

## Chapter 8: Correlation Questions

$$\bar{F}(x) = \frac{\#\{z_i \geq x\}}{N} \quad \text{if}$$

$z_i$  are iid

$$\text{Var}(\bar{F}(x)) = \frac{F(x)(1-F(x))}{N}$$

for

$$F(x) = P(z_i \geq x)$$

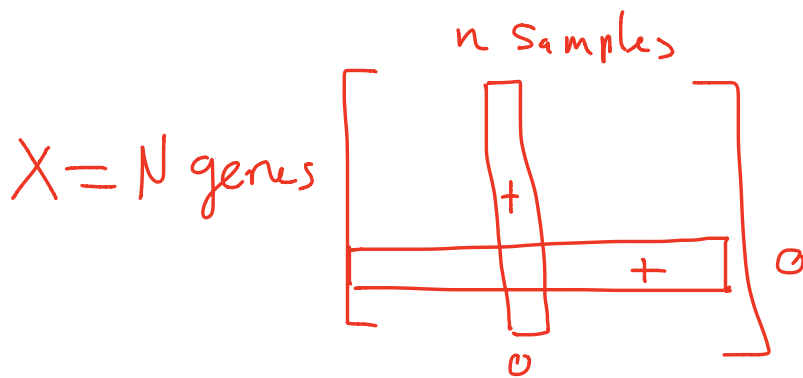
Chapter 7 focuses on the dependence version

$$\text{Var}(\bar{F}(x)) = \frac{\bar{F}(x)(1-\bar{F}(x))}{N} + \left\{ \frac{\hat{\alpha} \hat{\sigma}_d^2 \hat{f}^{(1)}(x)}{\sqrt{2}} \right\}^2$$

$$\text{For } \alpha^2 = \frac{1}{N(N-1)} \sum_{i \neq j} f_{ij}^2$$

average square correlation.

## Row and Column Correlations



· Assume row & column sums are zero.

· Next assume  $\sum_{i=1}^N x_{ij}^2 = N \sum_{j=1}^n x_{ij}^2 = n$

then the row correlation

$$\hat{\sigma}_{ii'} = \frac{1}{n} \sum_{j=1}^n x_{ij} x_{i'j}$$

next the column correlation

$$\hat{\Delta}_{jj'} = \frac{1}{N} \sum_{i=1}^N x_{ij} x_{ij'}$$

~ ~ ~ ~ ~

So in matrix notation

$$\hat{\Delta} = \frac{X^T X}{N} \quad \hat{\Sigma} = \frac{X X^T}{N}$$

Thrm: Suppose  $X = U D V^T$   $e_k = d_k^2$

then  $\hat{\Delta}, \hat{\Sigma}$  have mean 0 and

empirical variance  $c_2 = \sum_{k=1}^K \frac{e_k^2}{(N_n)^2}$

pf:

$$\sum_i \Delta_{ij} = \mathbf{1}^T \underbrace{\hat{\Delta} \mathbf{1}}_{\substack{\text{row} \\ \text{sums}}} = \mathbf{1}^T \mathbf{0} = 0$$

empirical variance of  $\Delta$

$$\frac{1}{n^2} \sum_{j=1}^n \sum_{j'=1}^n \Delta_{jj'}^2$$

$$= \frac{1}{n^2} \sum_{j=1}^n \sum_{j'=1}^n \Delta \circ \Delta$$

$$= \frac{1}{n^2} \text{tr}(\Delta \Delta)$$

$$= \frac{1}{n^2 N^2} \text{tr}((X^T X)^2)$$

$$= \frac{1}{n^2 N^2} \text{tr}(V d^2 V^T)^2$$

$$= \frac{1}{n^2 N^2} \text{tr}(d^2)^2 = \frac{1}{n^2 N^2} \sum_{k=1}^K e_k^2$$

$$= \sum_{k=1}^K \left( \frac{e_k}{nN} \right)^2$$

Remark: The standardization in some sense is decorrelating the sample-sample & gene-to-gene matrix.

Cor: The main diagonal sums should be 1. So the off diagonal entries of the column correlation

$$\hat{\mu} = -\frac{1}{n-1} \quad \hat{\sigma}^2 = \frac{n}{n-1} \left( c_2 - \frac{1}{n-1} \right)$$

Pf: Looking at the expectation of the off diagonal.

$$\frac{1}{n(n-1)} \sum_{j \neq j'} \Delta_{jj'} = \frac{1}{n(n-1)} \left( \sum_{j \neq j'} -n \right)$$

$\Rightarrow$

$$\frac{1}{n(n-1)} \sum_{j \neq j'} \Delta_{jj'} = -\frac{1}{n-1}$$

Estimating Variance

$$\alpha = \left[ \frac{\sum_{i < i'} s_{ii'}^2}{N(N-1)/2} \right]^{1/2}$$

$$\left[ \frac{N(N-1)}{2} \right]$$

$$\bar{x} = \left[ \frac{\sum_{i=1}^N x_i^2}{N(N-1)/2} \right]$$

$$\hat{\alpha} = \left[ \frac{n}{n-1} \left( \bar{x} - \frac{1}{n-1} \right) \right]^{1/2}$$

Multivariate Normal Calculations

$$X \sim N(\mu, \Sigma \otimes \Delta)$$

row by  
row  
covariance

column by  
column covariance.

$$\mathbb{E}(x_{ij}) = \mu_{ij} \quad \text{Cov}(x_{ij}, x_{ij}) = \sigma_{ij} \Delta_{jj}$$

here we are going to assume  
the samples are not correlated

$$\Delta = I.$$

Thm: Under the MUN model

$$n^2 = n \times n$$

$\alpha_n = \frac{1}{n+1} (\bar{\alpha}^2 - \frac{1}{n})$  is an

unbiased estimator.

$$\bar{\alpha}^2 = \frac{1}{N(N-1)} \sum_{i \neq i'} \hat{\sigma}_{ii'}^2$$

$$\mathbb{E}(\hat{\sigma}_{ii'}^2) = \mathbb{E}\left[\left(\frac{1}{n} \sum_{j=1}^n x_{ij} x_{i'j}\right) \left(\frac{1}{n} \sum_{j=1}^n x_{ij} x_{i'j}\right)\right]$$

$$= \frac{1}{n^2} \mathbb{E}\left[\sum_{j=1}^n x_{ij}^2 x_{i'j}^2 + \sum_{j \neq j'} x_{ij} x_{i'j} x_{ij'} x_{i'j'}\right]$$

$$= \frac{1}{n^2} \left\{ n(1 + 2\sigma_{ii'}) + n(n-1)(\sigma_{ii'}^2) \right\}$$

$$= \frac{1}{n} \left( 1 + (n+1)\sigma_{ii'}^2 \right)$$

Rules we used above

$$\mathbb{E}(x_1^2 x_2^2) = \sigma_1^2 \sigma_2^2 + 2\sigma_{12}$$

$$\begin{aligned} E(X_1 X_2 X_3 X_4) &= E(X_1 X_2) E(X_3 X_4) + \\ &\quad E(X_1 X_3) E(X_2 X_4) + \\ &\quad E(X_1 X_4) E(X_2 X_3) \end{aligned}$$

$$\begin{aligned} E(\bar{x}^2) &= \frac{1}{N(N-1)} \sum_{i \neq i'} \left\{ \frac{1}{n} (1 + (n+1) \sigma_{ii'}) \right\} \\ &= \frac{1}{n} + \frac{n+1}{n} \frac{1}{N(N-1)} \sum_{i \neq i'} \sigma_{ii'}^2 \end{aligned}$$

So

$$E\left(\bar{x}^2 - \frac{1}{n}\right) = \frac{n+1}{n} \underbrace{\frac{1}{N(N-1)} \sum_{i \neq i'} \sigma_{ii'}^2}_{\bar{x}^2}$$

and

$$\frac{n}{n+1} \left\{ \bar{x}^2 - \frac{1}{n} \right\} \text{ is unbiased.}$$



Thrm: Under the model the column covariance estimator  $\hat{\Delta} = \frac{X^T X}{N}$  has

mean and covariance  $\hat{\Delta} \sim \left( \Delta, \underbrace{\frac{\Delta^{(2)}}{N_{\text{eff}}}}_{\text{tensor}} \right)$

$$N_{\text{eff}} = \frac{N}{1 + (N-1)\alpha^2}$$

So what is effective sample size?  $N_{\text{eff}}$ .

$$\alpha = 0.2, \quad N_{\text{eff}} = 5$$

So even slightly correlated genes

$$\Delta_{jk, \text{en}}^{(2)} = \Delta_{j1} \Delta_{1k} + \Delta_{k2} \Delta_{2j}$$

## Chapter 9 Enrichment Analysis

o Used to compensate the lack

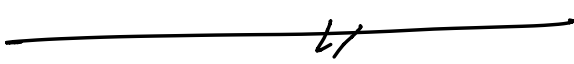
of power.

- Leverage biological data (from Gene Ontology usually)
- Let  $S$  is a specific gene set category.
- denote  $z_S = \{z_i : i \in S\}$
- Testing based on KS test

$$H_0: F^{(1)}(x) = F^{(2)}(x)$$

$$\text{test stat: } \sup_x |\hat{F}_1(x) - \hat{F}_2(x)|$$

$F_1(x)$  CDF of  $z_S$  on  $S$

$F_2(x)$    $S^c$