## I have the power and multiple testing



## Boulder 2008

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- Boring Statistical principles
- Power
- Simple example
- Formal definition
- Influences on Power
- Multiple testing
- Definition
- FDR
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## Importance of power calculation

- Help design studies that are likely to succeed
- Determine the minimum sample size necessary to achieve the desired level of statistical power (usually $>80 \%$ ), for a given effect size
- Determine the minimum effect size that can be detected with adequate statistical power, for a fixed sample size


## Importance of power calculation

- Help design studies that are likely to succeed
- Determine the minimum sample size necessary to achieve the desired level of statistical power (usually $>80 \%$ ), for a given effect size
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Usually obligatory for grant applications

## Simple example

- Investigate the linear relationship ( $\rho$ )
- between two random variables X and Y : $\rho=0$ vs. $\rho \neq 0$ (correlation coefficient).
- draw a sample, measure $X, Y$
- calculate the measure of association $\rho$ (Pearson product moment corr. coeff.)
- test whether $\rho \neq 0$.


## How to Test $\rho \neq 0$

- assumed the data are normally distributed
- defined a null-hypothesis $(\rho=0)$
- chosen a level (usually .05)
- utilized the (null) distribution of the test statistic associated with $\rho=0$
- $t=\rho \vee\left[(N-2) /\left(1-\rho^{2}\right)\right]$


## How to Test $\rho \neq 0$

Sample $\mathrm{N}=40$

- $r=.303, t=1.867, d f=38, p=.06 \alpha=.05$
- As $p>\alpha$, we fail to reject $\rho=0$
- have we drawn the correct conclusion?


## $\alpha=$ type I error rate probability of deciding $\rho \neq 0$ (while in truth $\rho=0$ )

## $\alpha$ is often chosen to equal .05...why? DOGMA

$N=40, r=0$, nrep=1000 - central $t(38)$, $\alpha=0.05$ (critical value 2.04)


## Observed non-null distribution ( $\rho=.2$ ) and null distribution



In $23 \%$ of tests of $\rho=0,|t|>2.024$
( $\alpha=0.05$ ), and thus draw the correct conclusion that of rejecting $\rho=0$.

The probability of rejecting the nullhypothesis ( $\rho=0$ ) correctly is $1-\beta$, or the power, when a true effect exists

## Hypothesis Testing

- Correlation Coefficient hypotheses:
- $h_{o}$ (null hypothesis) is $\rho=0$
$-h_{a}$ (alternative hypothesis) is $\rho \neq 0$
- Two-sided test, where $\rho>0$ or $\rho<0$ are one-sided
- Null hypothesis usually assumes no effect
- Alternative hypothesis is the idea being tested


## Summary of Possible Results

## H-0 true H-O false

accept H-0 $\quad 1-\alpha$
reject $\mathrm{H}-0$
$\alpha$

$$
\begin{aligned}
& \beta \\
& 1-\beta
\end{aligned}
$$

$\alpha=$ type 1 error rate
$\beta=$ type 2 error rate
$1-\beta=$ statistical power

## STATISTICS

|  | Rejection of $\mathrm{H}_{0}$ | Non-rejection of $\mathrm{H}_{0}$ |
| :---: | :---: | :---: |
| $\mathrm{H}_{0} \text { true }$ | Type I error at rate $\alpha$ | Nonsignificant result <br> (1- $\alpha$ ) |
| $\stackrel{\approx}{\sim} H_{\text {A true }}$ | Significant result | Type II error at rate $\beta$ |

## Power

- The probability of rejection of a false null-hypothesis depends on:
-the significance criterion ( $\alpha$ ) -the sample size ( N ) -the effect size ( $\Delta$ )
"The probability of detecting a given effect size in a population from a sample of size N , using significance criterion $\alpha$ "


## Standard Case

Sampling distribution if
$\mathrm{H}_{0}$ were true


## Increased effect size

Sampling distribution if
$\mathrm{H}_{0}$ were true

Sampling distribution if $\mathrm{H}_{\mathrm{A}}$ were true


## Standard Case

Sampling distribution if
$\mathrm{H}_{0}$ were true


## More conservative $\alpha$



## Less conservative $\alpha$

Sampling distribution if<br>$\mathrm{H}_{0}$ were true<br>alpha 0.01

Sampling distribution if


## Standard Case

Sampling distribution if
$\mathrm{H}_{0}$ were true


## Increased sample size

Sampling distribution if
$\mathrm{H}_{0}$ were true

Sampling distribution if $\mathrm{H}_{\mathrm{A}}$ were true


## Increased sample size

Sampling distribution if
$\mathrm{H}_{0}$ were true
alpha 0.05

Sampling distribution if $\mathrm{H}_{\mathrm{A}}$ were true


## $x^{2}$ distributions


http://www2.ipcku.kansai-u.ac.jp/~aki/pdf/chi21.htm

## Noncentral $\mathrm{X}^{2}$

- Null $\chi^{2}$ has $\mu=d f$ and $\sigma^{2}=2 d f$
- Noncentral $X^{2}$ has $\mu=d f+\lambda$ and $\sigma^{2}=2 d f+4$ $\lambda$
- Where df are degrees of freedom and $\lambda$ is the noncentrality parameter


## Noncentral $x^{2} 3$ degrees of freedom





http://www2.ipcku.kansai-u.ac.jp/~aki/pdf/chi21.htm

## Short practical on GPC

- Genetic Power Calculator is an online resource for carrying out basic power calculations
- For our $1^{\text {st }}$ example we will use the probability function calculator to play with power
- http://pngu.mgh.harvard.edu/~purcell/gpc/


## GPC Power Practical



## Parameters in probability function calculator

- Click on the link to probability function calculator
- 4 main terms:
- $X$ : critical value of the chi-square
- $P(X>x)$ : Power
- df: degrees of freedom
- NCP: non-centrality parameter


## $\square D$



## Probability Function Calculator

S. Purcell, 2000, 2005.

This site is designed to provide a calculator for the chi-squared and normal distributions. See below for notes on how to use the forms

$$
\begin{aligned}
& \text { X : critical value for statistic } \\
& \mathbf{P ( X > x )} \text { : probability of being above the critical value } \\
& \text { df: degrees of freedom }
\end{aligned}
$$

NCP : noncentrality parameter
For central chi-squared distribution, NCP $=0$
i.e. $\mathrm{df}=1, \mathrm{P}(\mathrm{X}>\mathrm{x})=0.05, \mathrm{NCP}=0$ gives $\mathrm{X}=3.84146$

For standard normal distribution, mean $=0, s d=1$
i.e. mean $=0, s d=1, P(X>x)=0.025$ give $X=1.95996$

1) Fill in three
2) Click the button
3) Reveals the fourth


## $\square D$



## BD



## Probability Function Calculator

This site is designed to provide a calculator for the chi-squared and normal distributions. See below for notes on how to use the forms.



## Exercises

1) Find the power when $\mathrm{NCP}=5$, degrees of freedom=1, and the critical $X$ is 3.84
2) Find the NCP for power of .8 , degrees of freedom=1 and critical $X$ is 13.8

## Answers

1) Power $=0.608922$, when $\mathrm{NCP}=5$, degrees of freedom=1, and the critical X is 3.84
2) $\mathrm{NCP}=20.7613$ when power of .8 , degrees of freedom=1 and critical X is 13.8

## Additional Factors

- Type of Data:
- Continuous > Ordinal > Binary
- Do not turn "true" binary into continuous
- Multivariate analysis
- Remove confounding/bias


## Effects on Power Recap

- Larger Effect Size
- Larger Sample Size
- Alpha Level shifts
- Beware the False Positive!!!
- Empirical significance/permutation


## When To Do Power Calculations?

- Generally study planning stages of study
- Occasionally with negative result
- No need if significance is achieved
- Computed to determine chances of success


## Steps in power calculation

- Specify
- Study design (e.g. case-control)
- Statistical test


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- Specify
- Study design (e.g. case-control)
- Statistical test
- Assume hypothetical values for 2 of the 3 parameters:
- Sample size
- Effect size (including "exposure" frequency)
- Statistical power


## Steps in power calculation

- Specify
- Study design (e.g. case-control)
- Statistical test
- Assume hypothetical values for 2 of the 3 parameters:
- Sample size
- Effect size (including effect frequency)
- Statistical power
- Calculate the remaining parameter



## Question 1

- What case control sample size do we need to achieve genome-wide significance for an odds ratio of 1.2 in a multiplicative model and an allele frequency of $20 \%$ when we directly type the locus for a disease with 5\% prevalence?


## Question 1



## Question 1



## Question 1



## Question 1



## Question 1



## Question 1



## Question 1



## Question 1



## Question 1



## Question 1



## Question 1



## Answer 1



## Answer 1



6,362 case samples required: total sample size 12,724

## Questions on your own

- For the same model as above, find the total sample size required for a TDT
- Hint: use TDT for discrete traits
- Try for different effect sizes and models (e.g. dominance)
- What is the effect of degrading LD in case-control data?
- Change the D' and keep allele freq the same
- Change allele freq and keep D' the same
- How well does the additive model capture a dominance only effect?
- Should you use $2 x$ population controls vs $1 x$ screened controls
- For a prevalence of 5\% and for a prevalence of 25\%?


## Answers

- Additive
- Total case number for CC: 6,362
- Total case number for TDT: 7,079
- Dominance only
-RR: 1; 1; 1.44
- 30,595 cases for CC
- 33,950 cases for TDT


## Impact of indirect association

If a direct association study of a causal SNP would provide an NCP of $\lambda$
Then an indirect association study of a SNP in LD with the causal SNP has NCP of $R^{2} \lambda$

## Impact of indirect association

If a direct association study of a causal SNP would provide an NCP of $\lambda$

Then an indirect association study of a SNP in LD with the causal SNP has NCP of $R^{2} \lambda$
i.e. NCP is linearly related to the magnitude of $\mathbf{R}^{2}$ between causal and genotyped SNP
Hence the appropriateness of using $\mathrm{R}^{2}$ as an LD metric for the selection of tag SNPs.

- Case-control for discrete traits

Disease $\quad \mathrm{K}=0.1$
Locus

$$
\begin{aligned}
& R_{\mathrm{AA}}=R_{\mathrm{Aa}}=2 \\
& \mathrm{MAF}=0.05
\end{aligned}
$$

Marker1
Marker2

Sample

MAF $=0.05 D^{\prime}=\{1,0.8,0.6,0.4,0.2,0\}$
MAF $=0.25 D^{\prime}=\{1,0.8,0.6,0.4,0.2,0\}$
500 cases, 500 controls

- Genotypic risk at marker1 (left) and marker2 (right) as a function of D'




## Additivity vs Dominance

- Recall from the biometrical model that
$-\mathrm{V}_{\mathrm{a}}=$


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$-V_{a}=2 p q[a+(q-p) d]^{2}$


## Additivity vs Dominance

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& -V_{a}=2 p q[a+(q-p) d]^{2} \\
& -V_{d}=
\end{aligned}
$$

## Additivity vs Dominance

- Recall from the biometrical model that
$-V_{a}=2 p q[a+(q-p) d]^{2}$
$-\mathrm{V}_{\mathrm{d}}=$ Chlamydia


## Additivity vs Dominance

- Recall from the biometrical model that

$$
\begin{aligned}
& -V_{a}=2 p q[a+(q-p) d]^{2} \\
& -V_{d}=[2 p q d]^{2}
\end{aligned}
$$

## Additivity vs Dominance

- Recall from the biometrical model that
$-V_{a}=2 p q[a+(q-p) d]^{2}$
$-\mathrm{V}_{\mathrm{d}}=[2 \mathrm{pqd}]^{2}$
- Therefore, there can still be association evidence when the two homozygous classes have the same trait value mean and the heterozygous class does not equal the homozygotes


## Additivity vs Dominance

- Recall from the biometrical model that
$-\mathrm{V}_{\mathrm{a}}=2 \mathrm{pq}[\mathrm{a}+(\mathrm{q}-\mathrm{p}) \mathrm{d}]^{2}$
$-\mathrm{V}_{\mathrm{d}}=[2 \mathrm{pqd}]^{2}$
- $V_{a}=0$ can only be achieved if $a=0$ and $p$
$=q$ or $a=(p-q) d$


## Answers

- Should you use $2 x$ population controls vs 1x screened controls
- For a prevalence of $5 \%$ and for a prevalence of $25 \%$ ?
- For a prevalence of $5 \%$ the $2 x$ population controls are more powerful; for a prevalence of $25 \%$ the 1 x screened controls are more powerful


## Answers

The effect of adding misclassified cases


## Answers

Increase in NCP as a function of including unselected controls


## Power and NCP (df=1)

$\alpha=0.01,0.001,0.0001,0.00001,0.000001,0.0000001$


## Ways to enhance power

- Increase sample size
- Combination of studies: meta-analysis
- Increase marker density
- Increase accuracy of phenotype measurements
- Increase accuracy of genotyping
- Rigorous quality control and error checking
- Collect and adjust for environmental covariates


## Ways to enhance power

- Appropriate treatment of heterogeneity (including geneenvironment interaction)
- Appropriate treatment of population substructure
- Select individuals with highest genetic loading as cases, and individuals with lowest genetic loading as controls (e.g. use quantitative endophenotypes and select individuals in the two extreme tails of the trait distribution)
- Well thought-through and sophisticated analysis plan, making full use of phenotype and genotype information


## Simulation using PLINK

- PLINK simulation file-format
\#SNPs label lower-freq upper-freq geno-rel-risk
- Exercise, to replicate result of analytic power calculation
- See PLINK web-page on simulation
- 600 cases, 600 controls
- disease variant 20\% MAF and GRR of 1.5
- simulate and test 100,000 markers under the model
- calculate power for type I error rate of $1 \times 10^{-4}$
- Hint. To determine how many passing SNPs, you have several options:
- Load results into R
- Use --pfilter and wc Unix command
- Use awk / gawk
- Use Haploview to examine PLINK results file
- File sim1.txt


## 100000 alt 0.2 0.2 1.5

- Generate and test SNPs on-the-fly
./plink --simulate sim1.txt
--simulate-ncases 600
--simulate-ncontrols 600
--simulate-prevalence 0.01
-     - assoc
- Calculate power
awk ' \$9 < 1e-4 ' plink.assoc | wc -l


## Simulation using PLINK

- To specify 2-SNP haplotypes, given SNP frequencies and D' (not documented on current www yet) add the flag--simulate-tags also
\#SNPs label $\frac{\text { l-freq u-freq }}{} \begin{array}{cccc}\text { Disease variant } & & \text { Marker locus } \\ \text { (not observed) }\end{array}$
- Now simulate a $2 \%$ disease allele, with 5 -fold (multiplicative) effect, that is in complete LD with a marker allele of $20 \%$ MAF
- what is power now at the $20 \%$ genotype?
- verify this using the GPC calculator
- what is the apparent odds-ratio at the genotyped SNPs
- what is the LD in terms of $r^{2}$ between the two loci (from GPC)?
- File sim2.txt

$$
100000 \text { alt } 0.020 .02 \quad 0.20 .21 .05 .0
$$

- Generate and test SNPs on-the-fly

$$
\begin{aligned}
\text {./plink } & - \text {-simulate sim2.txt } \\
& - \text {-simulate-tags } \\
& - \text {-simulate-ncases } 600 \\
& - \text {-simulate-ncontrols } 600 \\
& \text {--simulate-prevalence } 0.01 \\
& \text {--assoc }
\end{aligned}
$$

- Calculate power
awk ' \$9 < 1e-4 ' plink.assoc | wc -l


## Working with NCPs

- Expected chi-square $=\mathrm{NCP}+\mathrm{df}$
- The NCP scales linearly with sample N
- for same case/control ratio
- Two useful properties
- combine independent tests by summing NCPs
- NCP at marker $\sim r^{2} \times$ NCP at disease locus
- To calculate power given NCP
- using R
> 1 - pchisq( qchisq( 1 - 1e-4 , df=1 ) , df = 1 , ncp = 17.96 )
[1] 0.6358291
- or PDF utility in GPC


## Hodgepodge anyone?

- Multiple testing
- Where it comes from
- Why is it a problem
- False discovery
- Theory \& practice


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## What do we test

- Raise your hand if:


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- You have analyzed more than 1 phenotype on a dataset


## What do we test

- Raise your hand if:
- You have analyzed more than 1 phenotype on a dataset
- Used more than one analytic technique on a dataset (e.g. single marker association and haplotype association)


## What do we test

- Raise your hand if:
- You have analyzed more than 1 phenotype on a dataset
- Used more than one analytic technique on a dataset (e.g. single marker association and haplotype association)
- Picked your best result from the bunch


## Genome-wide association



High throughput genotyping

## Other multiple testing considerations

- Genome-wide association is really bad
- At 1 test per SNP for 500,000 SNPs
- 25,000 expected to be significant at $\mathrm{p}<0.05$, by chance alone


## Other multiple testing considerations

- Genome-wide association is really bad
- At 1 test per SNP for 500,000 SNPs
$-25,000$ expected to be significant at $p<0.05$, by chance alone
- To make things worse
- Dominance (additive/dominant/recessive)
- Epistasis (multiple combinations of SNPs)
- Multiple phenotype definitions
- Subgroup analyses
- Multiple analytic methods


## Bonferroni correction

- For testing 500,000 SNPs
- 5,000 expected to be significant at $p<0.01$
- 500 expected to be significant at $p<0.001$
- ......
- 0.05 expected to be significant at $p<0.0000001$
- Suggests setting significance level to $\alpha=10^{-7^{*}}$
- Bonferroni correction for $m$ tests
- set significance level for $p$-values to $\alpha=0.05$ / m
- (or adjust the p -values to $\mathrm{m} \times \mathrm{p}$, before applying the usual $\alpha=$ 0.05 significance level)
- *See Risch and Merikangas 1999


## Genome-wide significance

- Multiple testing theory requires an estimate of the number of 'independent tests'
- Risch and Merikangas 1996 estimated a threshold of $10^{-6}=\left(0.05 /\left(5^{*} 10,000\right)\right)$
- HapMap 2005 estimate $10^{-8}$ based on encode deep sequencing in ENCODE regions
- Dudbridge and Gusnato, and Pe'er et al. 2008 Genetic Epidemiology estimate based on 'infinite density' like Lander and Kruglyak 1995 generate $5 \times 10^{-8}$


## Implication for sample size

Genetic Power Calculator

| m | $\alpha$ | $\chi^{2}$ | NCP <br> $(80 \%$ power) | Ratio |
| :---: | :---: | :---: | :---: | :---: |
| 1 | 0.05 | 3.84 | 7.85 | 1 |
| 500 | $10^{-4}$ | 15.14 | 22.39 | 2.85 |
| $500 \times 10^{3}$ | $10^{-7}$ | 28.37 | 38.05 | 4.85 |
| $500 \times 10^{6}$ | $10^{-10}$ | 41.82 | 53.42 | 6.81 |

Large but not "impossible" increase in sample size

## Technical objection

Conservative when tests are non-independent
Nyholt (2004)
Spectral decomposition of correlation matrix
Effective number of independent tests
May be conservative: Salyakina et al (2005)
False Discovery
Permutation procedure

## Philosophical objection

"Bonferroni adjustments are, at best, unnecessary and, at worst, deleterious to sound statistical inference" Perneger (1998)

- Counter-intuitive: interpretation of finding depends on the number of other tests performed
- The general null hypothesis (that all the null hypotheses are true) is rarely of interest
- High probability of type 2 errors, i.e. of not rejecting the general null hypothesis when important effects exist


## A Bayesian perspective

For each significant test, we can consider the probability that $\mathrm{H}_{0}$ is in fact true (i.e. false positive probability)

## Prob ( $\mathrm{H}_{0}$ True | $\mathrm{H}_{0}$ Rejected)

Using Bayes' rule

$$
\begin{aligned}
\mathrm{P}\left(H_{0} \mid p \leq \alpha\right) & =\frac{\mathrm{P}\left(p \leq \alpha \mid H_{0}\right) \mathrm{P}\left(H_{0}\right)}{\mathrm{P}\left(p \leq \alpha \mid H_{0}\right) \mathrm{P}\left(H_{0}\right)+\mathrm{P}\left(p \leq \alpha \mid H_{1}\right) P\left(H_{1}\right)} \\
& =\frac{\alpha \pi_{0}}{\alpha \pi_{0}+(1-\beta)\left(1-\pi_{0}\right)}
\end{aligned}
$$

## Taking the formula apart

$$
\begin{aligned}
\mathrm{P}\left(H_{0} \mid p \leq \alpha\right) & =\frac{\mathrm{P}\left(p \leq \alpha \mid H_{0}\right) \mathrm{P}\left(H_{0}\right)}{\mathrm{P}\left(p \leq \alpha \mid H_{0}\right) \mathrm{P}\left(H_{0}\right)+\mathrm{P}\left(p \leq \alpha \mid H_{1}\right) P\left(H_{1}\right)} \\
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$$



Alpha level:
Rate of false positives

## Taking the formula apart

$$
\begin{aligned}
\mathrm{P}\left(H_{0} \mid p \leq \alpha\right) & =\frac{\mathrm{P}\left(p \leq \alpha \mid H_{0}\right) \mathrm{P}\left(H_{0}\right)}{\mathrm{P}\left(p \leq \alpha \mid H_{0}\right) \mathrm{P}\left(H_{0}\right)+\mathrm{P}\left(p \leq \alpha \mid H_{1}\right) P\left(H_{1}\right)} \\
& =\frac{\alpha \pi_{0}}{\alpha \pi_{0}+(1-\beta)\left(1-\pi_{0}\right)}
\end{aligned}
$$

Proportion of tests
that follow the null distribution

## Taking the formula apart

$$
\begin{aligned}
\mathrm{P}\left(H_{0} \mid p \leq \alpha\right) & =\frac{\mathrm{P}\left(p \leq \alpha \mid H_{0}\right) \mathrm{P}\left(H_{0}\right)}{\mathrm{P}\left(p \leq \alpha \mid H_{0}\right) \mathrm{P}\left(H_{0}\right)+\mathrm{P}\left(p \leq \alpha \mid H_{1}\right) P\left(H_{1}\right)} \\
& =\frac{\alpha \pi_{0}}{\alpha \pi_{0}+(1-\beta)\left(1-\pi_{0}\right)} \\
& \begin{array}{c}
\text { Power to detect } \\
\text { association }
\end{array}
\end{aligned}
$$

## Taking the formula apart

$$
\begin{aligned}
& \mathrm{P}\left(H_{0} \mid p \leq \alpha\right)=\frac{\mathrm{P}\left(p \leq \alpha \mid H_{0}\right) \mathrm{P}\left(H_{0}\right)}{\mathrm{P}\left(p \leq \alpha \mid H_{0}\right) \mathrm{P}\left(H_{0}\right)+\mathrm{P}\left(p \leq \alpha \mid H_{1}\right) P\left(H_{1}\right)} \\
&=\frac{\alpha \pi_{0}}{\alpha \pi_{0}+(1-\beta)} \\
& \begin{array}{l}
\text { Proportion of tests } \\
\text { that follow the } \\
\text { alternative distribution }
\end{array}
\end{aligned}
$$

## Taking the formula apart



## A Bayesian perspective

Re-expressing the equation in term of $\alpha$ :

$$
\alpha=\frac{\mathrm{P}\left(H_{0} \mid p \leq \alpha\right)}{1-\mathrm{P}\left(H_{0} \mid p \leq \alpha\right)} \frac{1-\pi_{0}}{\pi_{0}} \frac{1-\beta}{1}
$$

## A Bayesian perspective

Re-expressing the equation in term of $\alpha$ :


## Implications

- Justification of traditional choice $\alpha=0.05$
- False positive rate $\sim \alpha$, when $\pi_{0} \sim 1 / 2$ and 1- $\beta \rightarrow 1$


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- Justification of traditional choice $\alpha=0.05$
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- Maintenance of low false positive rate requires $\alpha$ to be set proportional to
- 1- $\beta$
(power)
- $\left(1-\pi_{0}\right) / \pi_{0}$
(proportion of tests that follow the null)


## Implications

- Justification of traditional choice $\alpha=0.05$
- False positive rate $\sim \alpha$, when $\pi_{0} \sim 1 / 2$ and 1- $\beta \rightarrow 1$
- Maintenance of low false positive rate requires $\alpha$ to be set proportional to
- 1- $\beta$
(power)
$-\left(1-\pi_{0}\right) / \pi_{0}$
(proportion of tests that follow the null)
- Multiple testing usually reflects lack of strong hypotheses and therefore associated with high $\pi_{0}$
- Bonferroni adjustment effectively sets $\alpha \propto 1 / \mathrm{m}$, which is equivalent to assuming $\pi_{0}=\mathrm{m} /(\mathrm{m}+1)$. But is this reasonable?


## Fixed significance level

- Use fixed value of $\pi_{0}$ based on a guesstimate of the proportion of SNPs in the genome that have an effect, e.g. $1-\pi_{0}=$ $25 / 10^{7}=2.5 \times 10^{-6}$
- Power $=0.8$
- False positive rate $=0.05$
- Then $\alpha \sim 10^{-7}$ (regardless of $m$ )


## Adaptive significance level

- Use the availability of multiple tests to our advantage, because the empirical distribution of $p$-values can inform us about the suitable significance level
- Suppose that out of 500,000 SNPs, 100 are observed to be significant at $\alpha=0.00001$. Since the expected number of significant SNPs occurring by chance is 5 , the false positive rate given by setting $\alpha=0.00001$ is $5 / 100$
- Therefore a desired false positive rate can be obtained by setting $\alpha$ appropriately, according to the observed distribution of $p$-values (False Discovery Rate method)


## Hodgepodge anyone?

- Multiple testing
- Where it comes from
- Why is it a problem
- False discovery
- Theory \& practice


## Benjamini-Hochberg FDR method

Benjamini \& Hochberg (1995) Procedure:

1. Set FDR (e.g. to 0.05)
2. Rank the tests in ascending order of $p$-value, giving $p_{1} \leq$ $p_{2} \leq \ldots \leq p_{r} \leq \ldots \leq p_{m}$
3. Then find the test with the highest rank, $r$, for which the $p$-value, $p_{r}$, is less than or equal to $(r / m) \times F D R$
4. Declare the tests of rank $1,2, \ldots, r$ as significant

A minor modification is to replace $m$ by $m \pi_{0}$

## B \& H FDR method

$\mathrm{FDR}=0.05$

| Rank | P-value | $($ Rank $/ \mathrm{m}) \times$ FDR | Reject $\mathrm{H}_{0} ?$ |
| :---: | :---: | :---: | :---: |
| 1 | .008 | .005 | 1 |
| 2 | .009 | .010 | 1 |
| 3 | .165 | .015 | 0 |
| 4 | .205 | .020 | 0 |
| 5 | .396 | .025 | 0 |
| 6 | .450 | .030 | 0 |
| 7 | .641 | .035 | 0 |
| 8 | .781 | .040 | 0 |
| 9 | .901 | .045 | 0 |
| 10 | .953 | .050 | 0 |

## Modified FDR methods

## Storey 2002 procedure:

 Under the null P-values look like:Distribution of $P$-values under the null


## Modified FDR methods

## Storey 2002 procedure:

 Under the alternative P -values look like:

## Modified FDR methods

## Storey 2002 procedure:

 Under the alternative P -values look like:Distribution of P -values under alternative


## Modified FDR methods

## Storey 2002 procedure:

Combined distribution of P-values look like:

Distribution of P-values under combined distributions


## Modified FDR methods

## Storey 2002 procedure:

Combined distribution of P-values look like:

Distribution of P-values under combined distributions


## Modified FDR methods

## Storey 2002 procedure:

## Combined distribution of P-values look like:

This is the information that FDR detects

Distribution of P-values under combined distributions


## Modified FDR methods

## Storey 2002 procedure:

Combined distribution of P-values look like:

Distribution of P -values under combined distributions


## Modified FDR methods

## Storey 2002 procedure:

## Combined distribution of P-values look like:

Distribution of P -values under combined distributions


The number of tests above p $=.5$ is 47651 out of 100000

## Modified FDR methods

## Storey 2002 procedure:

## Combined distribution of P-values look like:



## Modified FDR methods

## Storey 2002 procedure:

## Combined distribution of P-values look like:



The number of tests above $p$ $=.5$ is 47651 out of 100000

So the proportion of tests that follows the null: 47651/50000 or $.95302=\pi_{0}$

So we replace the number of tests with the number of tests times $\pi_{0}$ or 95302.

## "Parametric FDR" methods

Mixture model: some test statistics follow the null distribution, while others follow a specified alternative distribution
Special cases:
Central and non-central chi-square distributions (Everitt \& Bullmore, 1999)

Central and non-central normal distributions (Cox \& Wong, 2004) Uniform and beta distributions (Allison et al, 2002)
From fitted model, calculates the posterior probability of each test belonging to the null distribution (i.e. of being a false discovery if declared significant)

## Pitfalls of the FDR method

- Assumption: $p$-values are distributed as $\mathrm{U}[0,1]$ under $\mathrm{H}_{0}$
- If untrue (e.g. biased genotyping, population substructure) then this could lead to an excess of small $p$-values and hence misleading FDR results
- Requires a large number of tests to work
- The accuracy of the FDR is not easy to determine
- Requires a distribution (detectable number) of tests under the alternative


## QQ Plots and You

- Q-Q plots stand for quantile-quantile plots
- A quantile is the value of a distribution at a given percentage
- The 100-quantiles are called percentile
- The 20-quantiles are called vigiciles
- The 12-quantiles are called duo-deciles
- The 10 -quantiles are called decile
- The 9-quantiles are called noniles
- The 5-quantiles are called quintiles
- The 4-quantiles are called quartiles
- The 3-quantiles are called tertiles or terciles


## QQ Plots and You

Null QQ plot


## QQ Plots and You



## QQ Plots and You

Five True GWS Effects Fifteen Extra Effects QQ plot


