

# Genotype Pattern Mining for pairs of interacting variants underlying digenic traits

Atsuko Okazaki, Sukanya Horpaopan, Qingrun Zhang, Matthew Randesi, and Jurg Ott

## Supplementary Material

The two programs discussed here are Multifactor Dimensionality Reduction (MDR) and Genotype Pattern Mining (GPM). *MDR* has been a mainstay in human case-control epistasis analysis [1, 2]. Below, we describe our implementation of *MDR* for permutation testing [3]. *GPM* has been newly developed and uses a general-purpose FIM algorithm, *fpgrowth* [4], as its pattern search engine. The starting point for each of the two approaches (our implementations) is a dataset in standard *plink* [5, 6] format, that is, as *\*.ped* and *\*.map* files. Small utility programs can then transform the *plink* files into a format useable by *MDR* and *GPM*. Both programs are currently available for Windows, and a Linux version is in preparation for *GPM*. Each program should be run in a command window (cmd).

### MDR, program parameters

The Multifactor Dimensionality Reduction (MDR) program furnishes variant patterns ordered by their Balanced Accuracy Overall (BAO) and lists as “Top Models” those with highest BAO [7]. It also judges patterns by a more complex combination of statistics and will declare a “best model”. In practice, the “best” and the “top” models are usually identical. We chose to strictly work with the BAO criterion [8] and built a standard permutation framework around *MDR* so that each variant pattern (“model”) can be assigned a significance level. *MDR* has a built-in possibility to carry out permutation testing but a *p*-value will only be issued for the best model, so we do not make use of *MDR*’s permutation feature. Calling *MDR* repeatedly from within our script, we apply the following parameter values:

```
-min= $n_1$ , -max= $n_2$ , -nolandscape, -top_models_landscape_size= $n_3$ ,
```

where the user furnishes relevant numbers as follows:  $n_1$  = minimum number of variants in a pattern,  $n_2$  = maximum number of variants in a pattern (recommended:  $n_1 = n_2 = 2$ ), and  $n_3$  = number of patterns with highest BAO output by *MDR*. Also specified is the desired number  $n_p$  of permutations. Permutations will include the observed data as a null dataset so that the smallest possible empirical significance level will be  $1/n_p$ . As recommended [7], *MDR* can be downloaded from <https://sourceforge.net/projects/mdr/>.

### GPM

This program package is available from <https://lab.rockefeller.edu/ott/programs>. It focuses on genotype (rather than variant) patterns and will output genotypes in each pattern found and the variants containing these genotypes. Missing genotypes are allowed but when *fpgrowth* furnishes

patterns containing missing genotypes, these patterns will be intercepted by the *GPM* main program. Like *MDR*, *GPM* can handle patterns of length two or more although patterns containing two genotypes are the default and are recommended (see Discussion in main paper).

Input parameters for *GPM* consist of three numbers, indicating (1) whether pattern frequencies and associated statistics should be obtained for cases or for controls, (2) minimum number of individuals carrying a pattern (support), and (3) minimum proportion of cases among individuals with the current pattern (confidence, in %). Optionally, two additional numbers can specify minimum and maximum lengths of patterns. Recommended minimum confidence is 80% (<https://borgelt.net/doc/fpgrowth/fpgrowth.html>) and minimum support should be chosen based on the sample size in the data; reasonable values are 5 or 10.

|       | X pattern | not X    |       |
|-------|-----------|----------|-------|
| Y     | $\alpha$  | $\beta$  | $N_2$ |
| not Y | $\gamma$  | $\delta$ | $N_1$ |
|       | $s$       | $N - s$  | $N$   |

Supplementary Table S1. Parametrization of the four types of observations in *GPM* analysis.

**Hypothesis testing.** For a given pattern,  $X$ , we want to test its association with a phenotype,  $Y$ , here, of being a case (affected by disease). Table S1 shows four types of observations,  $\alpha$  = number of cases carrying  $X$ ,  $\beta$  = number of cases not carrying  $X$ ,  $\gamma$  = number of controls with  $X$ , and  $\delta$  = number of controls lacking  $X$ . The *fpgrowth* program will furnish association rules,  $R = "X \rightarrow Y"$ , with associated observed support,  $s = \alpha + \gamma$ , and observed confidence,  $c = \alpha / (\alpha + \gamma)$ , which is an estimate for the conditional probability of being a case,  $P(Y|X)$ , given an individual carries the  $X$  pattern. Thus, we can retrieve the  $2 \times 2$  table above as  $\alpha = c \times s$ ,  $\beta = N_2 - \alpha$ ,  $\gamma = s - \alpha$ , and  $\delta = N_1 - \gamma$ , and compute an appropriate test statistic in support of the alternative hypothesis of association between  $X$  and  $Y$ . We chose the likelihood ratio chi-square as our test statistic.

## References

1. Moore JH, Hahn LW. A cellular automata approach to detecting interactions among single-nucleotide polymorphisms in complex multifactorial diseases, Pac Symp Biocomput 2002:53-64.
2. Moore JH, Ritchie MD. STUDENTJAMA. The challenges of whole-genome approaches to common diseases, Jama. 2004;291:1642-1643.
3. Manly BFJ, Navarro Alberto JA. Randomization, bootstrap and monte carlo methods in biology. Chapman & hall/crc texts in statistical science. Boca Raton: Taylor & Francis, 2021, 1 online resource.
4. Borgelt C. An implementation of the FP-growth algorithm. Proceedings of the 1st international workshop on open source data mining: frequent pattern mining implementations. Chicago, Illinois: Association for Computing Machinery, 2005, 1-5.

5. Purcell S, Neale B, Todd-Brown K et al. PLINK: a tool set for whole-genome association and population-based linkage analyses, *Am J Hum Genet* 2007;81:559-575.
6. Chang CC, Chow CC, Tellier LC et al. Second-generation PLINK: rising to the challenge of larger and richer datasets, *Gigascience* 2015;4:7.
7. Moore JH, Andrews PC. Epistasis Analysis Using Multifactor Dimensionality Reduction. In: Moore J. H., Williams S. M. eds). *Epistasis: Methods and Protocols*. New York, NY: Springer New York, 2015, 301-314.
8. Winham SJ, Motsinger-Reif AA. An R package implementation of multifactor dimensionality reduction, *BioData Min* 2011;4:24.