

## Power Analysis for Single and Rare Variant Aggregate Association Analyses

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## Why Estimate Sample Sizes and/or Power?

- To avoid wasting time and money
  - Does not make sense to perform an inadequately powered study for which it is unlikely to correctly reject the null hypothesis due to inadequate sample size
    - Collaborations can aid in increasing sample sizes
      - Caveats
        - » Disease definition may not be the same between studies
        - » Study subjects may be drawn for different populations
        - » Processing of genetic material may not be consistent
- Almost always necessary for grant proposals
  - Can be denied funding if unable to demonstrate planned study has adequate power
    - Realistic disease models are necessary when performing power calculations
    - Correctly adjust alpha for multiple testing which will be performed
      - e.g., use genome-wide significant level of  $5 \times 10^{-8}$  for GWAS studies

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## Power and Sample Size Estimation for Case-Control Data

- The correct  $\alpha$  must be used for sample size estimation/power analysis
- Type I ( $\alpha$ ) the probability of rejecting the null hypothesis of no association when it is true
- Due to multiple testing a more stringent value than  $\alpha=0.05$  is used in order to control the Family Wise Error Rate

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## Power and Sample Size Estimation for Case-Control Data

- GWAS of common variants where each variant is tested separately
  - $\alpha=5 \times 10^{-8}$  (Bonferroni Correction for testing 1,000,000 variant sites)
  - Shown to be a good approximation for the effective number of tests
    - Valid even when more than 1,000,000 variant sites tested
  - Effective number of tests is dependent of the linkage disequilibrium (LD) structure
- Single variant tests using whole genome sequence data
  - Many more rare variants than common variants
    - Lower levels of LD between rare variants than between common variants
  - The number of effective tests for rare variants is higher than for analysis limited to common variants
  - $\alpha$  is yet to be determined for association analysis of whole genome sequence data

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## An Example of Determining Genome-wide Significance Levels for Common Variants

- Using genotypes from the Wellcome Trust Case-Control Consortium
- Dudbridge and Gusnato, Genet Epidemiol 2008
- Estimated a genome-wide significance threshold for the UK European population
- By sub-sampling genotypes at increasing densities and using permutation to estimate the nominal p-value for a 5% family-wise error
- Then extrapolating to infinite density
- The genome wide significance threshold estimate  $\sim 7.2 \times 10^{-8}$
- Estimate is based on LD structure for Europeans
  - Not sufficiently stringent for populations of African Ancestry

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## Power and Sample Size Estimation for Aggregate Rare Variant Tests

- For gene-based rare variant aggregate methods a Bonferroni correction for the number of genes/regions tested is used
  - e.g., 20,000 genes significance level  $\alpha=2.5 \times 10^{-5}$ 
    - Can use a less stringent criteria
      - Not all genes have two or more variants
        - » Divide 0.05 by number of genes tested
    - If units other than genes are used
      - A more stringent criteria may be necessary
- For rare variants – very low levels of LD between variants in separate genes
  - Therefore, a Bonferroni correction is not overly stringent
    - The number of tests  $\approx$  effective number tests
      - This would not be the case for variants in LD

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### Power and Sample Size Estimation for Replication Studies

- For replication studies can base the significance level ( $\alpha$ )
- On the number of genes/variants being brought from the discovery (stage I) study
- To replication (stage II)
- For example, if it is hypothesized that 20 genes and 80 independent variants will be brought to stage II (replication)
  - A Bonferroni correct can be made for performing 100 tests
    - An  $\alpha = 5.0 \times 10^{-3}$  can be used for a family wise error rate of 0.05

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### Estimating Power/Sample Sizes For Single Variant Tests

- Can be obtained analytically
- Information necessary
  - Prevalence
  - Risk allele frequency
  - Effect size (odds ratio-for case control data)
  - Genetic model for the susceptibility variant
    - Recessive ( $\gamma_1=1$ )
    - Dominant ( $\gamma_2=\gamma_1$ )
    - Additive ( $\gamma_2=2\gamma_1-1$ )
    - Multiplicative ( $\gamma_2=\gamma_1^2$ )

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### Estimating Power/Sample Sizes For Individual Variants

- Usually, information on disease prevalence is known from epidemiological data
- A range of risk allele frequencies and effect sizes are used
- A variety of genetic models can also used
  - Dominant
  - Additive
  - Multiplicative

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### Armitage Trend Test

- Power and Sample size
  - Calculated under different models
    - Where  $\gamma$  is the relative risk
      - Multiplicative
        - »  $\gamma_2=\gamma_1^2$
      - Additive
        - »  $\gamma_2=2\gamma_1-1$
      - Dominant
        - »  $\gamma_2=\gamma_1$
      - Recessive
        - »  $\gamma_1=1$

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### Gamma is the Relative Risk not the Odds Ratio

- Most software for power calculations/sample size estimation use the relative risk ( $\gamma$ ) and not the odds ratio
- The relative risk only approximates the odds ratio when disease is rare (Prevalence  $\sim < 0.1\%$ )
  - The relative risk is not appropriate for common traits when a case-control design is used

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### Correspondence Between the Odds Ratio and Relative Risk

#### Dominant Model

Disease Prevalence	1/2* RR=1.5	2/2** RR=1.5
0.01	1.51	1.51
0.10	1.59	1.59
0.20	1.71	1.71

#### Multiplicative Model

Disease Prevalence	1/2 RR=1.5	2/2 RR=2.25
0.01	1.51	2.28
0.10	1.59	2.61
0.20	1.71	3.25

Marker minor allele and disease allele frequency 0.01

D' and  $r^2=1$

\*1/2 genotype – heterozygous (one copy of the alternative allele)

\*\*2/2 genotype - homozygous for the alternative allele

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## Armitage Trend Test - Power Calculations

- Information need
  - Population prevalence
  - Genetic Model
  - Risk allele frequency
- Tools
  - <http://ihg.gsf.de/cgi-bin/hw/power2.pl>
  - Reference Slager and Schaid 2001

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## Armitage Test for Trend

sample size approximations for Armitage's test for trend:

Disease prevalence	0.01
High risk allele frequency	0.05
Type I error (alpha)	0.0000005
Power (1 - beta)	0.8
Gamma 1	2
Gamma 2	2
Cases / (cases + controls)	0.5

Cases necessary = 1502  
Controls necessary = 1502  
Cases and controls necessary = 3004

Submit | Reset

Gamma1 (genotypic relative risk):  
Under a multiplicative model,  $\text{gamma2} = \text{gamma1}^2$ ; under an additive model,  $\text{gamma2} = 2 * \text{gamma1} - 1$ ;  
under a dominant model,  $\text{gamma2} = \text{gamma1}$ ; under a recessive model,  $\text{gamma1} = 1$ .

Adapted from:  
Slager SL, Schaid DJ: Case-control studies of genetic markers:  
Power and sample size approximations for Armitage's test for trend.  
Hum Hered 52, 149-153 (2001).  
and  
Freidlin B, Zheng G, Li Z, Gastwirth JL:  
Trend tests for case-control studies of genetic markers:  
Power, sample size and robustness.  
Hum Hered 53, 146-152 (2002).  
[View M. Slager](#)

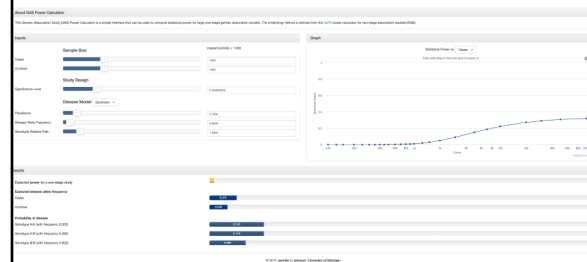
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## Genetic Association Study (GAS) Power Calculator

- [http://csg.sph.umich.edu/abecasis/cats/gas\\_power\\_calculator/index.html](http://csg.sph.umich.edu/abecasis/cats/gas_power_calculator/index.html)
- A one-stage study power calculator
  - Which is derived from CaTs
    - Which is to perform two-stage genome wide association studies
      - Skol et al. 2006
- Cochran Armitage Trend Test
- Displays graphs of the results

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## GAS Power Calculator



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## Genetic Power Calculator

- <http://zzz.bwh.harvard.edu/gpc/>
- S Purcell & P Sham
- Uses the methods described in Sham PC et al. (2000) Am J Hum Genet 66:1616-1630
  - VC QTL linkage for sibships
  - VC QTL association for sibships
  - VC QTL linkage for sibships conditional on the trait
  - TDT for discrete traits
  - Case-Control for discrete traits
  - TDT for quantitative traits
  - Case-Control quantitative traits
- Although input is the relative risk
  - Displays odds ratios

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## Genetic Power Calculator

Case - control for discrete traits

High risk allele frequency (A)	: 0.01	(0 - 1)
Prevalence	: 0.2	(0.0001 - 0.9999)
Genotype relative risk Aa	: 1.5	(> 1)
Genotype relative risk AA	: 1.5	(> 1)
D-prime	: 1	(0 - 1)
Marker allele frequency (B)	: 0.01	(0 - 1)
Number of cases	: 10000	(0 - 10000000)
Control : case ratio	: 1	(> 0)
(1 = equal number of cases and controls)		
<input checked="" type="checkbox"/> Unselected controls? (* see below)		
User-defined type I error rate	: 0.00000005	(0.00000001 - 0.5)
User-defined power: determine N	: 0.80	(0 - 1)
(1 - type II error rate)		

Process | Reset

Created by [Shaun Purcell](#) 24.Oct.2008

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The screenshot shows the Genetic Power Calculator interface. It includes sections for 'Genetic parameters', 'Linkage disequilibrium', 'Power parameters', and 'Results'. The results table shows power values for different sample sizes and effect sizes.

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## Power Association With Errors (PAWE)

- <http://compugen.rutgers.edu/pawe/>
- Implements the linear trend test
- Four different error models can be used
  - See online documentation for complete explanation
- Can either perform:
  - Power calculations for a fixed sample size
  - Sample size calculations for a fixed power
- The genotype frequencies can be generated either using a:
  - Genetic model free method or
  - Genetic model-based method

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## Quanto

- Provides sample size and power calculations for
- Genetic and environmental main effects
- Interactions
  - Gene x gene
  - Gene x environment
- Sample & power calculations can be carried for:
  - Case-control
    - Unmatched
    - Matched
  - Case-sibling
  - Case-parent (trios)
    - Quantitative
    - Qualitative
  - Independent sample of individuals
    - Quantitative traits
      - Assumption sampled from a random population
- Can only be run under windows
  - <https://pphs.usc.edu/download-quanto/>

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## Linkage Disequilibrium (LD)

- Power will be reduced if causal variant is not in perfect LD ( $r^2=1$ ) with the tag SNP
- Can adjust sample size when  $r^2 < 1$  to increase power to the same level as when  $r^2=1$
- Can estimate sample size when  $r^2 \neq 1$ 
  - $N/r^2 = N'$
  - Valid only for multiplicative model
  - (Pritchard and Przeworski, 2001)
- Power calculation almost always assume that  $r^2=1$
- For whole genome sequence data this should be the case since usually the causal variant would be included in the data

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## Power Analysis for Rare Variant Aggregate Association Tests

- Many unknown parameters must be modeled
  - Allelic architecture within a genetic region
    - Varied across genes and populations
  - Effects of variants within a region
    - Fixed or varied effect sizes of causal variants
    - Bidirectional effect of variants
    - Proportion of non-causal variants
- Power estimated empirically
- Simplified assumptions can be made to obtain analytical estimates
  - All variants have the same effect size
  - No non-causal variants within a region that is analyzed in aggregate

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## Simplistic Analytical Power Calculation for Rare-variant Aggregate Association Analysis

- Assumption
  - All rare variants are causal and have the same effect size
- Although usual not be correct
  - Provides a gestalt of the power for a given samples or sample size for a given power
- Use aggregate of allele frequencies
  - For example, assume a cumulative allele frequency of 0.025
  - Use an exome-wide significant level e.g.,  $2.5 \times 10^{-6}$
- Provide disease prevalence and penetrance model
- Perform calculations in the same manner as was described for single variants

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### Empirical Power Calculations

- A variety of methods can be used to generate variant data to empirically estimate power
- Variant data is generated
  - Based upon a penetrance model samples of cases and controls are generated
  - Or a quantitative trait is generated based upon the genetic variance
- Multiple replicates are generated and analyzed
  - To determine the power

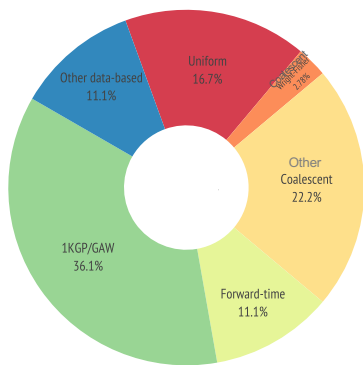
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### Empirical Power Calculations

- Examples
  - 5,000 replicates are generated each with 20,000 cases and 20,000 controls
    - The power is the proportion of replicates with p-value less than the specified threshold, e.g.,  $5 \times 10^{-8}$
  - For rare-variant aggregate tests all autosomal genes are generated and those genes with more than two rare variants (e.g., predicted loss of function) are analyzed
    - The power is the proportion of genes that were tested with p-value which is below a specified threshold, e.g.,  $2.5 \times 10^{-6}$

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### Simulation Methods



Note: Not all methods give a realistic distribution of variants & in particular for rare variants

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### Generating Exome Sequence Data Sets Forward-time Simulation

Data	Haplotype Counts	Demographics
Boyko	105,814*	
Kyrukov	1,800,000*	
Gazave	1,308,000*	

\*Selection coefficients used to define "variant type"  
 - "Missense" ( $1.0 \times 10^{-5}$  –  $1.8 \times 10^{-2}$ )  
 - "Nonsense, splice site and frameshift" ( $>1.8 \times 10^{-2}$ )

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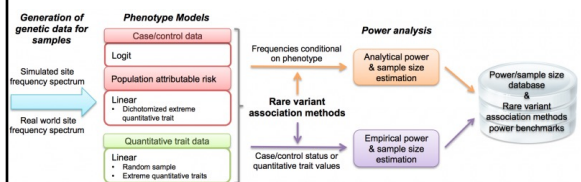
### SKAT Power Calculator

- R Library
- Provides a haplotype matrix
  - 10,000 haplotypes over 200kb region
  - Simulated using a calibrated coalescent model (cosi)
  - Mimicking linkage disequilibrium structure of European ancestry
  - User can also provide haplotype data
- Power and sample size calculations for binary and quantitative traits
- User specify proportion of variants that increase or lower risk

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### SEQPower

<http://www.bioinformatics.org/spower/>

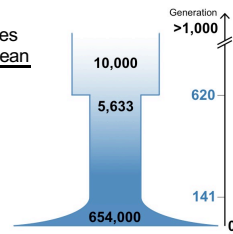


Wang et al. 2014 Bioinformatics

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## Generating Variants: Using a European Demographic Model and Exome Sequence Data

- Variant data generated on 18,397 genes
- Variant data simulated using a European population demographic model
  - Gazave et al. 2013
- Variants generated using exome sequence data
  - 4332 Exomes obtained from European American

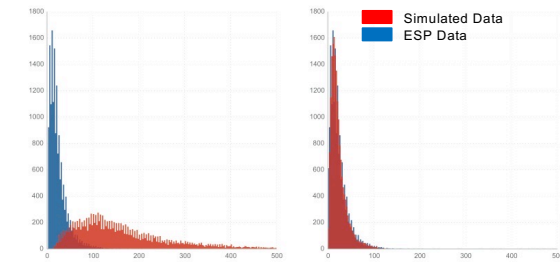


Which method performs better and why?

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## Does Generating Variant Data Using the European Population Demographic Model Perform Well?

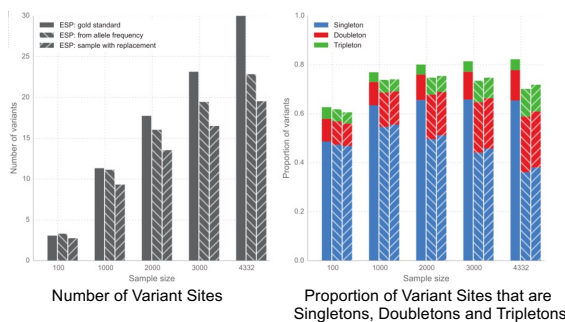
Distribution of number of variants per gene



- Simulated variant counts based on the entire simulated population
- Simulated variant counts based on haplotype pool down-sampled to ESP size

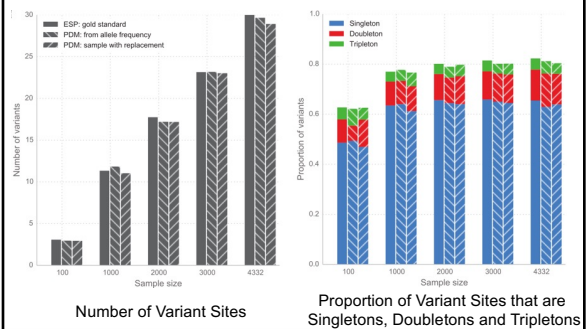
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## Simulating Data Using Sequence Data (ESP)



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## Simulating Data: Using Population Demographic Models (PDM)



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## Simulation Studies to Evaluate Power for Rare Variant Association Studies

- It is unknown which genes are important in disease etiology
  - Correct allelic architecture is unknown
- Can get a better understanding of power to detect associations by generating variants for the entire exome
- Use a variety of disease models
  - Odds ratios
  - Proportion of pathogenic variants
- Analyze all genes
  - e.g., those with 2 or more variant sites
- Determine power as the proportion of genes that meet exome-wide significance (e.g.,  $\alpha=2.5 \times 10^{-6}$ )

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## Power Analysis

- For tests of individual variants
  - Power depended on sample size, disease prevalence, minor allele frequency, genetic model and variant effect size
- For rare variants (aggregate association tests)
  - Also dependent on the allelic architecture
    - Cumulative variant frequency within analyzed region
    - Proportion of causal variants
      - How much contamination from non-causal variants
  - Effect sizes the same or different across gene regions
    - Effects of variants in the same or different directions
      - Protective and detrimental for binary traits
      - Increase and decrease quantitative trait values

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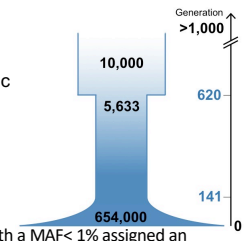
### Power Analysis Rare Variants (Aggregate Association Tests)

- Power will not only vary between traits greatly
- The power to detect an association will also vary drastically between genes for the same complex trait
  - For some causal genes even with hundreds of thousands of samples power will be low
  - While for other causal genes a few thousand samples may be sufficient

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### How Large of a Sample Size is Necessary to Detect Rare Variant Associations?

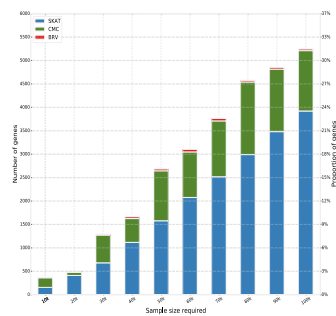
- Data generated on 18,397 genes
- Variant data simulated using a European population demographic model
  - Gazave et al. 2013



- Every missense, nonsense and splice with a  $MAF \leq 1\%$  assigned an odds ratio of 1.5
- Sample sizes to detect X number of genes determined for
  - $\alpha = 2.5 \times 10^{-6}$
  - power=0.8

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### Sample Sizes Necessary to Detect an Association (Case-Control Data)



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