

Multi-stage group testing with heterogeneous probabilities of disease positivity

Christopher R. Bilder¹, Joshua M. Tebbs², and Michael S. Black³

¹University of Nebraska–Lincoln, Department of Statistics

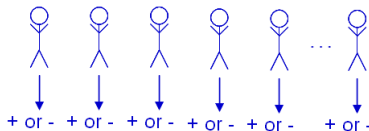
²University of South Carolina, Department of Statistics

³University of Wisconsin-Platteville, Department of Mathematics

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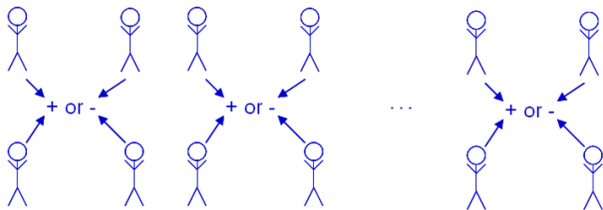
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- Screen a large number of individuals for an infectious disease
- Individual testing



- May not be feasible in high volume clinical specimen settings
 - Cost
 - Time

- Group testing (a.k.a., pooled testing)



- If the GROUP is negative, then all individuals are declared negative
- If the GROUP is positive, then at least ONE individual is positive
 - “Decode” the positive group
- Benefits:
 - Reduction in tests
 - Cost savings (less tests and labor)
- Overall disease prevalence needs to be small

- American Red Cross (Stramer et al. 2004; ARC 2014)
 - Millions of blood donations per year
 - HIV, hepatitis B, and hepatitis C
 - 1st stage - Initial group of size 16
 - 2nd stage - Individual testing
- HIV screening by public health clinics: Los Angeles three-stage hierarchical group testing
 - 1st stage - Initial group of size 90
 - 2nd stage - Subgroups of size 10
 - 3rd stage - Individual testing
- Number of tests can be further reduced by allowing more than two stages

- Informative retesting

- Incorporate factors that influence positive or negative disease status
- Estimate the probability that an individual is positive
- These probabilities are used to select
 - Number of subgroups
 - Subgroup sizes
 - Members of each subgroup

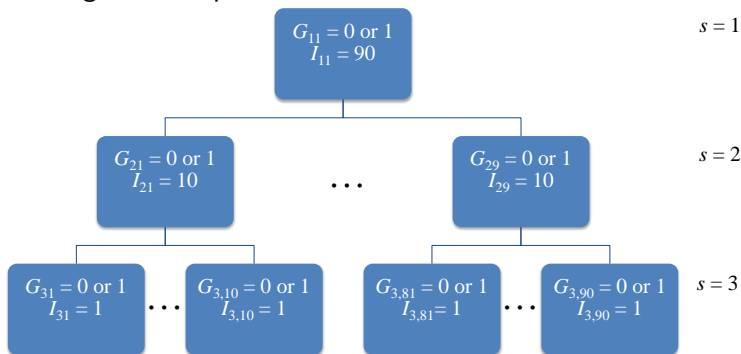
in order to form a **retesting configuration**

- Goal is to reduce the number of tests
- Papers include: Bilder et al. (*JASA*, 2010), McMahan et al. (*Biometrics*, 2012), McMahan et al. (*Biometrics*, 2012b), Black et al. (*JRSS-C*, 2012)

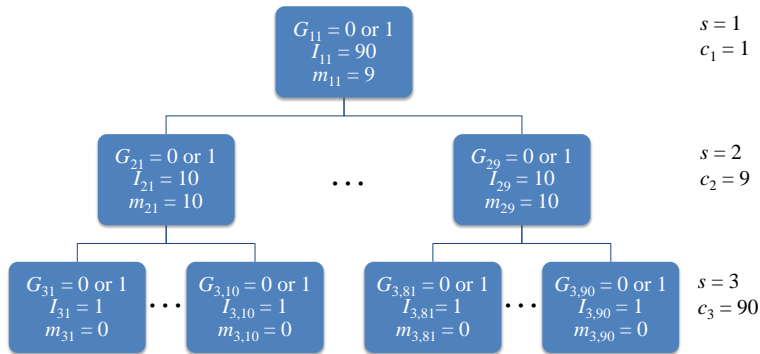
- Purpose

- Examine hierarchical group testing methods (three or more stages)
- Incorporate informative retesting ideas
- Determine the retesting configuration that minimizes the number of tests

- Consider a group with I individuals
- Define G_{sj} as a binary random variable denoting the test status for group j at the s th stage
 - $G_{sj} = 0$ for a negative test result
 - $G_{sj} = 1$ for a positive test result
- Define I_{sj} as the number of individuals in group j at the s th stage ($I_{11} \equiv I$)
- Los Angeles example:



- If $G_{sj} = 1$, the corresponding group is divided into m_{sj} subgroups
- Define c_s as the total number possible of subgroups at the s th stage
- Los Angeles example:



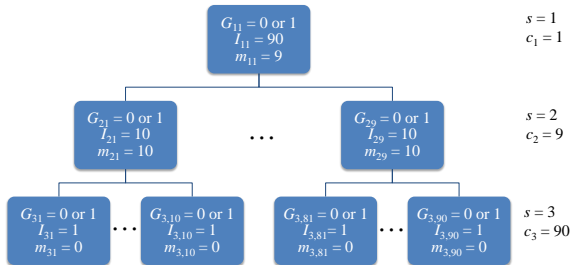
- Let T be the number of tests for one group
- The expected number of tests is

$$E(T) = 1 + \sum_{s=1}^{S-1} \sum_{j=1}^{c_s} m_{sj} P \left(\bigcap_{\{(s'j') : G_{s'j'}=1\}} \{G_{s'j'} = 1\} \right)$$

where S is the total number of stages

- Los Angeles example with $s = 2, j = 1$:

$$P \left(\bigcap_{\{(s'j') : \{G_{21}=1\}\}} \{G_{s'j'} = 1\} \right) = P(\{G_{11} = 1\} \cap \{G_{21} = 1\})$$



- Define \tilde{G}_{sj} as a binary random variable denoting the TRUE status for group j at the s th stage
- Accuracy of an assay
 - $S_e = P(G_{sj} = 1 | \tilde{G}_{sj} = 1)$ is the sensitivity
 - $S_p = P(G_{sj} = 0 | \tilde{G}_{sj} = 0)$ is the specificity

- Then
$$P\left(\bigcap_{\{(s'j') : G_{s'j'} = 1\}} \{G_{s'j'} = 1\}\right)$$

$$= (1 - S_p)^s \left\{ \prod_{i=1}^{I_1} (1 - p_i) \right\} + \sum_{a=1}^{s-1} S_e^a (1 - S_p)^{s-a} \left\{ \prod_{i \in B_{a+1,j'}} (1 - p_i) \right\}$$

$$+ S_e^s \left\{ 1 - \prod_{i \in B_{sj}} (1 - p_i) \right\}$$

where

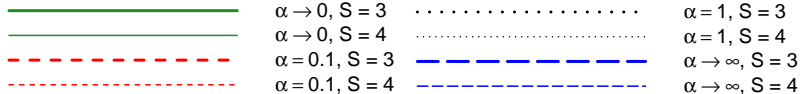
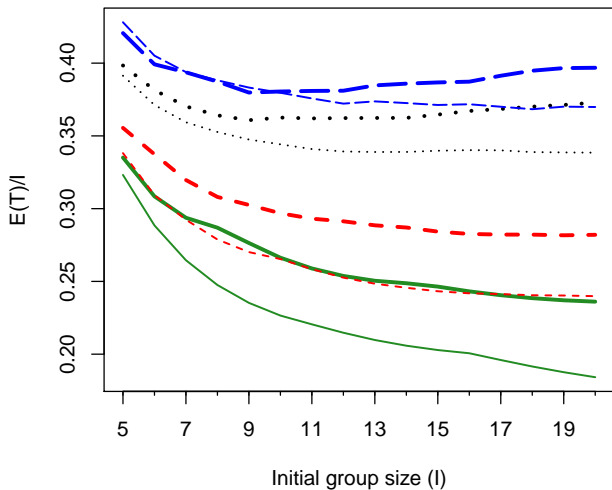
- p_i is the probability that individual i is truly positive
- $i \in B_{sj}$ means the set of individuals who belong to the j th ordered group at the s th stage
- $i \in \bar{B}_{sj}$ means the set of individuals who belong to the parent group of B_{sj} excluding those in B_{sj} itself

- Want to minimize the number of tests
- Find the **retesting configuration** that essentially achieves the above by minimizing $E(T)$
 - p_i is unknown
 - In practice, estimate p_i and minimize the estimated $E(T)$
- Simplification
 - Order individuals by p_i values
 - Individuals are assigned to subgroups successively by this ordering

- Examine ALL possible retesting configurations
 - Define configuration with minimum $E(T)$ as the **optimal retesting configuration (ORC)**
 - $(S - 1)^{I-1}$ possible configurations
- Use a search algorithm
 - Formulate as an integer program and use method of steepest descent
 - Define configuration resulting from algorithm as the **candidate retesting configuration (CRC)**
 - Algorithm is not guaranteed to find ORC, but we have found it to work well

- Examine $E(T)$ in specific situations
- Let $P_i \sim \text{beta}(\alpha, \alpha(1-p)/p)$ for $i = 1, \dots, I$, $\alpha > 0$, $0 < p < 1$, and $E(P_i) = p$
 - p represents the overall prevalence
 - As $\alpha \rightarrow \infty$, $\text{Var}(P_i) \rightarrow 0$; p_i 's become homogeneous
 - As $\alpha \rightarrow 0$, $\text{Var}(P_i)$ increases; p_i 's become more heterogeneous
- Use $E(P_{(i)})$ for p_i in $E(T)$
- $S_e = S_p = 0.95$
- CRC results in the same configurations as ORC
 - All $S = 3$ cases
 - All $S = 4$ cases where ORC was calculated ($I \leq 14$)

$p = 0.05$



- Sherlock et al. (2007)
 - Examines publicly funded HIV testing practices across United States
 - Three-stage hierarchical group testing

Location	Observed prevalence	1st stage group size	2nd stage group sizes
Los Angeles	0.0045	90	9 groups of size 10
North Carolina	0.0021	90	9 groups of size 10
San Francisco	0.0175	50	5 groups of size 10
Seattle-King County	0.0164	30	3 groups of size 10
Atlanta	0.0030	48	6 groups of size 8

- Quote from the paper:

... the use of pooled NAATs to detect acute HIV infection is becoming a popular strategy for the screening of large populations. However, the most efficient approach remains to be determined.

- Can we do better?
- ORC assuming **homogeneity**
 - Use observed prevalence as the true prevalence p
 - Find configuration that minimizes $E(T)$
- CRC accounting for **heterogeneity**
 - Exact amount of heterogeneity is unknown
 - $P_i \sim \text{beta}(\alpha, \alpha(1-p)/p)$ for $i = 1, \dots, I$, $\alpha > 0$, $0 < p < 1$, and $E(P_i) = p$
- Assume $S_e = S_p = 0.99$ and only examine the same 1st stage group size as originally used

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Location	ORC homogeneity 2nd stage group sizes	Reduction in $E(T)$ from CRC under heterogeneity		
		$\alpha = 1$	$\alpha = 0.5$	$\alpha = 0.1$
Los Angeles	10 groups of size 9	8.6%	15.2%	36.8%
North Carolina	10 groups of size 9	7.7%	13.6%	33.1%
San Francisco	2 groups of size 7, 6 groups of size 6	8.4%	15.1%	37.4%
Seattle-King County	6 groups of size 5	7.2%	12.2%	32.0%
Atlanta	6 groups of size 7, 1 group of size 6	6.5%	11.1%	27.3%

- Limitations

- Comparison of $E(T)$, not the actual number of tests that may occur
- Amount of heterogeneity is unknown
 - Levels of variability are not extreme
 - Los Angeles with $\alpha = 0.1$: 0.001 and 0.999 quantiles for beta distribution are slightly larger than 0 and approximately equal to 0.0445, respectively
- Potential for significant benefits from using ORC and CRC

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