

# Multiple Testing in Genetic Research

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# Key Concepts:

- A **Type 1 Error ( $\alpha$ )** occurs when we reject the null if it is true.
- Valid tests satisfy  $P(\text{T1 Error}) \leq \alpha$
- The **power ( $\beta$ )** of a test is  $P(\text{Reject the null when the alternative is true})$ .

|               |          | Reality   |   |
|---------------|----------|---|---|
|               |          | Positive  | Negative  |
| Study Finding | Positive | <b>True Positive</b><br>(Power)<br>( $1-\beta$ )      | False Positive<br><b>Type I Error</b><br>( $\alpha$ ) |
|               | Negative | False Negative<br><b>Type II Error</b><br>( $\beta$ ) | <b>True Negative</b>                                  |

# Setting The Stage

$H_0^1$  = Gene 1 not related to hair color

$H_0^2$  = Gene 2 not related to hair color

⋮

$H_0^{12000}$  = Gene 12000 not related to hair color

$H_1^1$  = Gene 1 is related to hair color

$H_1^2$  = Gene 2 is related to hair color

⋮

$H_1^{12000}$  = Gene 12000 is related to hair color

Suppose that  $H_0^k$  holds for all k e.g.hair color not related to any gene

$P(\text{T1 Error for test } k) \leq \alpha \text{ for all } k$

However,  $P(\text{any Type 1 Error for all 12,000 tests}) \approx 100\%$

If every hypothesis corresponds to one gene in a genetic study, conclusions may be incorrect because there are so many tests.

# Why is this bad?

- If we present all test results together, we cannot say anything meaningful about any single one.
- If 12,000 hypothesis tests are ran- are we rejecting a null because we discovered something meaningful, or is it because we ran so many tests?
- A correction for multiple testing is a process by which we can present the results of many tests together in a “meaningful” way. *(In this talk: control false discovery rate)*

# False Discovery Rate (FDR)

- Proportion of false discoveries (Type 1 Errors) among all discoveries (any rejection of a null).
- For example, controlling the FDR at 0.2 means that on average, no more than 20 out of 100 significant results will be false positives.

Benjamini-Hochberg:

1. Rank p-values corresponding to each gene from smallest to largest.
2.  $\text{Threshold}_i = \frac{i}{m} * Q$  where  $Q=\text{FDR}$ ,  $i=\text{rank}$ ,  $m=\text{total tests}$
3. Find largest p-value where  $p_i \leq \text{Threshold}_i$  and name it  $p_k$
4. All genes with  $p_i \leq p_k$  declared significant.

# Genetic Study Design/Background

- Investigating predictors of breast cancer from 5 breast cancer related datasets (Miecznikowski, et al, 2010).
- Focus on one dataset with 12,649 genes.
- Tested associations between genes and survival time.
- Controlled False Discovery Rate using Benjamini Hochberg at 0.2

RESEARCH ARTICLE

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Comparative survival analysis of breast cancer microarray studies identifies important prognostic genetic pathways

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# Results of the study

- 3,246 genes were found to be significant after controlling the FDR.
- Roughly 650 may be false positives.

# Interpretation of Results After FDR Control

- Recall: Our goal was to identify potential genes that could be linked to breast cancer, but we were worried about the large number of tests we were doing.
- The interpretation of our results after controlling FDR is that after focusing our attention to all of the genes seemingly related with breast cancer survival time, there is a 20% chance that any given gene is not actually related with breast cancer survival time.



# Conclusions

- Simultaneously testing tens of thousands of genes increases the risk of false positives.
- FDR controls expected proportion of false positives.
  - Less conservative than other measures.
- FDR balances discovery with high reliability.