Interlaboratory Comparisons: A Review *

Haben Michael and Ingram Olkin Stanford University

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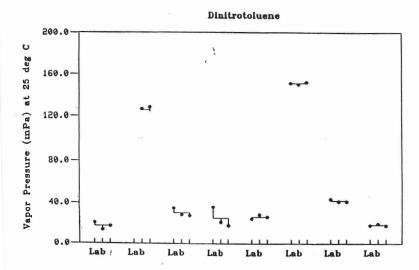
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- Examples from Federal Regulatory Agencies
 - Food & Drug Administration (FDA): administer federal food purity laws, cosmetics
 - Food Safety and Inspection Service (FISIS): safety of meat, poultry, eggs
 - Environmental Protection Agency (EPA): monitor > 90 contaminants
- Standards Agencies
 - National Institute of Standards & Technology (NIST): weights and measures, smoke detection; performance standards for emissions
 - ► Design & construction standards
 - United States Military Standards

Scenario

- Similar samples undergo independent analyses by a number of labs
- Examples
 - Pesticides in plants
 - Contaminants in food
 - Percent nutrients in food
 - Setting of weights and measures
 - Standards for medical devices
 - Pathology analyses
 - Powder burning times of fuses

 $\label{eq:Figure 1 - Vapor pressure readings from eight laboratories} \end{math}$ Vapor pressure readings from eight laboratories



	Obs. 1	Obs. 2	Obs. 3	Obs. 4	Obs. 5	Obs. 6	mean	sd
Α	2.963	2.996	2.979	2.970	2.979	2.977	2.977	0.011
В	2.958	2.964	2.955	2.932	2.941	2.950	2.95	0.012
C	2.956	2.945	2.963	2.950	2.975	2.958	2.958	0.01
D	2.948	2.960	2.953	2.944	2.950	2.951	2.951	0.005
Ε	2.953	2.961	2.961	2.953	2.949	2.955	2.955	0.005
F	2.941	2.940	2.931	2.942	2.930	2.937	2.937	0.005
G	2.963	2.928	2.925	2.940	2.934	2.938	2.938	0.014
Н	2.987	2.989	2.988	2.983	2.974	2.984	2.984	0.005
- 1	2.946	2.950	2.955	2.969	2.954	2.955	2.955	0.008
J	2.956	2.947	2.947	2.960	2.954	2.953	2.953	0.005

Table: Determination of Iron in Solution (%) (Olkin, Guttman, and Phillips 1995)

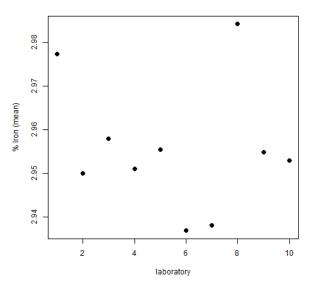


Figure: Determination of Iron in Solution (%). Laboratory means for 10_{\odot} laboratories.

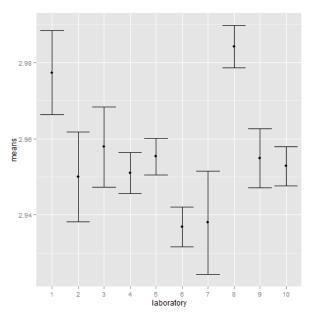


Figure: Iron in solution data with ± 1 standard deviation error bars

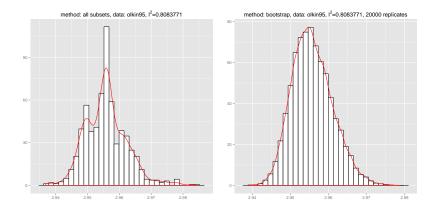


Figure: Histogram of summary statistic on samples drawn without replacement (left) and with replacement (right). (Iron in solution data.)

Potential Analyses: Searching for outliers

A. Nonparametric analyses

- ▶ Order observations: $X_{(1)} \leq ... \leq X_{(n)}$
- \triangleright Define X_{median} and residuals

$$u_i = |X_{(i)} - X_{median}|,$$

 $u_{(1)} \le u_{(2)} \le \dots u_{median} \le \dots \le u_{(n)}$

- ▶ Define outlier if $u_i \ge cu_{median}$, c = 3.5, 4.5, 5.2
- "Smallest proportion which may cause the test to fail"

B. Bayesian approach

- Set $C(j_1, \ldots, j_{\alpha})$ as posterior probability labs j_1, \ldots, j_{α} aberrant
- Fix α and find $C^*(\alpha) = maxC(j_1, \dots, j_{\alpha})$
- ▶ Then $\max_{\alpha} C^*(\alpha)$
- Example

$$C(8) = 0.982$$

 $C(1,8) = 0.998$
 $C(1,6,8) = 0.585$
 $C(1,6,7,8) = 0.930$

- ▶ A variation on the Bayesian procedure: minimize the within-cluster sum of squares. Set $C(J_1, ..., J_k)$ as the sum of cluster Q-statistics when the data is clustered as $J_1, ..., J_k$
- $\blacktriangleright \mathsf{Set} \; C^*(k) = \min_{J_1, \dots, J_k} C(J_1, \dots, J_k)$
- ► Look for an "elbow" in a scree plot, or use a resampling procedure (gap statistic)

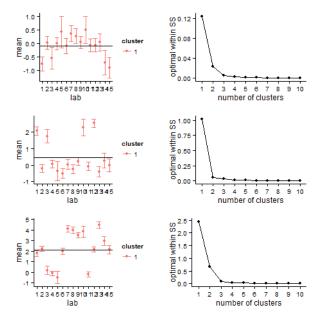


Figure: Scree plots for the minimum summed cluster Q statistic. The data is synthetic with 1 (homogenous), 2, and 3 clusters.

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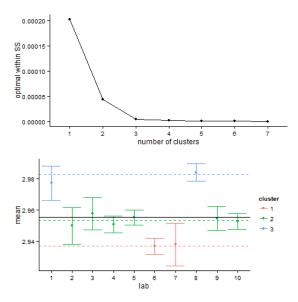


Figure: Minimum summed cluster Q statistic, for the iron in solution data. There appear to be 2 outlying clusters, one consisting of labs #s 1 and 8, the other labs #6 and #7.

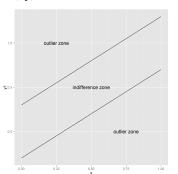
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C. Ranking and selection procedure

• Model
$$x_{ij} = \mu + \theta_j + \epsilon_{ij}$$

$$\mu =$$
 true mean $heta_j =$ parameter of jth lab $\epsilon_{ij} =$ independent, $\mathcal{N}(0,\sigma^2)$

- Screen out labs where $|\theta_i| \ge \delta$
- ▶ Indifference Zone: $|\theta_i| < \delta$ for some specified δ



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▶ Rule: Assign each lab to a group so that the mean in each group is at least δ away from mean in any other group

D. Resampling-based graphical methods. These methods compute a summary statistic on resampled sets of the original data. The heuristic is that if the original data is homogenous, the typical resampled sets should be as well.

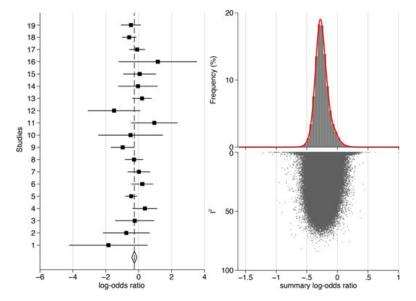


Figure: The histogram of summary statistics for all subsets is unimodal, suggesting homogeneity among the primary studies. (Data: Thrombolytics for acute myocardial infarction meta-analysis.)

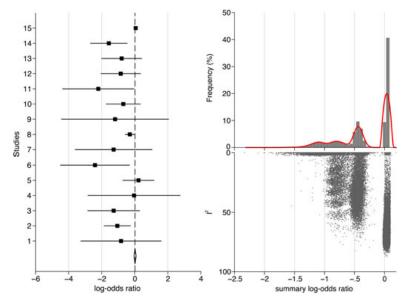


Figure: The histogram of summary statistics for all subsets is multimodal, suggesting heterogeneity among the primary studies. (Data: Magnesium for myocardial infarction meta-analysis.)

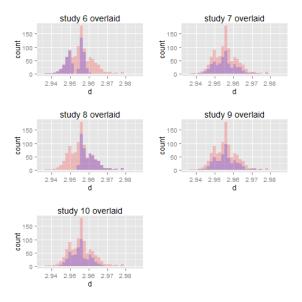


Figure: The histogram of summary statistics for subsets containing a given study is compared against the full histogram. Studies #6 and #8 are identified as potential outliers.

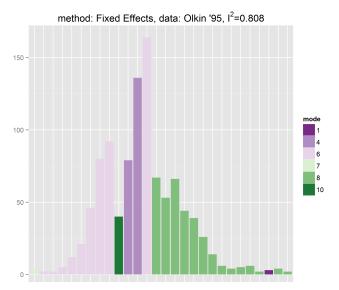


Figure: Coloring modes by bin (most frequently occurring lab among subsets in a bin). Lab #8 is overrepresented among the rightmost bins, lab #6 among leftmost.

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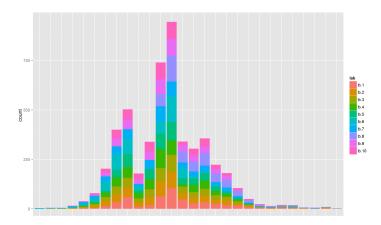


Figure: Stacked barplot of counts of labs per bin. Again, lab #8 is overrepresented among rightmost bins, lab #6 among leftmost.