# RegionScan: A comprehensive R package for region-level genome-wide association testing with integration and visualization of multiple-variant and single-variant hypothesis testing

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# 10 Abstract

11 Summary: RegionScan is an R package for comprehensive and scalable genome-wide 12 association testing of region-level multiple-variant and single-variant statistics and visualization 13 of the results. It implements various state-of-the-art region-level tests to improve signal detection 14 under heterogeneous genetic architectures and facilitates comparison of multiple-variant region-15 level and single-variant test results. It exploits local linkage disequilibrium (LD) structure for 16 genomic partitioning and LD-adaptive region definition. RegionScan is compatible with VCF 17 input file formats for genotyped and imputed variants, and options are available for analysis of 18 multi-allelic variants and unbalanced binary phenotypes. It accommodates parallel region-level 19 processing and analysis to improve computational time and memory efficiency and provides 20 detailed outputs and utility functions to assist results comparison, visualization, and 21 interpretation.

22 Availability and implementation: RegionScan is freely available for download on GitHub

- 23 (https://github.com/brossardMyriam/RegionScan).
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- 25 **Supplementary information:** Supplementary data are available at Bioinformatics online.

# 26 1. Introduction

27 Compared to genome-wide single-variant testing, region-level multi-variant association analysis can better capture signals under complex genetic architectures<sup>1</sup>. Because fewer tests are 28 29 conducted, multiple testing is reduced, and the genome-wide testing threshold can be relaxed. 30 However, for comprehensive genomic analysis, region-level testing requires appropriate region 31 definition, e.g. including intergenic, intronic, and exonic variants. It also faces analytical 32 challenges, including high dimensionality and multi-collinearity within regions produced by 33 complex and long-range linkage disequilibrium (LD) structure. Available region-level tests differ 34 according to the underlying assumptions, the construction of the test statistic, and thus are sensitive to different regional genetic architectures<sup>2,3</sup>. We focus on three classes of state-of-the-35 36 art region-level tests (Supplementary Information 1), including multi-variant linear/logistic regression tests with and without dimension reduction<sup>3–5</sup>, variance component score tests<sup>6,7</sup>, and 37 region-level minP tests<sup>8-10</sup>; sensitive to heterogeneous regional architectures. Our goal is to 38 39 integrate region definition with implementation of region-level and single-variant tests in one 40 scalable R package for comprehensive genome-wide region-level association analysis and 41 improve region discovery under heterogeneous regional architectures.

# 42 **2. Implementation and Key features**

We introduce the RegionScan R package for genome-wide discovery analysis and define regions using the gpart<sup>11</sup> R package for LD-based genomic partitioning, optimized for region-level analysis<sup>12</sup>. Although a major advantage of our approach is comprehensive analysis of the genome, including intergenic regions, RegionScan can also accommodate other user-specified region definitions.

#### 48 2.1 Capability and Scalability

49 The main function is called *regscan* (Supplementary Information 2, for a detailed description 50 and list of options). regscan takes four main inputs: data which includes genotypes (additively 51 coded); SNPinfo input with variant information; phenocov with phenotypes (quantitative or 52 binary) as well as covariates (if applicable) and a REGIONinfo input with region start/end positions, as produced with  $gpart^{11}$ . Alternatively, the auxiliary function *recodeVCF* can process 53 large VCF 4.0 files with vcftools<sup>13</sup> to produce a temporary subset VCF file by region, 54 55 subsequently processed in R to improve memory efficiency. *regscan* also deals optionally with 56 multi-allelic variants in addition to bi-allelic variants.

57 To improve scalability, regscan can process, recode and analyze each region in parallel. The 58 processing steps for each region include variant filtering and recoding based on minor allele 59 frequency (MAF), and an option to reduce multicollinearity by pruning variants within regions. 60 This is followed by application of region-level tests including regression-based tests ( $MLC^2$ , PC80<sup>3</sup>, LC<sup>4,5,14,15</sup>, generalized Wald tests), variance component score tests (SKAT<sup>16,17</sup>, SKAT-61  $O^{7}$ ), and region-level min P tests (simple  $M^{8}$ , GATES<sup>9</sup>, MinP<sup>10,18</sup>), in addition to single-SNP 62 63 tests for variants within regions. regscan includes an option to reduce finite-sample bias in logistic regression of unbalanced binary traits and/or variants with low minor allele counts, using 64 a Jeffreys-prior penalized likelihood<sup>19,20</sup>. For the MLC<sup>2</sup> region-level test, variants within each 65 region are clustered in LD bins based on pairwise correlation<sup>21</sup> for reduced-*df* region-level 66 67 testing adaptive to the number of LD bins, followed by variant recoding within each bin to 68 maximize variant pairs positive correlation (Supplementary Information 2, section 2.1.1); binlevel tests within regions are reported in addition to MLC region-level tests. 69

## 70 2.3 Detailed Outputs and Visualization

71 regscan produces six outputs detailing results for all regions analyzed (Supplementary 72 **Information 2**, section 2.1.3): (1) region-level output with results for all regions analyzed; (2) 73 *bin-level* output including bin-level test results for all bins within each region; (3) variant-level 74 output with variant positions, LD-bin assignments, and corresponding effect sizes and P-values 75 from single- and multi-variant regional regression models; within-region variance inflation factor 76 values (VIFs) are included to facilitate identification of multi-collinearity; (4) a list of variants 77 pruned out with reasons for exclusions; and optionally, (5) a single-variant output including 78 variant-to-LD bin assignments for all the variants (available before pruning) and (6) a *covariate* 79 output with covariate effects and P-values extracted from multi-variant regional regression 80 models.

81 Utility functions are implemented to visualize comparisons between region and/or variant-level 82 test results. For example, MiamiPlot produces a genome-wide comparison of -log10 P-values for 83 a pair of tests; LocusPlot displays results of several region-level tests in a set of contiguous 84 regions; QQPlot assesses consistency of the observed distribution of a specified region-level 85 statistic *P*-value with that expected under the null hypothesis and returns corresponding genomic 86 inflation factors. regscan also produces optional heatmap plots within each of a set of selected 87 region(s) to visualize correlation within region and within/across LD bins; it annotates variant positions according to the LD-bin assignment. 88

89 **3** Usage case

In <u>Supplementary Information 3</u>, we demonstrate RegionScan capabilities and computational
efficiency by genome-wide analysis of 1,340 individuals with type 1 diabetes (T1D) from the

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DCCT/EDIC<sup>22,23</sup> genetic study for LDL-cholesterol (LDL-c, measured at baseline). Fig. 1 gives
 an overview of RegionScan capabilities based on the results for chr19. In <u>Supplementary</u>
 <u>Information 4</u>, we report computation time by sample size and region size based on a realistic
 test dataset.

# 96 Conclusion

97 RegionScan is a flexible and versatile R package designed for scalable and comprehensive 98 genome-wide region-level analysis that leverages region definition adaptive to local LD structure 99 (or any other user-provided region definition). It implements multiple region-level tests sensitive 100 to heterogeneous genetic architecture, including LD-bin reduced-df region-level tests, facilitates 101 comparisons of region-level and single-variant test results, and includes options to deal with high 102 dimensionality and multi-collinearity arising from improving resolution of 103 genotyped/sequenced/imputed genetic data. Modular design is flexible for future developments.

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none declared.

## 108 Software, code and data availability

109 The R package RegionScan (<u>https://github.com/brossardMyriam/RegionScan</u>) is available on 110 GitHub and includes a vignette on how to install and run RegionScan in a realistic artificial 111 dataset provided. The DCCT/EDIC data are available to authorized users at

#### 112 <u>https://repository.niddk.nih.gov/studies/edic/</u>

#### 113 and <u>https://www.ncbi.nlm.nih.gov/projects/gap/cgi-bin/study.cgi?study\_id=phs000086.v3.p1</u>

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- 120 https://docs.computecanada.ca/wiki/Niagara#Niagara\_hardware\_specifications
- 121 and https://docs.scinet.utoronto.ca/index.php/Niagara\_Quickstart.

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**Fig. 1.** Overview of *RegionScan* for genome-wide region-level association analysis of LDL-c at baseline in 1,340 individuals from the DCCT/EDIC<sup>22,23</sup> Genetics Study of the Usage case study. 133 134 Details of analysis are described in Supplementary Information 3. To facilitate visualization 135 136 of the results, we illustrate results on chr19 which exhibits genome-wide region-level association 137 signals at the region- and variant-levels. Panel (A) illustrates a comparison between region-level 138 association results based, for example, on the MLC test (top panel) with single-SNP results 139 (bottom panel) for 89,001 regions analyzed genome-wide; the dotted lines indicate the genome-140 wide Bonferroni-corrected significance levels: 5.6E-7 for region-level tests (top panel) and 5E-8 141 (bottom panel) for single-SNP tests. Panel (B) illustrates partitioning results for 13 regions in 142 chr19: 45,257,201-45,436,657bp; gene positions are shown in GRCh37. The blocks are delimited 143 by triangles. Panel (C) illustrates comparison of results for multiple region-level tests for the 144 same 13 regions as illustrated in Panel (B); changes in grey shading facilitate visualization of 145 region boundaries. Panel (**D**) shows the LD bins constructed for the MLC test within the top 146 LDL-c associated region, overlapping APOE gene (chr19: region #1690, chr19:45,385,759-147 45,415,935). The left panel shows the heatmap of the SNP correlation matrix (with SNPs ordered 148 by position within LD bin, and LD bins ordered by number of SNPs assigned); the right panel 149 shows the SNP positions (X axis) along the LD bins (Y axis).

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chr19(bp)

# D.

A.



<b>1</b>
1 225
1 0.07-0.17
1 0290290.1+0.120.19
1 0.9 0.270.22-0.1-0.130.18
1 -0.1 -0.1 0.31 -0.170.1+0.0+0.08
1 0.070.150.160.23-0.190.070.190.09
1 053 0.1-0.240.25 0 -0.3-0.160.140.6
Correlation
1 0.8 0.8 0.1+0.1>0.0=0.0=0.0=0.1>0.1>0.0=0.0=0.0=0.0=0.0=0.0=0.0=0.0=0.0=0.0
1 0.45 0.35 0.34 0.37 0.21 0.39-0.060.1+0.120.220.180.070.35 0.59
<b>1 0.85</b> 0.39 0.59 0.58 0.28 0.32 0.31-0.090.120.140.25-0.2-0.080.25 0.46
1 0.170.140.110.130.130.040.55-0.050.050.140.140.150.250.150.030.55
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<b>1 0.87 0.7 0.99-0.14 0.14 0.14 0.14 0.12 0.54 0.22 0.56 0.14 0.15 0.3 0.26 0.15 0.00 62</b>
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