

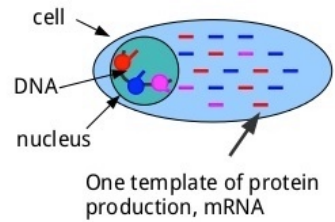
Correctly counting molecules
with a little help
from a well-known population model

Florian Pflug and Arndt von Haeseler

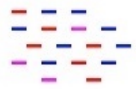


Edinburgh, July 17th 2018

The Basic RNA-Seq Workflow

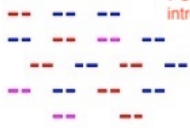


Extract mRNA and turn into cDNA

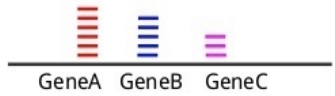


Fragment, ligate Adaptor, **amplify** size selection.

PCR amplification introduces biases!



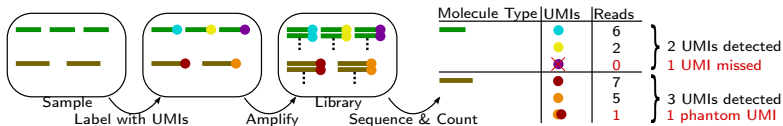
Put a fraction of the pool on a high throughput sequencer to read fragments.



RNA-Seq with Unique Molecular Identifiers (UMIs)



To measure absolute transcript counts, and avoid errors due to *PCR amplification bias*, mRNA transcripts are labelled with Unique Molecular Identifiers (UMIs; ●, ●, ●, ●, ●) *before amplification* ...

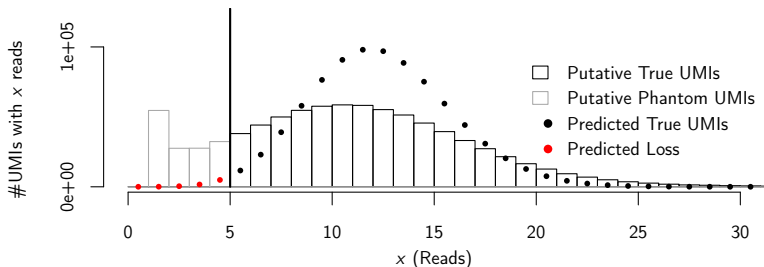


... and after sequencing, not *Reads* but *Unique UMIs* are counted to measure transcript abundance

Towards a model to predict the reads/UMI distribution



We sequence only a small percentage of all molecules...

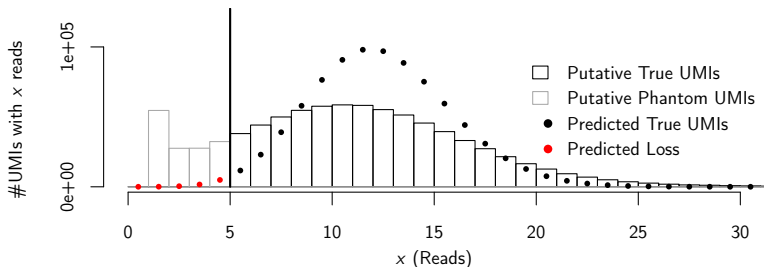


.. but there's more dispersion than stochastic sampling can explain

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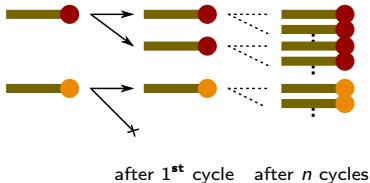
We must consider the stochasticity of the PCR

PCR as a supercritical Galton-Watson branching process



Of each UMI-labelled molecule there initially is a single copy.
During each cycle, each molecule is duplicated with probability E ,

$$M_0 = 1, \quad M_i = M_{i-1} + \text{Binom}(M_{i-1}, E), \quad \mathbb{E}M_i = (1 + E)^i$$



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We normalize M_0, M_1, \dots to have expected value 1,

$$F_i = \frac{M_i}{(1 + E)^i}$$

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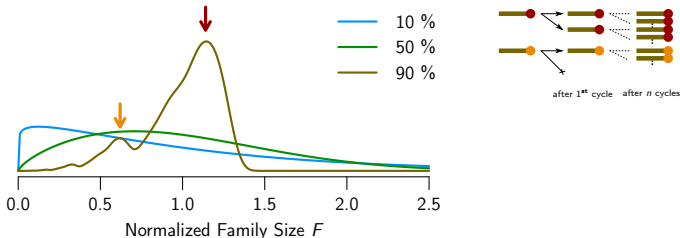
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We normalize M_0, M_1, \dots to have expected value 1,

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And call the limit $F = \lim_{i \rightarrow \infty} F_i$ (*normalized*) family size.

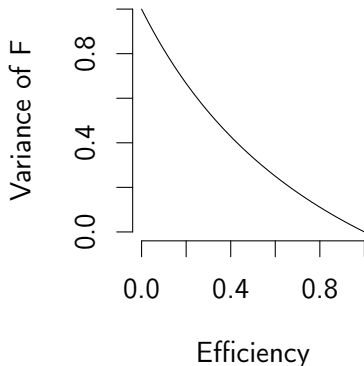


The family size distribution - Variance



While the density of the family size distribution doesn't seem to be analytically tractable, the variance has a simple analytic expression

$$\mathbb{V}F = \frac{1 - E}{1 + E}$$

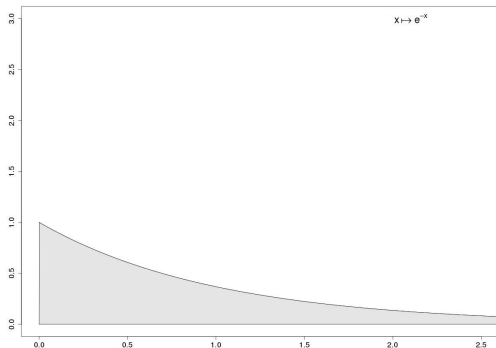


The family size distribution - Density



To compute the density, we must resort to numeric methods

We used simulations+KDE, but now a fast method developed by Straub and Neininger (Göthe-Universität Frankfurt) is available



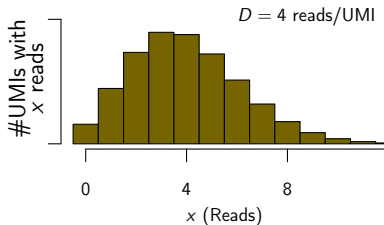
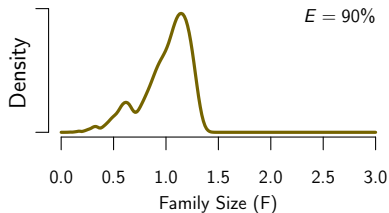
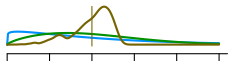
(Video due to Straub & Neininger)

From the family size to the reads/UMI distribution



Sequencing is Poissonian sampling from families of unknown size

$$\mathbb{P}(k) = \int_0^{\infty} \underbrace{\mathbb{P}(k | \lambda = D \cdot x)}_{\text{Poisson}} \cdot \underbrace{\mathbb{P}(\text{Fam. Size} = c | E)} dx.$$



The complete model has two parameters, depth D and efficiency E .

For the reads count C per UMI, we can analytically find

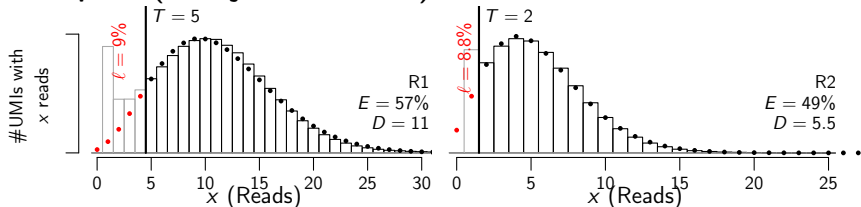
$$\mathbb{E}(C) = D, \quad \mathbb{V}(C) = D + D^2 \frac{1 - E}{1 + E}.$$

We can estimate D , E with the *method of moments*.

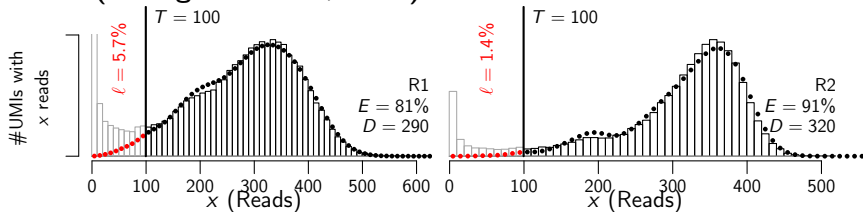
Observed & Expected Reads/UMI



Drosophila (Kivioja et al., 2012)

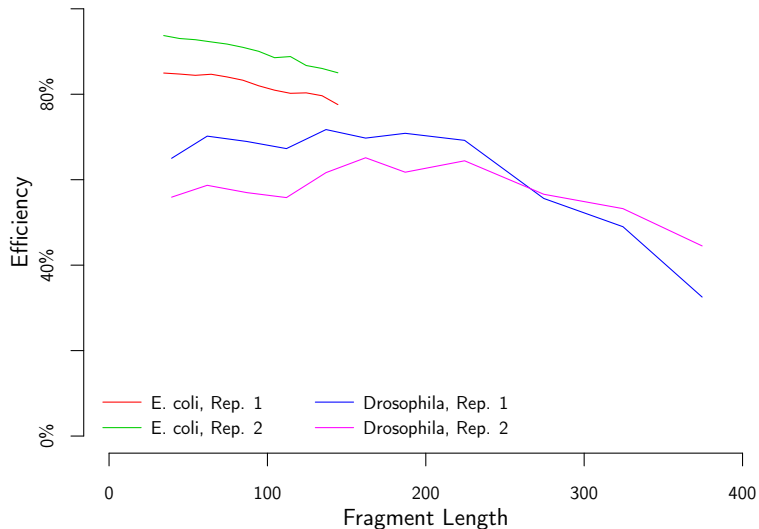


E. coli (Shiroguchi et al., 2012)

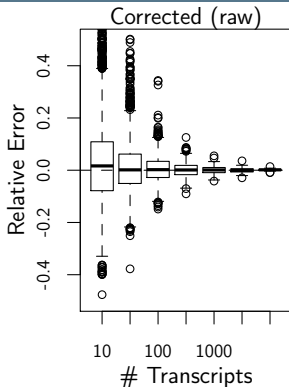


- Putative True UMIs
- Predicted True UMIs
- Putative Phantom UMIs
- Predicted Loss

PCR efficiency vs. length

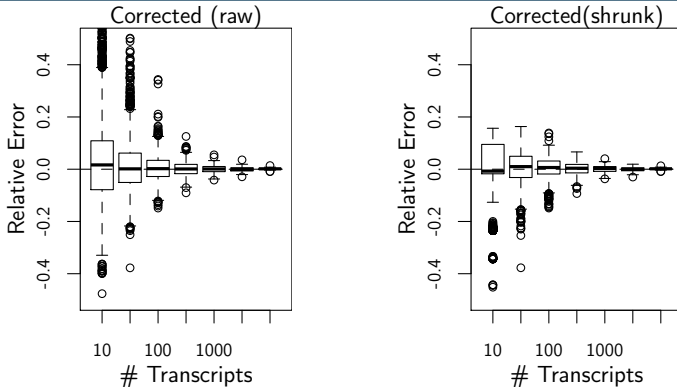


Correcting for gene-wise biases



For genes with few transcripts, we have little data to estimate D , E , and the correction hurts more than it helps...

Correcting for gene-wise biases



We *shrink* the gene-wise loss estimate $\hat{\ell}_g^{\text{raw}}$ towards global ones

$$\hat{\ell}_g^{\text{shrink}} = \lambda_g \cdot \hat{\ell}_g^{\text{raw}} + (1 - \lambda_g) \cdot \hat{\ell}_g^{\text{all}}$$




- The Galton-Watson branching process model captures the main stochastic properties of the PCR reaction
- while still allowing efficient parameter estimation
- and allows us to predict, detect & correct biases
- as well as studying of early-cycle PCR behaviour.

Most of this work was recently published in:

Florian G. Pflug and Arndt von Haeseler. TRUmiCount: Correctly counting absolute numbers of molecules using unique molecular identifiers.

Bioinformatics (2018).

And we provide an  package `gwpcR` which implements the family size distribution, Poisson mixture, and parameter estimation

Every at the **CIBIV**, in particular:

Olga Chernomor

Celine Prakash

Luis Paulin-Paz

Goethe-Universität Frankfurt:

Jasmin Straub & Günther Neining



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Thank You
for your Attention