



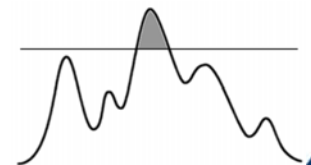
Sample size considerations in IM assays

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- Introduction
- Homogeneous population
- Mixed effects model
- Conclusions

■ Immunogenicity (IM)

- ◆ Immune response to therapeutic proteins
- ◆ Clinical effect: no effect at all to extreme harmful effects
- ◆ Drug development effect: product safety and efficacy.

■ IM assays

- ◆ Analytical method for assessment of IM
- ◆ Valid, sensitive
- ◆ Evolving through different development stages

■ Three groups of variables*

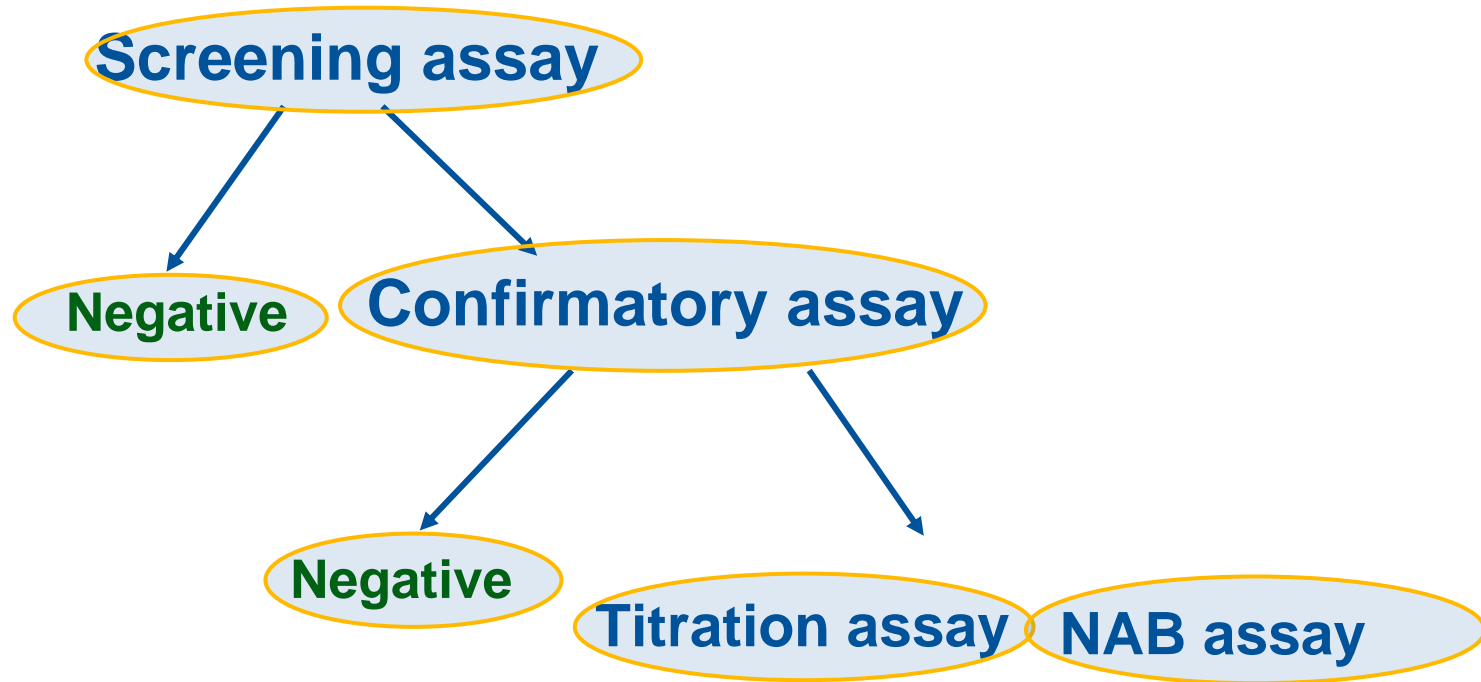
- ◆ affecting the incidence of antidrug antibodies (ADA)
- ◆ affecting the risk of consequences of ADAs
- ◆ affecting patient safety

■ IM assessment based on risk levels

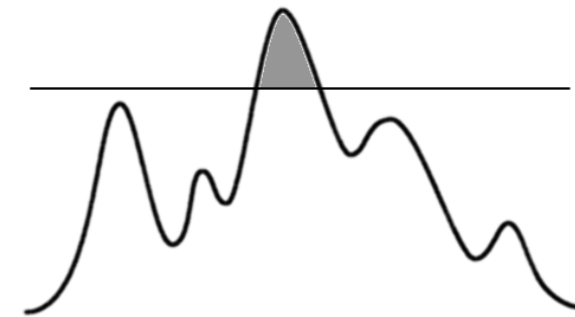
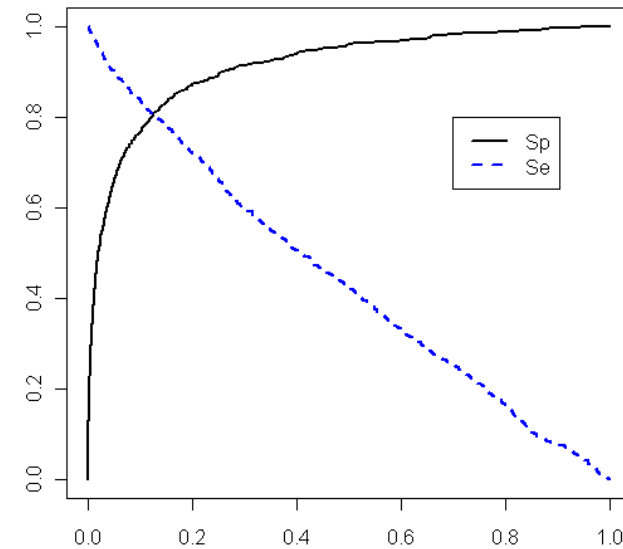
- ◆ Low risk products: titer and relative concentration of ADA may be sufficient
- ◆ Medium risk products: neutralizing antibody (Nab) assay should be considered
- ◆ High risk products: high sensitivity of ADA and Nab assays

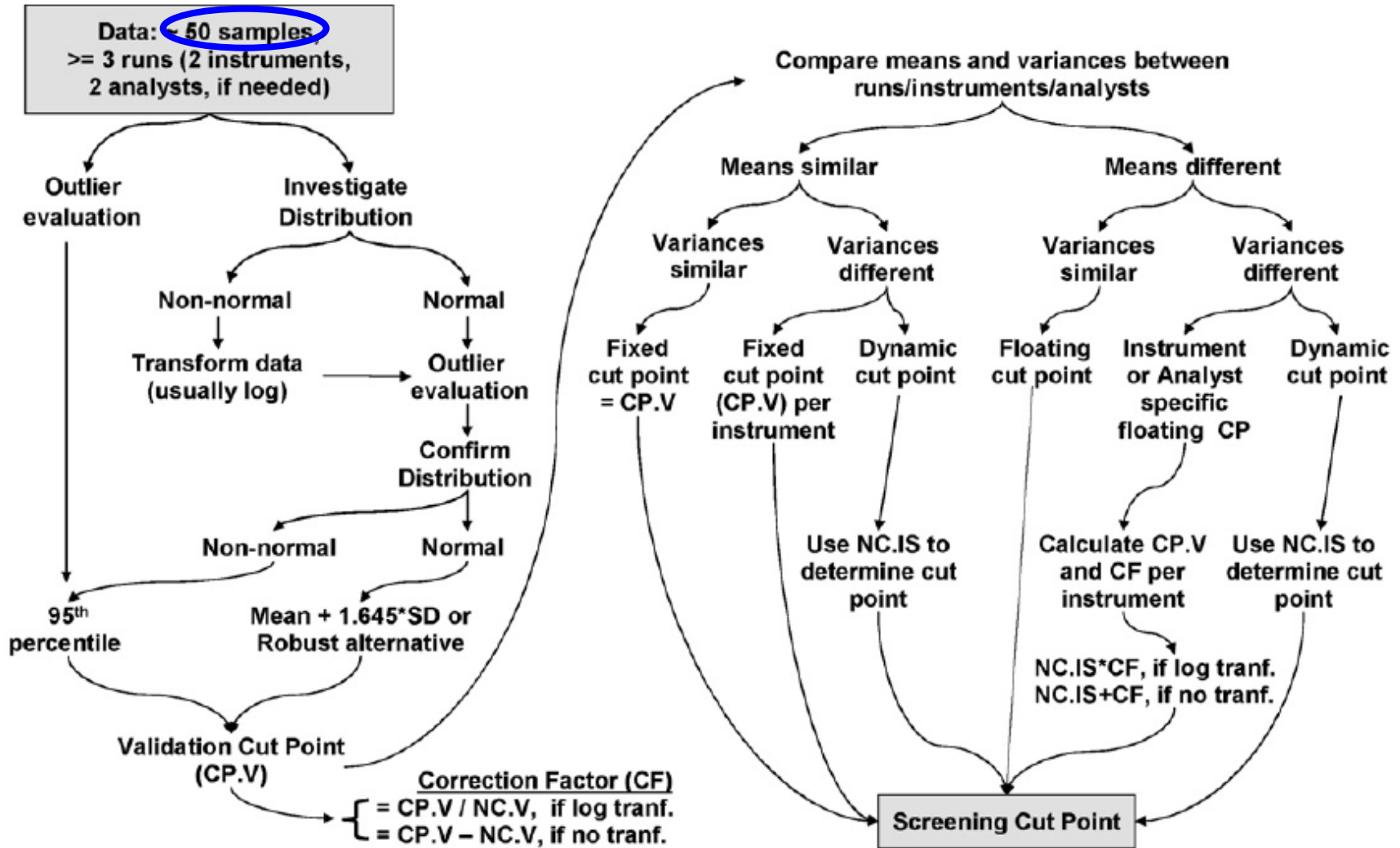
*Shankar, Pendley, Stein (2007)

A Multiple-Tiered Approach



- The cut point is defined as the level of response of an assay at and above which a sample is defined to be a positive (or reactive) for the presence of ADA, and below which it is probably negative.
 - ◆ Screening cut point
 - ◆ Confirmatory cut point
- Ideally we should use ROC analysis to guarantee a certain level of specificity and sensitivity
- Usually based on negative samples due to the lack of positive samples
 - ◆ Reduce to quantile estimation





*Shankar et al (2008)

- Design format (Shankar et al, 2008)

	Operator 1		Operator 2	
	Day 1	Day 2	Day 1	Day 2
Sample 1				
.....				
Sample n				

- At validation stage,
 - ◆ How many samples ($=n$) are needed?
 - ◆ How many replicates ($=r$) per sample are needed?
- A simplified version*:
 - ◆ How many data points ($=n \times r$) are needed for cut point evaluation?

- Literature/Guideline for number of samples:
 - ◆ FDA (2009): development 5-10; validation 50-100
 - ◆ EMA (2010): NA
 - ◆ Shankar et al (2008): nonclinical ≥ 15 ; clinical ≥ 50
 - ◆ Schlain et al (2010): Pre-study ≥ 30 ; In-study 60-240
 - ◆ Parish et al (2010): same as Shankar

Guesstimation



General Idea of Our Approach

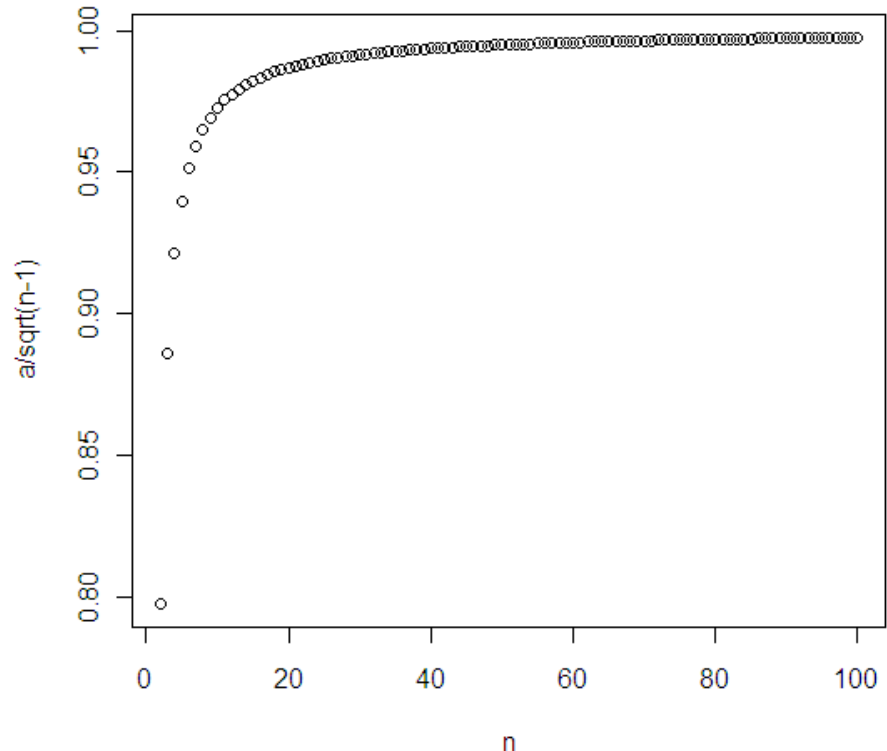
- The same idea as sample size estimation in clinical trial design
- Set up an acceptance criterion
- Determine sample size n to meet the acceptance criterion

Cut Point Estimation: Normal data

- Data (to be collected): x_1, \dots, x_n
- Mean and SD: μ, σ
- True cut point: $Q_\beta = \mu + z_\beta \sigma$
- Estimated cut point:

$$\hat{Q}_\beta = \bar{x} + z_\beta s \sqrt{n-1}/a$$

$$a = \sqrt{2} \frac{\Gamma(n/2)}{\Gamma((n-1)/2)}$$



Cut Point Interval Estimation: Normal data

- Interval estimate*

$$\hat{Q}_\beta \pm t_{\alpha/2, n-1} \left\{ \frac{1}{n} + z_\beta^2 \left(\frac{n-1}{a^2} - 1 \right) \right\}^{1/2} s$$

■ Interval width:

$$2t_{\alpha/2, n-1} s \left\{ \frac{1}{n} + z_{\beta}^2 \left[\frac{n-1}{a^2} - 1 \right] \right\}^{1/2}$$

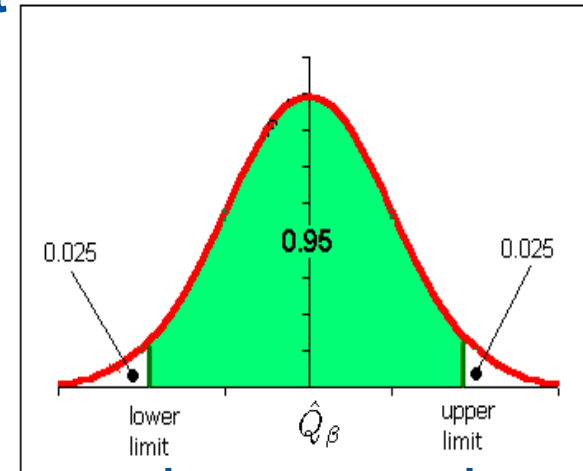
■ Precision:

$$\frac{2t_{\alpha/2, n-1} s \left\{ \frac{1}{n} + z_{\beta}^2 \left[\frac{n-1}{a^2} - 1 \right] \right\}^{1/2}}{\hat{Q}_{\beta}}$$

■ Set a precision threshold **d** (=20%, 10%, 5%, etc.)

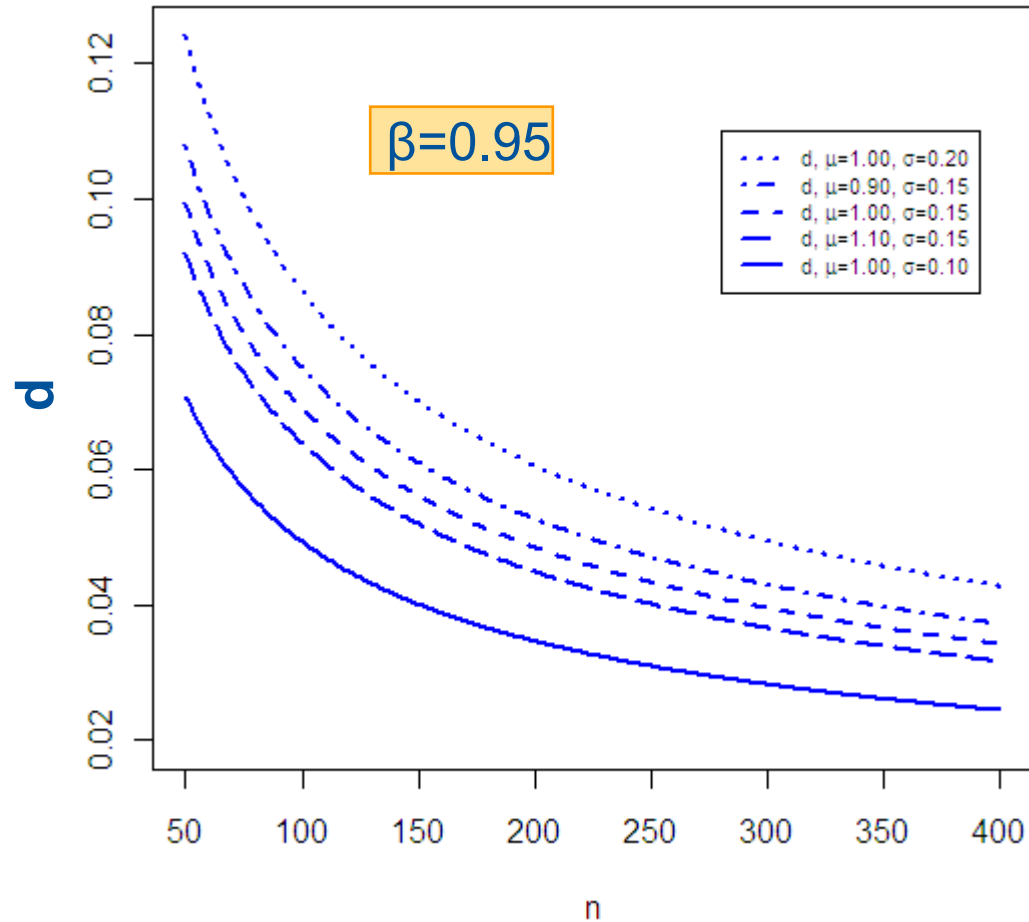
■ Acceptance Criterion:

$$\frac{2t_{\alpha/2, n-1} s \left\{ \frac{1}{n} + z_{\beta}^2 \left[\frac{n-1}{a^2} - 1 \right] \right\}^{1/2}}{\hat{Q}_{\beta}} \leq d$$

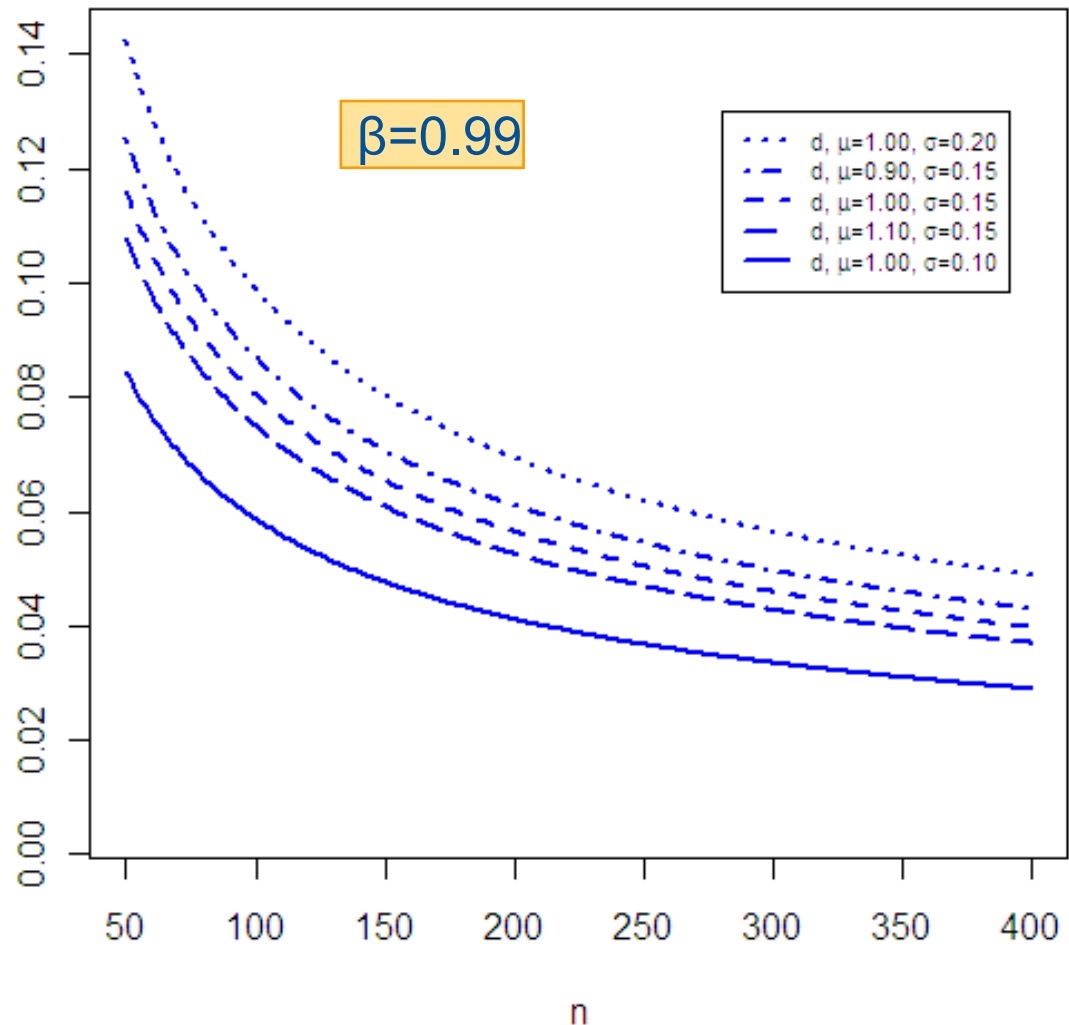


- Acceptance Criterion:
$$\frac{2t_{\alpha/2, n-1} s \left\{ \frac{1}{n} + z_{\beta}^2 \left[\frac{n-1}{a^2} - 1 \right] \right\}^{1/2}}{\hat{Q}_{\beta}} \leq d$$
- Solve the equation for n
- Need to have s and \hat{Q}_{β}
 - ◆ Estimate based on qualification data
- Proved that n can be uniquely determined.

- Take a sample of size 30 from a normal distribution
- Estimate s and \hat{Q}_β
- Solve for n with different d



- Take a sample of size 30 from a normal distribution
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- We used confidence interval width scaled by the percentile estimate as our acceptance criterion
 - ◆ similar to the idea of %CV
 - ◆ The larger the percentile estimate is, the higher precision with the same confidence interval width

- An alternative acceptance criterion is the width of the confidence interval
 - ◆ The same width may have different implication when the cut point has different values

- Under this paradigm
 - ◆ Sample size determination is reduced to constructing an interval estimate for the cut point
- Data are often not normally distributed.
 - ◆ A gamma distribution may be useful (Schlain et al, 2010)
 - ◆ Experimental design is not considered in the data analysis

- Design format (Shankar et al, 2008)

	Operator 1		Operator 2	
	Day 1	Day 2	Day 1	Day 2
Sample 1				
.....				
Sample n				

Mixed Effects Model (variance components model)

- Without taking care of the data structure, the data points are assumed independent
 - ◆ The major reason for non-normality of the data
 - ◆ Also may result in a lot of outliers

- After taking care of the data structure by viewing factors as random, the data points from the same factor level are correlated;
 - ◆ Recommended in Shankar's paper
 - ◆ Fixed effects
 - > interest centers on the effects of the chosen factor levels
 - ◆ Random effects
 - > factor levels are a sample from a larger population;
 - > inferences are desired about the populations of factor levels
 - > Easy to construct

Procedures of Cut Point Determination

- Fitting three-way random effect ANOVA (Analyst, day, sample)
- Residual analysis and outliers removal
- Refitting random effect ANOVA
- Estimation of total variability
- Determination of 95% quantile based on assumed normal distribution

Cut point under mixed effects model

■ The model

$$y_{ijk} = \mu + \tau_i + \beta_j + \gamma_k + \varepsilon_{ijk},$$

$$i = 1, \dots, a, j = 1, \dots, b, k = 1, \dots, n$$

$$\tau_i \sim N(0, \sigma_\tau^2), \quad \beta_j \sim N(0, \sigma_\beta^2)$$

$$\gamma_k \sim N(0, \sigma_\gamma^2), \quad \varepsilon_{ijk} \sim N(0, \sigma^2)$$

■ The cut point

$$y_{ijk} \sim N(\mu, \sigma_\tau^2 + \sigma_\beta^2 + \sigma_\gamma^2 + \sigma^2)$$

$$Q_p = \mu + z_p \sqrt{\sigma_\tau^2 + \sigma_\beta^2 + \sigma_\gamma^2 + \sigma^2}$$

Cut point under mixed effects model

- One-way model

$$y_{ij} = \mu + \tau_i + \varepsilon_{ij}, \quad i = 1, \dots, n, \quad j = 1, \dots, r$$

$$\tau_i \sim N(0, \sigma_\tau^2), \quad \varepsilon_{ij} \sim N(0, \sigma^2)$$

- Naïve method

- ◆ Ignoring data structure

$$\mathbf{cp}_N = \hat{\mu} + z_\beta s, \quad s = \sqrt{\frac{\sum (y_{ij} - \bar{y}_{..})^2}{nr - 1}}$$

- Mixed effects model method

$$\mathbf{cp}_M = \hat{\mu} + z_\beta \sqrt{\hat{\sigma}_\tau^2 + \hat{\sigma}^2}$$

**The Naïve method
Underestimates
the cut point!**

$$\frac{\mathbf{cp}_M - \hat{\mu}}{\mathbf{cp}_N - \hat{\mu}} = \frac{1}{1 - \frac{r-1}{nr-1} \hat{\rho}} > 1, \text{ if } \mathbf{r} > 1$$

$$\hat{\rho} = \frac{\hat{\sigma}_\tau^2}{\hat{\sigma}_\tau^2 + \hat{\sigma}^2}$$

$$\sigma_{\tau}^2 = 0.0824$$

$$\sigma^2 = 0.0089$$

$$\mu = 1$$

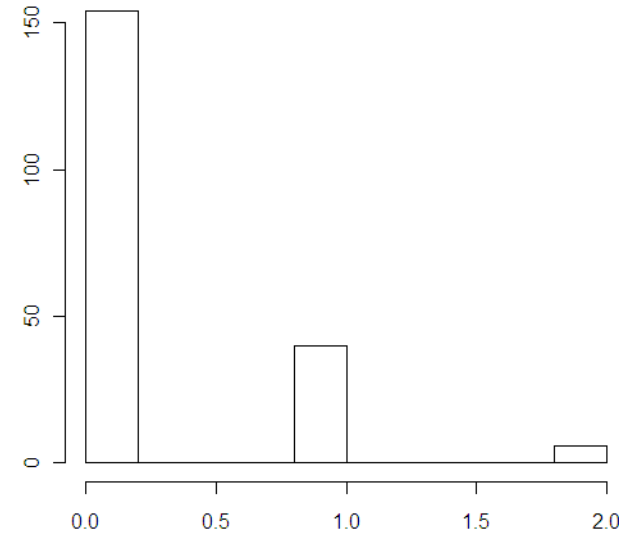
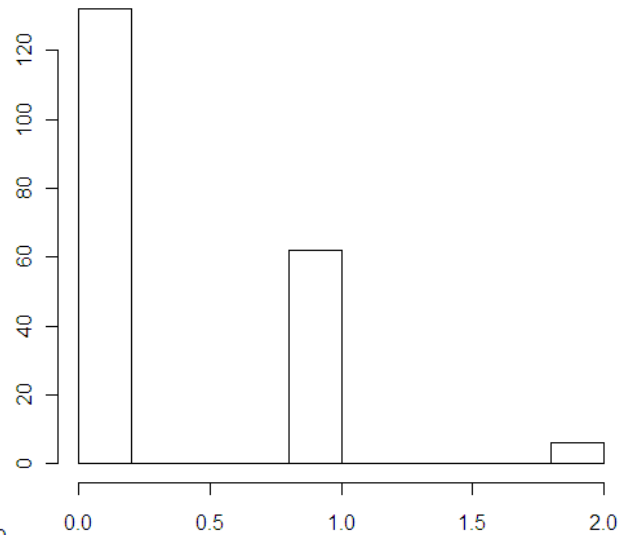
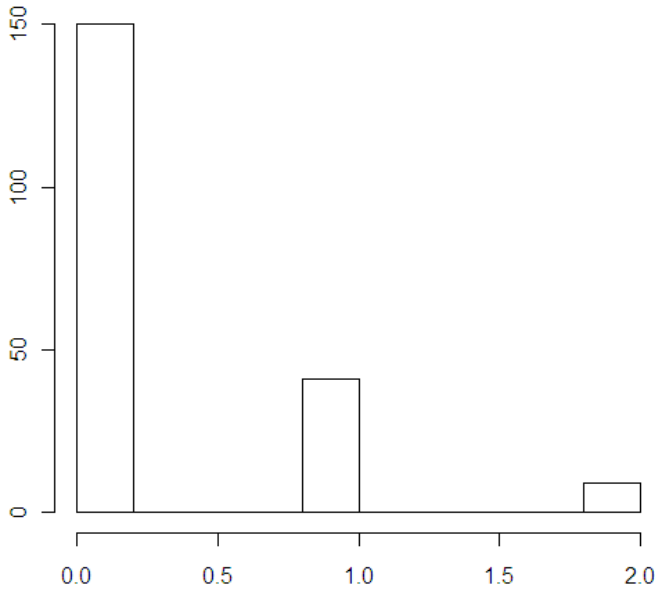
$$\hat{\sigma}_{\tau}^2 = 0.091$$

$$\hat{\sigma}^2 = 0.00796$$

$$\hat{\mu} = 1.01$$

$$\hat{\sigma}_y^2 = 0.0977$$

n	r	CP_N	CP_M
10	4	1.728	1.751
20	4	1.623	1.634
50	4	1.503	1.507



- $N=50$; $r=4$
- Naïve method:
 - ◆ 1.35
- Mixed effects model
 - ◆ 1.49
- It is of interest to consider sample size under the mixed effects model
 - ◆ Often all data are not normally distributed, even after log-transformation
 - ◆ A less biased estimator
 - ◆ Require statisticians' help

- Given variability due to sample, analyst, day and random error, what is the sample size to achieve a specific precision for cut point estimate?
- How to construct confidence interval of a quantile under mixed effects model?

- ◆ Asymptotic method
- ◆ Hoffman method
- ◆ Simulation

$$y_{ijk} \sim N(\mu, \sigma_{\tau}^2 + \sigma_{\beta}^2 + \sigma_{\gamma}^2 + \sigma^2)$$

$$Q_p = \mu + z_p \sqrt{\sigma_{\tau}^2 + \sigma_{\beta}^2 + \sigma_{\gamma}^2 + \sigma^2}$$

$$\Pr(Q_p \leq U) = 1 - \frac{\alpha}{2} \quad \Pr(Q_p \geq L) = 1 - \frac{\alpha}{2}$$

$$\Pr(L \leq Q_p \leq U) = 1 - \alpha$$

CI for cut point under mixed effects model

■ Modified large sample method* (One-way model: Balanced case)

$$y_{ij} \sim N(\mu, \sigma_\tau^2 + \sigma^2)$$

$$Q_p = \mu + z_p \sqrt{\sigma_\tau^2 + \sigma^2}$$

$$UCL = \hat{\mu} + \left\{ Z_p \sqrt{\frac{S_1^2}{r} + (1 - \frac{1}{r})S_2^2 + \left[\frac{H_1^2 S_1^4}{r^2} + \frac{(1-r)^2 H_2^2 S_2^4}{r^2} \right]^2} + Z_\alpha \frac{S_1^2}{nr} \right\}$$

$$LCL = \hat{\mu} + \left\{ Z_p \sqrt{\frac{S_1^2}{r} + (1 - \frac{1}{r})S_2^2 - \left[\frac{G_1^2 S_1^4}{r^2} + \frac{(1-r)^2 G_2^2 S_2^4}{r^2} \right]^2} - Z_\alpha \frac{S_1^2}{nr} \right\}$$

$$G_1 = 1 - \frac{1}{F_{\alpha; n-1, \infty}}, G_2 = 1 - \frac{1}{F_{\alpha; nr-n, \infty}}; H_1 = \frac{1}{F_{1-\alpha; n-1, \infty}} - 1, H_2 = \frac{1}{F_{1-\alpha; nr-n, \infty}} - 1$$

*Burdick and Graybill (1992)

Illustration: Sample size under mixed effect model

- Take a sample of size 30 from a normal distribution
- Estimate parameters
- Solve for n with different d

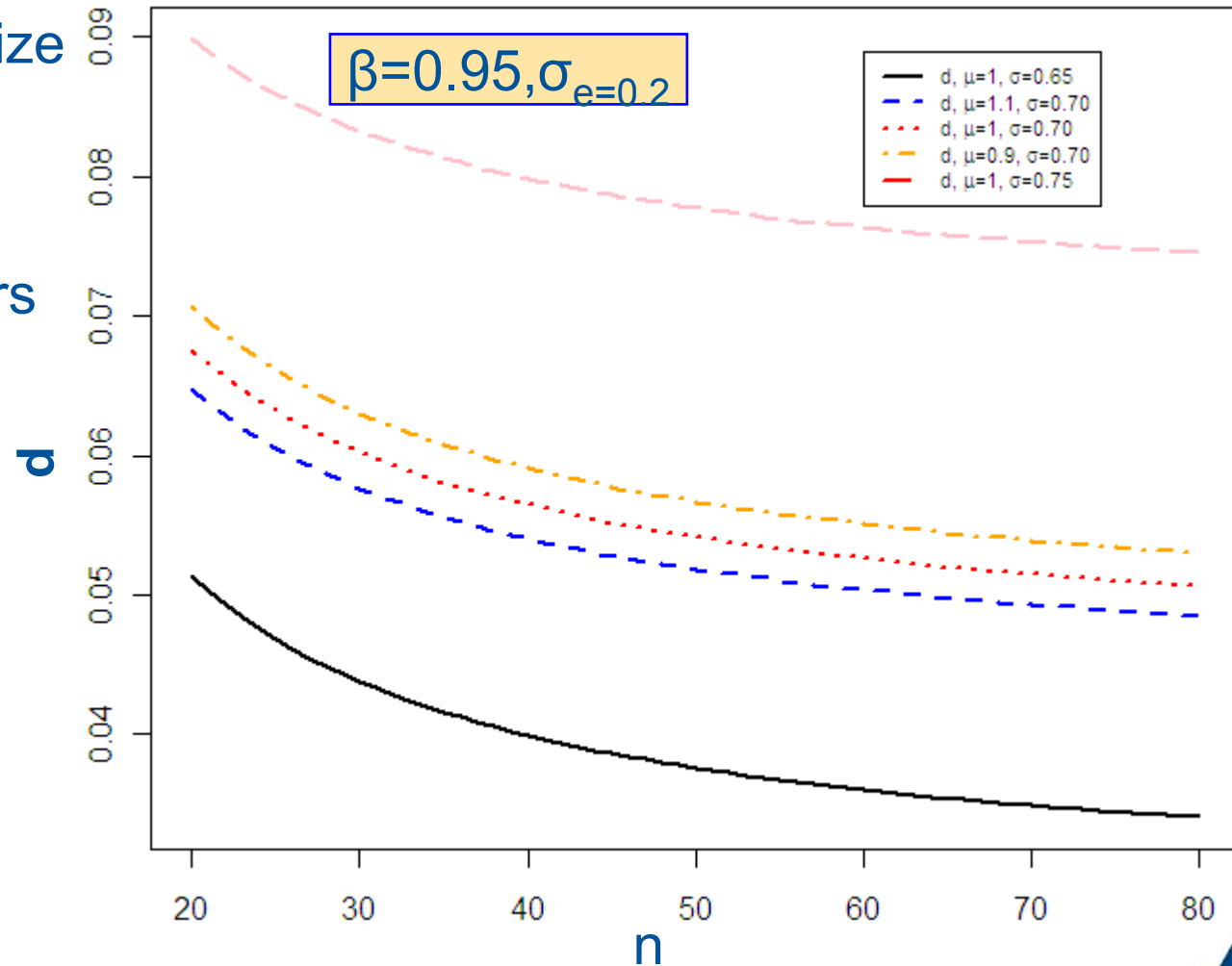
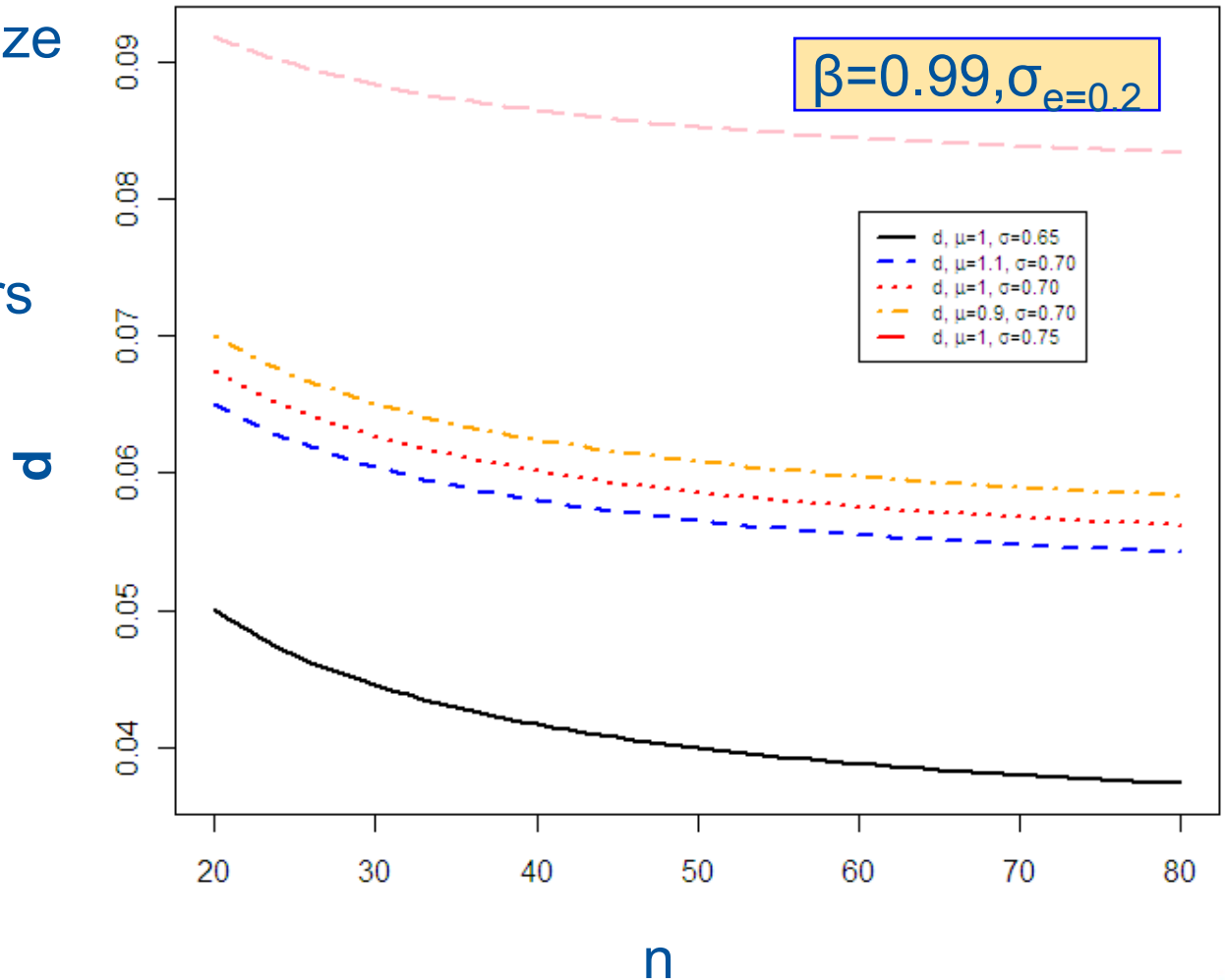


Illustration: Sample size under mixed effect model

- Take a sample of size 30 from a normal distribution
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Conclusions and Future considerations

■ Sample size

- ◆ There are no guidelines on sample size other than rules of thumb
- ◆ A systematic approach to determine sample size
- ◆ A desired precision needs to be prespecified
- ◆ If some data (qualification) are available and normal distribution can be reasonably assumed, then sample size determination is straightforward
- ◆ Mixed effects model can also be incorporated
- ◆ Ignoring data structure has negligible effect on cut point analysis

■ Future considerations

- ◆ Non-normally distributed
 - > Nonparametric
 - > Gamma distribution (Schlain et al)
- ◆ Unbalanced mixed effects models

- Jason Zhang
- Harry Yang
- Lingmin Zeng
- Wei Zhao

- Burdick and Graybill (1992). Confidence intervals on variance components.
- EMA (2010): Guideline on immunogenicity assessment of monoclonal antibodies intended for in vivo clinical use.
- FDA (2009): Guidance for Industry Assay Development for Immunogenicity Testing of Therapeutic Proteins
- Parish T., Finco D., Devanarayan V. (2010). Development and validation of immunogenicity assays for preclinical and clinical studies.
- Schlain B, Amaravadi L, Donley J, Wickramaserera A., Bennett D., Subramanyam M. (2010) A novel gamma-fitting statistical method for anti-drug antibody assays to establish assay cut points for data with non-normal distribution.
- Shankar et al (2008). Recommendations for the validation of immunoassays used for detection of host antibodies against biotechnology products.