

1  
2       **SeqBreed: a python tool to evaluate genomic prediction in complex scenarios**

3       **M. Pérez-Enciso<sup>1,2</sup>, L. C. Ramírez-Ayala<sup>1</sup>, L.M. Zingaretti<sup>1,3</sup>**

4

5       <sup>1</sup> Centre for Research in Agricultural Genomics (CRAG), CSIC-IRTA-UAB-UB, 08193

6       Bellaterra, Barcelona, Spain

7       <sup>2</sup> ICREA, Passeig de Lluís Companys 23, 08010 Barcelona, Spain

8       <sup>3</sup> Universidad Nacional de Villa María, IAPBCyA- IAPCH Villa María, Córdoba, Argentina

9

10      Corresponding author:

11      M. Pérez-Enciso

12      Centre for Research in Agricultural Genomics (CRAG)

13      08193 Bellaterra, Barcelona, Spain

14      Email: [miguel.perez@uab.es](mailto:miguel.perez@uab.es)

15

16      **Keywords:** Forward Simulation, Genomic Prediction, Quantitative Trait Locus.

17

18

19 **Abstract**

20 **Background:** Genomic Prediction (GP) is the procedure whereby molecular information is used  
21 to predict complex phenotypes. Although GP can significantly enhance predictive accuracy, it  
22 can be expensive and difficult to implement. To help in designing optimum experiments,  
23 including genome wide association studies and genomic selection experiments, we have  
24 developed SeqBreed, a generic and flexible python3 forward simulator.

25 **Results:** SeqBreed accommodates sex and mitochondrion chromosomes as well as  
26 autopolyplodity. It can simulate any number of complex phenotypes determined by any number  
27 of causal loci. SeqBreed implements several GP methods, including single step GBLUP. We  
28 demonstrate its functionality with Drosophila Genome Reference Panel (DGRP) sequence data  
29 and with tetraploid potato genotypes.

30 **Conclusions:** SeqBreed is a flexible and easy to use tool appropriate for optimizing GP or  
31 genome wide association studies. It incorporates some of the most popular GP methods and  
32 includes several visualization tools. Code is open and can be freely modified. Software,  
33 documentation and examples are available at <https://github.com/miguelperezenciso/SeqBreed>.

34 - - -

35 **Background**

36 Genomic prediction (GP) is the procedure whereby molecular information is used to predict  
37 complex phenotypes. The discovery of high-throughput single nucleotide polymorphisms (SNP)  
38 genotyping in a cost-effective manner has made GP to become a standard tool in the analysis and  
39 improvement of complex traits [1]. GP has revolutionized breeding programs in plants and  
40 animals, and GP methods are nowadays widely employed in human genetics or ecology.  
41 Nevertheless, GP is expensive and can be difficult to implement in practical scenarios, due in  
42 part to the difficulty of optimizing genotyping strategies and to the uncertainty on the genetic  
43 basis of complex traits. It is highly advisable then to evaluate its potential advantages and  
44 expected performance in advance. Unfortunately, GP accuracy depends on a number of factors  
45 that are impossible to assess analytically; in these situations, simulation is the most reliable  
46 option. Here we present a versatile python3 forward simulation tool, SeqBreed, to evaluate GP  
47 performance in generic scenarios and any genetic architecture (i.e., number of loci, genic action  
48 and number of traits).

49

50 SeqBreed is inspired by previous pSBVB fortran software [2], but the whole code has been  
51 rewritten in python3 and many new options have been added. Python can be much slower than  
52 compiled languages, but is much easier and friendlier to use, allowing direct interaction with the  
53 user to, e.g., make plots or control selection and breeding. Besides, many libraries in python such  
54 as ‘numpy’ XX or ‘pandas’ XX are wrappers on compiled languages such that careful  
55 programming significantly alleviates native python slowness. SeqBreed is then much more  
56 versatile than pSBVB and incorporates many new options, such as Genome Wide Association  
57 Studies (GWAS) or Principal Component Analysis (PCA). Most importantly, it allows automatic  
58 implementation of standard genomic selection procedures. SeqBreed usage details and main  
59 features are described in the following paragraphs and in the accompanying GitHub site  
60 <https://github.com/miguelperezenciso/SeqBreed>.

61

## 62 **Implementation**

63 SeqBreed is programmed in python3 using an object-oriented paradigm. The main classes are:

- 64 • Population: This class contains the main attributes for running selection experiments and  
65 is a container for Individual objects. It includes methods to add new individuals generated  
66 by mating two parents or randomly shuffling founder genomes in order to increase the  
67 number of base population animals (see [3]). It also prints basic population data and do  
68 summary plots.
- 69 • Individual: It allows generation, manipulation and printing of individual genotypes and  
70 phenotypes. Internally, an individual’s genome is represented by contiguous non  
71 recombining blocks rather than by the list of all SNP alleles, which allows dramatic  
72 savings in memory and increases in efficiency (see Figure 1 in Pérez-Enciso et al. [3]).
- 73 • Genome: All genome characteristics are stored and can be accessed by methods in this  
74 class. It specifies ploidy, number and class of chromosomes, recombination rates or SNP  
75 positions
- 76 • GFounder: SeqBreed requires as minimum input the genotypes of the so-called ‘founder  
77 population’, which makes the parents of the rest of individuals to be generated. This class  
78 stores these genotypes and automatically retrieves main genome features such as SNP  
79 positions, number of chromosomes, etc. Initial genotypes can be filtered by minimum  
80 allele frequency (MAF).

81     • QTNs: Determines genetic architecture for every phenotype. It has methods to determine  
82         environmental variance given desired heritability, and to plot QTN variance components.  
83         So far, SeqBreed allows for dominance and additive actions, but not epistasis.  
84     • Chip: This class is basically a container for a list of SNPs included in a genotyping array.  
85         It allows easy specification of different genomic selection strategies.

86

87     SeqBreed minimally requires a genotype file from base population in vcf [4] or plink-like format  
88     [5]. A file with causative SNPs (QTNs) and their effects for each trait can be provided or  
89     simulated. Sex and mitochondria chromosomes can be accommodated as well as auto polyploidy  
90     of any level. Local and / or sex-specific recombination rates can be specified in a map file.  
91     Otherwise a ratio 1cM = 1 Mb is assumed. SeqBreed automatically adjusts environmental  
92     variance to retrieve desired heritabilities for each trait.

93

94     The generic SeqBreed flowchart can be visualized in Figure 1 whereas examples of SeqBreed  
95     usage are in the GitHub's jupyter notebook  
96     [https://github.com/miguelperezenciso/SeqBreed/blob/master/SeqBreed\\_tutorial.ipynb](https://github.com/miguelperezenciso/SeqBreed/blob/master/SeqBreed_tutorial.ipynb) and in the  
97     python script <https://github.com/miguelperezenciso/SeqBreed/blob/master/main.py>. A typical  
98     SeqBreed run consists of at least the following steps:

99

100     1- Upload founder sequence genotypes and a GFounder object is created. A file with all  
101         SNP positions in sequence is generated.  
102     2- Initialize Genome class. Optionally, sex or mitochondrial chromosomes are specified as  
103         well as local recombination maps.  
104     3- Genetic architectures for every trait are specified via a QTNs object. Environmental  
105         variances are also inferred.  
106     4- A Population object is generated, optionally via gene-dropping along a predetermined  
107         pedigree.

108

109     Once Population is initialized, SeqBreed allows a number of operations to be performed, such as  
110         implementing several selection procedures, detailed below. At any stage, PCA plots or GWAS  
111         can be performed. Several statistics can be extracted using the methods in each class. Selection

112 can be automatically configured and run, as documented in the GitHub examples  
113 (<https://github.com/miguelperezenciso/SeqBreed>). From a methodologically point of view, most  
114 GP implementations are based on penalized linear methods (e.g., de los Campos *et al.*, 2013).  
115 SeqBreed has built-in some of the GP most popular options, such as BLUP [7], GBLUP [8] and  
116 single-step [9]; mass selection is also implemented. SeqBreed allows other custom GP methods  
117 to be easily incorporated. This would require writing a specific python function or exporting  
118 molecular data from SeqBreed, running a genetic evaluation externally and importing estimated  
119 breeding values. Any number of complex phenotypes can be simulated, allowing a very flexible  
120 modeling of phenotypes in diploids or auto-polyploids. The program can be run along a  
121 predetermined pedigree or a combination of options (several examples are provided in the  
122 GitHub site). Generating new individuals interactively is also possible. To speed up  
123 computations and to avoid unnecessary memory usage, only recombination breaks and ancestor  
124 haplotype ids are stored for each individual [10].

125

126 It is usually difficult to find real sequence data to generate a reasonably sized founder population.  
127 An interesting feature of SeqBreed is the possibility of generating ‘dummy’ founder individuals  
128 by randomly combining recombinant haplotypes. This can be done in two ways, either  
129 generating a random pedigree and simulating a new founder individual by gene-dropping along  
130 this pedigree, or directly simulating a number of recombining breakpoints and assigning random  
131 founder genotypes to each block between recombination breakpoints  
132 (<https://github.com/miguelperezenciso/SeqBreed/blob/master/README.md#breeding-population>).  
133

134

## 135 Examples

136 The basic functioning of SeqBreed is illustrated by the main.py script, available at  
137 <https://github.com/miguelperezenciso/SeqBreed/blob/master/main.py>. This script, or its  
138 equivalent jupyter notebook ([SeqBreed\\_tutorial.ipynb](#)), show the basic commands to run  
139 SeqBreed and its dependencies.

140

141 A useful and novel feature of SeqBreed, as compared to our previous software pSBVB, is the  
142 capability of graphical outputs. Figure 2 illustrates some of the plots that can be performed

143 automatically. Figure 2A shows the results of QTNs.plot() function, which plots the individual  
144 QTN variance as a function of allele frequency (MAF), the histogram of QTN variances or the  
145 cumulative variance when QTNs are sorted by MAF. This is performed for each phenotype and  
146 for both additive and dominant variances. Additionally, PCA plots using all sequence or custom  
147 defined SNP sets (Figure 2B) or GWAS plots showing p-values or False Discovery Rate (FDR)  
148 values (Figure 2C) are also available. Raw data can also be exported.

149

150 Further, we illustrate the software with sequence data from the Drosophila Genome Reference  
151 Panel (DGRP, [11]), parsed and filtered as detailed in [12], and genotype data from tetraploid  
152 potato [13], parsed as described in [2]. Data and scripts are in  
153 <https://github.com/miguelperezenciso/SeqBreed/tree/master/DGRP> and in  
154 <https://github.com/miguelperezenciso/SeqBreed/tree/master/POTATO> for DGRP and potato  
155 examples, respectively. DGRP scripts allow us to illustrate the specific recombination map of  
156 Drosophila, where males do not recombine, as shown in the ‘dgrp.map’ file. The example  
157 provided in GitHub consists of a small experiment to compare genomic and mass selection. Plots  
158 in the jupyter notebook are implemented to track phenotypic changes by generation. Potato data  
159 is used to illustrate how to generate a F2 cross between extreme lines and to perform a GWAS  
160 experiment in polyploids. GWAS results using PCA corrected phenotypes are also shown.

161

## 162 **Conclusions and Future Developments**

163 Other programs can be used for similar purposes as SeqBreed, including our own pSBVB [2], or  
164 AlphaSim [14] and its successor AlphaSimR (<https://alphagenes.roslin.ed.ac.uk/wp/software-2/alphasimr/>), PedigreeSim [15], simuPOP [16] or QMSim [18]. SeqBreed, however, offers a  
165 unique combination of useful features for GP studies of complex traits, such as built-in  
166 implementation of several GP methods, possibility of simulating polyploid genomes, and several  
167 options to specify QTNs or SNP arrays. It also allows generating new individuals interactively  
168 and doing graphical plots. It is easy to use, easy to install and software options are illustrated  
169 with several examples in the GitHub site. Given the interactive nature of python and its graphical  
170 features, SeqBreed is especially suited for education purposes. In contrast, SeqBreed will not be  
171 as efficient for large scale simulations as some fortran counterparts such as AlphaSim or pSBVB.

173

174 Note that SeqBreed is conceived to evaluate GP or GWAS performances over a short time span,  
175 i.e., new mutations are not generated. To investigate realistic scenarios, the recommended input  
176 is real sequence data. SeqBreed is not designed to investigate the long term effects of  
177 demography or selection on DNA variability, where Slim [17] or similar tools are more  
178 appropriate.

179

180 For the future, we plan to include additional features to generalize available genetic architectures  
181 (e.g., imprinting, epistasis), to make integration with machine learning tools (scikit, keras) easier,  
182 to develop an educational tool with html-based interface, and improving output and plotting  
183 features.

184

## 185 **Availability and requirements**

186 Project name: SeqBreed

187 Project home page: <https://github.com/miguelperezenciso/SeqBreed>

188 Operating systems: Tested in linux and mac. It should also run in windows python.

189 Programming language: Python.

190 License: GNU GPLv3

191 Any restrictions to use by non-academics: None.

192

## 193 **List of abbreviations**

194 BLUP: Best Linear Unbiased Prediction

195 FDR: False Discovery Rate

196 GBLUP: Genomic BLUP

197 GP: Genomic Prediction

198 GWAS: Genome Wide Association Study

199 MAF: Minimum Allele Frequency

200 SNP: Single Nucleotide Polymorphism

201 QTN: Quantitative Trait Nucleotide polymorphism

202

## 203 **Declarations:**

### 204 **Ethics approval and consent to participate**

205 Not applicable

206 **Consent for publication**

207 Not applicable

208 **Availability of data and materials**

209 <https://github.com/miguelperezenciso/SeqBreed>

210 **Competing interests**

211 None declared.

212 **Funding**

213 This work was supported by a PhD grant from the Ministry of Economy and Science (MINECO,  
214 Spain) to LMZ, by MINECO grant AGL2016-78709-R and from the EU through the BFU2016-  
215 77236-P (MINECO/AEI/FEDER, EU) to MPE and the "Centro de Excelencia Severo Ochoa  
216 2016-2019" award SEV-2015-0533. LCRA is funded by "Don Carlos Antonio López" Graduate  
217 program (BECAL) from Paraguay.

218

219 **Authors' contributions**

220 MPE conceived research. MPE and LMZ wrote software and documentation. LCRA tested and  
221 validated the program.

222

223 **References**

224 1. Meuwissen T, Hayes B, Goddard M. Accelerating Improvement of Livestock with Genomic  
225 Selection. *Annu Rev Anim Biosci.* 2013;1:221–37. doi:10.1146/annurev-animal-031412-103705.

226 2. Zingaretti ML, Monfort A, Pérez-Enciso M. pSBVB: A Versatile Simulation Tool To  
227 Evaluate Genomic Selection in Polyploid Species. *G3 (Bethesda)*. 2019;9:327–34.

228 doi:10.1534/g3.118.200942.

229 3. Pérez-Enciso M, Forneris N, de Los Campos G, Legarra A. Evaluating Sequence-Based  
230 Genomic Prediction with an Efficient New Simulator. *Genetics*. 2017;205:939–53.

231 doi:10.1534/genetics.116.194878.

232 4. Li H, Handsaker B, Wysoker A, Fennell T, Ruan J, Homer N, et al. The Sequence  
233 Alignment/Map format and SAMtools. *Bioinformatics*. 2009;25:2078–9.

234 doi:10.1093/bioinformatics/btp352.

235 5. Chang CC, Chow CC, Tellier LC, Vattikuti S, Purcell SM, Lee JJ. Second-generation PLINK:

236 rising to the challenge of larger and richer datasets. *Gigascience*. 2015;4:7. doi:10.1186/s13742-  
237 015-0047-8.

238 6. de los Campos G, Hickey JM, Pong-Wong R, Daetwyler HD, Calus MPL. Whole-genome  
239 regression and prediction methods applied to plant and animal breeding. *Genetics*.  
240 2013;193:327–45.

241 7. Henderson CR. Applications of linear models in animal breeding. Guelph; 1984.

242 8. VanRaden PM. Efficient methods to compute genomic predictions. *J Dairy Sci*.  
243 2008;91:4414–23. doi:10.3168/jds.2007-0980.

244 9. Legarra A, Aguilar I, Misztal I. A relationship matrix including full pedigree and genomic  
245 information. *J Dairy Sci*. 2009;92:4656–63. doi:10.3168/jds.2009-2061.

246 10. Pérez-Enciso M, Varona L, Rothschild MF. Computation of identity by descent probabilities  
247 conditional on DNA markers via a Monte Carlo Markov Chain method. *Genet Sel Evol*.  
248 2000;32:467. doi:10.1186/1297-9686-32-5-467.

249 11. Huang W, Massouras A, Inoue Y, Peiffer J, Ràmia M, Tarone AM, et al. Natural variation in  
250 genome architecture among 205 *Drosophila melanogaster* Genetic Reference Panel lines.  
251 *Genome Res*. 2014;24:1193–208. doi:10.1101/gr.171546.113.

252 12. Forneris NS, Vitezica ZG, Legarra A, Pérez-Enciso M. Influence of epistasis on response to  
253 genomic selection using complete sequence data. *Genet Sel Evol*. 2017;49:66.

254 13. Enciso-Rodriguez F, Douches D, Lopez-Cruz M, Coombs J, de Los Campos G. Genomic  
255 Selection for Late Blight and Common Scab Resistance in Tetraploid Potato (*Solanum*  
256 *tuberosum*). *G3 (Bethesda)*. 2018;8:2471–81. doi:10.1534/g3.118.200273.

257 14. Faux A-M, Gorjanc G, Gaynor RC, Battagin M, Edwards SM, Wilson DL, et al. AlphaSim:  
258 Software for Breeding Program Simulation. *Plant Genome*. 2016;9:0.  
259 doi:10.3835/plantgenome2016.02.0013.

260 15. Voorrips RE, Maliepaard CA. The simulation of meiosis in diploid and tetraploid organisms  
261 using various genetic models. *BMC Bioinformatics*. 2012;13:248. doi:10.1186/1471-2105-13-  
262 248.

263 16. Peng B, Kimmel M. simuPOP: A forward-time population genetics simulation environment.  
264 *Bioinformatics*. 2005;21:3686–7. doi:10.1093/bioinformatics/bti584.

265 17. Messer PW. SLiM: simulating evolution with selection and linkage. *Genetics*.  
266 2013;194:1037–9. doi:10.1534/genetics.113.152181.

267 18. Sargolzaei, M., & Schenkel, F. S. (2009). QMSim: A large-scale genome simulator for  
268 livestock. *Bioinformatics*, 25(5), 680–681. <http://doi.org/10.1093/bioinformatics/btp045>

269

270 **Figure legends**

271 **Fig. 1: Outline of SeqBreed typical pipeline.** Inputs are shown in magenta boxes, violet boxes  
272 are internal data, main operations are indicated in dark blue, and the output plots are in red (QTN  
273 variances, GWAS and PCA are shown);  $\mathbf{G}$  and  $\mathbf{y}$  refer to genotypes and phenotypes,  
274 respectively. The bottom loop represents selection, where new offspring is generated based on  
275 merit of selected parents. SeqBreed implements random drift, mass selection (Y), BLUP, GBLU  
276 and single-step GBLUP (SS-GBLUP). In the latter two cases, a list of SNPs in the genotyping  
277 array must be determined. A new cycle starts when these new offspring are added to current  
278 population. Plots can be performed at several stages.

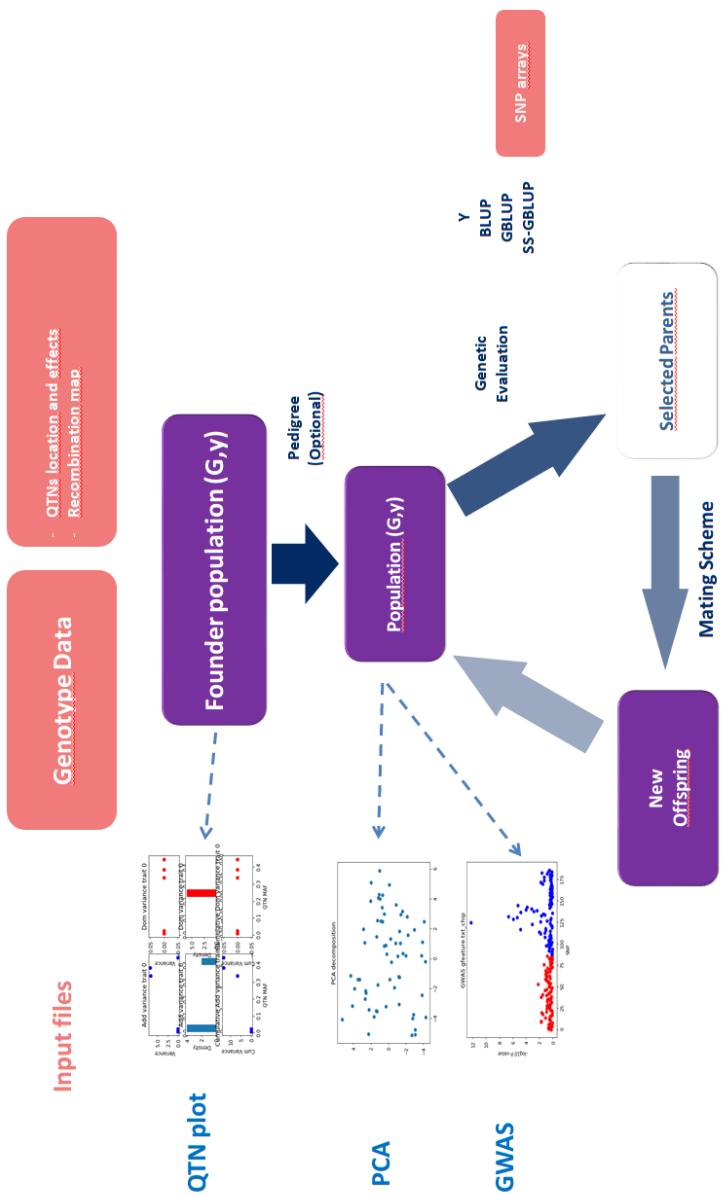
279

280 **Fig 2: Some plots produced by SeqBreed.** **A)** Contribution of each QTN to total variance. Top,  
281 individual QTN variances as a function of minimum allele frequency (MAF); middle, histogram  
282 of QTN variances; bottom, cumulative variance when QTNs are sorted by MAF. In blue,  
283 additive variances; in red, dominance variances. The figure shows a fully additive phenotype so  
284 dominance variance is zero. **B)** Principal Component Analysis plot; individuals of different  
285 generations are in different color. **C)** Genome wide association study showing False Discovery  
286 Rate values (-log10 scale). SNPs from each successive chromosome are represented in alternate  
287 colors.

288

11

289 **Fig. 1: Outline of SeqBreed typical pipeline.** Inputs are shown in magenta boxes, violet boxes are internal data, main operations are  
290 indicated in dark blue, and the output plots are in red (QTN variances, GWAS and PCA are shown); **G** and **y** refer to genotypes and  
291 phenotypes, respectively. The bottom loop represents selection, where new offspring is generated based on merit of selected parents.  
292 SeqBreed implements random drift, mass selection (**Y**), BLUP, GBLUP and single-step GBLUP (SS-GBLUP). In the latter two cases, a  
293 list of SNPs in the genotyping array must be determined. A new cycle starts when these new offspring are added to current population.  
294 Plots can be performed at several stages.  
295



296  
297

298 **Fig 2: Some plots produced by SeqBreed.** A) Contribution of each QTN to total variance. Top, individual QTN variances as a  
 299 function of minimum allele frequency (MAF); middle, histogram of QTN variances; bottom, cumulative variance when QTNs are  
 300 sorted by MAF. In blue, additive variances; in red, dominance variances. The figure shows a fully additive phenotype so dominance  
 301 variance is zero. B) Principal Component Analysis plot; individuals of different generations are in different color. C) Genome wide  
 302 association study showing False Discovery Rate values (-log10 scale). SNPs from each successive chromosome are represented in  
 303 alternate colors.

