

Regression for counts

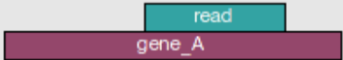
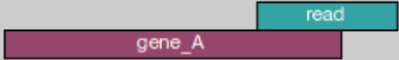


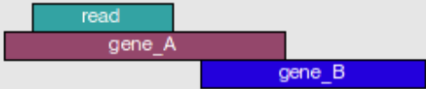
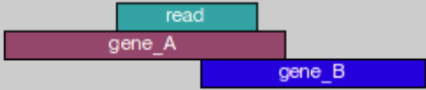

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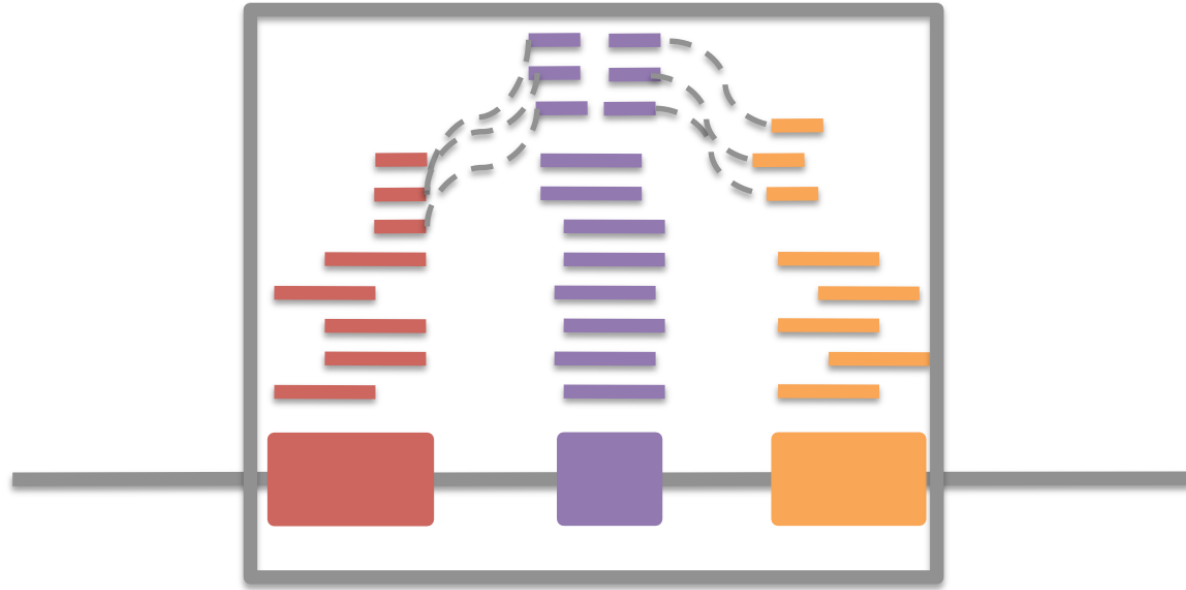
Data aren't always “Normal”

Sequencing data is often counts

	gene_A	gene_B	no_feature
	gene_A	gene_A	gene_A
	gene_A	no_feature	gene_A
	gene_A	no_feature	gene_A
	gene_A	gene_A	gene_A
	gene_A	gene_A	gene_A
	ambiguous	gene_A	gene_A
	ambiguous	ambiguous	ambiguous

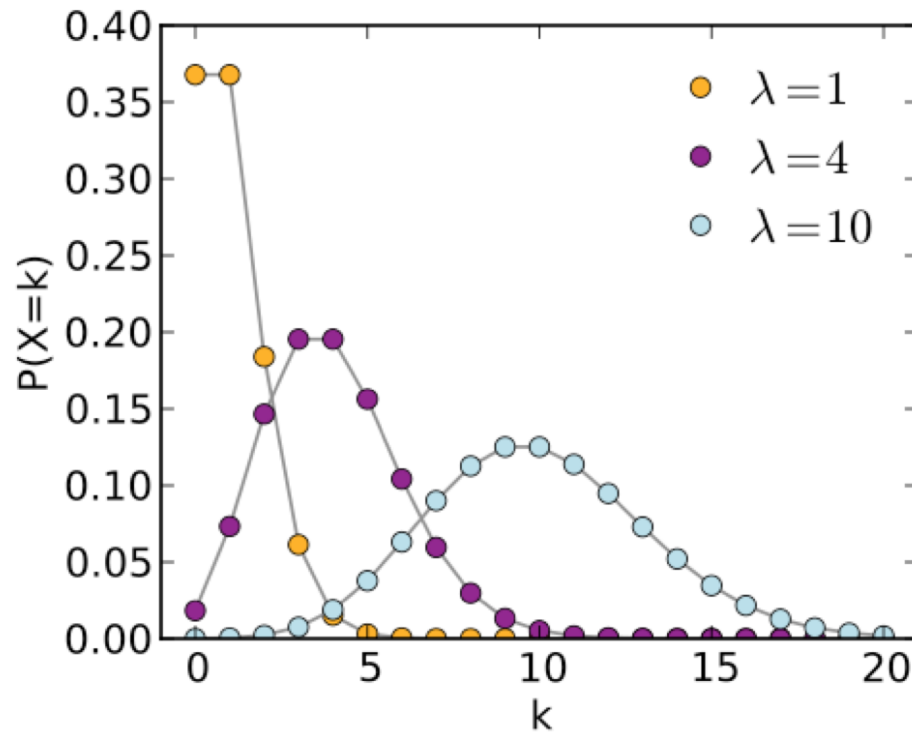
Union of all exons

Genome



	sample1	sample2	sample3
gene1	0	0	0
gene2	0	12	1
gene3	1000	2000	100
gene4	10	20	2

Poisson is a common assumption



$$f(k; \lambda) = \frac{e^{-\lambda} \lambda^k}{k!}$$

Mean & Variance: λ

Fit a regression on log of
expectation of the counts

Normalized Counts
For Gene i , Sample j



Normalization Constant
For Sample j



$$g(E[f(c_{ij}) | y_j]) = b_{i0} + \eta_i \log(q_j) + b_{i1} y_j$$



Link Function

Group Indicator

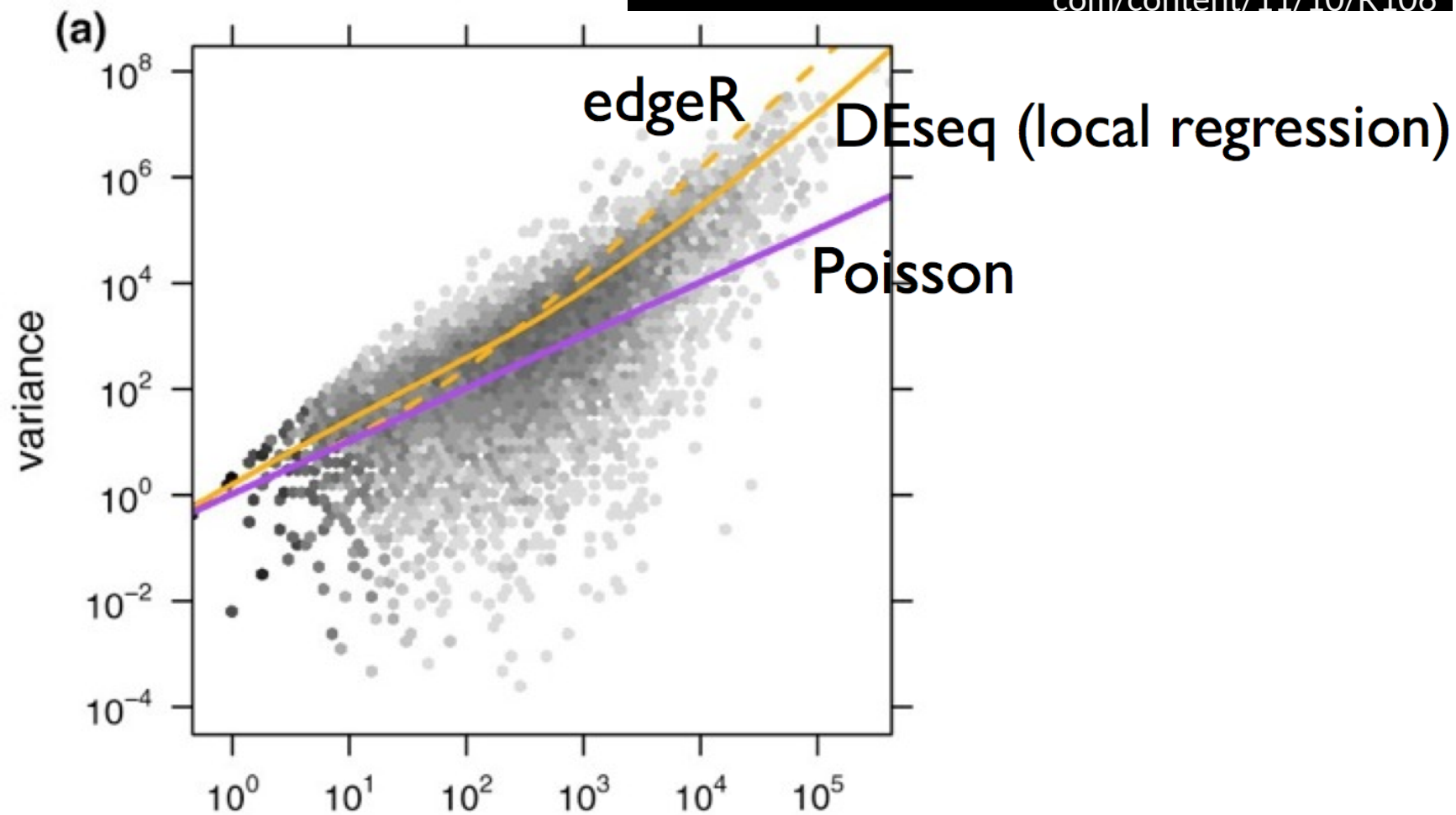


Parameter We Test

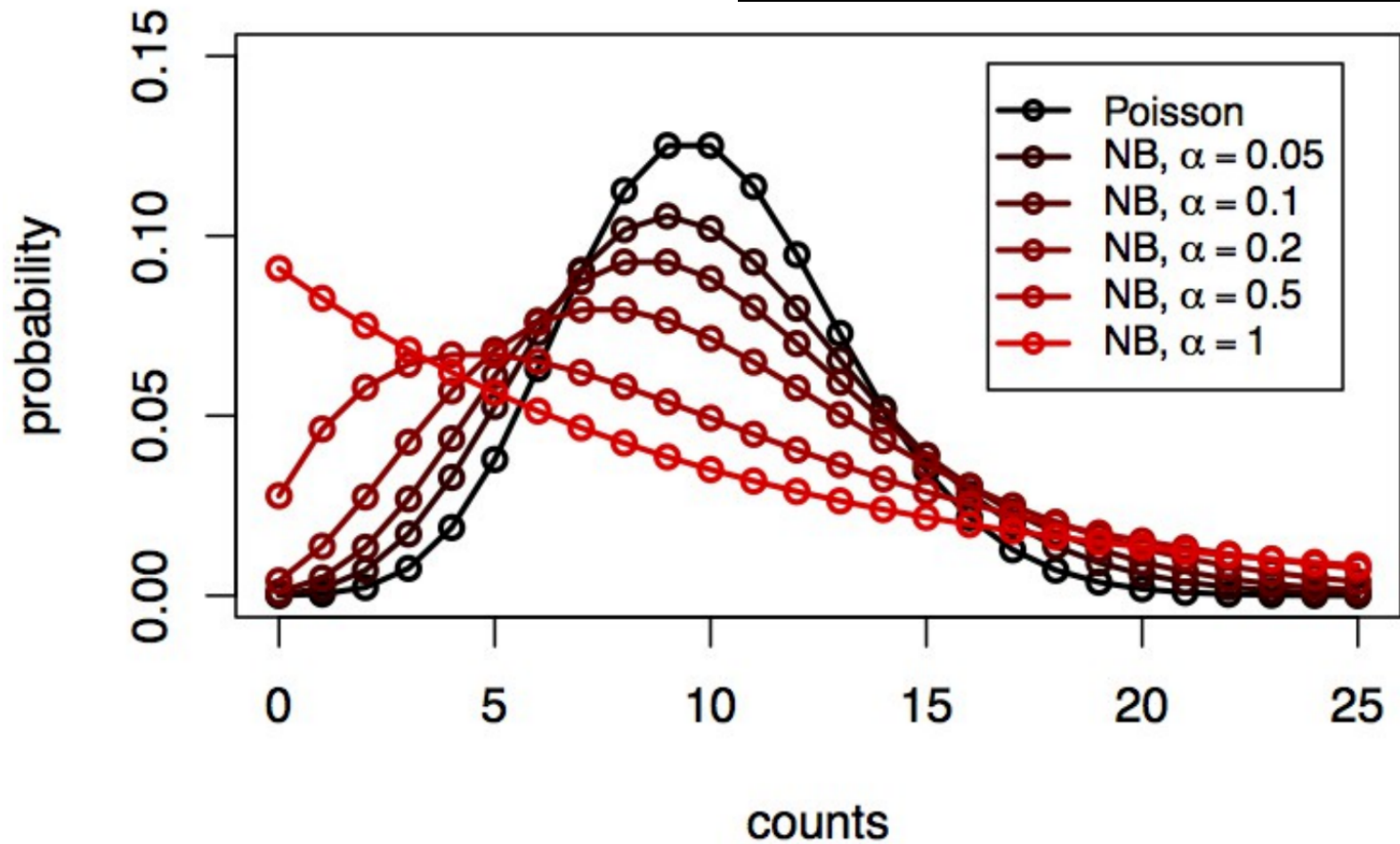
Mean and variance relationship

They are often not exactly equal

The relationship can be modeled



Negative binomial distribution
Is more flexible for modeling
2 parameters instead of one



$$K_{ij} \sim \text{NB}(\mu_{ij}, \alpha_i)$$

$$\mu_{ij} = s_j q_{ij}$$

$$\log_2(q_{ij}) = x_{j*} \vec{\beta}_i$$

K_{ij}	counts of reads for gene i , sample j
μ_{ij}	fitted mean
α_i	gene-specific dispersion
s_j	sample-specific size factor
q_{ij}	parameter proportional to the expected true concentration of fragments
x_{j*}	the j -th row of the design matrix X
$\vec{\beta}_i$	the log fold changes for gene i for each column of X

Notes and further reading

- Negative binomial/Poisson regression are “generalized linear models”
 - https://en.wikipedia.org/wiki/Generalized_linear_model
- A nice set of lecture notes
 - <http://data.princeton.edu/wws509/notes/>
- This is again a huge topic and we have only scratched the surface.