Reason 3: Multiple Hypothesis Testing

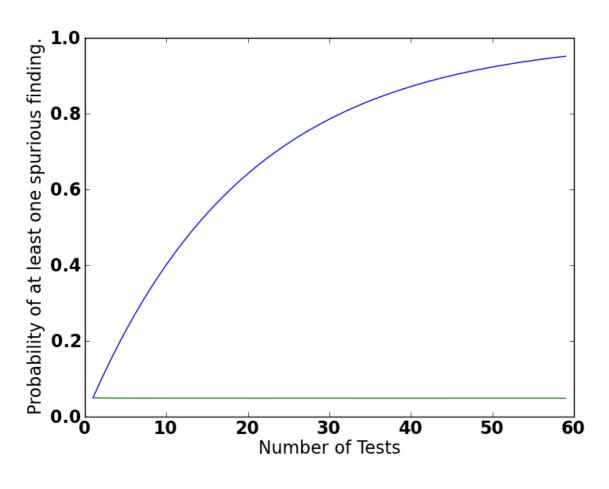
- If you perform experiments over and over, you're bound to find something
- This is a bit different than the publication bias problem: Same sample, different hypotheses
- Significance level must be adjusted down when performing multiple hypothesis tests

P(detecting an effect when there is none) = α = 0.05

P(not detecting an effect when there is none) = $1 - \alpha$

P(not detecting an effect when there is none on every experiment) = $(1 - \alpha)^k$

P(detecting an effect when there is none on at least one experiment) = $1 - (1 - \alpha)^k$



$$\alpha = 0.05$$

"Familywise Error Rate"

Familywise Error Rate Corrections

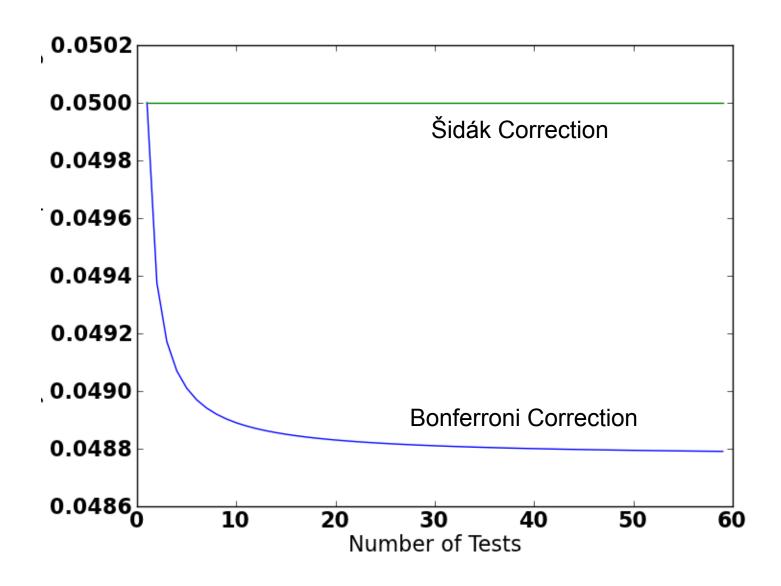
- Bonferroni Correction
 - Just divide by the number of hypotheses

$$\alpha_c = \frac{\alpha}{k}$$

- Šidák Correction
 - Asserts independence

$$\alpha = 1 - (1 - \alpha_c)^k$$

$$\alpha_c = 1 - (1 - \alpha)^{\frac{1}{k}}$$



False Discovery Rate

	Reject H0	Do Not Reject H0	Total
H0 is true	FD	TN	T
H0 is false	TD	FN	F
Total	D	N	TFDN

T/F = True/False D/N = Discovery/Nondiscovery

$$Q = FDR = \frac{FD}{D}$$

FDR (2)

- Bonferroni correction and other FWER corrections tend to wipe out evidence of the most interesting effects; they suffer from low power.
- FDR control offers a way to increase power while maintaining a bound on the ratio of wrong conclusions
- Intuition:
 - 4 false discoveries out of 10 rejected null hypotheses

is a more serious error than

20 false discoveries out of 100 rejected null hypotheses.

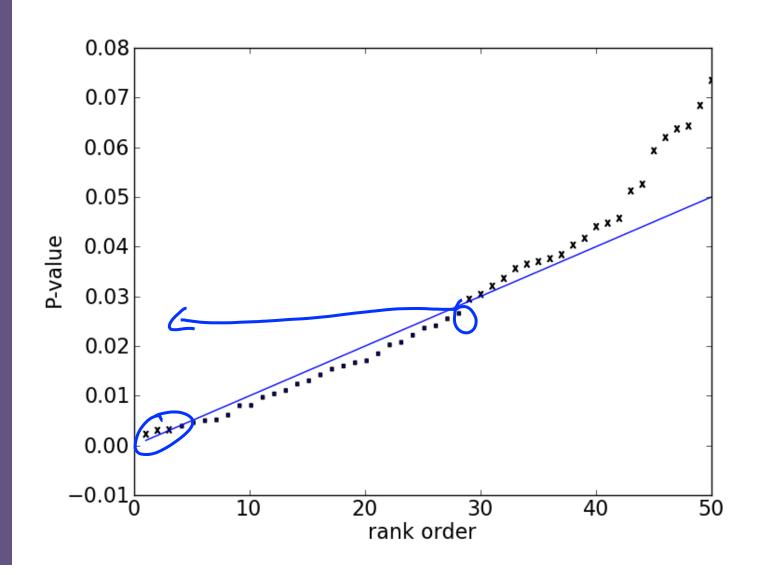
adapted from a slide by Christopher Genovese

Benjamini-Hochberg Procedure

- Compute the p-value of m hypotheses
- Order them in increasing order of p-value
 - That is, most likely hypotheses are first

$$P_i \leq rac{i}{m} lpha$$
 $rac{i}{m} lpha rac{i}{m} lpha rac{i}{m} lpha rac{i}{n} rac{i}{n} lpha rac{i}{n} lpha lpha lpha rac{i}{n} rac{i}{n} lpha rac{i}{n} lpha rac{i}{n} lpha rac{i}{n}$

Benjamini-Hochberg Procedure



$$m = 50$$

 $\alpha = 0.05$