

Inference on the AUC with clustered data

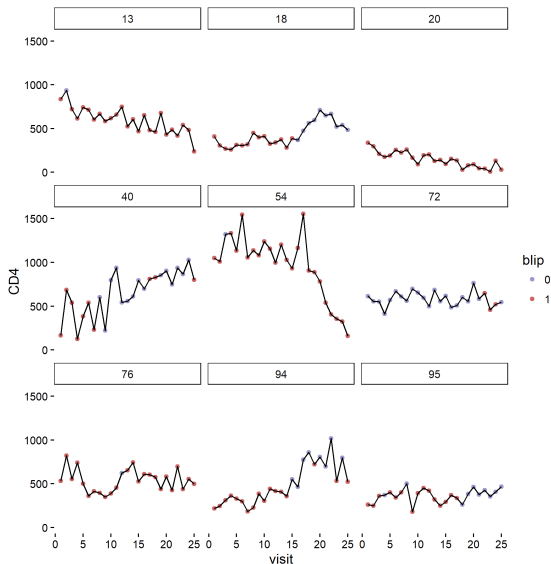
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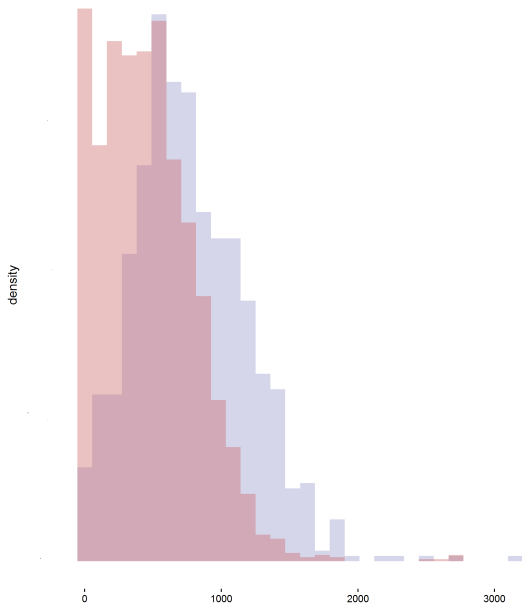
A motivating example

Data: The Yale
Prospective
Longitudinal HIV
Cohort

Problem: Evaluate
CD4 as a predictor
of blip status



CD4



	control	case
obs. # 1	X_1	
\vdots	\vdots	
obs. # k	X_k	
obs. # k+1		Y_{k+1}
\vdots		\vdots
obs. # N		Y_N

The AUC is the probability that an observation drawn from a negative/control/non-diseased subject is less than an independent observation from a positive/case/diseased subject.

$$\text{AUC} = P(X < Y) = E(F_X(Y))$$

$$\widehat{\text{AUC}} = \frac{1}{k(N-k)} \sum_{i,j} \{X_i < Y_j\}$$

	control	case
obs. # 1	$(X_{11}, \dots, X_{1m_1})$	$(Y_{11}, \dots, Y_{1n_1})$
\vdots	\vdots	\vdots
obs. # N	$(X_{N1}, \dots, X_{Nm_N})$	$(Y_{N1}, \dots, Y_{Nn_N})$

- Assume iid observations. Denote AUC between cluster i controls and cluster j cases as

$$\phi_{ij} = \frac{1}{m_i n_k} \sum_{j=1}^{m_i} \sum_{l=1}^{n_k} \{X_{ij} < Y_{kl}\} \quad \phi = \begin{pmatrix} \phi_{11} & \dots & \phi_{1N} \\ \vdots & \vdots & \vdots \\ \phi_{N1} & \dots & \phi_{NN} \end{pmatrix}$$

- Generalize AUC to clustered data as

$$\theta = \text{AUC} = E(\phi_{ij}), i \neq j$$

$$\hat{\theta} = \widehat{\text{AUC}} = \bar{\phi}_{..} = \frac{1}{N^2} \sum_{i,j} \phi_{ij}$$

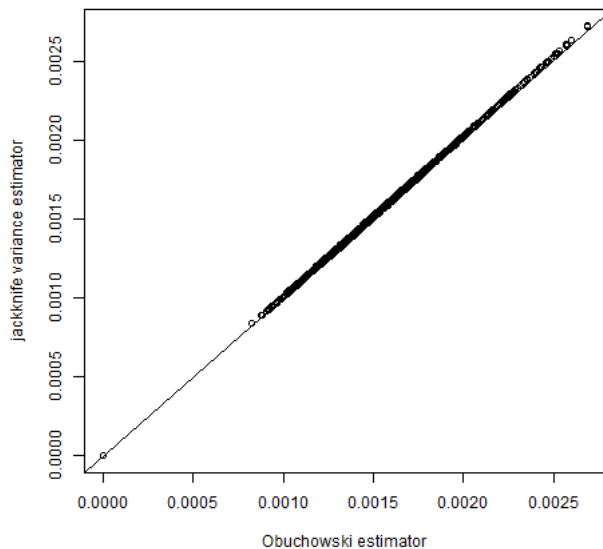
- ▶ markers: longitudinal measurements of tumour antigens (CEA, CA15-3, TPS) as markers, response: progression/non-progression of breast cancer (Emir 2000)
- ▶ markers: two measurements of the distortion product otoacoustic emissions taken from the left and right ears ((think this should be ears)) of each patient, response: neonatal hearing impairment (Wu 2019)
- ▶ markers: longitudinal measurements of levels of vascular endothelial growth factor and a soluble fragment of Cytokeratin 19, response: progression/non-progression of non-small cell lung cancer (Wu, Wang 2011)

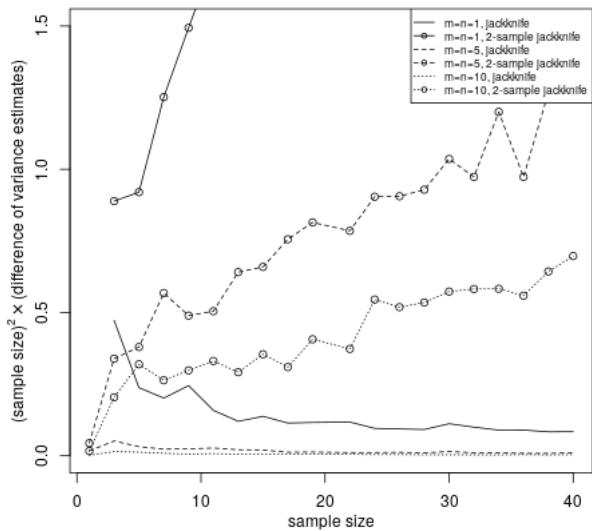
- ▶ Fix cluster sizes $m_i = m, n_j = n, 1 \leq i, j \leq N$
- ▶ Obuchowski '97 estimates the variance of $\bar{\phi}_{..} = \widehat{\text{AUC}}$ as

$$\begin{aligned}\hat{\sigma}_{obu}^2 &= \frac{1}{N(N-1)} \sum_i (\bar{\phi}_{i.} + \bar{\phi}_{.i} - 2\bar{\phi}_{..})^2 \\ &= \frac{1}{N} \widehat{\text{var}}(\bar{\phi}_{i.} + \bar{\phi}_{.i})\end{aligned}$$

$$(\bar{\phi}_{..} - E(\bar{\phi}_{..}))/\hat{\sigma}_{obu} \rightsquigarrow N(0, 1)$$

- ▶ Alternatively: Use the bootstrap. Sample the iid clusters without replacement, compute $\bar{\phi}_{..}$ on the sample, repeat. Take the sample variance of the resulting $\bar{\phi}_{..}$'s.





Objective is

$$\begin{aligned} &\propto \frac{2N-1}{N^2} \sum_j (\bar{\phi}_{j\cdot} + \bar{\phi}_{\cdot j} - 2\hat{\theta})^2 \\ &- \frac{2}{N} \sum_j (\bar{\phi}_{j\cdot} + \bar{\phi}_{\cdot j} - 2\hat{\theta}) \left(\phi_{jj} - \frac{\text{tr}(\phi)}{N} \right) \\ &+ \text{lower order terms} \end{aligned}$$

- ▶ When $m = n = 1$, clusters can be ordered by y_i (“case”) observations

- ▶ $\phi_{ij} = \{x_i < y_j\}$, e.g., $\phi = \begin{pmatrix} 0 & 1 & 1 \\ 0 & 0 & 1 \\ 1 & 1 & 1 \end{pmatrix}$

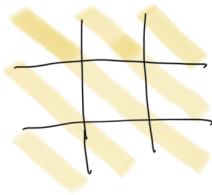
- ▶ $a_i := \phi_i$. the row sums, $0 \leq a_i \leq N$ $F_a(x) = \sum_{i=1}^N \{a_i \leq x\}$
the observed CDF of the a_i objective is

$$\begin{aligned} &\propto \frac{1}{N^2} \sum_i a_i^2 + \frac{2}{N} a_i (1 - F_a(N - i)) \\ &+ \sum_i (1 - F_a(N - i))^2 + \frac{2}{N^2} \left(\sum_i a_i \right) \left(\sum_i (1 - F_a(N - k)) \right) \\ &- \sum_i (1 - F_a(N - k)) \{a_i > N - i\} - \frac{4}{N^3} \left(\sum_i a_i \right)^2 \\ &- \frac{1}{N} \sum_i a_i \{a_i > N - i\} \end{aligned}$$

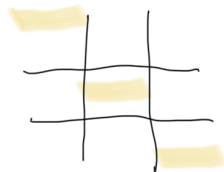
View the objective as a quadratic form Q in the N^2 entries of ϕ



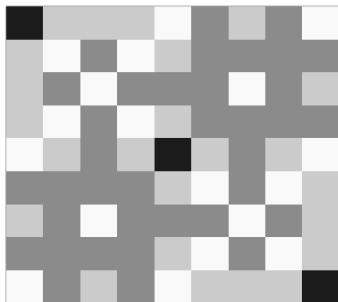
$$\sum \phi_{i,i}^2$$



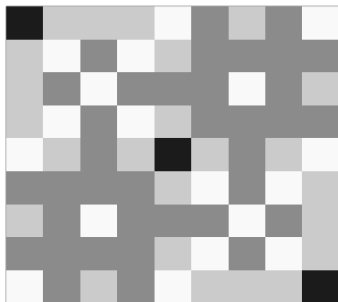
$$\sum \phi_{i,j}^2$$



$$-\sum \phi_{i,i} \phi_{i,i}$$



- ▶ N^2 $N \times N$ blocks
- ▶
$$Q_{pqrs} = \frac{1}{N^2}(\{p = q\} + \{r = s\} + \{q = r\} + \{p = s\} + \{s = q\} + \{p = r\}) - \frac{1}{2N}(\{p = q = r\} + \{p = q = s\} + \{p = r = s\} + \{q = r = s\}) - \frac{4}{N^3}$$
 is symmetric in p, q, r, s
- ▶ Q is symmetric about the diagonal, anti-diagonal, and 180° rotations



- ▶ $Q = (P \otimes P)^t Q (P \otimes P)$ for a permutation matrix P (shuffling iid clusters)

- ▶ characteristic polynomial $x^{N^2-2(N-1)}(2x^2 - \frac{N-2}{N^2})^{N-1}$
- ▶ $Q^{2k+1} = \lambda^{2k}Q$ and $Q^{2k} = \lambda^{2(k-1)}Q^2$
- ▶ Q is the scaled difference of two orthogonal projection matrices onto two $N - 1$ dimensional subspaces

$$Q = \lambda(Q_1 - Q_2)$$

(aside) Relate the traces of powers $t_j = \text{tr}(Q^j)$ to the coefficients c_j of the characteristic polynomial

$$c_1 = t_1$$

$$c_2 = \frac{1}{2}(t_1^2 - t_2)$$

$$c_3 = -\frac{1}{6}t_1^3 + \frac{1}{2}t_1t_2 - \frac{1}{3}t_3$$

$$\vdots$$

With our traces and coefficients,

$$\begin{aligned} & -\frac{N-1}{k} + \frac{(N-1)^2}{2!} \sum_{i_1+i_2=k} \frac{1}{i_1 i_2} - \frac{(N-1)^3}{3!} \sum_{i_1+i_2+i_3=k} \frac{1}{i_1 i_2 i_3} + \dots \\ & + (-1)^{k-1} \frac{(N-1)^{k-1}}{(k-1)!} = (-1)^{N+k} \binom{N-1}{k} \end{aligned}$$

(aside) i.e. $(-1)^k \binom{N-1}{k}$ is the coefficient of x^k in

$$\sum_{m=1}^{N-1} (-1)^m \frac{(N-1)^m}{m!} (x + x^2/2 + x^3/3 + \dots + \frac{x^{N-1}}{N-1})^m.$$

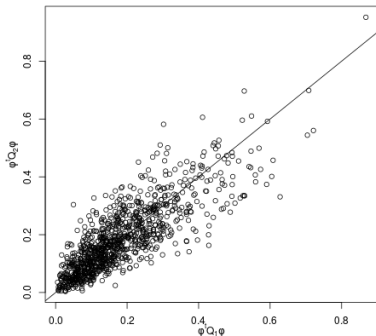
$$\sum_{i_1 + \dots + i_m} \frac{1}{i_1 \cdot \dots \cdot i_m} = \frac{|s_m^k|}{k!}$$

with $|s_m^k|$ the Stirling number of the first kind

$$x^{\underline{k}} = \frac{x!}{(x-k)!} = \sum_{m=1}^k s_m^k x^m$$

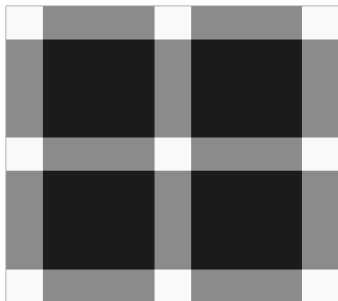
e.g.

$$x^{\underline{4}} = x(x-1)(x-2)(x-3) = x^4 - 6x^3 + 11x^2 - 6x$$



- ▶ nullspace has dimension $N^2 - 2(N - 1)$
- ▶ need Q -null vectors v , $(v, Qv) = 0$, and relate these to the structure of ϕ

(Aside)



- Element-wise ratio Q_2/Q_1
only takes 3 values:

$-1, r_N, 1/r_N$

N	r_N
3	$17 + 12\sqrt{2} = \epsilon_0(2)^4$
4	Inf
5	$49 + 20\sqrt{6} = \epsilon_0(6)^2$
6	$17 + 12\sqrt{2} = \epsilon_0(2)^4$
7	$19.7270\dots$
8	$7 + 4\sqrt{3} = \epsilon_0(3)^2$
9	$10.8679\dots$
10	9
12	$7/2 + 3/2\sqrt{5} = \epsilon_0(5)^4$
20	4

Mutually Q -orthogonal vectors include (vectorizations of)

▶ constant row/column ϕ e.g. $\begin{pmatrix} 1 & 0 & 0 \\ 1 & 0 & 0 \\ 1 & 0 & 0 \end{pmatrix}, \begin{pmatrix} 0 & 0 & 0 \\ 1 & 1 & 1 \\ 0 & 0 & 0 \end{pmatrix}$

▶ constant diagonal ϕ e.g. $\begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix}$

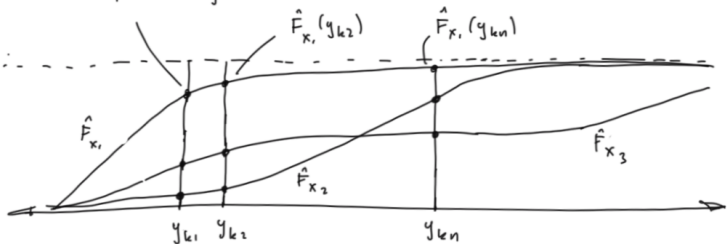
▶ upper triangular ϕ in $N(Q)$ $\begin{pmatrix} 1 & 1 & 1 \\ 0 & 1 & 1 \\ 0 & 0 & 1 \end{pmatrix}$

i.e., stack bases for the above to form a matrix B , then $B^t Q B = 0$

- ▶ structure of matrix given by $\phi_{ij} = \mathbb{E} F_{X_j}(Y_j)$
- ▶ can't order y (case) clusters when $n > 1$
- ▶ but ϕ is a mixture of totally ordered vectors
 $0 \leq v_1 \leq v_2 \leq \dots \leq v_n \leq m$

$$\phi = \frac{1}{mn} \begin{pmatrix} \vdots & \vdots & & \vdots \\ v_1 & v_2 & \cdots & v_{Nn} \\ \vdots & \vdots & & \vdots \end{pmatrix} \begin{pmatrix} 1 & 0 & & 0 \\ 0 & 1 & & 1 \\ \vdots & \vdots & \cdots & \vdots \\ 1 & 0 & & 1 \end{pmatrix} \begin{matrix} \text{row sums} = 1 \\ \text{col sums} = n \end{matrix}$$

$$\hat{F}_{x_i}(y_{k1}) = \frac{1}{m} \sum_{j=1}^m \{x_{ij} < y_{k1}\}$$



$$\frac{1}{n} \sum_{p=1}^n \hat{F}_{x_i}(y_{kp}) = \frac{1}{mn} \sum_{p=1}^n \sum_{j=1}^m \{x_{ij} < y_{kp}\} = \phi_{ik}$$

$$mn\phi =$$

$$\begin{matrix} \text{row sums}=m & \begin{pmatrix} 0 & 1 & \cdots & 1 \\ 1 & 0 & \cdots & 0 \\ & & \vdots & \\ 0 & 0 & \cdots & 0 \end{pmatrix} & \begin{pmatrix} 1 & 1 & \cdots & 1 \\ 0 & 1 & \cdots & 1 \\ & & \ddots & \\ 0 & 0 & \cdots & 1 \end{pmatrix} & \begin{pmatrix} 1 & 0 & & 0 \\ 0 & 1 & & 1 \\ \vdots & \vdots & \cdots & \vdots \\ 1 & 0 & & 1 \end{pmatrix} & \text{row sums}=1 \\ & \text{col sums}=1 & & \text{col sums}=n & \end{matrix}$$

If the 1st and 3rd matrices are permutation matrices, ϕ is in the nullspace of Q

- ▶ Project ϕ onto a subset of the Q -null vectors and examine residual
- ▶ Let $P = (1, \dots, N)$ and $\bar{\phi}_{\cdot p} = (\bar{\phi}_{\cdot 1}, \dots, \bar{\phi}_{\cdot N})$

$$\text{Var}(\bar{\phi}_{\cdot p}) - \text{Cov}^2(\bar{\phi}_{\cdot p}, \frac{P}{\text{sd}(P)})$$

- ▶ $D(x) = |\text{Cov}((x_{(1)}, \dots, x_{(N)}), \frac{P}{\text{sd}(P)})|$ can be viewed as a measure of statistical dispersion of (x_1, \dots, x_N)

$$D(ax + b) = |a|D(x) + b$$

- ▶ $\text{Var}(x) - D^2(x) \geq 0$, equals 0 when $x \propto (1, \dots, N)$ i.e., (x_1, \dots, x_N) are evenly spaced
- ▶ conjecture it is maximized for $0 \leq x \leq 1$ when $x = (0, 0, \dots, 0, 1)$, where the value is $O(1/N)$
- ▶
 - ▶ Maximizing a positive semi-definite function over a polytope
 $0 \leq x_1 \leq \dots \leq x_N \leq 1$
 - ▶ Maximum occurs at a corner point given by the intersection of N hyperplanes
 - ▶ N of the $N + 1$ restrictions
 $0 \leq x_1, x_1 \leq x_2, \dots, x_{N-1} \leq x_N, x_N \leq 1$ are active
 - ▶ Only need to check x of the form $(0, \dots, 0, 1, \dots, 1)$.

The difference between the jackknife and Obuchowski variance estimates is $O(1/N^2)$ when ϕ is lower right triangular

Future work

- ▶ stochastic result needed or sharpen constants
- ▶ varying cluster sizes