

# Rare-Variant Association Testing for Exome Data

The Sequence Kernel Association Test

# Sequence Kernel Association Test (SKAT)

- Gene-level (or SNP set) analysis approach
- Tests an association between SNP sets and continuous or discrete phenotypes
- Bypasses the problem of different tagging SNPs being associated with outcomes of interest across ethnic groups

# SKAT Main Effects Model

$$Y_i = \alpha_0 + \alpha' X_i + \beta' G_i + \epsilon_i$$

- $Y_i$  = outcome for subject  $i$
- $\alpha_0$  = intercept term
- $X_i$  = vector of non-genetic covariates
- $G_i$  = vector of genotypes
- $\epsilon_i$  = error term; follows any distribution with mean 0 and variance  $\sigma^2$
- Assume each  $\beta_j$ ,  $j=1, \dots, p$ , follows an arbitrary distribution with mean 0 and variance  $w_j \tau$ 
  - Where the weights ( $w_j$ ) are specified by the user

# SKAT basics

- Testing  
 $H_0: \beta = 0$  is equivalent to testing  $H_0: \tau = 0$
- The score test for variance component in the corresponding mixed model is of the form:

$$Q_\rho = (1 - \rho) Q_S + \rho Q_B$$

- where  $\rho$  is the parameter of the unified test,  $Q_S$  is a test statistic of SKAT, and  $Q_B$  is a score test statistic of weighted burden test

# Kernel

- There are pre-specified 6 types of kernels:
  - "linear"
  - "linear.weighted"
  - "IBS"
  - "IBS.weighted"
  - "quadratic"
  - "2wayIX"
- You can use one of them or you can give your own kernel matrix as a parameter.

# Default Kernel

- The default kernel is the weighted linear kernel
- The kernel matrix for the weighted linear kernel is

$$**K = GWWG**$$

- Where **G** is the  $n \times p$  matrix of genotype data and **W** is the  $p \times p$  diagonal matrix of the weights corresponding to each variant.

# Q Statistic

$$Q_{\rho} = (1 - \rho) Q_s + \rho Q_B$$

- The Q statistic has a mixture of chi-squared distribution under the null hypotheses that can be evaluated explicitly and used as a reference distribution to compute the p-values.

# Weights

- The matrix  $W$  is a diagonal matrix that contains the weights of the  $p$  variants
- Good choices of weights can improve power
- Weights are pre-specified
- If weight  $j$  is large, then that variant makes a large contribution to the  $Q$  statistic
- Upweighting a causal variant (which is expected to have a large effect) can improve the power
- We don't know which variants are causal and thus we don't always know which weights to use



# Weights

- SKAT authors suggest using

$$\sqrt{w_j} = \text{Beta}(MAF_j; \alpha_1, \alpha_2)$$

- Beta PDF:  $\frac{x^{\alpha-1}(1-x)^{\beta-1}}{B(\alpha, \beta)}$

Where B denotes the Beta function, alpha and beta (in our weight equation, alpha-1 and alpha-2) are shape parameters and the function is evaluated when  $x = MAF_j$

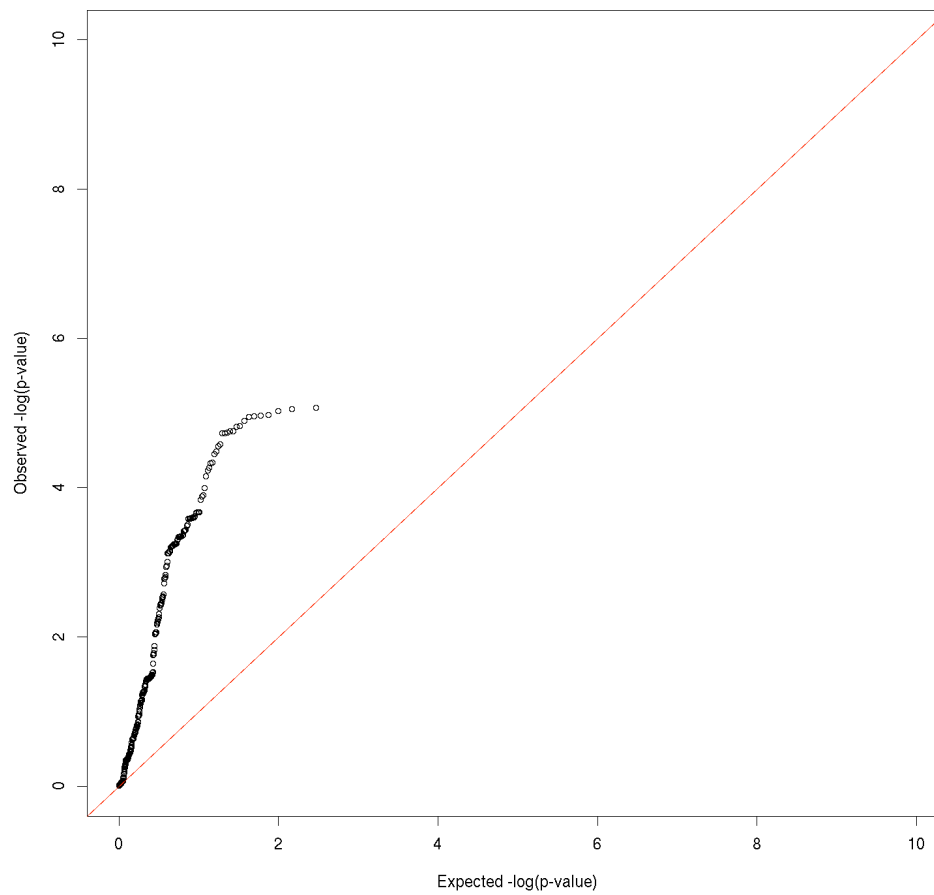
# Results

- The Q statistic and associated p-value will tell us if the SNP set is associated with the outcome.
- $H_0: \tau = 0$ , assesses whether there is any variance in the SNP set ( $B_j$ s) from the mean of 0 in any (+/-) direction

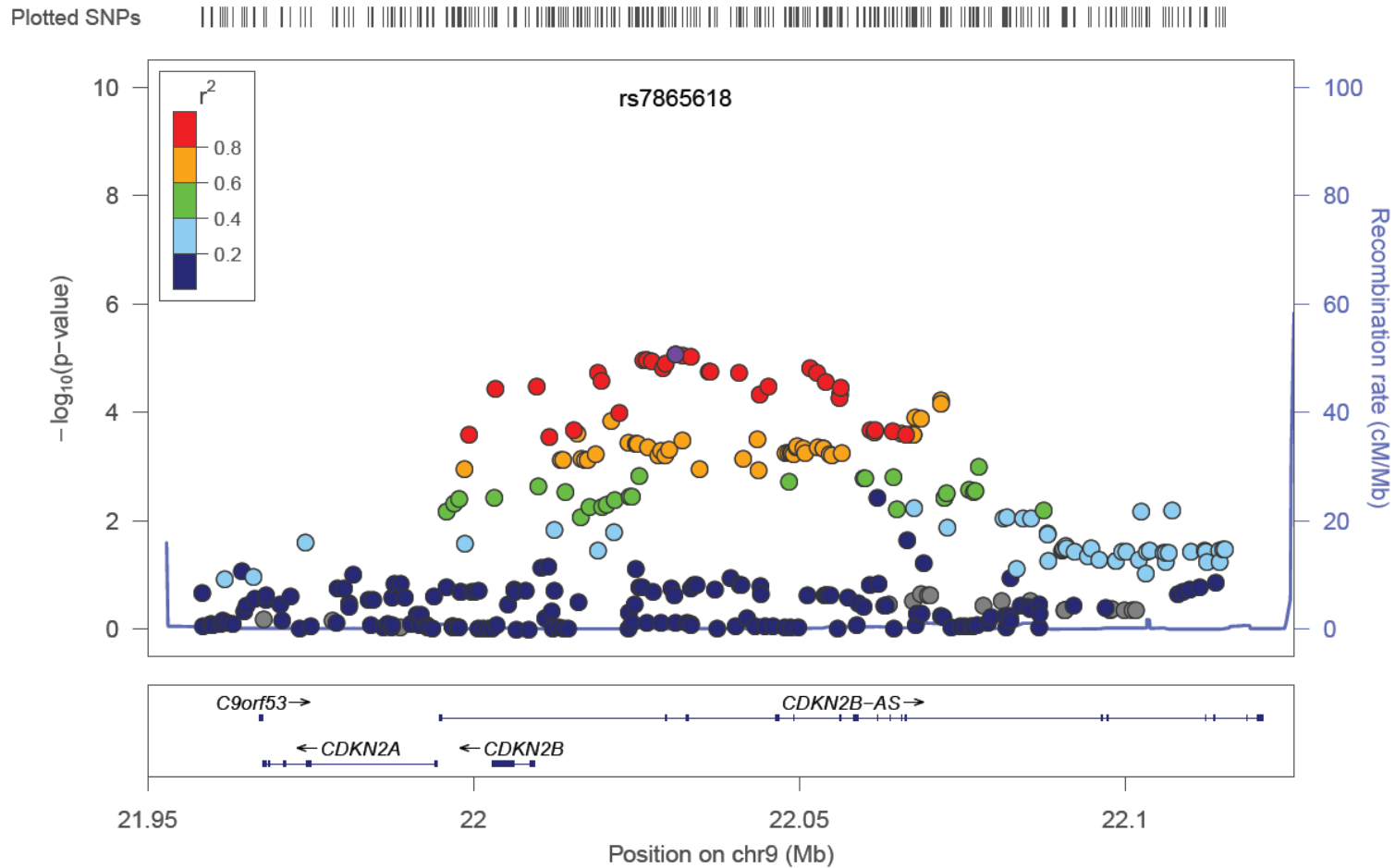
# Example

- The association between SNPs in the Chr9p21 region and the Gene Expression
- **Predictor:** SNPs in the Chr9p21 region (297 SNPs)
- **Outcome:** gene expression of the genes across the whole genome
- Single SNP Association Test
  - Gene expression=single SNP + random(family) (297 tests)
- Sequence Kernel (SNP set) association (SKAT)
  - Gene expression (after familiar adjustment)= All SNPs (1 test)

# Single SNP Association Analysis Between CDKN2BAS and SNPs in the Chr9p21



# Single SNP Association Analysis Between CDKN2BAS and SNPs in the Chr9p21



# CDKN2BAS (SKAT p=0.429)

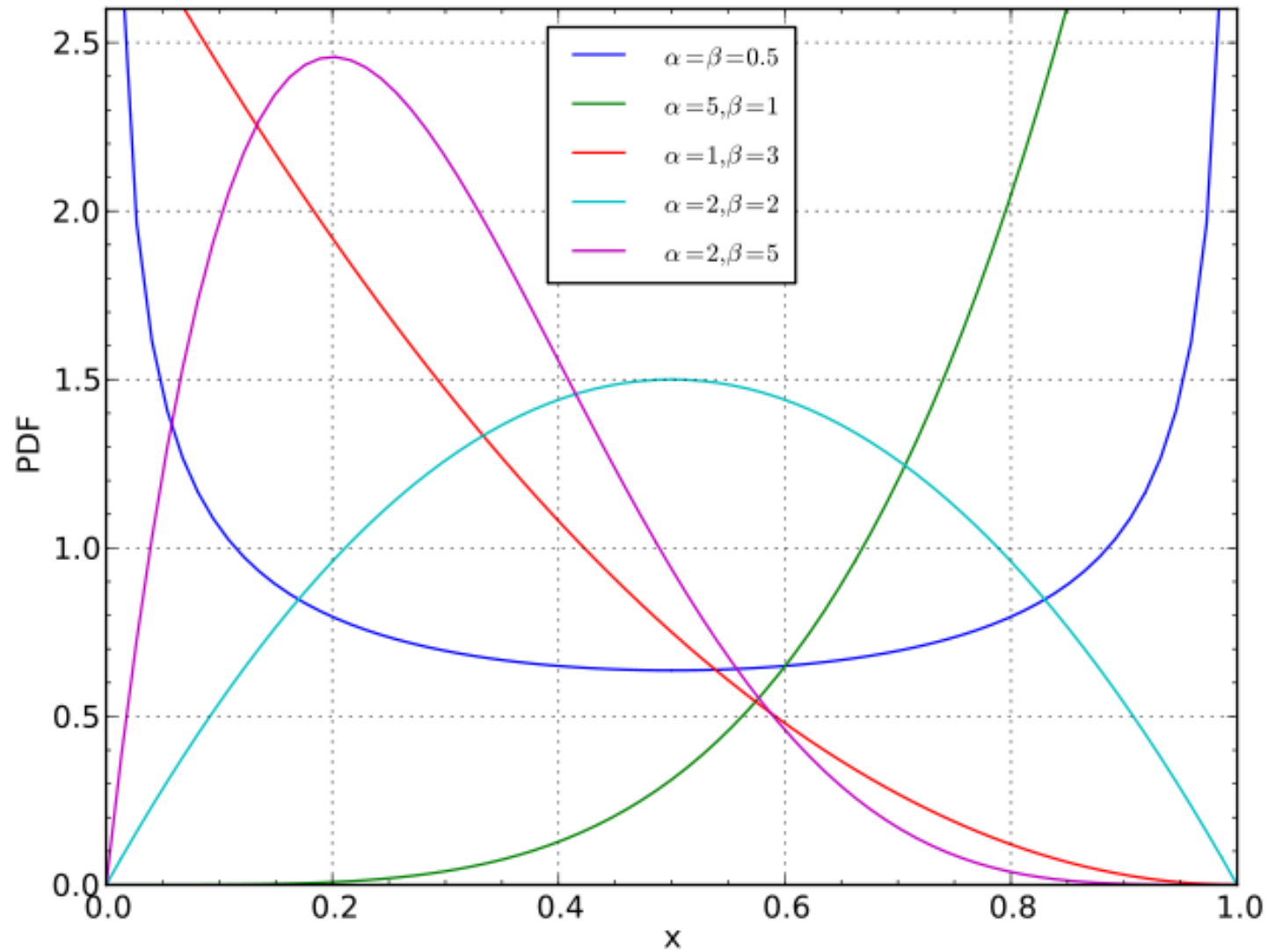
SNP	MAF	B SNP P CDKN2BAS
rs7865618	0.446317	8.58E-06
rs634537	0.44901	8.93E-06
rs2157719	0.495097	9.34E-06
rs613312	0.439054	1.07E-05
rs615552	0.453232	1.09E-05
rs543830	0.438996	1.11E-05
rs599452	0.438958	1.13E-05
rs564398	0.440362	1.28E-05
rs679038	0.439493	1.51E-05
rs944801	0.459316	1.52E-05

# Specifying weights

- Beta (1, 25)
  - Up regulate rare variants and down regulate common variants
- Beta (1, 1)
  - Equal weights to all variants
- Beta (0.5, 0.5)
  - Madsen & Browning weight

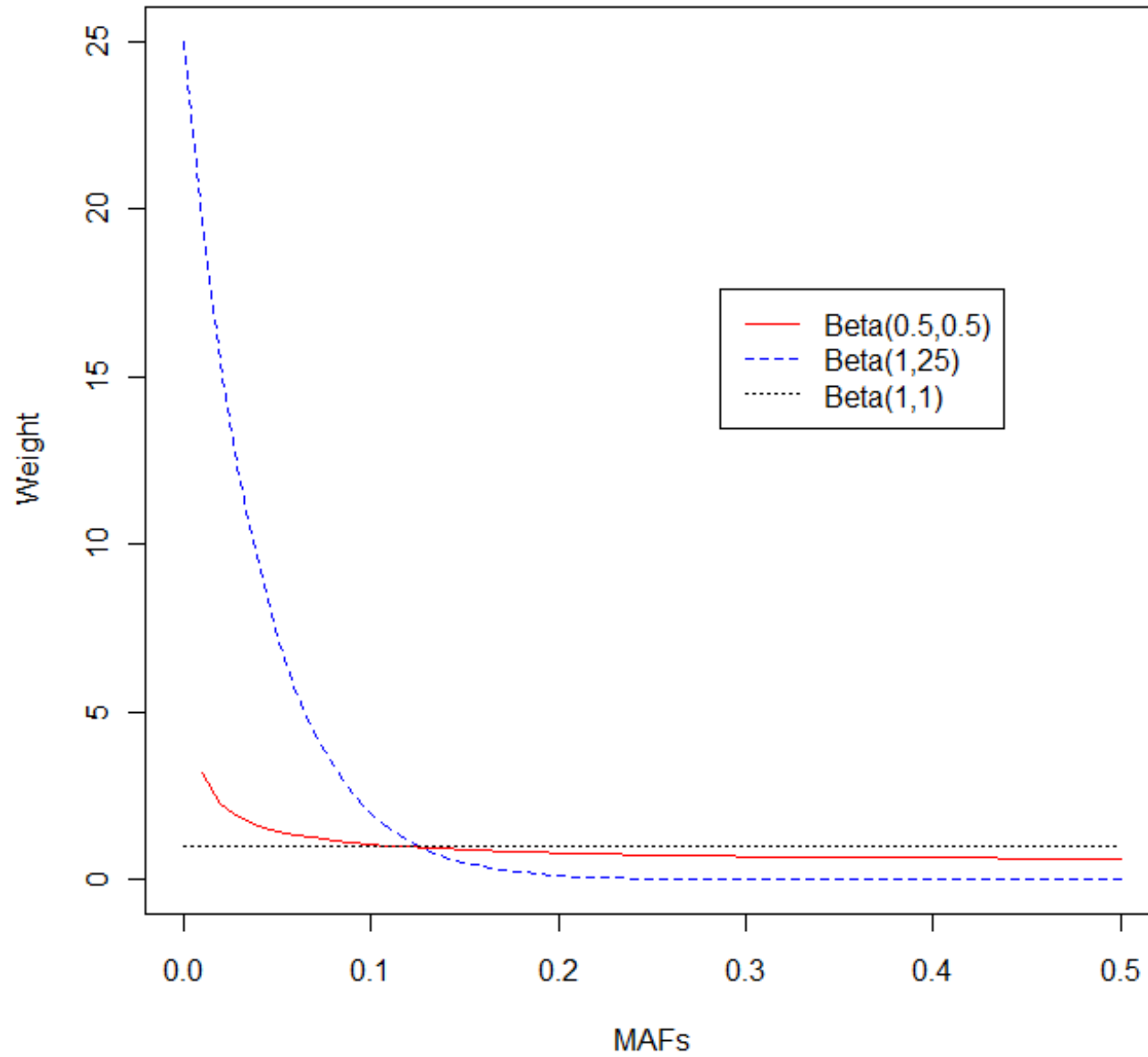
$$\sqrt{w_j} = 1 / \sqrt{MAF_j(1 - MAF_j)}$$

# Beta distributions





### Beta functions for $w_j$



# Applying Different Weight to CDKN2BAS

	Beta (1, 25)	Beta (1, 1)	Beta (0.5, 0.5)
SKAT p value	0.429	0.0020	0.0021

## Example p-values

Adjusting Weight Changes Results Dramatically:  
Top Results with Weight beta (0.5, 0.5)

Transcript	N	Pvalue beta 1 25	Pvalue beta 1 1	Pvalue_ beta 0.5 0.5
ENST00000301908	801	0.036968216	0.000178972	0.000130954
ENST00000370551	801	0.684927084	0.000178319	0.000217497
ENST00000412318	801	0.112609677	0.000302452	0.00026976
ENST00000497037	801	0.241666486	0.000345966	0.00034696

# Conclusion

- Choosing appropriate weight is very important in SKAT
- Beta (1, 25) gives very little weight, if any, to the common variants
- Beta (1, 1) has very little power picking up signals from rare variants
- Beta (0.5, 0.5) can pick up signals from both common and rare variants, but suffers from lower power.

# Next Steps

- We've been working with Shawn Lee to test his SKAT programs for:
  - Gene-environment kernels (currently unweighted)
  - Gene-gene kernels (currently unweighted)
  - Meta-analysis subroutines (Meta-SKAT)
  - Modifications for family data