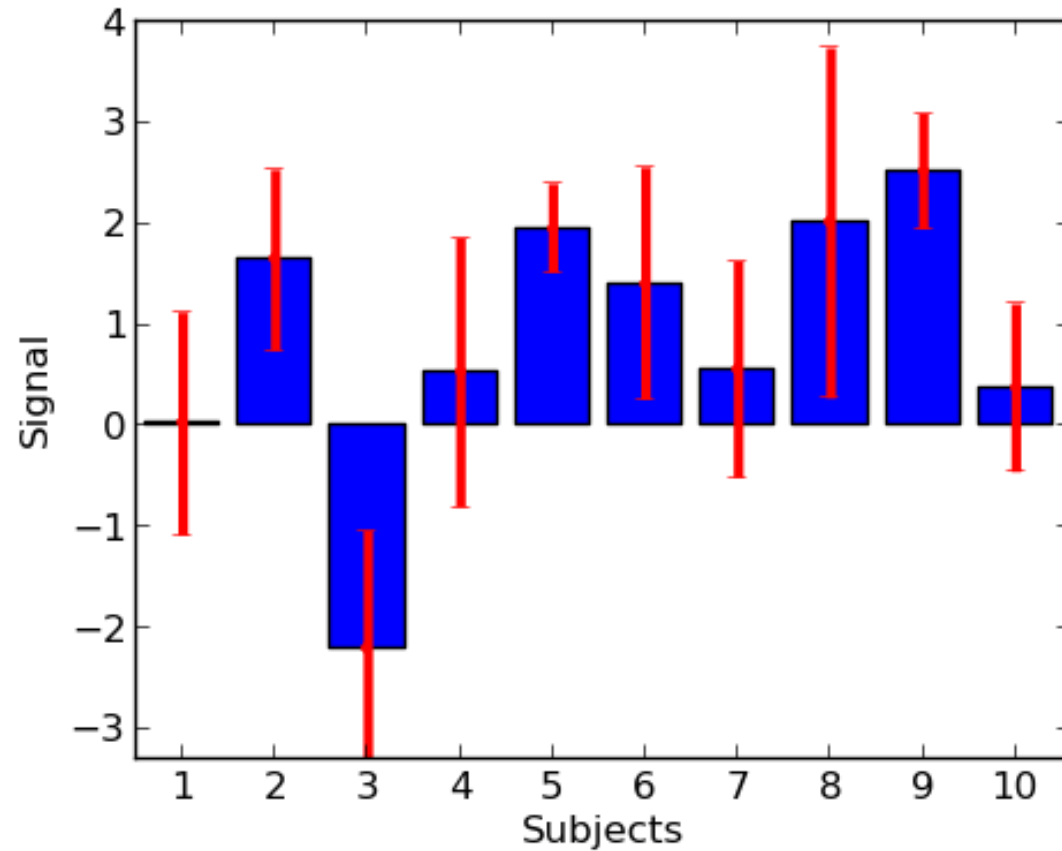


Fixed effects

We make observations of random variables $(\beta_i)_{i=1..n}$, that are assumed to be instances of unique random variable β . For each $i \in [1..n]$, let $\hat{\beta}_i$ and σ_i^2 be the empirical estimate and variance of β_i . What is the linear combination of these variables $\hat{\beta} = \sum_{i=1}^n w_i \beta_i$ s.t. $\sum_{i=1}^n w_i = 1$ and $w_i > 0 \forall i \in [1..n]$ such that $\hat{\beta}$ has the minimal variance ? What are the corresponding variance and effect estimates ?

Illustration



Fixed effects

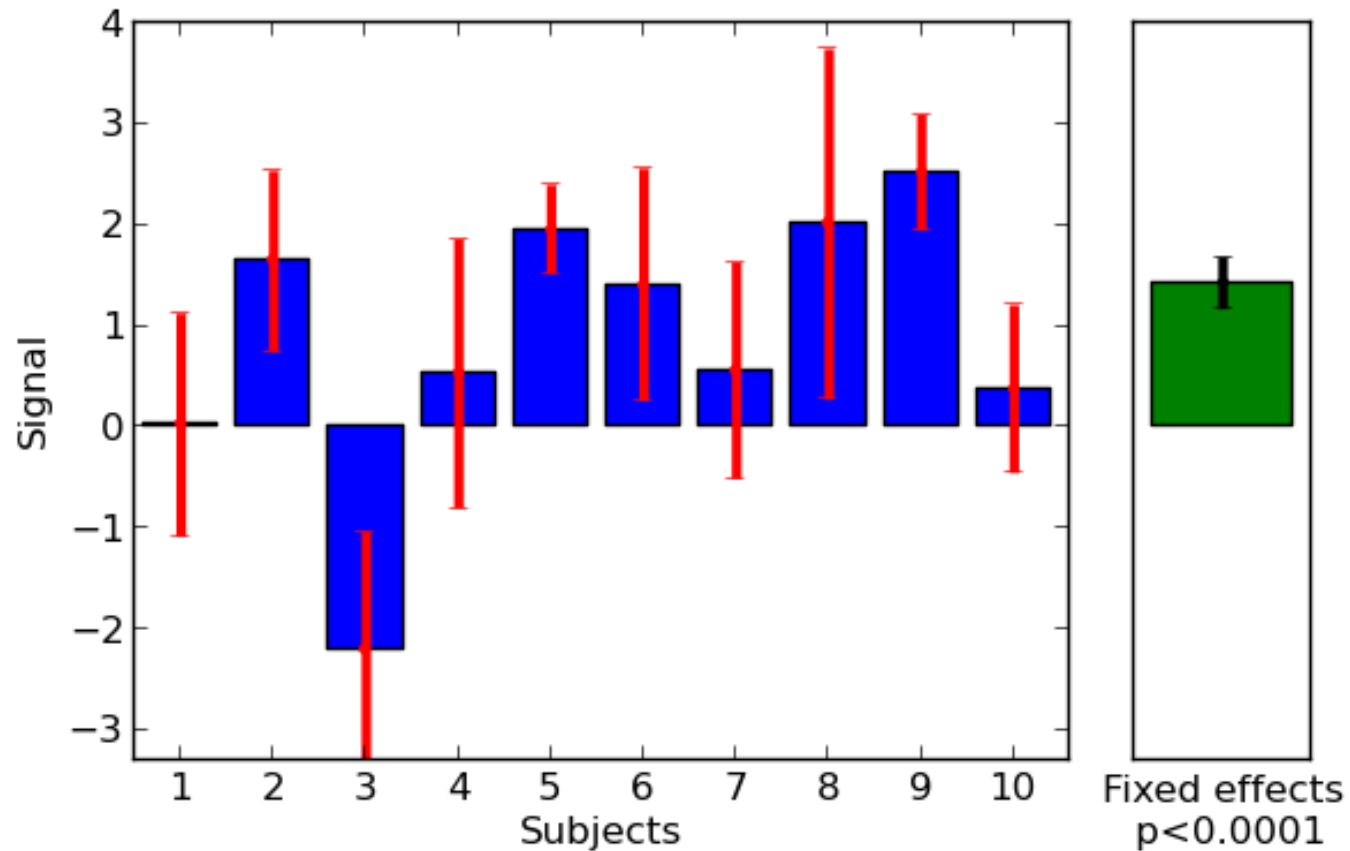
$$\min_{(w_i)} \sum_{i=1}^n w_i^2 \sigma_i^2 \text{ s.t. } \sum_{i=1}^n w_i = 1$$

$$\text{Constrained opt. } w_i \propto \frac{1}{\sigma_i^2} \implies w_i = \frac{1}{\sigma_i^2} \left(\sum_{j=1}^n \frac{1}{\sigma_j^2} \right)^{-1}$$

$$\text{Effect estimate: } \bar{\beta} = \sum_{i=1}^n \frac{\hat{\beta}_i}{\sigma_i^2} \left(\sum_{i=1}^n \frac{1}{\sigma_i^2} \right)^{-1}$$

$$\text{Effect variance: } \bar{\sigma}^2 = \left(\sum_{i=1}^n \frac{1}{\sigma_i^2} \right)^{-1}$$

Illustration



On the meaning of p-values

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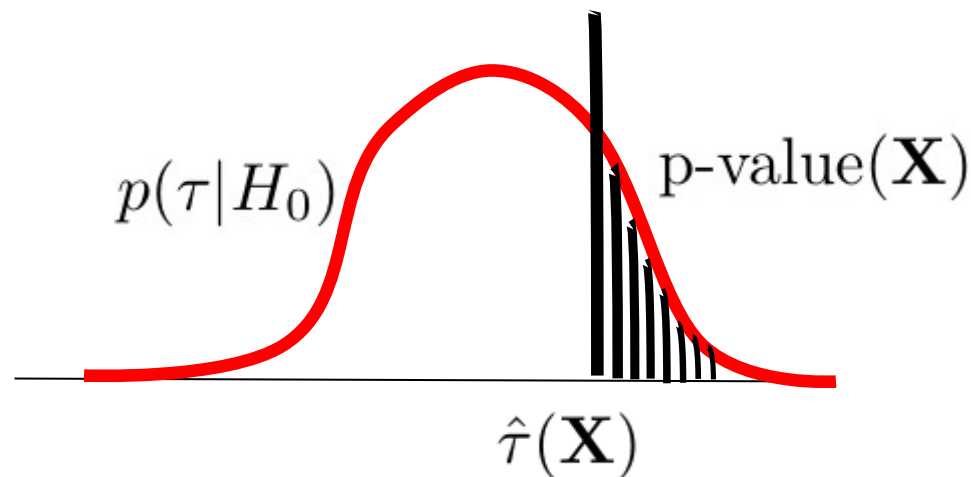
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Not to be confused with Bayesian posterior:

$$p(H_0 | \mathbf{X}) = \frac{p(\mathbf{X} | H_0)p(H_0)}{p(\mathbf{X} | H_0)p(H_0) + p(\mathbf{X} | H_1)p(H_1)}$$

Resampling in high dimension: multiple tests

[Arlot et al. Annals of Stats 2010]

Setting | Sample $\mathbf{X} = (\mathbf{X}^1, \dots, \mathbf{X}^n) \in \mathbb{R}^{n \times p}$, $\mu_i = \text{mean}(\mathbf{X}_i)$
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For instance: if covariance = $\sigma \mathbb{I}_p$; Bonferroni $t_\alpha^{bonf} = \sigma \Phi^{-1}(1 - \frac{\alpha}{p})$

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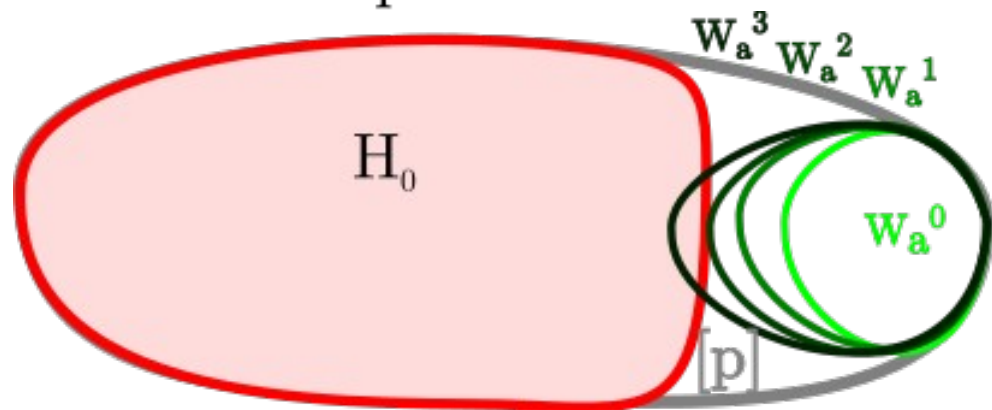
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Note: Generalization to multi-step procedure: "step-down"

$$W_\alpha^{j+1} = \{i \in [p] : \bar{\mathbf{X}}_i > t_\alpha([p] - W_\alpha^j)\}$$

$\bigcup_j W_\alpha^j$ controls the FWER



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$$\begin{aligned}\mathbb{P}_{\mathbf{X}}(\sup_{i \in H_0} \bar{\mathbf{X}}_i > t_\alpha([p])) &= \mathbb{P}_{\mathbf{X}}(\sup_{i \in H_0} Z\bar{\mathbf{X}}_i > t_\alpha(Z\mathbf{X}, [p])) \text{ for any } Z \\ &= \mathbb{E}_Z \mathbb{P}_{\mathbf{X}}(\sup_{i \in H_0} Z\bar{\mathbf{X}}_i > t_\alpha(Z\mathbf{X}, [p])) \\ &= \mathbb{E}_{\mathbf{X}} \mathbb{P}_Z(\sup_{i \in H_0} Z\bar{\mathbf{X}}_i > t_\alpha(\bar{\mathbf{X}}, [p])) \\ &= \mathbb{E}_{\mathbf{X}} \mathbb{P}_Z(\sup_{i \in H_0} Z\bar{\mathbf{X}}_i > t_\alpha([p])) \\ &\leq \alpha\end{aligned}$$

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Notes:

- this holds for any non-Gaussian symmetric distribution
- Can be combined with step-down procedure