

JULIUS-MAXIMILIANS UNIVERSITÄT WÜRZBURG

DOCTORAL THESIS

**Quantitative genetics - from genome
assemblies to neural network aided
omics based prediction of quantitative
traits**

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A thesis submitted in fulfillment of the requirements

for the degree of Ph.D.

in the

Research group for evolutionary genomics

GSLs

October 25, 2019

Declaration of Authorship

I, Jan Alexander FREUDENTHAL, declare that this thesis titled, “Quantitative genetics - from genome assemblies to neural network aided omics based prediction of quantitative traits” and the work presented in it are my own. I confirm that:

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- Where any part of this thesis has previously been submitted for a degree or any other qualification at this University or any other institution, this has been clearly stated.
- Where I have consulted the published work of others, this is always clearly attributed.
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“Wit beyond measure is man’s greatest treasure”

Rowena Rawenclaw

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Abstract

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Ph.D.

**Quantitative genetics - from genome assemblies to neural network aided omics
based prediction of quantitative traits**

by Jan Alexander FREUDENTHAL

The Thesis Abstract is written here (and usually kept to just this page). The page is kept centered vertically so can expand into the blank space above the title too...

Acknowledgements

The acknowledgments and the people to thank go here, don't forget to include your project advisor. . .

Contents

Declaration of Authorship	i
Abstract	iii
Acknowledgements	iv
1 Benchmarking of Chloroplast Genome Assembly tools	1
1.1 Introduction	1
1.2 Material and Methods	3
1.2.1 Methods	3
1.2.2 Tools	3
1.2.3 Evaluation	3
Quantitative	3
Qualitative	4
Consistency	4
1.2.4 Data	4
Simulated	4
Real data set	4
Novel data set	4
1.3 Results	4
1.3.1 Qualitative	4
1.3.2 Quantitative	4
Simulated data	4
Real data sets	5

Consistency	7
Real data sets	7
Novel	8
1.4 Discussion	9
2 Understanding the haplotype structure of <i>Arabidopsis thaliana</i>	10
2.1 Introduction	10
2.2 Haplotyping of <i>A. thaliana</i>	10
2.3 Results	10
2.4 Disucssion	10
3 GWAS-Flow a gpu-accelerated software for large-scale genome-wide association studies	17
3.1 Introduction	17
3.2 Methods	19
GWAS Model	19
The GWAS-Flow Software	19
Calculation of permutation-based thresholds for GWAS	20
Benchmarking	21
3.3 Results	22
3.4 Disucssion	23
4 Genomic prediction of phenotypic values of quantitative traits using Artificial neural networks	27
4.1 Introduction	27
4.1.1 A brief history of machine learning	27
Basic perceptron model	27
Activation functions	29
Gradient descent algorithm	32
Optimizers	34

Backpropagation	36
Regularization parameters	36
4.1.2 On the nature of quantitative traits	38
4.1.3 Artificial selection in plant and animal breeding in the ge- nomics era	42
4.1.4 Genomic selection using artificial neural networks	43
4.2 Proof of concept for ANN-based genomic selection	46
4.3 Material	48
4.3.1 DH populations derived from MAZE landraces	48
4.3.2 <i>A. thaliana</i>	48
4.4 Methods	48
4.4.1 ANN	48
4.4.2 GBLUP	48
4.5 Results	48
4.6 Discussion	48
5 GWAS	49
5.1 Reevaluation of 463 phenotypes from the AraPheno database	49
5.1.1 Introduction	49
5.1.2 Material and Methods	49
5.1.3 Results	49
5.1.4 Results	49
5.1.5 Disucssion	49
5.2 GWAS in DH landrace populatios of maze across and within environ- ments	49
5.2.1 Introduction	49
5.2.2 Material and Methods	49
5.2.3 Results	49
5.2.4 Results	49

5.2.5 Disucssion	49
A Source code GWAS-Flow	50
A.1 gwas.py	50
A.2 main.py	53
A.3 herit.py	58
Bibliography	60

List of Figures

1.1	Structure of a chloroplast genome	2
1.2	Score of assemblies of simulated data sets	4
1.3	Scores of assemblies from real data sets	6
1.4	Comparison between two runs with the same assembler for consistency testing	7
1.5	Upset plot comparing the success rates for novel data sets	8
1.6	Upset plot comparing the success rates of of all assemblers	9
2.1	Haplotype strutcure of chromosome 1 of <i>A. thaliana</i>	11
2.2	Haplotype strutcure of chromosome 2 of <i>A. thaliana</i>	12
2.3	Haplotype strutcure of chromosome 3 of <i>A. thaliana</i>	13
2.4	Haplotype strutcure of chromosome 4 of <i>A. thaliana</i>	14
2.5	Haplotype strutcure of chromosome 5 of <i>A. thaliana</i>	15
2.6	blabl	16
3.1	Computation time vs number of markers	23
3.2	Computations time vs accessions	24
3.3	Computational time of GWA Analyses on real <i>A. thaliana</i> data sets . .	26
4.1	Basic perceptron model	27
4.2	Schematic layout of a simple multi-layer perceptron	29
4.3	Popular activation functions for neural networks	30
4.4	Training vs. validation loss over time	37

List of Tables

1.1	Scores of assemblies of simulated data	5
1.2	Mean scores of chloroplast genome assemblers	5
4.1	Simple simulated phenotypes and genotypes for genomic prediction with genotypes $G_1 \dots G_4$, M_1 and M_2 and phenotypes based on addi- tive effects or <i>and</i> , <i>or</i> , <i>xor</i> logic gates.	46
4.2	Results of genomic prediction from phenotypes and genotypes in ta- ble 4.1	47

List of Abbreviations

Adadelata	Adaptive delta
Adagrad	Adaptive Gradient Algorithm
Adam	Adaptive Moment estimation
ANN	Artificial Neural Network
AUC	Area Under the Curve
BLUE	Best Linear Unbiased Estimator
BLUP	Best Linear Unbiased Predictor
BP	Base Pair
CPU	Core Processing Unit
DH	Doubled Haploid
DNA	DeoxyriboNucleic Acid
DNA	RiboNucleic Acid
EMMA	Efficient Mixed Model Associations
FCL	Fully Connected Layer
GBLUP	Genomic Best Linear Unbiased Predictor
GD	Gradient Descent
GP	Genomic Prediction
GPU	Graphical Processing Unit
GS	Genomic Selection
GUI	Graphical User Interface
GWAIS	Genome Wide Interaction Association Studies
GWAS	Genome Wide Association Studies
HDF	Hierarchical Data Format

IR	I nverted R epeat
LCL	L ocally C onnected L ayer
LD	L inkage D isequilibrium
LMM	L inear M ixed M odel
LSC	L arge S ingle C opy
MLP	M ulti L ayer P erceptron
ML	M achine L earning
MSE	M ean S quare E rror
Nadam	N esterov- a ccelerated A daptive M oment E stimation
NAG	N esterov A ccelerated M omentum
QTL	Q uantitative T rait L ocus
ReLU	R ectified L inear U nits
RKHS	R eproducing K ernel H ilbert S paces
RMSE	R oot M ean S quare E rror
RMSProp	R oot M ean S quare P ropagation
ROC	R eciever O perating C haracteristics
RSS	R esidual S um of S quares
SGD	S tochastic G radient D escent
SNP	S ingle N ucleotide P olymorphism
SSC	S mall S ingle C opy
TRN	T Rai N ing subset
TST	T e S Ting subset
WGS	W hole G enome S equencing
XOR	e Xclusive O R
MBP	M ega B ase P air

For/Dedicated to/To my...

1 Benchmarking of Chloroplast Genome Assembly tools

This chapter orientates on *Freudenthal et al., 2019b* only the chapters from the publication which the author majorly contributed to are included.

1.1 Introduction

Circular DNA of a size between 120 kBP to 160 kBP *Palmer, 1985*. First chloroplast sequenced as early as 1986 *Marchantia polymorpha* and *Nico Ohyama et al., 1986*; *Shinozaki et al., 1986*. Review genome structure *Green, 2011*; *Wicke et al., 2011*. Chloroplast genomes widely used in evolutionary studies *Martin et al., 2002*; *Xiao-Ming et al., 2017*. Chloroplast genomes are small through endosymbiotic gene transfer *Martin et al., 2002*; *Deiner et al., 2017*. Up to 14 % of the the core genome of *Arabidopsis thaliana* is made up of genes previously from the chloroplast (fancy citation), while 100-120 genes remain on the chloroplast *Wicke et al., 2011*. However chloroplast between plant species show large variety e.g. parasitic plants. Chloroplast genomes are much smaller than core genomes e.g. *A. thaliana* ca. 125 MBP. Highly conserved high gene content, therefore changes are more likely to be functional. Single chloroplast contain up to hundreds of copies of its genome *Kumar, Oldenburg, and Bendich, 2014*; *Bendich, 1987*, and photosynthetic activate cells contain multiple chloroplasts, therefore the copy number of chloroplast genomes is much higher than number of core genomes per cell. Structurally chloroplast genomes consist of two inverted repeats (IR) - IR_A and IR_B - ranging from 10 kbp to 76 kB the divide the chloroplast

genome into two distinct regions the large single copy (LSC) and the small single copy (SSC) as shown in 1.1 Palmer, 1985. Taking into account that the majority of assembly tools has been designed to assemble linear core genomes, the structure of chloroplast genomes is a major obstacle when wanting to assemble those genomes with modern short read technologies, especially solving and aligning the IR Wang et al., 2018.

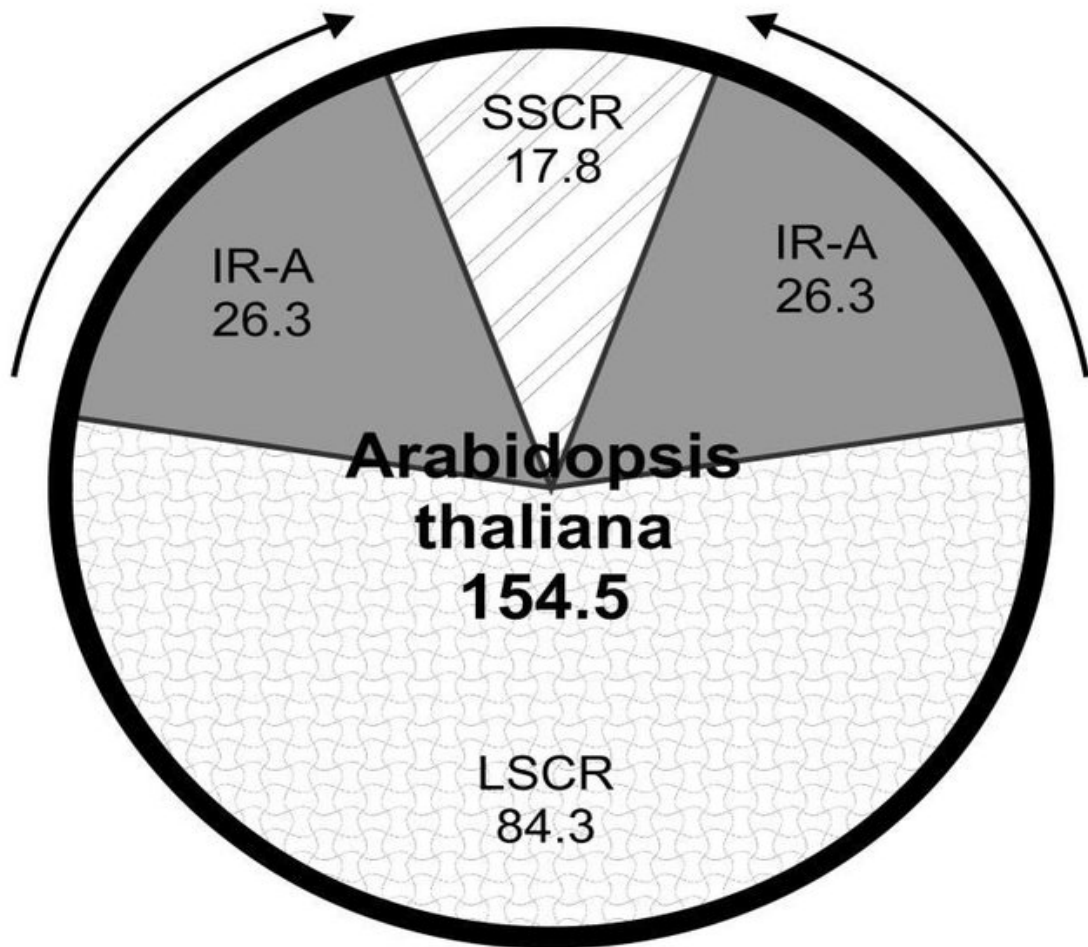


FIGURE 1.1: Structure of the chloroplast genome of *A. thaliana* with SSC-Region and LSC-Region. Length of the genome and its parts in kbp.

1.2 Material and Methods

1.2.1 Methods

1.2.2 Tools

1.2.3 Evaluation

Quantitative

$$score = \frac{1}{4} \cdot \left(cov_{ref} + cov_{qry} + \min \left\{ \frac{cov_{qry}}{cov_{ref}}, \frac{cov_{ref}}{cov_{qry}} \right\} + \frac{1}{n_{contiguous}} \right) \cdot 100 \quad (1.1)$$

Qualitative

Consistency

1.2.4 Data

Simulated

Real data set

Novel data set

1.3 Results

1.3.1 Qualitative

1.3.2 Quantitative

Simulated data

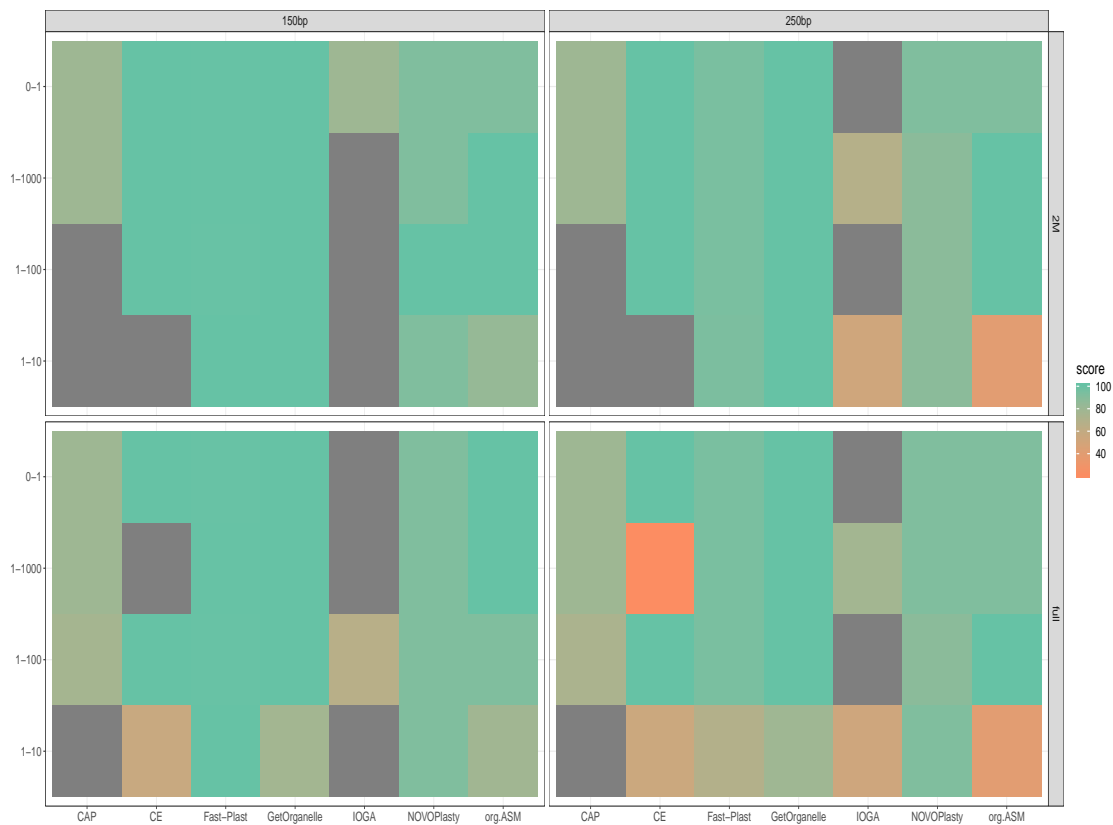


FIGURE 1.2: Results of assemblies executed with simulated data sets.

TABLE 1.1: Scores of assemblies of simulated data

	data set	CAP	CE	Fast-Plast	GetOrganelle	IOGA	NOVOPlasty
1	sim_150bp.0-1	79.10	100.00	99.48	100.00		91.52
2	sim_150bp.0-1.2M	79.10	100.00	99.72	100.00	79.10	91.52
3	sim_150bp.1-10		56.44	100.00	76.98		91.52
4	sim_150bp.1-10.2M			99.97	100.00		91.52
5	sim_150bp.1-100	75.72	100.00	99.48	100.00	66.09	91.52
6	sim_150bp.1-100.2M		100.00	99.47	100.00		100.00
7	sim_150bp.1-1000	79.10		99.72	100.00		91.52
8	sim_150bp.1-1000.2M	79.10	100.00	99.72	100.00		91.52
9	sim_250bp.0-1	79.10	100.00	93.82	100.00		91.52
10	sim_250bp.0-1.2M	79.10	100.00	93.83	100.00		91.52
11	sim_250bp.1-10		54.98	68.45	78.89	52.71	91.52
12	sim_250bp.1-10.2M			93.00	100.00	52.67	87.40
13	sim_250bp.1-100	72.81	100.00	93.82	100.00		87.40
14	sim_250bp.1-100.2M		100.00	93.83	100.00		87.40
15	sim_250bp.1-1000	79.10	21.30	93.83	100.00	76.96	91.52
16	sim_250bp.1-1000.2M	79.10	100.00	93.83	100.00	67.55	87.40

Real data sets

TABLE 1.2: Mean scores of chloroplast genome assemblers

	assembler	Median	IQR	N_perfect	N_tot
1	CAP	45.25	50.19	0	369
2	CE	56.55	71.50	14	369
3	Fast-Plast	92.80	23.59	113	369
4	GetOrganelle	99.83	20.94	210	360
5	IOGA	71.10	11.21	0	338
6	NOVOPlasty	75.95	48.69	58	369
7	org.ASM	67.35	91.69	46	348

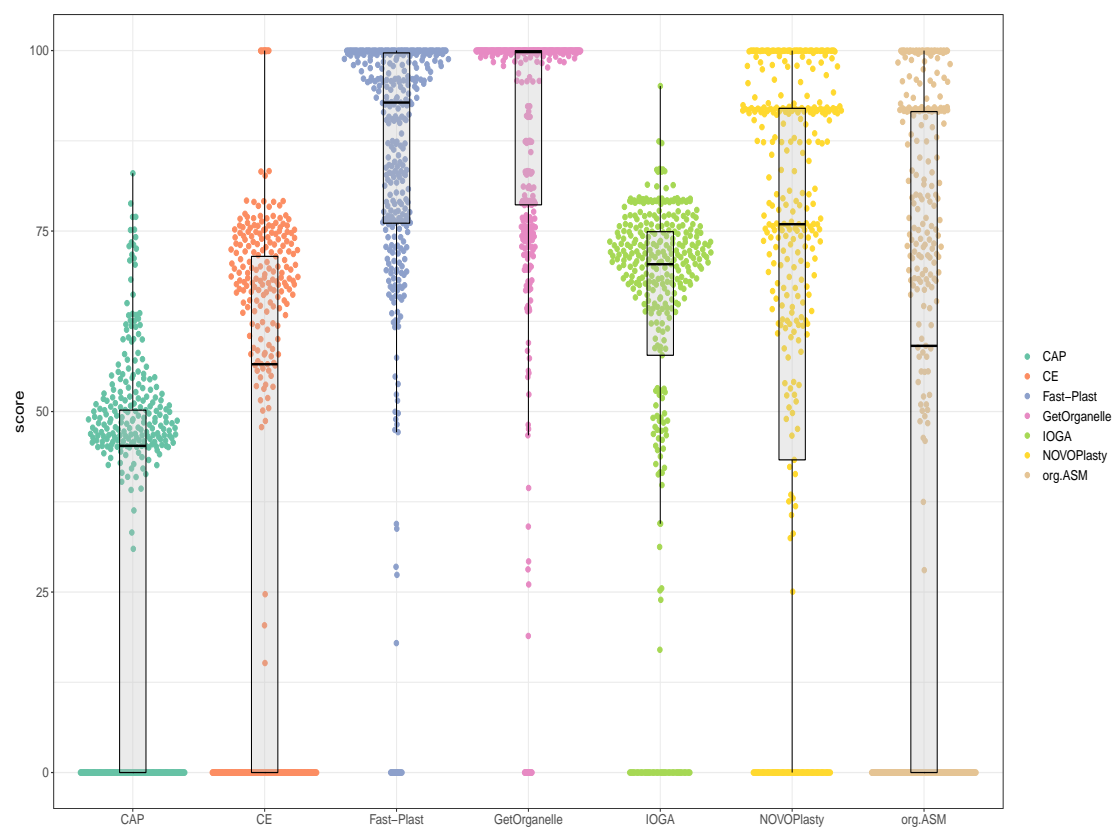


FIGURE 1.3: Box and swarm plots depict the results from the scoring shown in 1.1

Consistency

Real data sets

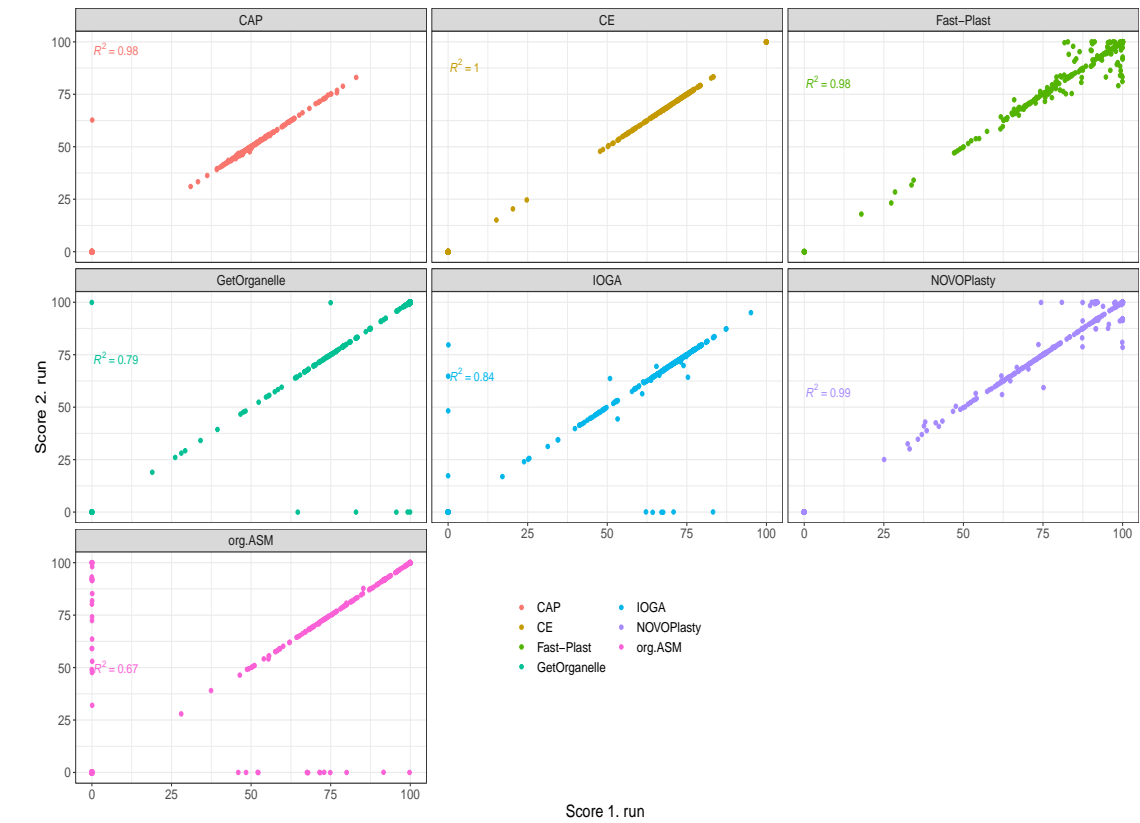


FIGURE 1.4: Swarm plots depict the results from the scoring shown in 1.1 for two independent runs for each assembler on each of the data sets

Novel

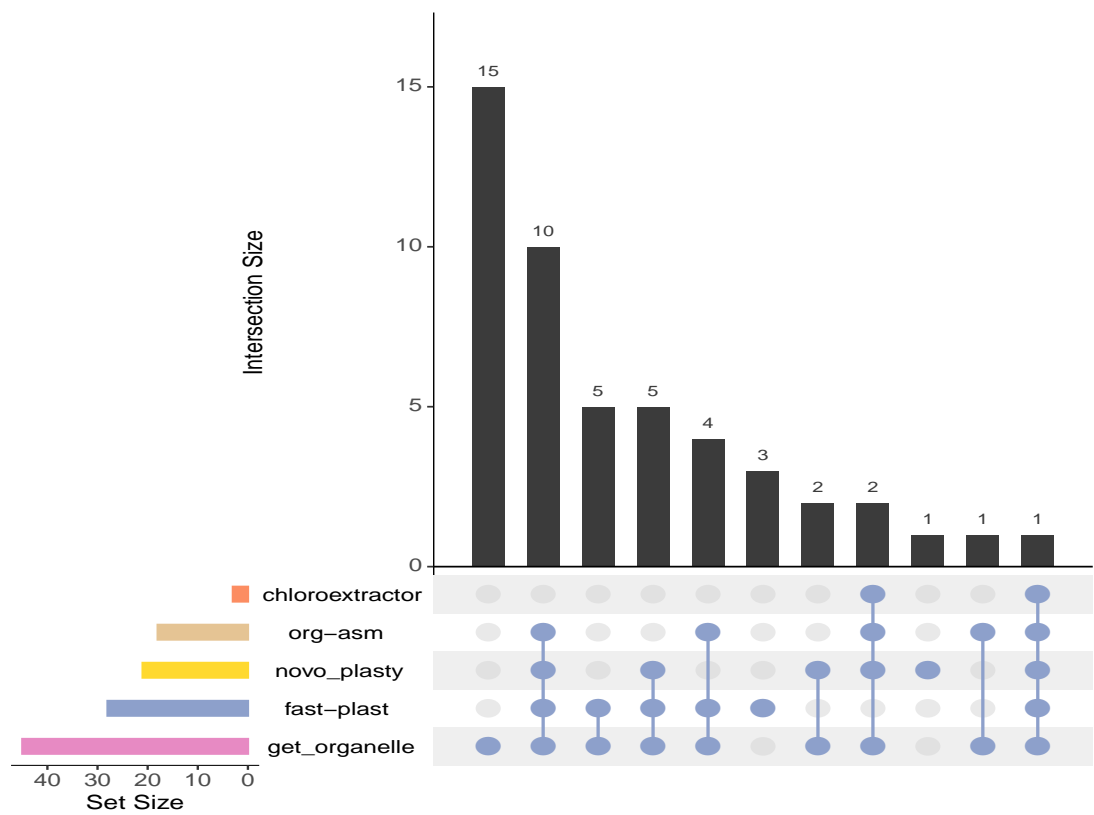


FIGURE 1.5: nls

1.4 Discussion

FIGURE 1.6: Upset plot showing the intersections of success rates between assemblers. A successful assembly was defined with a score > 99 according to equation 1.1

2 Understanding the hapoltype structure of Arabidopisis thaliana

2.1 Introduction

2.2 Haplotyping of A. thaliana

2.3 Results

2.4 Disucssion

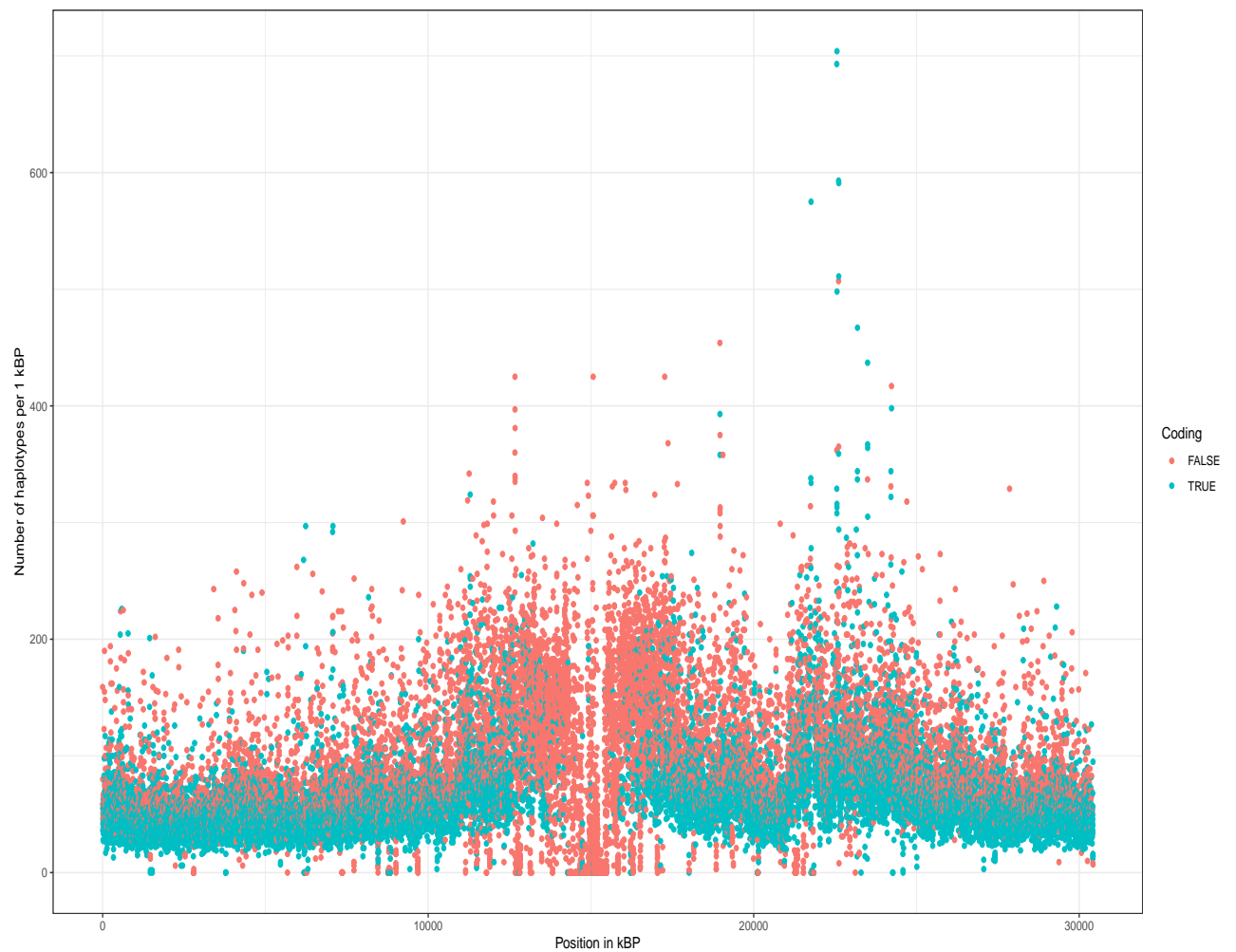


FIGURE 2.1: The number of segregating haplotypes with a polymorphism in at least one position over a stretch of 1 kBP.

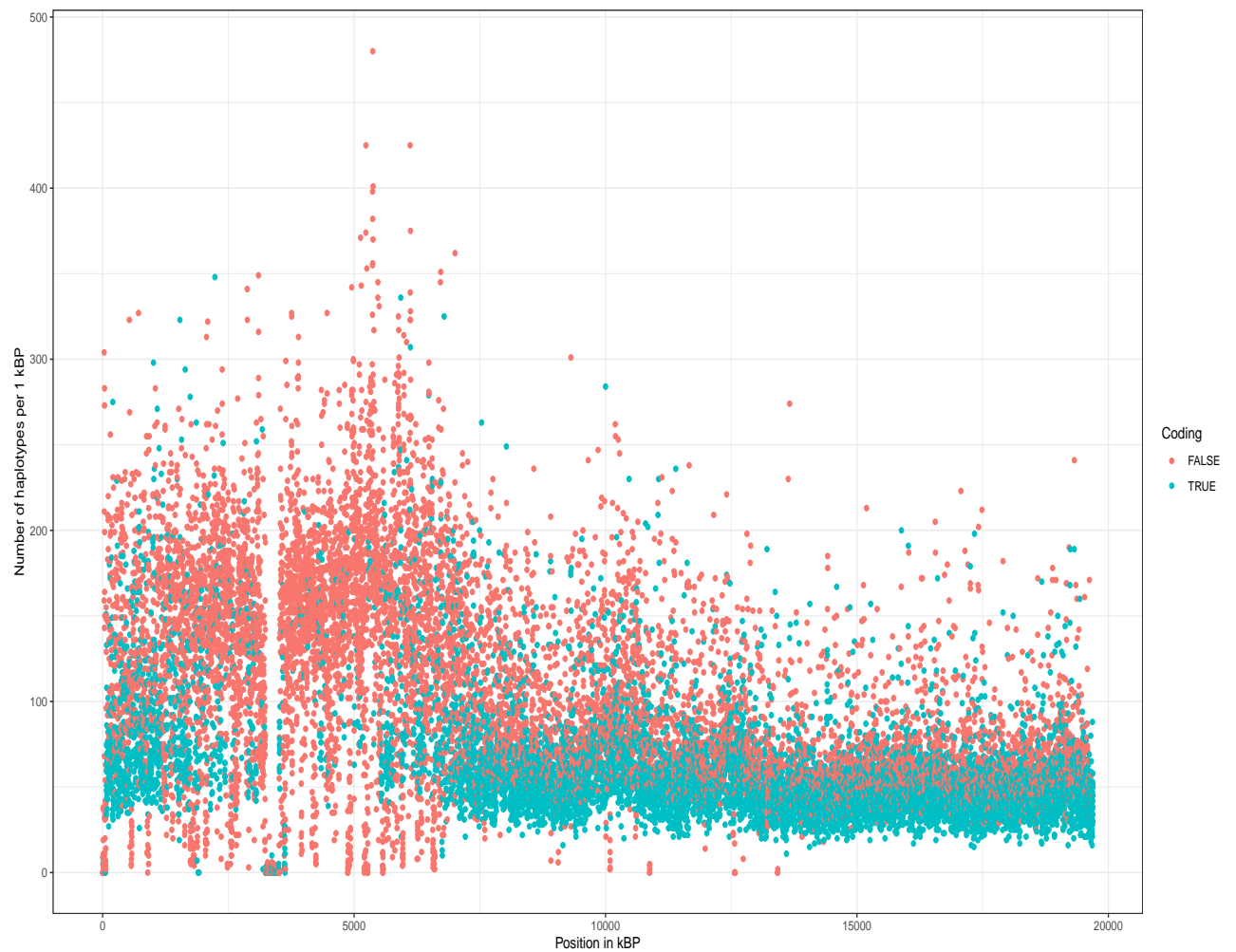


FIGURE 2.2: Number of segregating haplotypes with a polymorphism in at least one position over a stretch of 1 kBP.

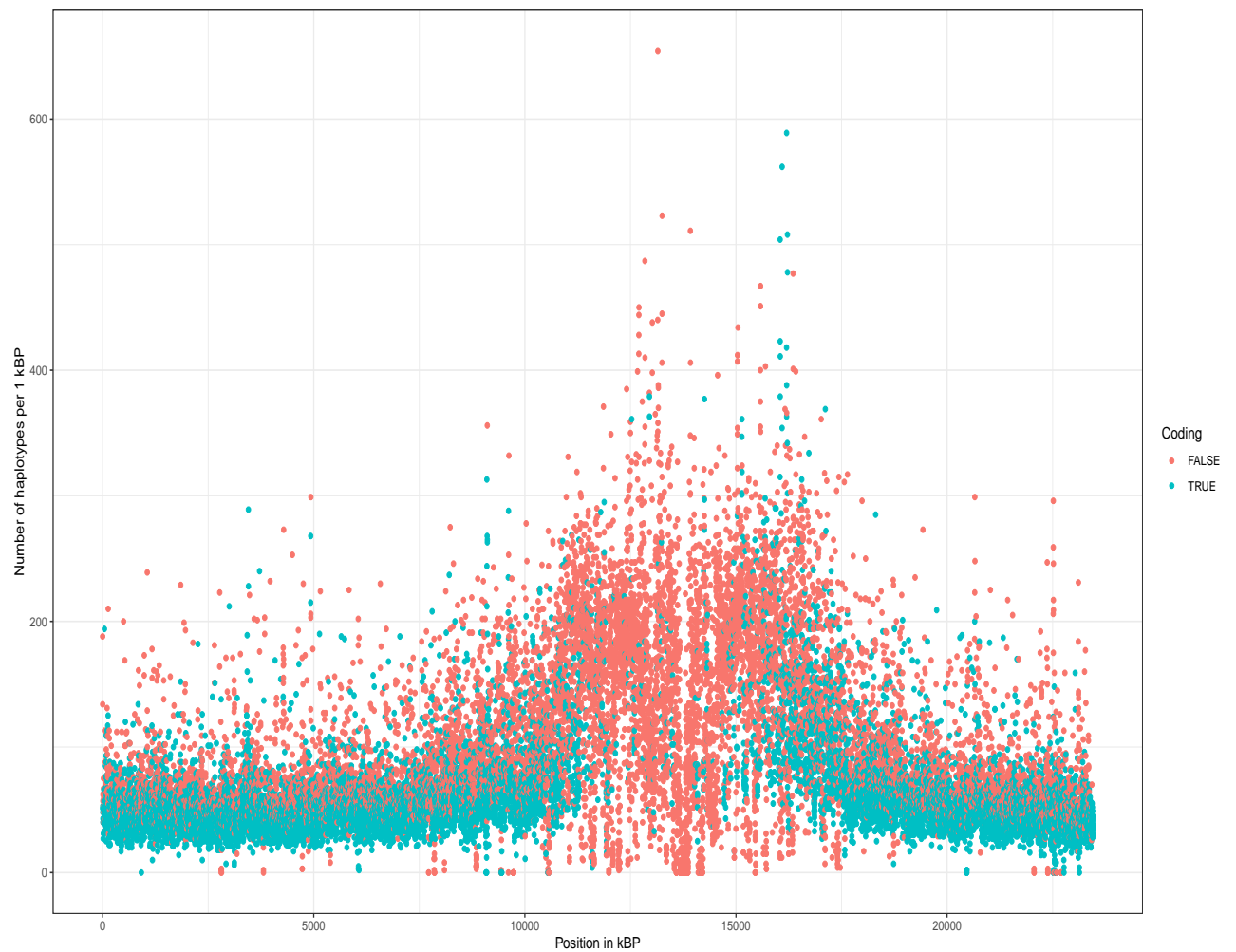


FIGURE 2.3: Number of segregating haplotypes with a polymorphism in at least one position over a stretch of 1 kBP.

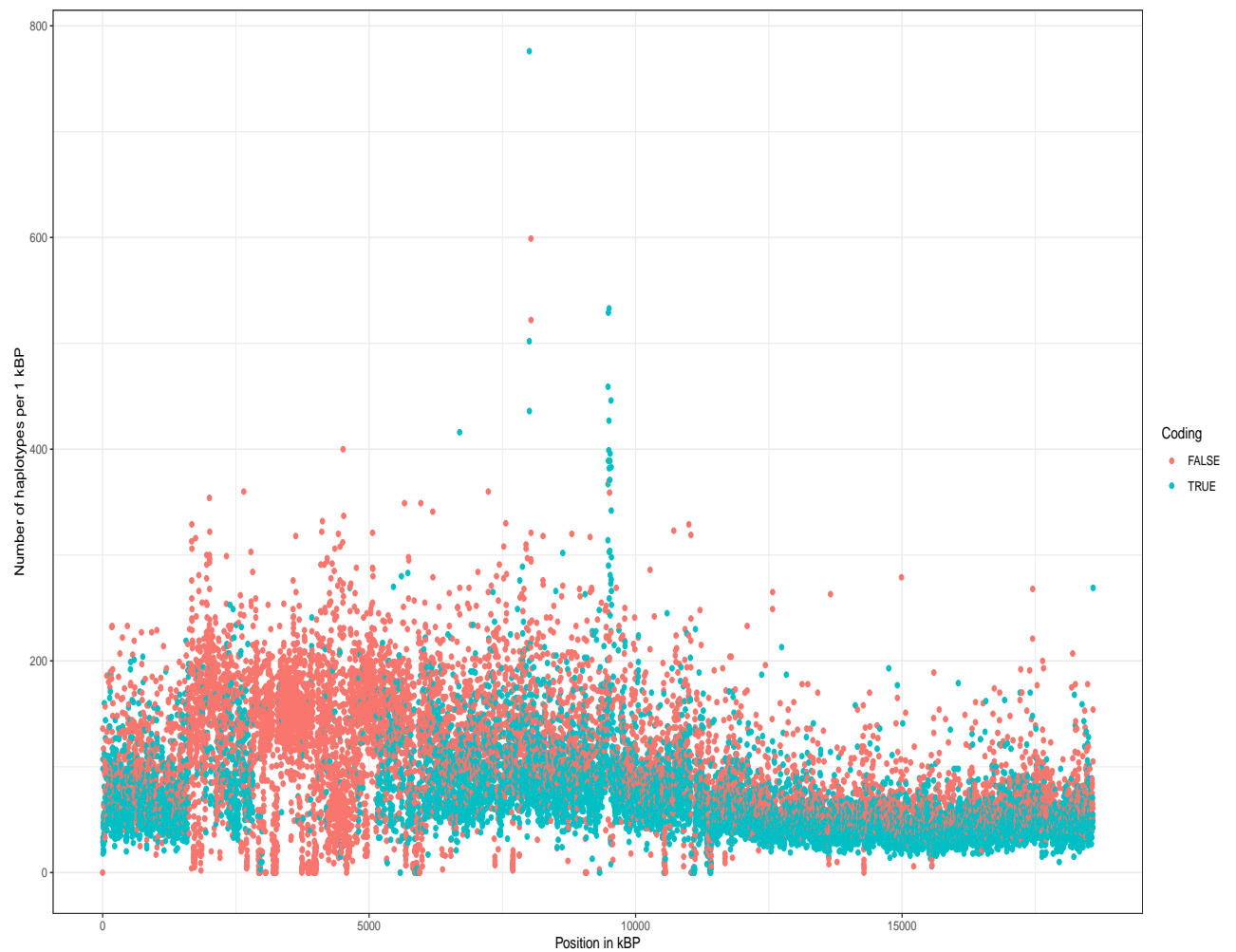


FIGURE 2.4: Number of segregating haplotypes with a polymorphism in at least one position over a stretch of 1 kBP.

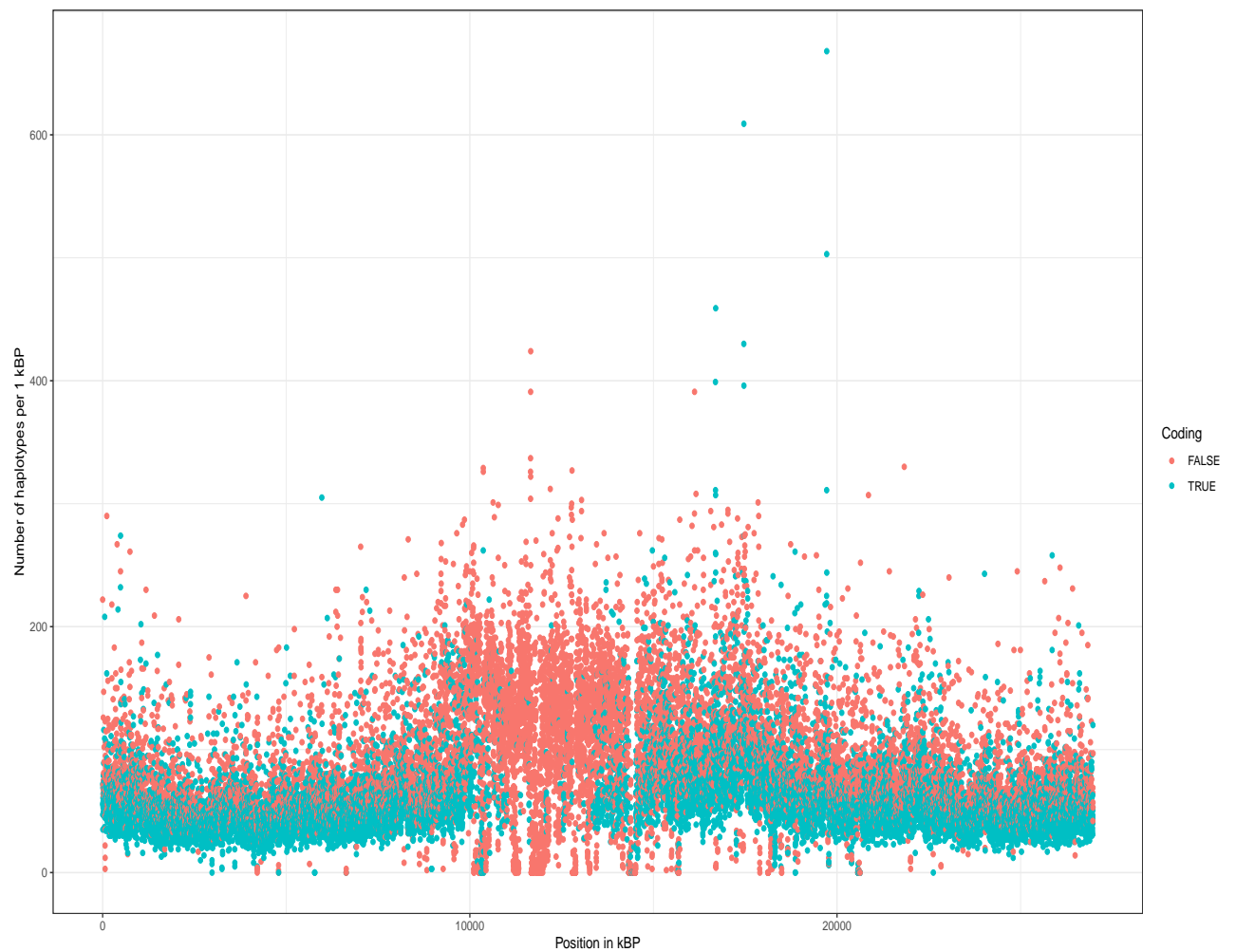


FIGURE 2.5: Number of segregating haplotypes with a polymorphism in at least one position over a stretch of 1 kBP.

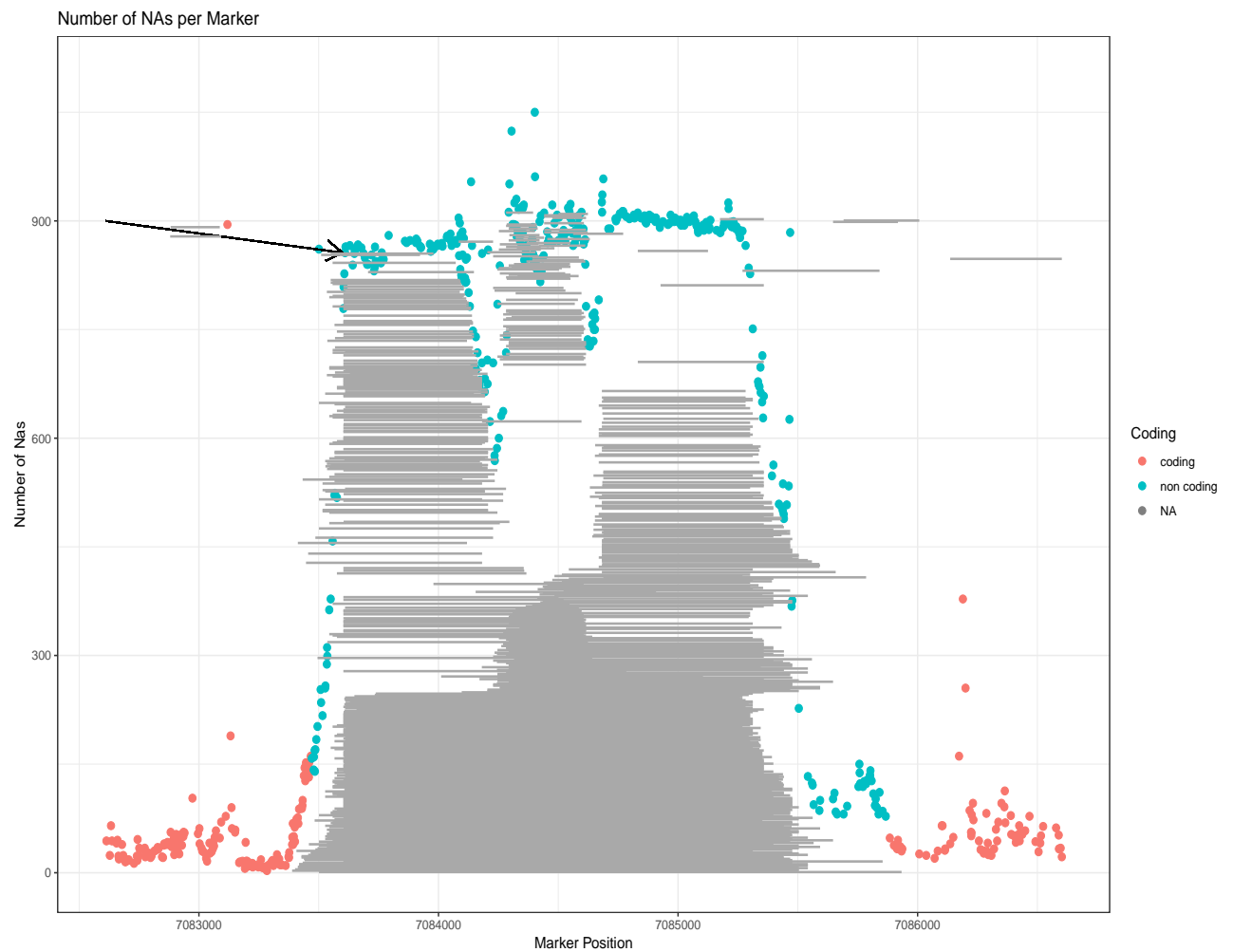


FIGURE 2.6: Number of segregating haplotypes with a polymorphism in at least one position over a stretch of 1 kBP.

3 GWAS-Flow a gpu-accelerated software for large-scale genome-wide association studies

The following chapter has been published in a similar version on the bioRxiv preprint server *Freudenthal et al., 2019a* and has been submitted for publication to Oxford Bioinformatics. The experiments and the software have been designed and conducted author. The manuscript has been prepared by the author, with minor corrections from Prof. Arthur Korte & Dominik Grimm. All authors approved of the final manuscript.

3.1 Introduction

Genome-wide association studies, pioneered in human genetics *Hirschhorn and Daly, 2005* in the last decade, have become the predominant method to detect associations between phenotypes and the genetic variations present in a population. Understanding the genetic architecture of traits and mapping the underlying genomic polymorphisms is of paramount importance for successful breeding both in plants and animals, as well as for studying the genetic risk factors of diseases. Over the last decades, the cost for genotyping have been reduced dramatically. Early GWAS consisted of a few hundred individuals which have been phenotyped and genotyped on a couple of hundreds to thousands of genomic markers. Nowadays, marker density

for many species easily exceed millions of genomic polymorphisms. Albeit commonly SNPs are used for association studies, standard GWAS models are flexible to handle different genomic features as input. The *Arabidopsis* 1001 genomes project features for example 1135 sequenced *Arabidopsis thaliana* accessions with over 10 million genomic markers that segregate in the population *Alonso-Blanco et al., 2016*. Other genome projects also yielded large amounts of genomic data for a substantial amount of individuals, as exemplified in the 1000 genomes project for humans *Siva, 2008*, the 2000 yeast genomes project or the 3000 rice genomes project *Li, Wang, and Zeigler, 2014*. Thus, there is an increasing demand for GWAS models that can analyze these data in a reasonable time frame. One critical step of GWAS is to determine the threshold at which an association is termed significant. Classically the conservative Bonferroni threshold is used, which accounts for the number of statistical tests that are performed, while many recent studies try to significance thresholds that are based on the false-discovery rate (FDR) *Storey and Tibshirani, 2003*. An alternative approach are permutation-based thresholds *Che et al., 2014*. Permutation-based thresholds estimate the significance by shuffling phenotypes and genotypes before each GWAS run, thus any signal left in the data should not have a genetic cause, but might represent model mis-specifications or uneven phenotypic distributions. Typically this process is repeated hundreds to thousands of times and will lead to a distinct threshold for each phenotype analyzed *Togninalli et al., 2017*. The computational demand of permutation-based thresholds is immense, as per analysis not one, but at least hundreds of GWAS need to be performed. Here the main limitation is the pure computational demand. Thus, faster GWAS models could easily make the estimation of permutation-based thresholds the default choice.

3.2 Methods

GWAS Model

The GWAS model used for GWAS-Flow is based on a fast approximation of the linear-mixed-model described in Kang et al., 2010; Zhang et al., 2010, which estimates the variance components σ_g and σ_e only once in a null model that includes the genetic relationship matrix, but no distinct genetic markers. These components are thereafter used for the tests of each specific marker. Here, the underlying assumption is, that the ratio of these components stays constant, even if distinct genetic markers are included into the GWAS model. This holds true for nearly all markers and only markers which possess a big effect will alter this ratio slightly, where now σ_g would become smaller compared to the null model. Thus, the p-values calculated by the approximation might be a little higher (less significant) for strongly associated markers.

The GWAS-Flow Software

The GWAS-Flow software was designed to provide a fast and robust GWAS implementation that can easily handle large data and allows to perform permutations in a reasonable time frame. Traditional GWAS implementations that are implemented using Python Van Rossum and Drake Jr, 1995 or R R Core Team, 2019 cannot always meet these demands. We tried to overcome those limitations by using TensorFlow Abadi et al., 2015, a multi-language machine learning framework published and developed by Google. GWAS calculations are composed of a series of matrix computations that can be highly parallelized, and easily integrated into the architecture provided by TensorFlow. Our implementation allows both, the classical parallelization of code on multiple processors (CPUs) and the use of graphical processing units (GPUs). GWAS-Flow is written using the Python TensorFlow API. Data import is done with pandas McKinney, 2010 and/or HDF5 for Python Collette, 2013. Preprocessing of the data (e.g filtering by minor Allele count (MAC)) is performed with numpy

Oliphant, 2006. Variance components for residual and genomic effects are estimated with a slightly altered function based on the Python package *limix* Lippert et al., 2014. The GWAS model is based on the following linear mixed model that takes into account the effect of every marker with respect to the kinship:

$$Y = \beta_0 + X_i\beta_i + u + \epsilon, u \sim N(0, \sigma_g K), \epsilon \sim N(0, \sigma_e I) \quad (3.1)$$

From this LMM the residual sum of squares for marker i are calculated as described in 3.2

$$RSS_i = \sum Y - (X_i\beta_0 + I_i\beta_1) \quad (3.2)$$

The residuals are used to calculate a p-value for each marker according to an overall F-test that compares the model including a distinct genetic effect to a model without this genetic effect:

$$F = \frac{RSS_{env} - R1_{full}}{\frac{R1_{full}}{n-3}} \quad (3.3)$$

Apart from the p-values that derive from the F-distribution, GWAS-Flow also report summary statistics, such as the estimated effect size (β_i) and its standard error for each marker.

Calculation of permutation-based thresholds for GWAS

To calculate a permutation-based threshold, we essentially perform n repetitions ($n > 100$) of the GWAS on the same data with the sole difference that before each GWAS we randomize the phenotypic values. Thus any correlation between the phenotype and the genotype will be broken and indeed for over 90% of these analyses the estimated pseudo-heritability is close to zero. On the other hand, the phenotypic distribution will stay unaltered by this randomization. Hence, any remaining signal in the GWAS has to be of a non-genetic origin and could be caused by e.g. model mis-specifications. Now we take the lowest p-value (after filtering for the

desired minor allele count) for each permutation and take the 5% lowest value as the permutation-based threshold for the GWAS.

Benchmarking

For benchmarking of GWAS-Flow we used data from the *Arabidopsis* 1001 Genomes Project *Alonso-Blanco et al., 2016*. The genomic data we used were subsets between 10,000 and 100,000 markers. We chose not to include subsets that exceed 100,000 markers, because there is a linear relationship between the number of markers and the computational time demanded, as all markers are tested independently. We used phenotypic data for flowering time at ten degrees (FT10) for *A. thaliana*, published and downloaded from the AraPheno database *Seren et al., 2016*. We down- and up-sampled sets to generate phenotypes for sets between 100 and 5000 accessions. For each set of phenotypes and markers we ran 10 permutations to assess the computational time needed. All analyses have been performed with a custom R script that has been used previously *Togninalli et al., 2017*, GWAS-Flow using either a CPU or a GPU architecture and GEMMA *Zhou and Stephens, 2012*. GEMMA is a fast and efficient implementation of the mixed model that is broadly used to perform GWAS. All calculations were run on the same machine using 16 i9 virtual CPUs. The GPU version ran on an NVIDIA Tesla P100 graphic card. Additionally to the analyses of the simulated data, we compared the times required by GEMMA and both GWAS-Flow implementations for > 200 different real datasets from *A. thaliana* that have been downloaded from the AraPheno *Seren et al., 2016* database and have been analyzed with the available fully imputed genomic dataset of ca. 10 million markers, filtered for a minor allele count greater five.

3.3 Results

The two main factors influencing the computational time for GWAS are the number of markers incorporated in such an analysis and the number of different accessions, while the latter has an approximate quadratic effect in classical GWAS implementations *Zhou and Stephens, 2012*. Figure 1A shows the time demand as a function of the number of accessions used in the analysis with 10,000 markers. The quadratic increase in time demand is clearly visible for the custom R implementation, as well as for the CPU-based GWAS-Flow implementation and *GEMMA*. The GWAS-Flow implementation and *GEMMA* clearly outperforms the R implementation in general, while for a small number of accessions GWAS-Flow is slightly faster than *GEMMA*. For the GPU-based implementation the increase in run-time with larger sample sizes is much less pronounced. While for small ($< 1,000$ individuals) data, there is no benefit compared to running GWAS-Flow on CPUs or running *GEMMA*, the GPU-version clearly outperforms the other implementations if the number of accessions increases. Figure 1B shows the computational time in relation to the number of markers and a fixed amount of 2000 accessions for the two different GWAS-Flow implementations. Here, a linear relationship is visible in both cases. To show the performance of GWAS-Flow not only for simulated data, we also run both implementations on more than 200 different real datasets downloaded from the AraPheno database. Figure 1C shows the computational time demands for all analyses comparing both GWAS-Flow implementation to *GEMMA*. Here, the CPU-based GWAS-Flow performs comparable to *GEMMA*, while the GPU-based implementation outperforms both, if the number of accessions is above 500. Importantly all obtained GWAS results (p-values, beta estimates and standard errors of the beta estimates) are nearly (apart from some mathematical inaccuracies) identical between the three different implementations.

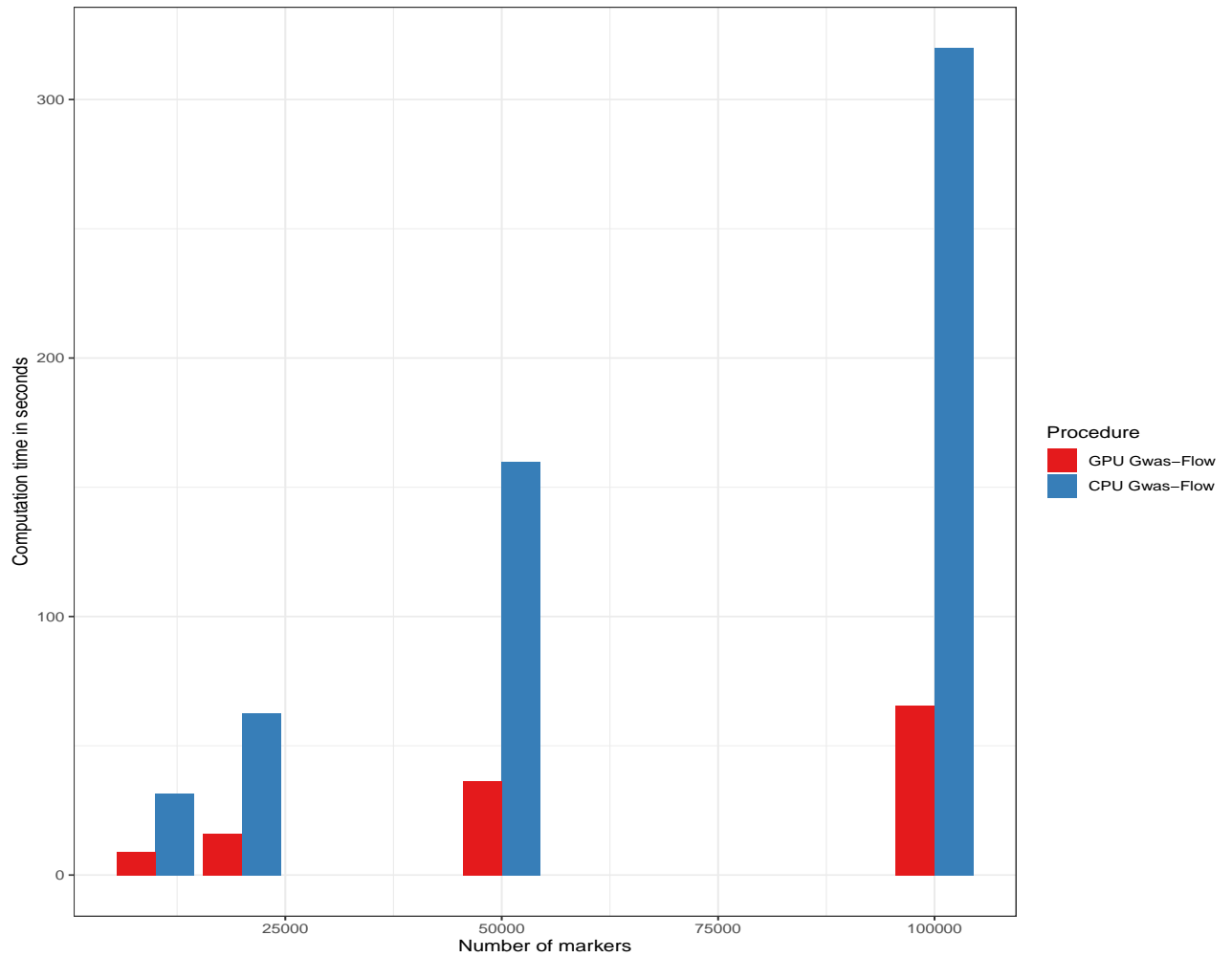


FIGURE 3.1: Computational time as a function of the number of genetic markers with constantly 2000 accessions for both GWAS-Flow versions

3.4 Disucssion

We made use of recent developments of computational architecture and software to cope with the increasing computational demand in analyzing large GWAS datasets. With GWAS-Flow we implemented both, a CPU- and a GPU-based version of the classical linear mixed model commonly used for GWAS. Both implementations outperform custom R scripts on simulated and real data. While the CPU-based version performs nearly identical compared to *GEMMA*, a commonly used GWAS implementation, the GPU-based implementation outperforms both, if the number of individuals, which have been phenotyped, increases. For analyzing big data, here the

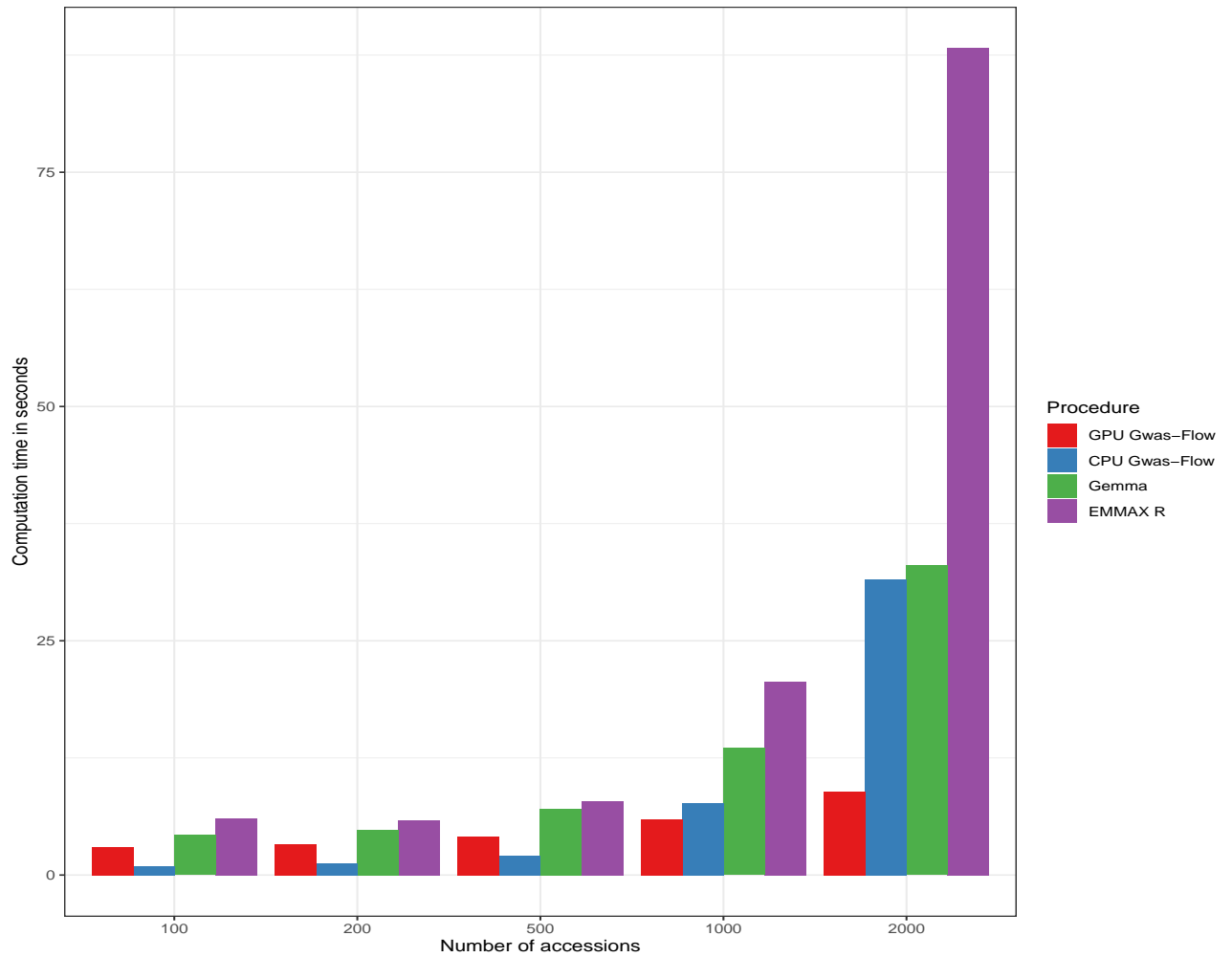


FIGURE 3.2: Computational time as a function of the number of accessions with 10000 markers each.

main limitation would be the RAM of the GPU, but as the individual test for each marker are independent, this can be easily overcome programmatically. The presented GWAS-Flow implementations are markedly faster compared to custom GWAS scripts and even outperform efficient fast implementations like *GEMMA* in terms of speed. This readily enables the use of permutation-based thresholds, as with GWAS-Flow hundred permutations can be performed in a reasonable time even for big data. Thus, it is possible for each analyzed phenotype to create a specific, permutation-based threshold that might present a more realistic scenario. Importantly the permutation-based threshold can be easily adjusted to different minor allele counts, generating different significance thresholds depending on the allele

count. This could help to distinguish false and true associations even for rare alleles. GWAS-Flow is a versatile and fast software package. Currently GWAS-Flow is and will remain under active development to make the software more versatile. This will e.g. include the compatibility with TensorFlow v2.0.0 and enable data input formats, such as PLINK *Purcell et al., 2007*. The whole framework is flexible, so it is easy to include predefined co-factors e.g. to enable multi-locus models *Segura et al., 2012* or account for multi-variate models like the multi-trait mixed model *Korte et al., 2012*. Standard GWAS are good in detecting additive effects with comparably large effect sizes, but lack the ability to detect epistatic interactions and their influence on complex traits *Mckinney and Pajewski, 2012; Korte and Farlow, 2013*. To catch the effects of these gene-by-gene or SNP-by-SNP interactions, a variety of genome-wide association interaction studies (GWAIS) have been developed, thoroughly reviewed in *Ritchie and Van Steen, 2018*. Here, GWAS-Flow might provide a tool that enables to test the full pairwise interaction matrix of all SNPs. Although this might be a statistic nightmare, it now would be computationally feasible.

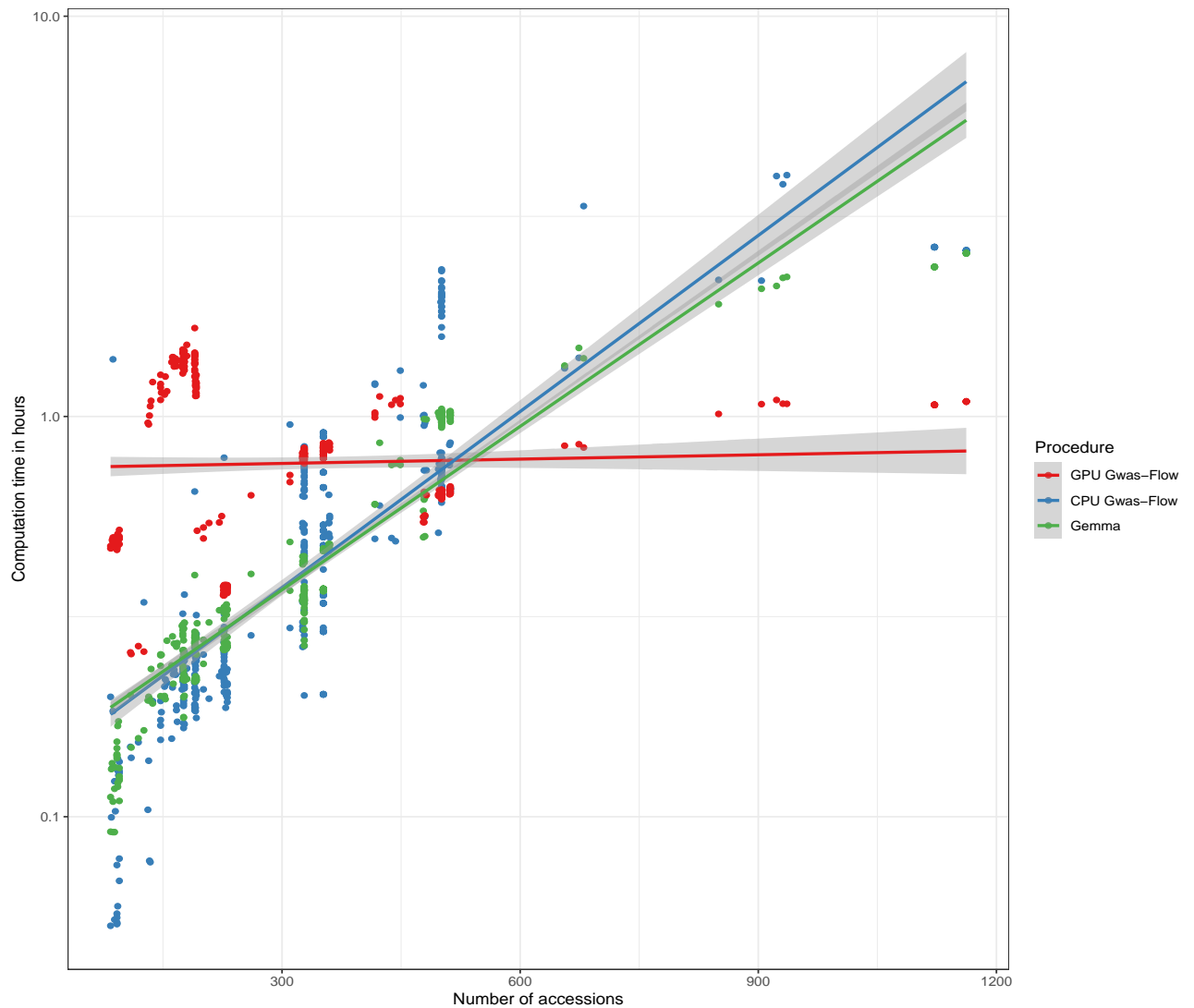


FIGURE 3.3: Comparison of the computational time for the analyses of > 200 phenotypes from *Arabidopsis thaliana* as a function of the number of accessions for GEMMA and the CPU- and GPU-based version of GWAS-Flow. GWAS was performed with a fully imputed genotype matrix containing 10.7 M markers and a minor allele filter of $MAC > 5$

4 Genomic prediction of phenotypic values of quantitative traits using Artificial neural networks

4.1 Introduction

4.1.1 A brief history of machine learning

Basic perceptron model

While machine learning, neural networks, deep learning became essential tools for many applications in more recent years, their mathematical principals date back to the early 1950s and 1960s. Figure 4.1 schematically show the basic perceptron model as proposed by Rosenblatt, which was designed to mimic the information flow in biological nervous systems *Rosenblatt, 1961*

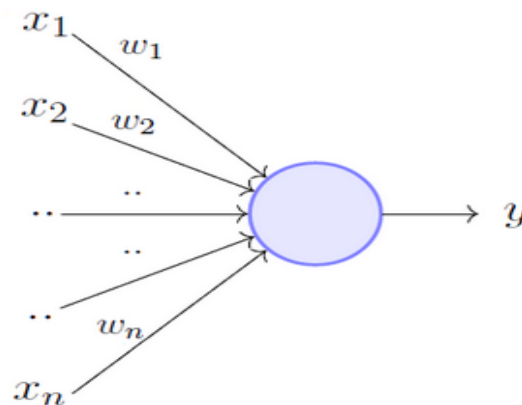


FIGURE 4.1: Basic perceptron model as proposed by Rosenblatt

This basic perceptron, which contrary to perceptrons used nowadays does not have an activation function, takes n binary inputs x_1, x_2, \dots, x_n and produces a single, likewise binary, output y after being processed by the perceptron or neuron. To achieve this Rosenblatt introduced the concept of weights which indicated a certain relative importance to the outcome of the output. w_1, w_2, \dots, w_n . The output y is determined by the weighted sum of the weights and biases $\sum_i w_i x_i$. If a certain threshold value is met the neuron is either activated and outputs 1 or not and outputs 0. This is algebraically represented in 4.1

$$0 = \text{if } \sum_i^n w_i x_i - \theta \leq 0 \quad (4.1a)$$

$$1 = \text{if } \sum_i^n w_i x_i - \theta > 0 \quad (4.1b)$$

Next to the weights w_n and the inputs x_n a third term θ is introduced in equation 4.1 which represents the activation threshold in per definition is negative. A single perceptron is a linear classifier and can only be trained on linearly separable functions and can be used as shown by Rosenblatt, 1961 to solve simple logical operations as AND, OR and not. The simple perceptron fails, due to non-linearity, to perform XOR operations as shown by Marvin and Seymour, 1969. This discovery led to a near still stance in the research of artificial neural networks in the 1970s. This time period is now often referred to as the first AI-winter. Another reason that massively hindered the applications and research of machine learning during that time, was the compared to modern times incredibly small amount of computational power available Nguyen and Widrow, 1990.

More complex decision making, like solving XOR problems, requires more complex structures than a single perceptron. Continuing the trend of mimicking human neural networks, multiple artificial neurons are stacked into layers and these layers, are connected to each other allowing communication between the many perceptrons

in a such generated network. Figure 4.2 shows schematically the basic structure of such a network, now container three types of layers. (i) the input layer, (ii) one or more hidden layers and (iii) one output layer, which in this case only consists of one neuron.

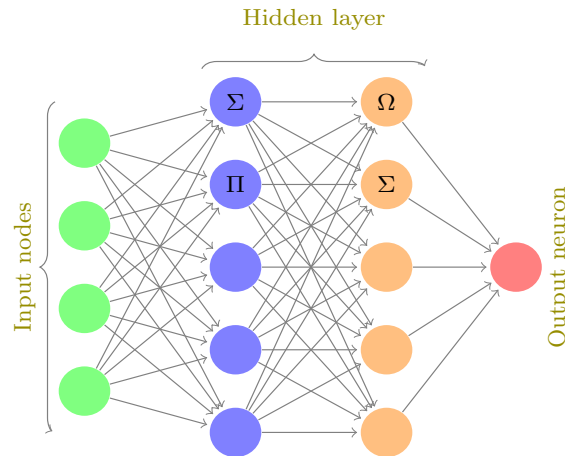


FIGURE 4.2: Schematic layout of a simple multi-layer perceptron

In the sample layout of figure 4.2 the neurons in the first column weigh the inputs and pass those the the neurons on the second layer. In this case all neurons on the first layer or connected to all neurons on the second layer, such layers are referred to fully-connected layers (FLC) , and their resulting networks are often called multi-layer perceptrons (MLP). This architecture enables the network to perform more complex calculations and result in more abstract decisions than single neurons or single layer architectures.

Activation functions

The neurons discussed so far are only capable of outputting binary results. Either 0 or 1, depending on the threshold values being met or not. For more complex estimations it is desirable that small changes in the input also result in small changes of the output. This requirement can not be met with binary outputs. Activation functions for a given node provides rules for the output in accordance to the inputs Žilinskas, 2006.

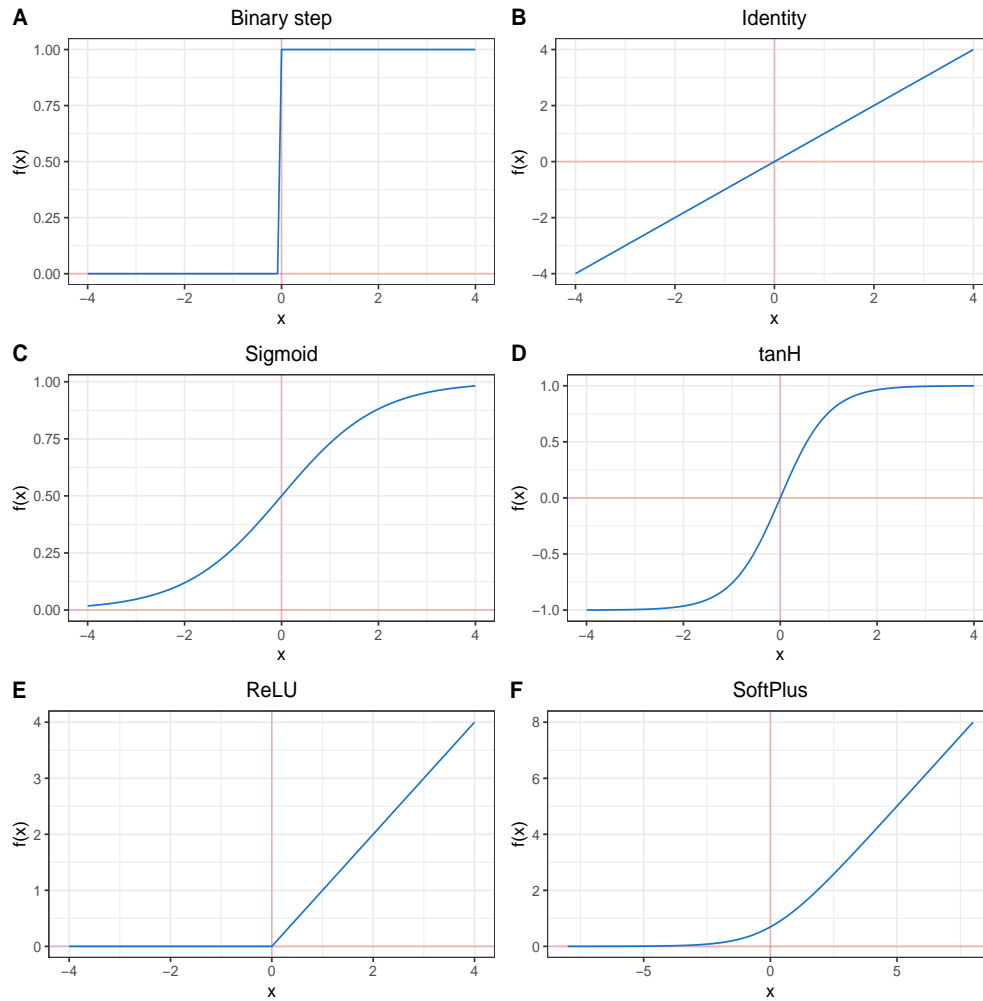


FIGURE 4.3: Popular activation functions used in neural networks. **A** Binary step activation function. **B** Identity activation function. **C** Sigmoid or logistic activation function. **D** tangens hyperbolicus activation function. **E** rectified linear units activation function. **F** SoftPlus activation function.

Figure 4.3 A shows six of the most commonly used activation functions Warner and Misra, 1996. The simplest one was introduced, is the binary step activation function equation 4.2, which properties have been discussed along the perceptron model. All other activation produce continuous outputs from any given input. Basically any mathematical function can serve as an activation function in neural nets, starting with a simple identity function 4.3, 4.3 B. Sigmoid figure 4.3 C, equation 4.4 and tanh figure 4.3 D, equation 4.5, when $x \rightarrow \infty$ or $x \rightarrow -\infty$ they have similar properties to the binary function, but produce continuous output around 0.

$$f(x) = \sigma(x) = \begin{cases} 0 & \text{for } x < 0 \\ 1 & \text{for } x \geq 0 \end{cases} \quad (4.2)$$

$$f(x) = \sigma(x) = x \quad (4.3)$$

$$f(x) = \sigma(x) = \frac{1}{1 + e^{-x}} \quad (4.4)$$

$$f(x) = \sigma(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \quad (4.5)$$

$$f(x) = \sigma(x) = \begin{cases} 0 & \text{for } x < 0 \\ x & \text{for } x \geq 0 \end{cases} \quad (4.6)$$

$$f(x) = \ln(1 + e^x) \quad (4.7)$$

ReLU (equation 4.6) and the softplus (equation 4.7) share similar properties as well, the latter one being a smoothed version of ReLU. Rectifiers as activation functions have been introduced in 2000s *Hahnloser et al., 2000* and have since then overtaken all others as the most popular activations functions in neural networks and deep learning today *LeCun, Bengio, and Hinton, 2015* and they have proven to be superior in deep-learning algorithms that sigmoid or logistic functions. One of the advantages leading to the superiority of ReLUs is that with randomly initialized weights only half of the ReLU neurons are activated, compared to tanh and sigmoid activation *Glorot, Bordes, and Bengio, 2011*. All activation functions shown in figure 4.3, but the binary step function, share one common property: a small change of the input weight will result in small changes in the output, while a small change of the input for the binary step function leads to either no or a complete change of the output. This property is, as described below, is an important prerequisite for networks being able to learn.

Gradient descent algorithm

Let the network shown in 4.2 be for the classification of a arbitrary phenotype like blue petals with $x_1...x_4$ on the input layers being genetic markers as features. And the output layer displaying a value from 0 to 1, meaning yes: blue petals from 0 - 0.5 and no blue petals from 0.5 to 1. To quantify how well the network performs on achieving that goal a loss function is applied *Schmidhuber, 2015*. There is a large variety of different loss functions available for neural networks like mean squared error (MSE), root mean squared error (RMSE), cross-entropy and many others. In general MSE, MSE are commonly used for regression problems, with the latter being less popular and cross-entropy also called log loss is used for binary or multi-class classification problems *Janocha and Czarnecki, 2017*. Since all problems presented in due course or regression problems, that use MSE as their loss function, this will be the only one emphasized.

$$MSE = \frac{1}{n} \sum_{i=1}^n (y_i - \tilde{y})^2 \quad (4.8)$$

Equation 4.8 shows the MSE function which is the sum of the squares of the differences of all the predicted and the real values. The same function can be rewritten with the previously used terminology of weights and biases in equation 4.8.

$$L(w, b) = \frac{1}{2n} \sum_x \|y(x) - \tilde{y}\|^2. \quad (4.9)$$

With w and b as the collection of all the weights and the biases in the network used to optimize the function $y(x)$. Giving the quadratic nature of the function the $L(w, b)$ will always be positive. And if $L(w, b) \rightarrow 0$ the loss is minimal, meaning that the real and predicted values are close together and the network found weights and biases that explain the output well.

A widely used function to find the optimum for such a loss function is gradient descent. Its objective is to find the minimum for the loss function *Bottou, 1991*. The behind gradient descent or other optimizing algorithms is start with randomly initialized weights and biases and repeatedly move them in direction Δw and Δb . This results in a change of the loss function as shown in equation 4.10, making use of partial derivatives.

$$\Delta L = \frac{\partial L}{\partial w} \Delta w + \frac{\partial L}{\partial b} \Delta b \quad (4.10)$$

Ideally ΔL is negative and the optimization algorithm found Δw and Δb that lead to a reduction of the loss. To simplify this problem let Δd be the vector of changes: $\Delta d = (\Delta w, \Delta b)^T$ and ∇L the vector of the partial derivatives: equation 4.11

$$\nabla L = \left(\frac{\partial L}{\partial w}, \frac{\partial L}{\partial b} \right)^T \quad (4.11)$$

Having defined ∇L and Δd the term 4.10 can be simplified as equation 4.12

$$\Delta C = \nabla L * \Delta d \quad (4.12)$$

Now the task of gradient descent or any other optimizer is to find Δd that results in ΔC being negative as shown in equation 4.13

$$\Delta d = -\eta \nabla L \quad (4.13)$$

In this case η is a small positive decimal number, commonly referred to as the learning rate, which usually, but not exclusively ranges from 0.1 to 0.001. However it can be larger or much smaller in some cases. Having found a way to ensure that ΔL always decreases according to equation 4.13 it is utilized to repeatedly update the gradient ∇L . To make the gradient descent algorithm efficient the learning rate η must be chosen correctly. If η is too large, the gradient ΔL might end up being larger than zero, leading to an increase of the loss, and if the step size is too small

convergence will either take too long or not take place at all *Bergstra et al., 2011*. In practical machine learning approaches different learning rates are tested. There are also algorithmic approaches. While equation 4.10 only accounts for two inputs features, it can be generalized to compute n inputs shown in equation 4.14.

$$\nabla L = \left(\frac{\partial L}{\partial w_1}, \dots, \frac{\partial L}{\partial w_n} \right)^T \quad (4.14)$$

Equation 4.15 shows the gradient descent how it is used to repetitively update the weights and biases to optimize the loss function $L(c, w)$ with w and b as the weight and bias matrices and the learning rate η . In machine learning each iterative update of the network is often called epoch or training epoch.

$$w = w_i - \eta \frac{\partial}{\partial w} L(w) \quad (4.15a)$$

$$b = b_i - \eta \frac{\partial}{\partial b} L(b) \quad (4.15b)$$

$$(4.15c)$$

Substituting the partial differentials with ∇L equation 4.15 a simplifies to:

$$w = w_i - \eta \nabla L \quad (4.16)$$

Optimizers

The previous section introduced the concept of gradient descent, an algorithm to minimize the loss function of the weights and biases of a neural network. All other optimizers introduced here, are either variations or extensions of the basic gradient descent algorithm (GD) shown in 4.15. One disadvantage of gradient descent is that

if the data sets grow larger, the demand in memory for computation increases exponentially. Taking into consideration machine learning is a popular method in big data applications this is a serious drawback. Methods to overcome that are stochastic gradient descent and mini-batch gradient descent. The idea behind the latter is to randomly divide the entity of the training data in sub-samples called mini-batches *Bottou and Bousquet, 2008*. The network is then trained iteratively over the mini batches. The batch size influences the accuracy and the training speed and is another hyperparameter which has to be tuned. If the batch size is 1 mini batch GD is also referred to as stochastic gradient descent (SGD). During the optimization process optimizers can find local minima in the cost function without being able to overcome them to find the desired global minimum. An algorithm extending GD to accelerate the search of the global minimum is momentum. Which allows the GD to speed up when the loss is decreasing and to slow down when going in the wrong direction - increasing the loss function $L(w, b)$. This is achieved by accounting for the gradient of the previous step in the calculation of the current step. This concept was introduced by *Polyak, 1964* and re-popularized alongside backpropagation learning by *Rumelhart, Hinton, and Williams, 1988*.

$$w = w_i - \eta \nabla L + \alpha \Delta w \quad (4.17)$$

Equation 4.17 shows how the momentum is mathematically represented in GD to update the weights w or likewise the biases the delta of the weights multiplied by the coefficient α - the momentum, which usually ranges from 0.1 to 0.9 and is another parameter to tuned for successful training. If the momentum is too small the GD will not be able to overcome local minima and if α is too large the loss functions tends to oscillate without finding an optimum *LeCun, Bengio, and Hinton, 2015*. For both of the momentum and the learning rate it is impractical to remain on the same level during all training epochs. Because after each epoch the loss function is either closer or further away from its global minima and depending on the distance to that

minimum it is desirable to have larger or smaller learning rates and momenta. This can be achieved with naive approaches for example using a step function to gradually decrease those values after each iteration, or to utilize algorithmic approaches *Michie, Spiegelhalter, and Taylor, 1994*. There is a large variety of optimizers trying to find optimal values for α and η and till today this field is under active research *Goodfellow, Bengio, and Courville, 2016*. Popular among those are: RMSprop *Hinton, Srivastava, and Swersky, 2012*; Nesterov momentum *Dozat, 2016*; Adadelta *Zeiler, 2012*; Adagrad *Ruder, 2016* and Adam *Kingma and Ba, 2014*. With Adam being the most widely used optimizer today. Nesterov momentum is slight change to the normal momentum capable of having huge impacts in practical applications, because it helps avoiding oscillations around the minimum by using intermediate information to adapt the momentum.

RMSProp - root mean square propagation - is a method aiming to adapt the learning rate algorithmically, by choosing η for each parameter. And lastly the wide-spread Adam optimizer combines both of the features of momentum and RMSProp and adapts the learning rate as well as the momentum iteratively *Kingma and Ba, 2014*.

Backpropagation

maybe i will leave out backpropagation ☺

Backpropagation *Rumelhart, Hinton, and Williams, 1988*

Regularization parameters

When applying the combined aforementioned algorithms and optimizers to find global minima of a loss function of a neural network a problem arises, because optimizers like Adam work “too” well. This issues is due to the fact that neural networks have 100s of thousand of free parameters to be trained, deep neural networks have billions and trillions of parameters. If training of the neural net continues for enough epochs eventually. The loss function will approach a minimum and as $L(w, b) \rightarrow 0$ the initial conclusion could be that the training was quite successful,

but when trying to apply the network trained on the training data set (TRN) to a testing data set (TST). The loss and accuracy of the prediction of TST and TST are very large or accordingly small. This phenomenon is know as overfitting and a lot of fine tuning of hyperparameters is devoted to minimizing this effect Tetko, Livingstone, and Luik, 1995. Figure 4.4 visualizes the effects of overfitting during training Goodfellow, Bengio, and Courville, 2016.

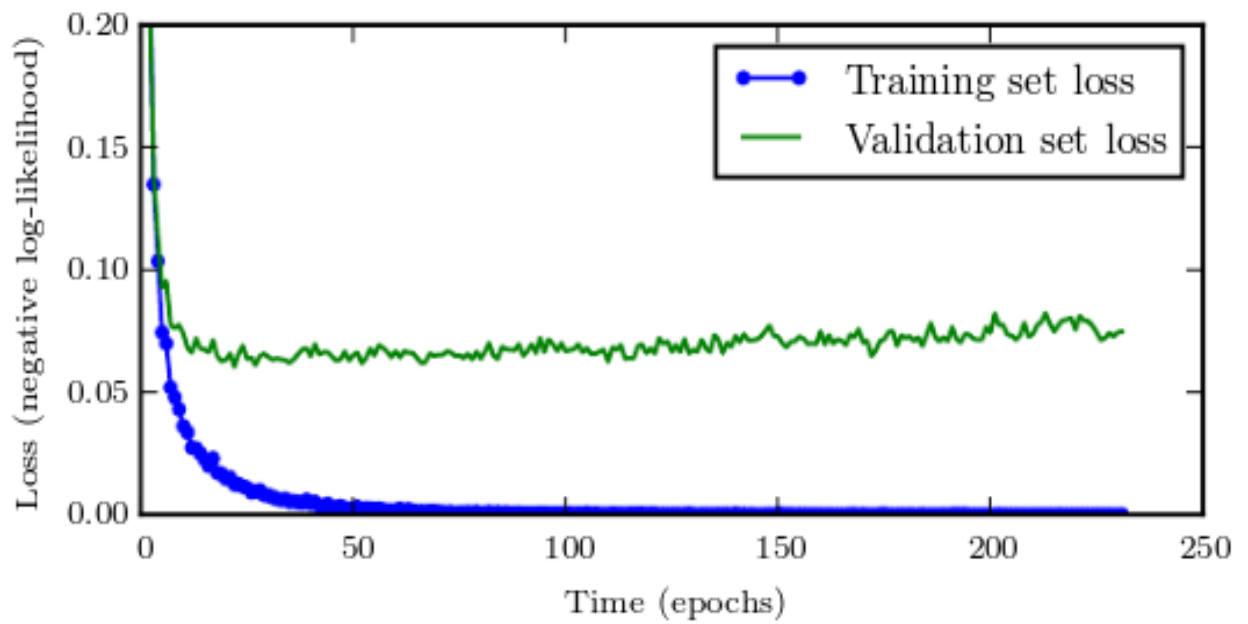


FIGURE 4.4: Learning curves showing how a loss function changes during training in the loss and validation data set. While the training loss approaches 0 the validation loss starts increasing after hitting a minimum. This effect is due to overfitting on the training data set. Figure from Goodfellow, Bengio, and Courville, 2016.

Cross-validation

A method that is used in basically every training of neural network is splitting up the data sets in multiple sub-sets. More specifically a training set (TRN) and a testing set (TST). The training set is used to minimize the loss functions and its success is evaluated on the TRN set, by comparing the predicted values \hat{y} with the

real values in TST y . For all neural nets in this study person's correlation coefficient was chosen as performance metric, as in equation 4.18 *Soper et al., 1917*.

$$\rho(y, \hat{y}) = \frac{cov(y, \hat{y})}{\sigma_y \sigma_{\hat{y}}} \quad (4.18)$$

There are other popular performance metrics, especially for classification problems, like AUC (area under the curve) and ROC (receiver operating characteristics), which basically evaluate by weighing sensitivity and specificity. In cross-validation compared to single validation the initial data set is split into TRN and TST multiple times e.g. if the ratio is 80:20 5 times, and each TRN-TST pair is evaluated individually. Sometimes it becomes necessary to use a third subset - the validation data. Because hyperparameter tuning is performed with the TRN and TST sets, a third portion of the data needs to be assessed to check whether the neural network is able to generalize on global data.

L1 and L2 loss

L1 and L2

Dropout

4.1.2 On the nature of quantitative traits

According to the omnigenic model which is an extension of the polygenic model proposed by *Boyle, Li, and Pritchard, 2017* and thoroughly reviewed in *Timpson et al., 2018* all traits or phenotypic values are influenced by a great number or all genes in the genome. Therefore resulting in traits following certain gradual statistical distributions instead of being binned in classes or even binary. Intuitively this might be contradicting with the foundation of modern Genetics - Mendel's three laws. That where derived from observations with where mainly influenced by one locus. But staying with one of Mendel's examples the round or wrinkled surfaces of peas

Pisum sativum, an assessment of a couple of thousands peas, would most likely inevitably lead to the conclusion that from the “roundest” to the “wrinkliest” pea any gradual step between those is possible and observable. Mendel’s third law of independent segregation also only holds true under certain assumptions. The most simplest one being that the traits under investigation have to be located on different linkage groups. Otherwise for the 7 traits used in Mendel’s initial studies would not have segregated independently. The odds of 7 randomly selected traits being on 7 different linkage groups are rather small, especially taking into account, that the genome of the *P. sativum* consists of only 7 chromosomes itself Kalo et al., 2004. Mendel probably new about traits not following its own laws, as well as being aware of the quantitative nature of traits such as the constitution of surfaces of peas or the color of petals. But being the pioneer of a then rather unexplored field of science, some of which big questions we fail to satisfactory answer today, he did not have the resources or the knowledge to explain behavior’s not “mendeling”, that were only able to be deciphered in later decades and centuries based on his ground-breaking work.

Initially thought to be contradicting to Mendel’s ideas Darwin proposed the concept’s of evolution due to natural selection which also introduce the idea of traits following a gradual distribution Darwin, 1859. This contrast led to a long lasting debate in the scientific community in the early 1900s, between the Mendelians and the biometricians who believed in the quantitative nature of continuous traits. This conflict has eventually been solved by Fisher’s fundamental work published in 1918 Fisher, 1919. His theories combined the then in all fields of science popular research of distributions with genomics. He he mathematically proved that traits influenced by many genes, with randomly-sampled alleles follow a continuous normal distribution in a population. While this combined the ideas of Mendel and the biometricians it opened an other long debated question of effect size and the overall architecture of complex traits. While in the theory of monogenic traits the effect size of the single gene on the trait is 1 or 100 % with an increasing number of genes

influencing a complex traits the *per se* contribution of single gene has to decrease with an increasing number of loci determining the value a given trait. In the 1990s it has been thought, that complex traits are predominantly controlled from few genes with a large to medium effect size, while others had a minimal influence *Zhang et al., 2018*.

With the upcoming popularity of GWAS as the favored method to decipher genetic architectures of traits, or having pioneered in human genetics it became clear that the majority of the effect sizes are tiny $< 1\%$ while there are very few loci which have a moderate effect on the phenotypic variance of a population with around 10% or less *Korte and Farlow, 2013, Stringer et al., 2011*. This nature of quantitative traits present great challenges to animal *Goddard and Hayes, 2009* and plant breeding *Würschum, 2012*, in further improving crop or livestock performances, as well complicating the decomposition of genomic causes for diseases like schizophrenia or autism in human medicine *De Rubeis et al., 2014, Purcell et al., 2014*.

While the complex nature of the architecture of quantitative traits provide enough challenges as is, all traits will also be influenced by the environment from which an individual originates. Therefore the distribution of trait values in a given population can be expressed as the addition of the variances of its genetic and the environmental effects [4.19](#).

$$\sigma_P = \sigma_G + \sigma_E \quad (4.19)$$

The genomic and the environmental effects not only influence the phenotypic variance directly, but the environment also has an influence on gene expression methylation of DNA bases etc. and therefore the equation [4.19](#) needs to be extend by the variance of the gene-environment interactions $\sigma_{G \times E}$ [4.20](#), *Lynch and Walsh, 1998, Walsh and Lynch, 2018*.

$$\sigma_P = \sigma_G + \sigma_E + \sigma_{G \times E} \quad (4.20)$$

Equation 4.20 shows the decomposition of the phenotypic variance, to thoroughly understand complex genetic architectures of traits the genetic variance needs to be decomposed further in its additive, dominance and epistatic components 4.21

$$\sigma_G = \sigma_A + \sigma_D + \sigma_I \quad (4.21)$$

The additive effects are caused by single, for this model mostly homozygous, loci while the variance caused by dominance effects, is caused by heterozygous loci and their resulting interactions being full-, over-, co- or underdominant. And lastly the interaction effects that are a result of two or more genes only having an impact if the involved genes co-occur in a certain state. The resulting variance is commonly known as gene-gene interactions and/or epistasis *Falconer and Mackay, 1996*. Since possible interactions in a genome can happen between additive or dominant or a combination of those loci. The variance due to interaction effects σ_I can be further dissembled in the variance resulting from additive-additive σ_{AA} dominant-dominant σ_{DD} and additive-dominant σ_{AD} terms as represented in equation 4.22.

$$\sigma_I = \sigma_{AxA} + \sigma_{DxD} + \sigma_{AxD} \quad (4.22)$$

Knowledge of the variance components involved in the expression of a trait in population, lead up to the estimation of the total influence of all genetic variances and the environmental variance on the phenotypic distribution. This concept is called heritability. The heritability of a trait H^2 accounts for the proportion of the phenotypic variance controlled by the total genetic variance as shown in equation 4.23. This is also referred to as broad sense heritability, because all genetic effects including additive, dominance and epistatic effects are included *Brooker, 1999*.

$$H^2 = \frac{\sigma_A + \sigma_D + \sigma_I}{\sigma_P} \quad (4.23)$$

The concept of narrow-sense heritability 4.24 is similar to the broad-sense heritability, but only the additive genetic effects are included in the genetic part of the equation. This differentiation is important for natural and artificial selection and thus is commonly used in evolutionary genomics and breeding. Because in diploid species each parent only passes down on a single allele of a given locus. Dominance effects or interaction effects are not commonly inherited from one parent. Therefore it is mainly the additive genetic effects of a parent that influences its offspring. While the dominance and epistatic variances are controlled by the combination of the parents Falconer and Mackay, 1996, Walsh and Lynch, 2018.

$$h^2 = \frac{\sigma_A}{\sigma_P} \quad (4.24)$$

4.1.3 Artificial selection in plant and animal breeding in the genomics era

Genomic prediction has been applied to almost all relevant crop and model species. Including: *A. thaliana* Hu et al., 2015; Shen et al., 2013. Alfalfa (*Medicago sativa*) Li and Brummer, 2012; Annicchiarico et al., 2015; Li et al., 2015; Biazzi et al., 2017; Hawkins and Yu, 2018. Barley Neyhart, Lorenz, and Smith, 2019; Oakey et al., 2016; Zhong et al., 2009. Cassava (*Manihot esculenta*) Elias et al., 2018a; Elias et al., 2018b. Cauliflower (*Brassica oleracea* spp) Thorwarth, Yousef, and Schmid, 2018. Cotton (*Gossypium* spp. Gapare et al., 2018. Maze (*Zea mays*) Moeiniazade et al., 2019; Allier et al., 2019; Brauner et al., 2018; Schrag et al., 2018; Schopp et al., 2017b; Sousa et al., 2017; Schopp et al., 2017a; Kadam et al., 2016; Bustos-Korts et al., 2016a; Montesinos-López et al., 2015; Owens et al., 2014; Lehermeier et al., 2014; Technow et al., 2014; Peiffer et al., 2014; Riedelsheimer et al., 2013; Guo et al., 2013; Technow, Bürger, and Melchinger, 2013; Windhausen et al., 2012; Rincant et al., 2012. Potato (*Solanum tuberosum*); Enciso-Rodriguez et al., 2018; Endelman et al., 2018. Rape seed (*Brassica naps*) Würschum, Abel, and Zhao, 2014; Jan et al., 2016; Luo et al., 2017; Werner et al., 2018; Snowdon and Iniguez Luy,

2012; Qian, Qian, and Snowdon, 2014. Rice (*Oryza sativa*) Momen et al., 2019; Hassen et al., 2018; Xu, 2013; Grenier et al., 2015. Rye (*Secale cereale*) Auinger et al., 2016; Bernal-Vasquez et al., 2014; Wang et al., 2014; Bernal-Vasquez et al., 2017; Marulanda et al., 2016. Soybean (*Glycine max*) Stewart-Brown et al., 2019; Jarquin, Specht, and Lorenz, 2016; Xavier, Muir, and Rainey, 2016. Switchgrass (*Panicum virgatum*) Poudel et al., 2019; Ramstein and Casler, 2019; Ramstein et al., 2016. Wheat (*Triticum aestivum*) Cuevas et al., 2019a; Howard et al., 2019; Krause et al., 2019; Rincent et al., 2018; Norman et al., 2018; Belamkar et al., 2018; Ovenden et al., 2018; Sukumaran et al., 2016; Bustos-Korts et al., 2016b; Gianola et al., 2016; Crossa et al., 2016; Thavamanikumar, Dolferus, and Thumma, 2015; Lopez-Cruz et al., 2015. As well as various tree species Almeida Filho et al., 2019; Rincent et al., 2018; Kainer et al., 2018; Ratcliffe et al., 2017; El-Dien et al., 2016; Kumar et al., 2015; Jaramillo-Correa et al., 2014; Zapata-Valenzuela et al., 2013; Holliday, Wang, and Aitken, 2012; Resende et al., 2012.

4.1.4 Genomic selection using artificial neural networks

Genomic selection (GS) has been successfully applied in animal Gianola and Rosa, 2015, Hayes and Goddard, 2010 and plant breeding Crossa et al., 2010, Desta and Ortiz, 2014, Heffner et al., 2010, Crossa et al., 2017a as well as in medical applications, since it was first reported Hayes and Goddard, 2001. Since then the repertoire of methods for predicting phenotypic values has increased rapidly e.g. De Los Campos et al., 2009, Habier et al., 2011, Gianola, 2013, Crossa et al., 2017b. The most commonly applied methods include GULP and a set of related algorithms known as the bayesian alphabet Gianola et al., 2009. Genomic prediction in general has repeatedly been shown to outperform pedigree-based methods Crossa et al., 2010, Albrecht et al., 2011 and is nowadays used in many plant and animal breeding schemes. It has also been shown that using whole-genome information is superior to using only feature-selected markers with known QTLs for a given trait Bernardo and Yu, 2007, Heffner,

Jannink, and Sorrells, 2011 in some cases. A more recent study Azodi et al., 2019 compared 11 different genomic prediction algorithms with a variety of data sets and found contradicting results, indicating that feature selection can be useful in some cases when the whole genome regression is performed by neural nets. While every new method is a valuable addition to the tool-kits for genomic selection, some fundamental problems remain unsolved, of which the $n \gg p$ problematic stands out. Usually in genomic selection settings the size of the training population (TRN) with n phenotypes is substantially smaller than the number of markers (p) Fan, Han, and Liu, 2014. Making the number of features immensely large, even when SNP-SNP interactions are not considered. Furthermore each marker is treated as an independent observation neglecting collinearity and linkage disequilibrium (LD). Further difficulties arise through non-additive, epistatic and dominance marker effects. The main problem with epistasis in quantitative genetics is the almost infinite amount of different marker combinations, that cannot be represented within the size of TRN in the thousands, the same problem arises for example in GWA studies Korte and Farlow, 2013. With already large p the number of possible additive SNP-SNP interactions potentiates to $p^{(p-1)}$. Methods that attempt to overcome those issues are EGBLUP, using an enhanced epistatic kinship matrix and reproducing kernel Hilbert space regression (RKHS) Jiang and Reif, 2015, Martini et al., 2017.

In the past 10 years, due to increasing availability of high performance computational hardware with decreasing costs and parallel development of free easy-to-use software, most prominent being googles library TensorFlow Abadi et al., 2016 and Keras Chollet, 2015, machine learning (ML) has experienced a renaissance. ML is a set of methods and algorithms used widely for regression and classification problems. popular among those are e.g. support vector machines, multi-layer perceptrons (MLP) and convolutional neural networks. The machine learning mimics the architecture of neural networks and are therefore commonly referred to as artificial neural networks (ANN). Those algorithms have widely been applied in many biological fields Min, Lee, and Yoon, 2017, Lan et al., 2018, Mamoshina et al., 2016,

Angermueller et al., 2016 , Webb, 2018, Rampasek and Goldenberg, 2016.

A variety of studies assessed the usability of ML in genomic prediction González-Camacho et al., 2018, González-Camacho et al., 2016, Ogutu, Piepho, and Schulz-Streeck, 2011, Montesinos-López et al., 2019a, Grinberg, Orhobor, and King, 2018 , Cuevas et al., 2019b, Montesinos-López et al., 2019b, Ma et al., 2017, Qiu et al., 2016, González-Camacho et al., 2012 Li et al., 2018. Through all those studies the common denominator is that there is no such thing as a gold standard for genomic prediction. No single algorithm was able to outperform all the others tested in a single of those studies, let alone in all. While the generally aptitude of ML for genomic selection has been repeatedly shown, how no evidence exists that neural networks can outperform or in many cases perform on that same level as mixed-model approaches as GBLUP Hayes and Goddard, 2001. While in other fields like image classification neural networks have up to 100s of hidden layers He et al., 2016 the commonly used fully-connected networks in genomic prediction of 1 - 3 hidden layers. With 1 layer networks often being the most successful among those. Contradicting to the idea behind machine learning in genomic selection 1 hidden layer networks will be inapt to capture interactions between loci and thus only account for additive effects. As shown in Azodi et al., 2019 convolutional networks perform worse than fully-connected networks in genomic selection, which again is contradicting to other fields where convolutional layers are applied successfully, e.g natural language processing Dos Santos and Gatti, 2014 or medical image analysis Litjens et al., 2017. Instead of using convolutional layers and fully-connected layers only, as show in Pook et al 2019, we also propose to use locally-connected layer in combination with fully-connected layers. While CL and LCL are closely related they have a significant difference. While in CL weights are shared between neurons in LCLs each neuron as its own weight. This leads to a reduced number of parameters to be trained in the following FCLs, and should therefore theoretically lead to a decrease in overfitting a common problem in machine learning. To evaluate the results of Pook et al. 2019 accomplished with simulated data we used the data sets generated in the scope of the 1001 genome

project of *Arabidopsis thaliana* Alonso-Blanco et al., 2016

4.2 Proof of concept for ANN-based genomic selection

Having established the quantitative architecture of traits in section 4.1.2 and the basics of machine learning and neural nets in section 4.1.1, that knowledge can be used to provide a proof of concept that neural networks are a candidate for GP. Table 4.1 provides also the possible genotypes that can be derived by two bi-allelic markers $G_1 \dots G_4$ on a fictional haploid organism. In this simulation the effect sizes for each marker β_1 and β_2 are constant with a value of 1.

TABLE 4.1: Simple simulated phenotypes and genotypes for genomic prediction with genotypes $G_1 \dots G_4$, M_1 and M_2 and phenotypes based on additive effects or *and*, *or*, *xor* logic gates.

	M_1	M_2	Y_{ADD}	Y_{AND}	Y_{OR}	Y_{XOR}
G_1	0	0	0	0	0	0
G_2	0	1	1	0	1	1
G_3	1	0	1	0	1	1
G_4	1	1	2	1	1	0

The four phenotypes Y_{ADD} , Y_{AND} , Y_{OR} and Y_{XOR} , which were derived from their respective marker effects. Y_{ADD} is a phenotype with purely additive effects. So in the nomenclature introduced in chapter 4.1.2 $\sigma_A = \sigma_G$ and $\sigma_I = 0$. Since the hypothetical organism is haploid there are dominance effects to be accounted for $\sigma_D = 0$. Since all the genetic effects are caused by additive effects and there are now environmental effects σ_E , the narrow sense heritability h^2 - equation 4.24 - and the broad sense heritability H^2 - equation 4.23 - are equally 1. The other three phenotypes are based on epistatic effects σ_I generated by passing the markers M_1 and M_2 through their respective logic gates. This theoretically results in $h^2 = 0$ and $H^2 = 1$, because there are no additive effects. For y_{AND} however $h \approx 0.5$, because

there is a correlation between Y_{ADD} and Y_{AND} . In practical applications this allows methods like GBLUP, designed to account for additive genetic effects to capture some of the epistatic effects of σ_I *Vieira et al., 2017*.

According to chapter 4.1.1 a single perceptron would fail to solve *xor* gates. While a network with multiple nodes and layers should be able to overcome that deficit. A relatively simple neural network with two fully-connected hidden layers with 10 and 5 nodes, was trained for the prediction of each phenotypes. To keep the simulation as possible, no regularization parameters, dropout etc. was included. The activation function was ReLU (4.6) with an Adam optimizer. The results of the prediction are shown in table 4.2.

TABLE 4.2: Results of genomic prediction from phenotypes and genotypes in table 4.1

	M_1	M_2	\hat{Y}_{ADD}	\hat{Y}_{AND}	\hat{Y}_{OR}	\hat{Y}_{XOR}
G_1	0	0	0.01	0.00	0.00	0.01
G_2	0	1	0.99	0.01	0.99	0.98
G_3	1	0	0.99	0.00	0.99	1.01
G_4	1	1	1.99	0.98	1.01	0.02

Not surprisingly, the simple network is able to solve all four phenotypes and predicting the phenotypes accurately. The task was rather easy because the training data set and the testing data set were the same, but it served the purpose of showing that neural networks are generally apt to solve different marker interactions. *In natura* those interactions and the overall genetic architecture is much more complex. Effect sizes are not constant and epistasis may be caused by interactions of more than just two markers, and with an increasing number of markers n the number of possible two-way interactions increases even more so to 2^{n-1} . Smaller interaction effects could be obscured under larger additive effects, gene-environment might have a significant influence leading to a model that does not converge.

4.3 Material

4.3.1 DH populations derived from MAZE landraces

4.3.2 A. thaliana

4.4 Methods

4.4.1 ANN

4.4.2 GBLUP

4.5 Results

4.6 Discussion

5 GWAS

5.1 Reevalulation of 463 phenotypes from the AraPheno database

5.1.1 Introduction

5.1.2 Material and Methods

5.1.3 Results

5.1.4 Results

5.1.5 Disucssion

5.2 GWAS in DH landrace populatios of maze across and within environments

5.2.1 Introduction

5.2.2 Material and Methods

5.2.3 Results

5.2.4 Results

5.2.5 Disucssion

A Source code GWAS-Flow

A.1 gwas.py

```
1 import os
2 import sys
3 import time
4 import numpy as np
5 import pandas as pd
6 import main
7 import h5py
8
9 # set defaults
10 mac_min = 1
11 batch_size = 500000
12 out_file = "results.csv"
13 m = 'phenotype_value'
14 perm = 1
15 mac_min= 6
16
17 X_file = 'gwas_sample_data/AT_geno.hdf5'
18 Y_file = 'gwas_sample_data/phenotype.csv'
19 K_file = 'gwas_sample_data/kinship_ibs_binary_mac5.h5py'
20
21
22
23 for i in range (1,len(sys.argv),2):
24     if sys.argv[i] == "-x" or sys.argv[i] == "--genotype":
25         X_file = sys.argv[i+1]
26     elif sys.argv[i] == "-y" or sys.argv[i] == "--phenotype":
27         Y_file = sys.argv[i+1]
28     elif sys.argv[i] == "-k" or sys.argv[i] == "--kinship":
```

```

29     K_file = sys.argv[i+1]
30     elif sys.argv[i] == "-m":
31         m = sys.argv[i+1]
32     elif sys.argv[i] == "-a" or sys.argv[i] == "--mac_min":
33         mac_min = int(sys.argv[i+1])
34     elif sys.argv[i] == "-bs" or sys.argv[i] == "--batch-size":
35         batch_size = int(sys.argv[i+1])
36     elif sys.argv[i] == "-p" or sys.argv[i] == "--perm":
37         perm = int(sys.argv[i+1])
38     elif sys.argv[i] == "-o" or sys.argv[i] == "--out":
39         out_file = sys.argv[i+1]
40     elif sys.argv[i] == "-h" or sys.argv[i] == "--help":
41         print("-x , --genotype :file containing marker information in
42 csv or hdf5 format of size")
43         print("-y , --phenotype: file container phenotype information
44 in csv format" )
45         print("-k , --kinship : file containing kinship matrix of size
46 k X k in csv or hdf5 format")
47         print("-m : name of columnn containing the phenotype : default
48 m = phenotype_value")
49         print("-a , --mac_min : integer specifying the minimum minor
50 allele count necessary for a marker to be included. Default a = 1"
51 )
52         print("-bs, --batch-size : integer specifying the number of
53 markers processed at once. Default -bs 500000" )
54         print("-p , --perm : single integer specifying the number of
55 permutations. Default 1 == no perm ")
56         print("-o , --out : name of output file. Default -o results.
57 csv ")
58         print("-h , --help : prints help and command line options")
59         quit()
60     else:
61         print('unknown option ' + str(sys.argv[i]))
62         quit()
63
64 print("parsed commandline args")

```

```

58
59 start = time.time()
60
61 X,K,Y_,markers = main.load_and_prepare_data(X_file,Y_file,K_file,m)
62
63
64 ## MAF filterin
65 markers_used , X , macs = main.mac_filter(mac_min,X,markers)
66
67 ## prepare
68 print("Begin performing GWAS on ", Y_file)
69
70 if perm == 1:
71     output = main.gwas(X,K,Y_,batch_size)
72     if( X_file.split(".")[ -1] == 'csv'):
73         chr_pos = np.array(list(map(lambda x : x.split("- "),
74 markers_used)))
75     else:
76         chr_reg = h5py.File(X_file,'r')['positions'].attrs['
chr_regions']
77         mk_index= np.array(range(len(markers)),dtype=int)[macs >=
mac_min]
78         chr_pos = np.array([list(map(lambda x: sum(x > chr_reg[:,1]) +
1, mk_index)), markers_used]).T
79         my_time = np.repeat((time.time()-start),len(chr_pos))
80 pd.DataFrame({
81     'chr' : chr_pos[:,0] ,
82     'pos' : chr_pos[:,1] ,
83     'pval': output[:,0] ,
84     'mac' : np.array(macs[macs >= mac_min],dtype=np.int) ,
85     'eff_size': output[:,1] ,
86     'SE' : output[:,2]}) .to_csv(out_file,index=False)
87 elif perm > 1:
88     min_pval = []
89     perm_seeds = []
90     my_time = []
91     for i in range(perm):
92         start_perm = time.time()

```

```

92     print("Running permutation ", i+1, " of ",perm)
93     my_seed = np.asscalar(np.random.randint(9999,size=1))
94     perm_seeds.append(my_seed)
95     np.random.seed(my_seed)
96     Y_perm = np.random.permutation(Y_)
97     output = main.gwas(X,K,Y_perm,batch_size)
98     min_pval.append(np.min(output[:,0]))
99     print("Elapsed time for permuatation",i+1 ," with p_min",
min_pval[i]," is",": ", round(time.time() - start_perm,2))
100     my_time.append(time.time()-start_perm)
101     pd.DataFrame({
102         'time': my_time ,
103         'seed': perm_seeds ,
104         'min_p': min_pval }).to_csv(out_file,index=False)
105
106 print("done")
107
108 end = time.time()
109 eltime = np.round(end -start,2)
110
111 if eltime <= 59:
112     print("Total time elapsed", eltime, "seconds")
113 elif eltime > 59 and eltime <= 3600:
114     print("Total time elapsed", np.round(eltime / 60,2) , "minutes")
115 elif eltime > 3600 :
116     print("Total time elapsed", np.round(eltime / 60 / 60,2), "hours"
117 )
118

```

A.2 main.py

```

1     import pandas as pd
2     import numpy as np
3     from scipy.stats import f
4     import tensorflow as tf
5     import limix
6     import herit

```

```

7     import h5py
8     import limix
9     import multiprocessing as mlt
10
11     def load_and_prepare_data(X_file,Y_file,K_file,m):
12         type_K = K_file.split(".")[1]
13         type_X = X_file.split(".")[1]
14
15         ## load and preprocess genotype matrix
16         Y = pd.read_csv(Y_file,engine='python').sort_values(['accession_id',
17         '']).groupby('accession_id').mean()
18         Y = pd.DataFrame({'accession_id' : Y.index, 'phenotype_value' : Y
19         [m]})
20
21         if type_X == 'hdf5' or type_X == 'h5py' :
22             SNP = h5py.File(X_file,'r')
23             markers= np.asarray(SNP['positions'])
24             acc_X = np.asarray(SNP['accessions'][:],dtype=np.int)
25
26         elif type_X == 'csv' :
27             X = pd.read_csv(X_file,index_col=0)
28             markers = X.columns.values
29             acc_X = X.index
30             X = np.asarray(X,dtype=np.float32)/2
31
32         else :
33             sys.exit("Only hdf5, h5py and csv files are supported")
34
35         if type_K == 'hdf5' or type_K == 'h5py':
36             k = h5py.File(K_file,'r')
37             acc_K = np.asarray(k['accessions'][:],dtype=np.int)
38
39         elif type_K == 'csv':
40             k = pd.read_csv(K_file,index_col=0)
41             acc_K = k.index
42             k = np.array(k, dtype=np.float32)
43
44         acc_Y = np.asarray(Y[['accession_id']]).flatten()
45         acc_isec = [isec for isec in acc_X if isec in acc_Y]
46
47         idx_acc = list(map(lambda x: x in acc_isec, acc_X))
48         idy_acc = list(map(lambda x: x in acc_isec, acc_Y))

```

```

43     idk_acc = list(map(lambda x: x in acc_isec, acc_K))
44
45     Y_ = np.asarray(Y.drop('accession_id',1),dtype=np.float32)[idy_acc
46         ,:]
47
48     if type_X == 'hdf5' or type_X == 'h5py' :
49         X = np.asarray(SNP['snps'][0:(len(SNP['snps'])+1),],dtype=np.
50             float32)[: ,idx_acc].T
51         X = X[np.argsort(acc_X[idx_acc]),:]
52         k1 = np.asarray(k['kinship'][:])[idk_acc,:]
53         K = k1[:,idk_acc]
54         K = K[np.argsort(acc_X[idx_acc]),:]
55         K = K[:,np.argsort(acc_X[idx_acc])]
56     else:
57         X = X[idx_acc,:]
58         k1 = k[idk_acc,:]
59         K = k1[:,idk_acc]
60
61     print("data has been imported")
62     return X,K,Y_,markers
63
64 def mac_filter(mac_min, X, markers):
65     ac1 = np.sum(X,axis=0)
66     ac0 = X.shape[0] - ac1
67     macs = np.minimum(ac1,ac0)
68     markers_used = markers[macs >= mac_min]
69     X = X[:,macs >= mac_min]
70     return markers_used, X, macs
71
72 def gwas(X,K,Y,batch_size):
73     n_marker = X.shape[1]
74     n = len(Y)
75     ## REML
76     K_stand = (n-1)/np.sum((np.identity(n) - np.ones((n,n))/n) * K) *
77     K

```

```

77     vg, delta, ve = herit.estimate(Y, "normal", K_stand, verbose = False
78 )
79     print(" Pseudo-heritability is " , vg / (ve + vg + delta))
80     print(" Performing GWAS on ", n , " phenotypes and ", n_marker , "
81 markers")
82     ## Transform kinship-matrix, phenotypes and estimate intercpt
83     Xo = np.ones(K.shape[0]).flatten()
84     M = np.transpose(np.linalg.inv(np.linalg.cholesky(vg * K_stand +
85 ve * np.identity(n))))).astype(np.float32)
86     Y_t = np.sum(np.multiply(np.transpose(M), Y), axis=1).astype(np.
87 float32)
88     int_t = np.sum(np.multiply(np.transpose(M), np.ones(n)), axis=1).
89 astype(np.float32)
90     ## EMMAX Scan
91     RSS_env = (np.linalg.lstsq(np.reshape(int_t, (n, -1)) , np.reshape(
92 Y_t, (n, -1))))[1]).astype(np.float32)
93     ## calculate betas and se of betas
94     def stderr(a, M, Y_t2d, int_t):
95         x = tf.stack((int_t, tf.squeeze(tf.matmul(M.T, tf.reshape(a, (n
96 , -1))))), axis=1)
97         coeff = tf.matmul(tf.matmul(tf.linalg.inv(tf.matmul(tf.
98 transpose(x), x)), tf.transpose(x)), Y_t2d)
99         SSE = tf.reduce_sum(tf.math.square(tf.math.subtract(Y_t, tf.
100 math.add(tf.math.multiply(x[:, 1], coeff[0, 0]), tf.math.multiply(x
101[:, 1], coeff[1, 0])))))
102         SE = tf.math.sqrt(SSE / (471 - (1 + 2)))
103         StdERR = tf.sqrt(tf.linalg.diag_part(tf.math.multiply(SE , tf
104 .linalg.inv(tf.matmul(tf.transpose(x), x))))) [1]
105         return tf.stack((coeff[1, 0], StdERR))
106     ## calculate residual sum squares
107     def rss(a, M, y, int_t):
108         x_t = tf.reduce_sum(tf.math.multiply(M.T, a), axis=1)
109         lm_res = tf.linalg.lstsq(tf.transpose(tf.stack((int_t, x_t),
110 axis=0)), Y_t2d)
111         lm_x = tf.concat((tf.squeeze(lm_res), x_t), axis=0)
112         return tf.reduce_sum(tf.math.square(tf.math.subtract(tf.
113 squeeze(Y_t2d), tf.math.add(tf.math.multiply(lm_x[1], lm_x[2:]), tf.
114 multiply(lm_x[0], int_t)))))

```

```

101     ## loop over the batches
102     for i in range(int(np.ceil(n_marker/batch_size))):
103         tf.reset_default_graph()
104         if n_marker < batch_size:
105             X_sub = X
106         else:
107             lower_limit = batch_size * i
108             upper_limit = batch_size * i + batch_size
109             if upper_limit <= n_marker :
110                 X_sub = X[:,lower_limit:upper_limit]
111                 print("Working on markers ", lower_limit , " to ",
upper_limit, " of ", n_marker )
112             else:
113                 X_sub = X[:,lower_limit:]
114                 print("Working on markers ", lower_limit , " to ",
n_marker, " of ", n_marker )
115             config = tf.ConfigProto()
116             n_cores = mlt.cpu_count()
117             config.intra_op_parallelism_threads = n_cores
118             config.inter_op_parallelism_threads = n_cores
119             sess = tf.Session(config=config)
120             Y_t2d = tf.cast(tf.reshape(Y_t,(n,-1)),dtype=tf.float32)
121             y_tensor = tf.convert_to_tensor(Y_t,dtype = tf.float32)
122             StdERR = tf.map_fn(lambda a : stderr(a,M,Y_t2d,int_t), X_sub.T
)
123             R1_full = tf.map_fn(lambda a: rss(a,M,Y_t2d,int_t), X_sub.T)
124             F_1 = tf.divide(tf.subtract(RSS_env, R1_full),tf.divide(
R1_full,(n-3)))
125             if i == 0 :
126                 output = sess.run(tf.concat([tf.reshape(F_1,(X_sub.shape
[1],-1)),StdERR],axis=1))
127             else :
128                 tmp = sess.run(tf.concat([tf.reshape(F_1,(X_sub.shape
[1],-1)),StdERR],axis=1))
129                 output = np.append(output,tmp,axis=0)
130             sess.close()
131             F_dist = output[:,0]
132             pval = 1 - f.cdf(F_dist,1,n-3)

```



```

133     output[:,0] = pval
134     return output
135
136
137

```

A.3 herit.py

```

1
2 def estimate(y, lik, K, M=None, verbose=True):
3     from numpy_sugar.linalg import economic_qs
4     from numpy import pi, var, diag
5     from glimix_core.glmm import GLMMEExpFam
6     from glimix_core.lmm import LMM
7     from limix._data._assert import assert_likelihoood
8     from limix._data import normalize_likelihoood, conform_dataset
9     from limix.qtl._assert import assert_finite
10    from limix._display import session_block, session_line
11    lik = normalize_likelihoood(lik)
12    lik_name = lik[0]
13    with session_block("Heritability analysis", disable=not verbose):
14        with session_line("Normalising input...", disable=not verbose):
15            :
16                data = conform_dataset(y, M=M, K=K)
17                y = data["y"]
18                M = data["M"]
19                K = data["K"]
20                assert_finite(y, M, K)
21                if K is not None:
22                    # K = K / diag(K).mean()
23                    QS = economic_qs(K)
24                else:
25                    QS = None
26                if lik_name == "normal":
27                    method = LMM(y.values, M.values, QS, restricted=True)
28                    method.fit(verbose=verbose)
29                else:
30                    method = GLMMEExpFam(y, lik, M.values, QS, n_int=500)

```

```
30         method.fit(verbose=verbose, factr=1e6, pgtol=1e-3)
31     g = method.scale * (1 - method.delta)
32     e = method.scale * method.delta
33     if lik_name == "bernoulli":
34         e += pi * pi / 3
35     v = var(method.mean())
36     return g , v , e
```

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