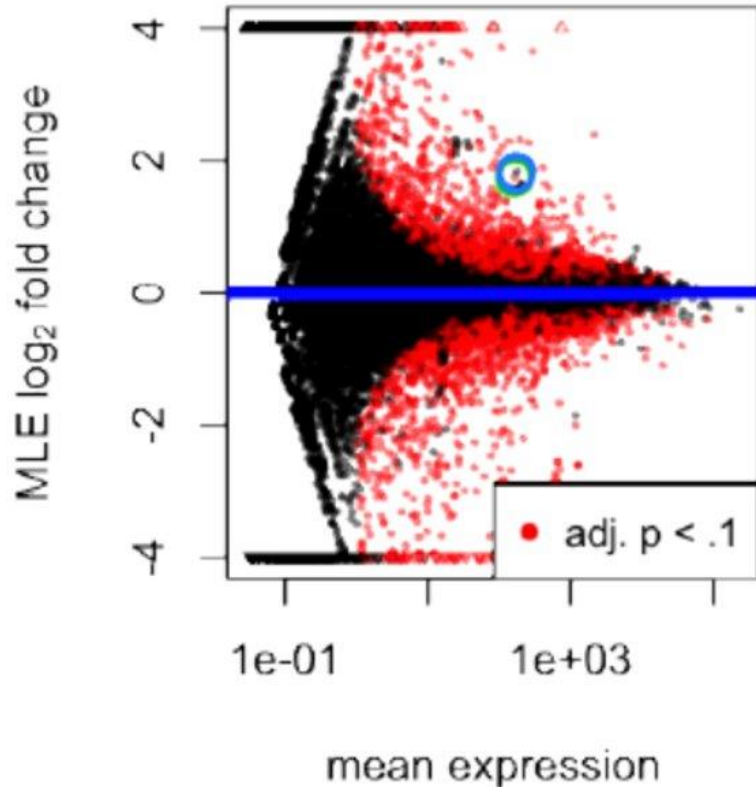
- **Quasi-likelihood F-test** : generally preferred
- **Likelihood Ratio Test** : when "the dispersions are very large and the counts are very small, whereby some of the approximations in the QL framework seem to fail"
<https://support.bioconductor.org/p/84291/>

DE results: MA plot

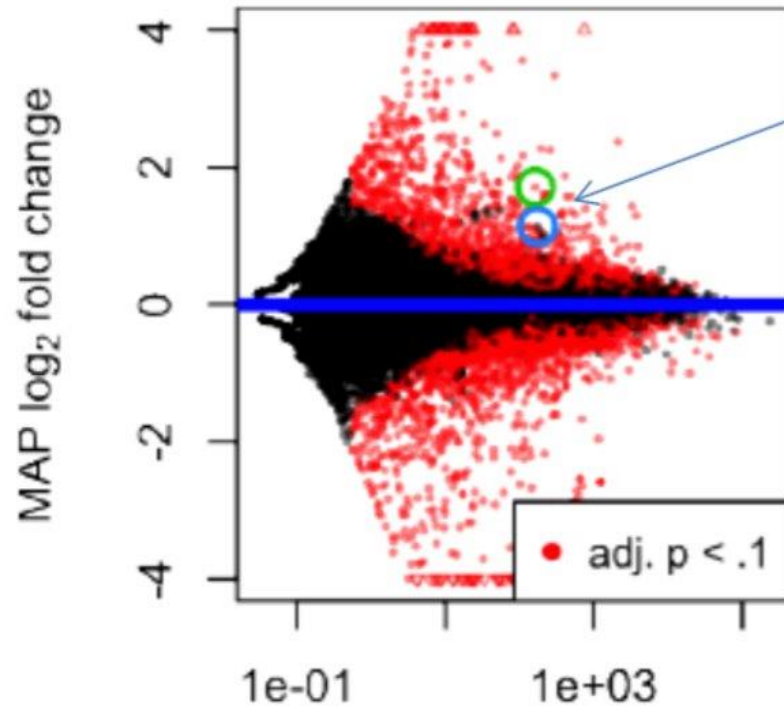


DESeq2 : shrinkage of log-fold change

A Original LFC estimates



B Shrunk LFC estimates

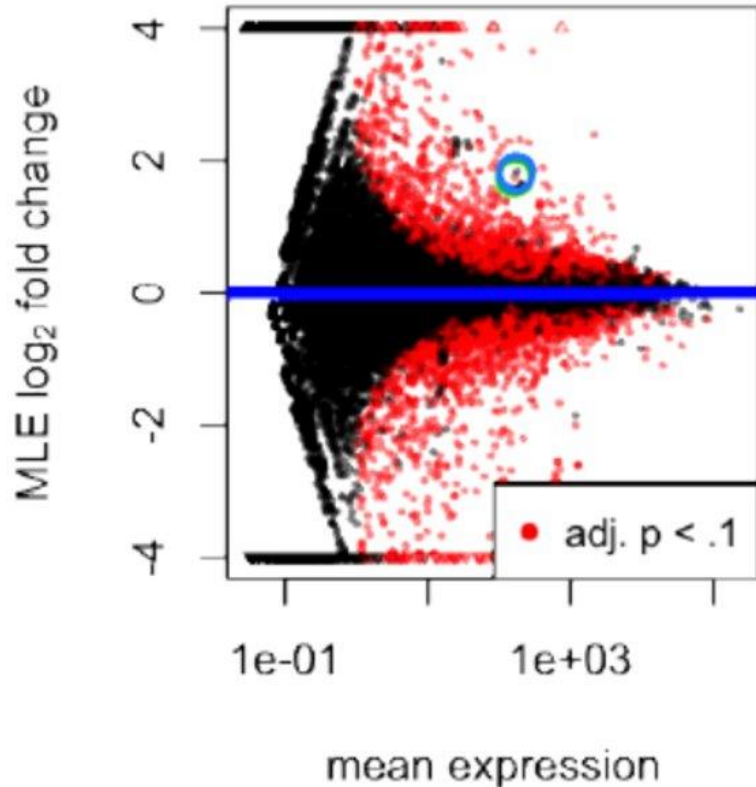


Blue gene has larger dispersion than green gene

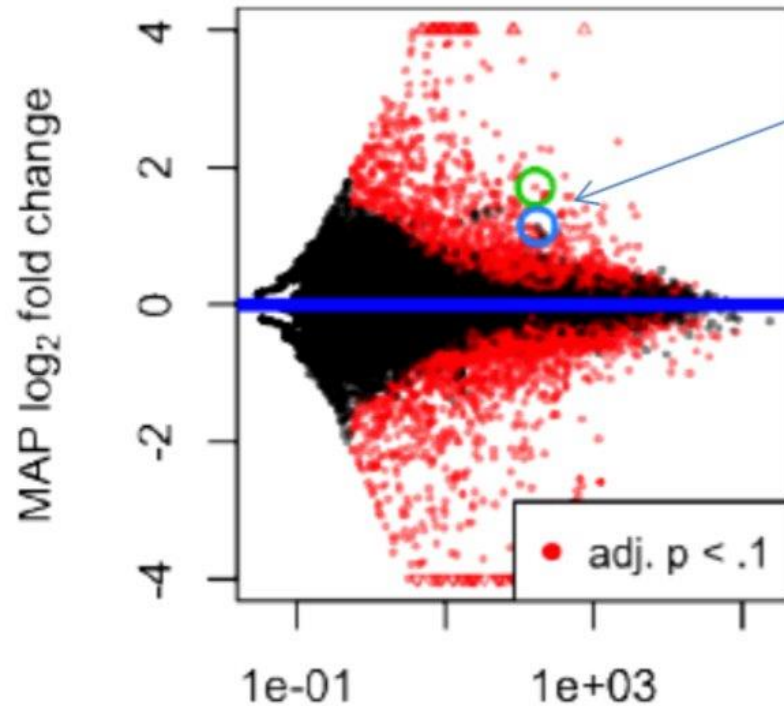
Love *et al.* 2014

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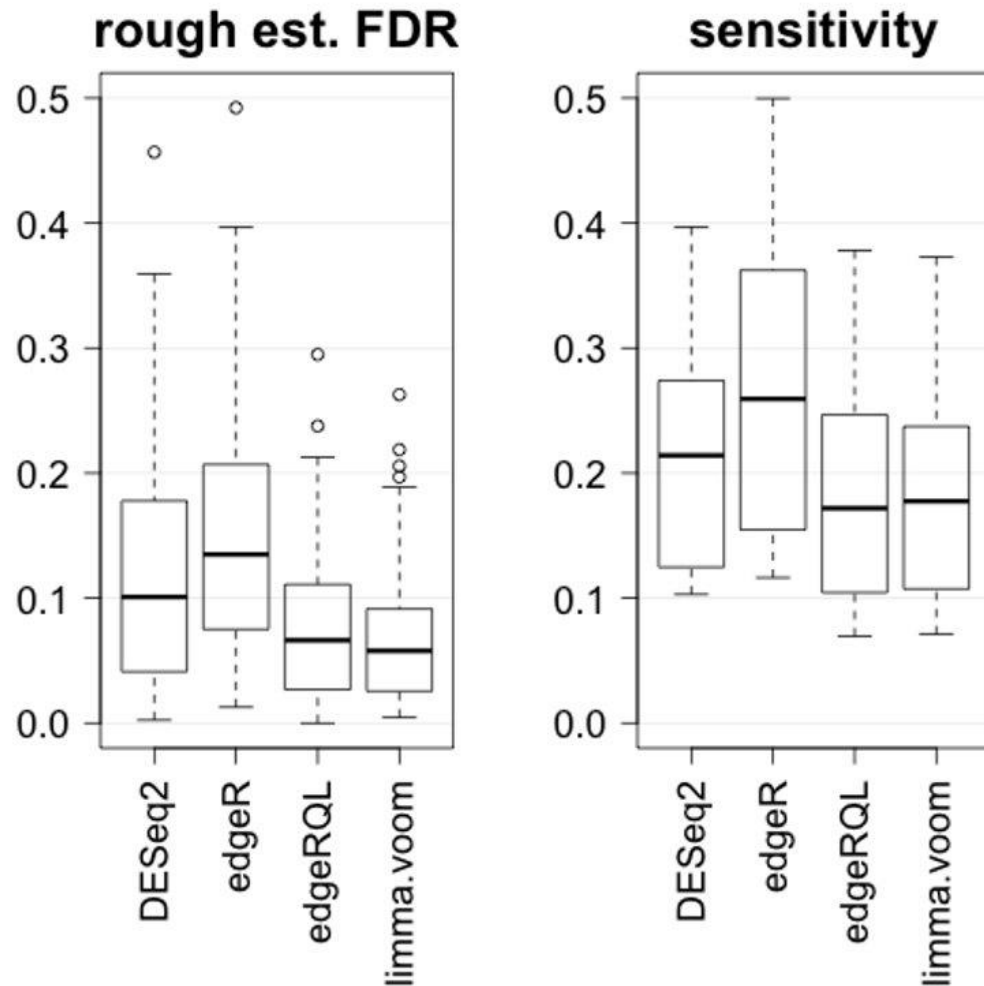


Blue gene has larger dispersion than green gene

Makes log-fold change values more useful for down-stream analysis

Love *et al.* 2014

edgeR vs DESeq2



- edgeR exact test : more sensitive
- edgeR QL : more conservative
- DESeq2 : tight FDR control

Love *et al.* 2014

<https://mikelove.wordpress.com/2016/09/28/deseq2-or-edger/>

Practical

