

## ‘Which model . . . ?’ is the wrong question

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Statistics: making *decisions* in the presence of *uncertainty* (analysis)  
and with limited *resources* (design)

Model as a conduit:

If I knew *the* model, then the analysis/inference would be efficient

— *absolutely not* true, and sometimes not relevant

*Select a model* and use it for all related inferences (*a bad idea*) *vs.*

*Combine estimators* for a particular purpose (e.g., min MSE for a target)

The false rationale for model selection:

Let's find a model that looks 'good', and then ...

— such a model is a *random* entity — *model uncertainty*

Examples in which the search for a model is/would be a distraction:

- Textbook ANOVA (one-way, with homoscedasticity and normality)
- Clinical trials for comparing two treatments (randomisation)
- Small-area estimation (inference about districts of a country)

What is 'good' inference (estimation, hypothesis test, confidence interval)?

Integrity: Adhere to *this* criterion, without any conditioning

A bad (*circular*) criterion: 'Good' means: based on a well selected model

# One-way ANOVA

(Longford, 2005, JRSS A; 2008, SORT):

Textbook:

Test the hypothesis of equal means — use the selected-model estimator

    This estimator is extremely inefficient in some common settings

Use the same model for estimating  $\sigma^2$

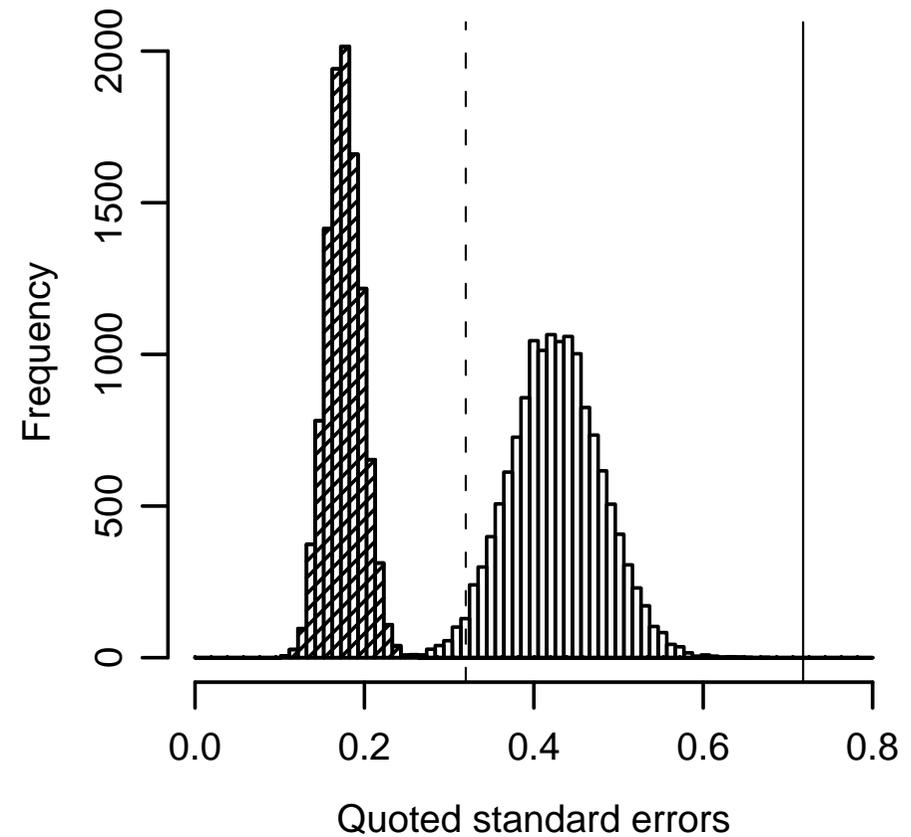
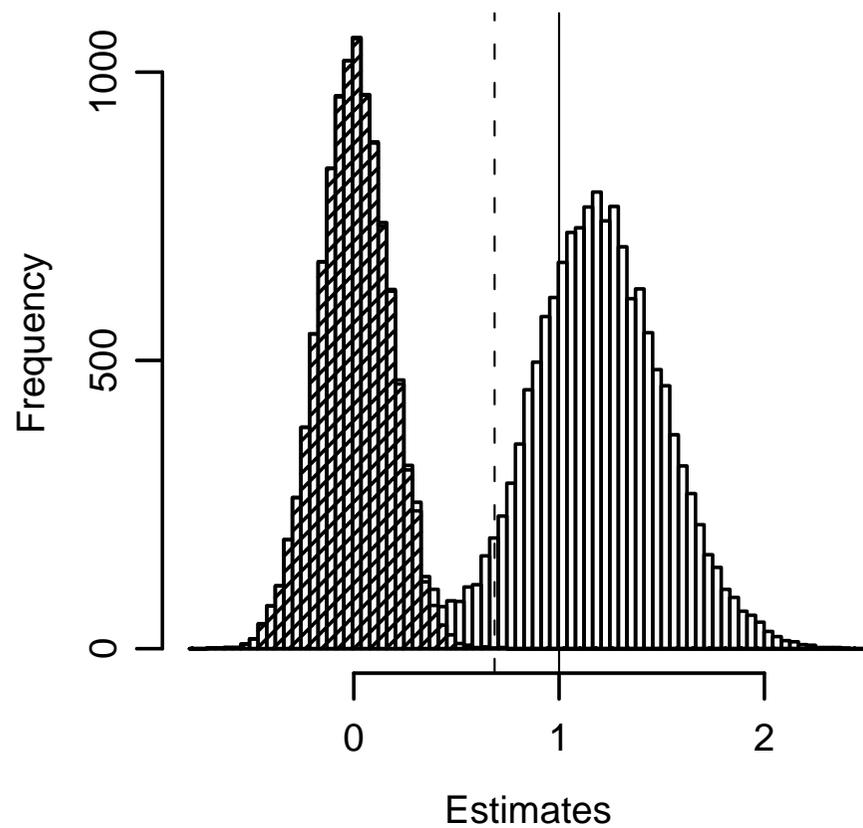
    — a poor strategy (look at the degrees of freedom)

The problem is not with hypothesis testing, but *with model choice* in general

    Bayes factors — no relief/no solution

Combine estimators, with weights specific to the target/estimand

    The goal: small MSE



Gross inefficiency of the selected-model based estimator in one-way ANOVA  
 (Longford, 2008; SORT)



## Model selection

Elementary estimators:  $\hat{\mu}_1 \sim \mathcal{N}\left(\mu_1, \frac{1}{n_1} \sigma^2\right)$  and  $\hat{\mu} \sim \mathcal{N}\left(\mu, \frac{1}{n} \sigma^2\right)$

Model selection:  $\mathcal{I}$  — indicator of selecting model A

$$\hat{\mu}_1^\dagger = (1 - \mathcal{I})\hat{\mu}_1 + \mathcal{I}\hat{\mu}$$

$$\mathbb{E}\left(\hat{\mu}_1^\dagger\right) = \mu_1 + p_B \left\{ \mathbb{E}\left(\hat{\mu} \mid \mathcal{I} = 1\right) - \mathbb{E}\left(\hat{\mu}_1 \mid \mathcal{I} = 1\right) \right\}$$

$$\begin{aligned} \text{MSE}\left(\hat{\mu}_1^\dagger; \mu_1\right) &= p_A \text{var}\left(\hat{\mu}_1 \mid \mathcal{I} = 0\right) + p_B \text{var}\left(\hat{\mu} \mid \mathcal{I} = 1\right) \\ &\quad + p_A \left\{ \mathbb{E}\left(\hat{\mu}_1 \mid \mathcal{I} = 0\right) - \mu_1 \right\}^2 + p_B \left\{ \mathbb{E}\left(\hat{\mu} \mid \mathcal{I} = 1\right) - \mu_1 \right\}^2 \end{aligned}$$

$p_A = \mathbb{P}(\mathcal{I} = 0)$ ;  $p_B = 1 - p_A$ . Note:  $\mathcal{I}$  and  $\hat{\mu}_1$  are correlated

Bias and *large* MSE are (almost) guaranteed

## Combination of estimators

$$\tilde{\mu}_1 = (1 - b_1)\hat{\mu}_1 + b_1\hat{\mu},$$

$$\text{MSE}(\tilde{\mu}_1; \mu_1 | b_1) = b_1^2 \{g_1 \sigma^2 + (\mu_1 - \mu)^2\} - 2b_1 g_1 \sigma^2 + \frac{\sigma^2}{n_1}$$

$$b_1^* = \frac{g_1}{g_1 + \frac{(\mu_1 - \mu)^2}{\sigma^2}}$$

where  $g_1 = \frac{1}{n_1} - \frac{1}{n}$

Substitute  $\hat{b}_1^*$  for  $b_1^*$

Assess the consequences of over/under-estimating  $(\mu_1 - \mu)^2/\sigma^2$

Scope for incorporating prior information, not necessarily Bayesian

(Longford, 2008, Chapter 1)

## Clinical trials

*Randomised* allocation of subjects to two treatments

Estimation of the (constant) treatment effect

Including ‘important’ covariates in (a regression) analysis

— wasting degrees of freedom (Better model — Worse inference)

*Crossover trials* (within-subject contrasts) with design ‘AB and BA’

Freeman (1989, *Stat. Med.*): Do not estimate the *carryover*

— waste of the data from the 2nd period

Longford (2001, *Stat. Med.*): Composition:

— reduce the ‘weight’ given to the 2nd period

Do not choose! — combine!!

## Small-area estimation

A country with districts  $d = 1, \dots, D$  and quantities  $\theta_d$ ; ‘national’ value  $\theta$

Notation:  $\hat{\theta}_d \sim \mathcal{Z}(\theta_d, v_d)$ ,  $\hat{\theta} \sim \mathcal{Z}(\theta, v)$  and  $c_d = \text{cov}(\hat{\theta}_d, \hat{\theta})$

A setting similar to ANOVA, except that  $D \gg$  — random effects (??)

Sample size sufficient for estimating  $\theta$ , but not for  $\theta_d$  for some  $d$

ANOVA irrelevant — composition of (unbiased) estimators  $\hat{\theta}_d$  and  $\hat{\theta}$ :

$$\tilde{\theta}_d = (1 - b_d) \hat{\theta}_d + b_d \hat{\theta}$$

$$b_d^* = \frac{v_d - c_d}{v_d + v - 2c_d + \sigma_B^2} \doteq \frac{v_d}{v_d + \sigma_B^2}$$

$\sigma_B^2 = \text{var}_{\mathcal{D}}(\theta_d)$  — estimate  $\sigma_B^2$  and study sensitivity ( $\hat{v}_d$ )

Extensions for auxiliary information (Longford, 2005)

## Conclusion

The importance of model selection is vastly over-rated because of not appreciating the pervasiveness of uncertainty and ignoring the basics of conditional probabilities and distributions

Asymptotic theory (for AIC, BIC, u&IC) is questionable for an essentially small-sample problem

Hypothesis testing (and intermediate decision, incl. model selection) — a *steam engine* in the age of the *iPod*

because it is oblivious to the *consequences* of the errors I and II

*Examples:* 1. The Albanian long jumper Shenki Xhadni (2044);  
2. Crossing the road in uptown Bendery during a Euro game.

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