JULIUS-MAXIMILIANS UNIVERSIÄT

WÜRZBURG

DOCTORAL THESIS

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

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Declaration of Authorship

"Wit beyond measure is man's greatest treasure"

Rowena Rawenclaw

JULIUS-MAXIMILIANS UNIVERSIÄT WÜRZBURG

Abstract

Faculty Name

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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…

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List of Abbreviations

Adadelta	**Ada**ptive **delta**
Adagrad	**Ada**ptive **Grad**ient Algorithm
Adam	**Ada**ptive **M**oment estimation
ANN	**A**rtificial **N**eural **N**etwork
API	**A**pplication **P**rogramming **I**nterface
AUC	**A**rea **U**nder the **C**urve
BLUE	**B**est **L**inear **U**nbiased **E**stimator
BLUP	**B**est **L**inear **U**nbiased **P**redictor
BP	**B**ase **Pair**
CPU	**C**ore **P**rocessing **U**nit
DH	**D**oubled **H**aploid
DNA	**D**eoxyribo**N**ucleic **A**cid
DNA	**R**ibo**N**ucleic **A**cid
EMMA	**E**fficient **M**ixed **M**odel **A**ssociations
FCL	**F**ully **C**onnected **L**ayer
GBLUP	**G**enomic **B**est **L**inear **U**nbiased **P**redictor
GD	**G**radient **D**escent
GEBC	**G**enomic **E**stimated **B**reeding **V**alues
GPL	**G**eneral **P**ublic **L**icense
GP	**G**enomic **P**rediction
GPU	**G**raphical **P**rocessing **U**nit
GRM	**G**enomic **R**elationship **M**atrix
GS	**G**enomic **S**election

GUI	**G**raphical **U**ser **I**nterface
GWAIS	**G**enome **W**ide **I**nteraction **A**ssociation **S**tudies
GWAS	**G**enome **W**ide **A**ssociation **S**tudies
HL	**H**idden **L**ayer
HDF	**H**ierarchical **D**ata **F**ormat
HPC	**H**igh **P**erformance **C**omputing
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
MAF	**M**inor **A**llele **F**requncy
MBP	**M**ega **B**ase **P**air
MCMC	**M**arkov **C**hain **M**onte **C**arlo
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
NCBI	**N**ational **C**enter for **B**iotechnological **I**nformation
QTL	**Q**uantitative **T**rait **L**ocus
ReLU	**Re**ctified **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 **Prop**agation
ROC	**R**eceiver **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
SRA	**S**equence **R**ead **A**rchive
SSC	**S**mall **S**ingle **C**opy
TRN	**TR**ai**N**ing subset
TST	**T**e**ST**ing subset
WGS	**W**hole **G**enome **S**equencing
XOR	e**X**clusive **OR**

For/Dedicated to/To my...

Chapter 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 are included. If not cited otherwise the plots even though they were published along the aforementioned paper, were designed and generated by the author.

1.1 Introduction

1.1.1 Motivation

Certain organelles like mitochondria and chloroplasts contain their own genetic information from which they are able to synthesize certain proteins independent of the core genome. Evolutionary this developed during endosymbiosis. Its underlying theory seeks to explain how eukaryotic cells formed from prokaryotes *Mereschkowsky*, 1905; *Kutschera* and *Niklas*, 2005. The widely acknowledged theory explains how in the early evolution of eukaryotes, other cells were incorporated in those cells from which today's known organelles descent. In the case of a chloroplast this was most likely a photosynthetic bacteria or similar organism *Archibald*, 2015. Until today the structure of chloroplast genomes resembles more that of a prokaryotic genome than that of its eukaryotic host cells. A typical

chloroplast genome consists of circular DNA with a size between 120 kBP to 160 kBP *Palmer*, 1985. The first chloroplast have been sequenced as early as 1986 and were isolated from *Marchantia polymorpha* and *Nico Ohyama* et al., 1986; *Shinozaki* et al., 1986. Complete reviews of the genome structure of chloroplast genomes were written by *Green*, 2011; *Wicke* et al., 2011. Chloroplast genomics is widely applied in evolutionary studies *Martin* et al., 2002; *Xiao-Ming* et al., 2017. The genome has been reduced in size over the course of evolution through endosymbiotic gene transfer *Martin* et al., 2002; *Deiner* et al., 2017. This is still an ongoing process, which can be observed *in vitro Bock*, 2017; *Fuentes* et al., 2014; *Stegemann* and *Bock*, 2009. Up to 14 % of the the core genome of *Arabidopsis thaliana* is made up of genes previously located on the chloroplast (fancy citation), while 100-120 genes remain on the chloroplast *Wicke* et al., 2011 itself, which by far would not be enough to function independently. Chloroplast genomes are much smaller than core genomes e.g *A. thaliana* has a core genome size of ca. 125 MBP and are highly conserved with a large gene content, therefore polymorphisms are more likely to cause functional changes in the metabolism. Single chloroplast contain up to hundreds of copies of its genome *Kumar*, *Oldenburg*, and *Bendich*, 2014; *Bendich*, 1987. Photosynthetic activate cells contain multiple chloroplasts, therefore the copy number of the chloroplast genomes is much higher than the number of core genomes per cell which is most cases is 1.

Structurally chloroplast genomes are made up of 4 distinct regions: two inverted repeats (IR) - IR_A and IR_B - ranging from 10 kbp to 76 kbp. They divide the genome into two areas: 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.

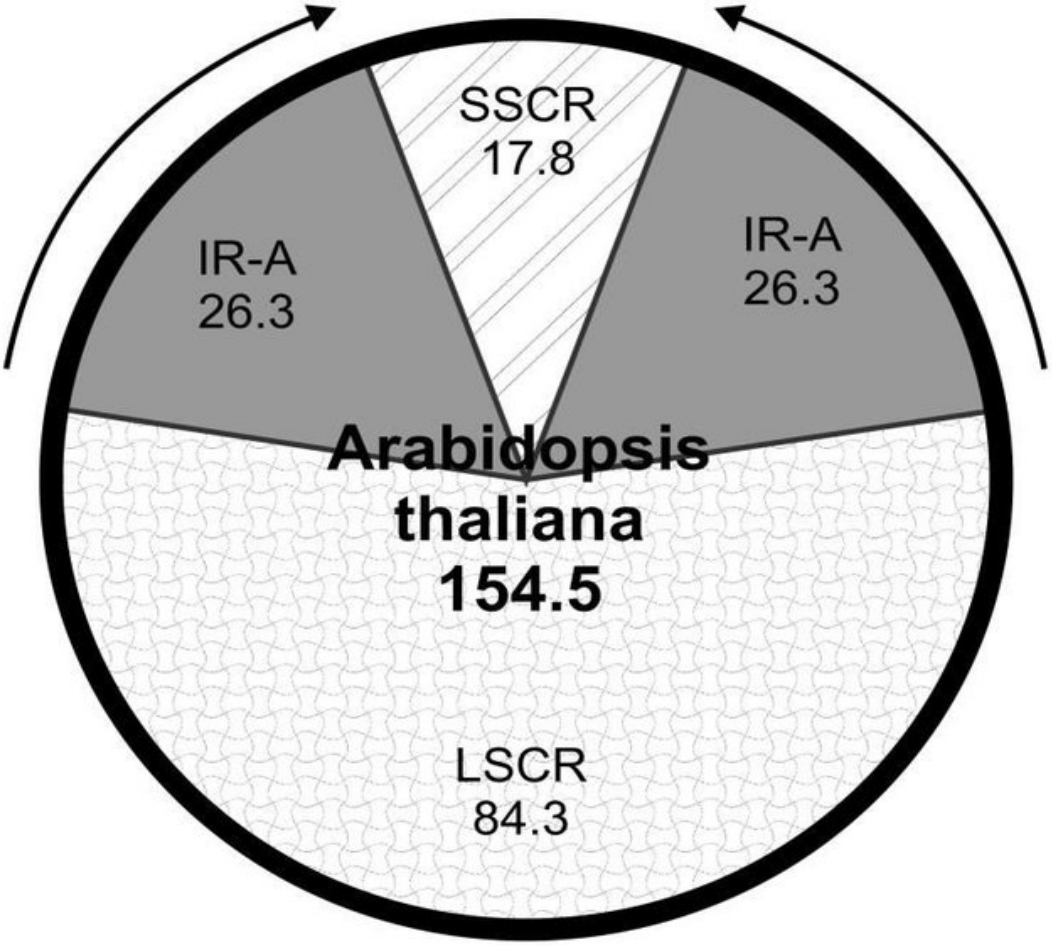


FIGURE 1.1: Structure of the chloroplast genome of *A. thaliana* with SSC-Region and LSC-Region. Length of the genome and its parts in kbp. Graphic from *Olejniczak* et al., 2016

Chloroplast genomes present biologist with many obstacles of which heteroplasmy stands out and immensely complicated genome assemblies and downstream analyses *Corriveau* and *Coleman*, 1988; *Chat* et al., 2002. Heteroplasmy describes the phenomenon of co-existence of multiple versions of the chloroplast genomes in a single organism and single cells of that respective organism. The underlying evolutionary mechanisms behind heteroplasmy are no fully elucidated and eventually existing fitness advantages fueling heteroplasmy cannot be explained satisfactory by evolutionary methods *Scarcelli* et al., 2016. There is a variety of databases containing short read data for species without an chloroplast

genome available. For example NCBI's the short read archive (SRA) *Leinonen* et al., 2010. Because most plant DNA extraction protocols use green leaf tissue as basis, they usually contain a large amount of plastid DNA. Having larger number of assembled and annotated chloroplast genomes publicly available would be beneficial for evolutionary studies and could be a useful addition to bar-coding and super-barcoding *Coissac* et al., 2016 and other biotechnological applications *Daniell* et al., 2016. To achieve this there is a variety of tools available. The study presented in this chapter, assesses the availability, usability and overall performance of 7 of those tools and ultimately makes use of the newly gained insights to attempt *de novo* assemble more than 100 chloroplasts.

1.1.2 Extraction of chloroplast reads from whole genome data and general assembly workflow

There is a variety of strategies to assemble chloroplast genomes from raw sequencing data *Twyford* and *Ness*, 2017. In general the process involves three steps: (i) extraction of plastid reads from the WGS data, (ii) assembly of the plastid genome, (iii) solving the circular structure of the chromosome with the IRs. There are two distinct ways to tackle step (i): The first one is to map all the reads to a reference chloroplast *Vinga* et al., 2012, which works reasonably well if there is one available for the same, or at least a closely related species. The second is to make use of the much larger coverage of chloroplast DNA compared to core DNA, with a k-mer analysis *Chan* and *Ragan*, 2013, this is for example done by `chloroExtractor`*Ankenbrand* et al., 2018. The third way to accomplish this is to combine as done by `NOVOPlasty`*Dierckxsens*, *Mardulyn*, and *Smits*, 2017. Figure 1.2 shows the general workflow of chloroplast assembly too.

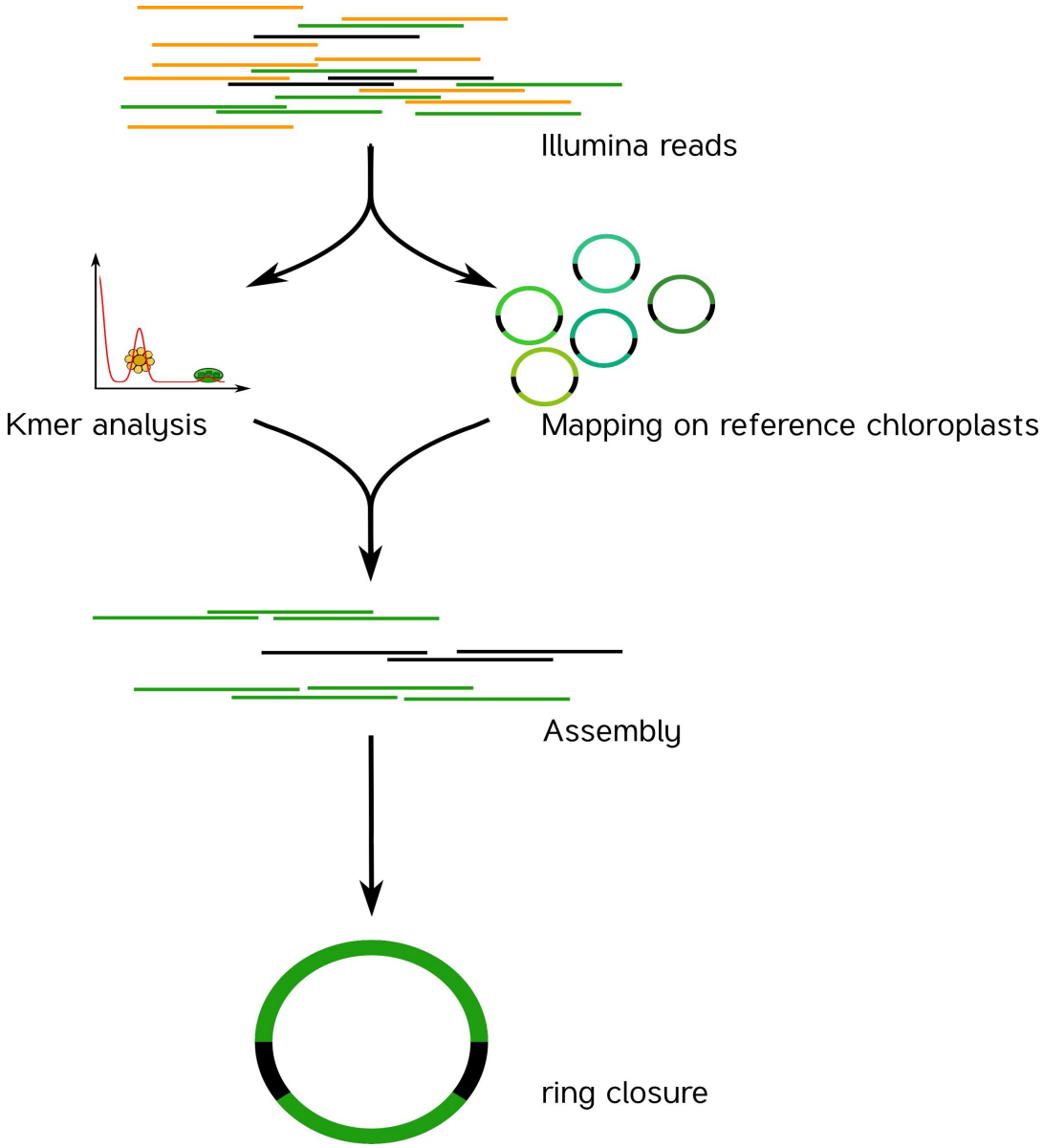


FIGURE 1.2: Standard workflow of chloroplast genome assembly. Graphic from *Ankenbrand* et al., 2018

Purpose and scope of benchmarking the landscape of chloroplast assembly tools

The purpose of this study is to provide insights into the landscape of chloroplast assembly tools, to recommend best practices for organelle genome assemblies

and to provide *de novo* assemblies for many species and family's without a reference chloroplast available so far. To be included into this study the software including the source code must be publicly available and published under the terms of a liberal free open source software e.g. GPL or MIT-license. The study was also limited to paired-end Illumina data sets as their sole input source, because they are abundantly available for this benchmark.The seven tools that me the requirements and were therefore included in this study were: `chloroExtractor`, `ORG.Asm`, `Fast-Plast`, `IOGA`, `NOVOPlasty`, `GetOrganelle`and `Chloroplast assembly protocol`. As later thoroughly described in section 1.3, there are huge differences between those tools and some will not be recommend to be used in scientific applications, while others outstand for most but not all cases.

1.2 Material and Methods

1.2.1 Methods

Data and code availability

All the source code and data used in the scope of this study is publicly available under the terms of the MIT-License. The source code has been published on github *GitHub Repository for Benchmark Project* and archived on zenodo *Förster* and *Ankenbrand*, 2019 . The docker images are available on dockerhub *Docker Hub Group for Benchmark Project*

Tools

There were certain requirements to be met to be included into the study as aforementioned. The only technical requirements was, being able to assemble chloroplast genomes from paired-end Illumina reads. The other requirements were due to reproducibility. (i) The software must be open-source and available under

the terms of a liberal software license. In the authors opinion obscuring reproducibility under paywalls cannot be considered good scientific practice. (ii) It must be a command line tool, GUI-only tools are not suited for highly repetitive automated analyses. In total there were 7 tools that met those requirements: (i) `chloroExtractor` *Ankenbrand* et al., 2018; (ii) `Chloroplast assembly protocol` *Sancho* et al., 2018; (iii) `GetOrganelle` *Jin* et al., 2018; (iv) `ORG.Asm` *Coissac* et al., 2016; (v) `IOGA` *Bakker* et al., 2016; (vi) `Fast-Plast` *McKain* and *Afinit*, 2017; (vii) `NOVOPlasty` *Dierckxsens*, *Mardulyn*, and *Smits*, 2017. There are other tools available, that did not meet the requirements.

Standardization and reproducibility

The main goal of the study was to provided deep insights into the landscape of chloroplast assembly tools. To accomplish that we tried to use the highest standards in bioinformatics when it comes to standardization and reproducibility. Along the study we also wanted to publish easy and ready-to-use versions of all the involved programs, working with standardized input. To accomplish that we decided to make us of containerization in form of docker containers *Merkel*, 2014 to work with the containers in a closed HPC environments we decided a related software - singularity *Kurtzer*, *Sochat*, and *Bauer*, 2017. Therefore users do not have anything else to do than provide two files one for the forward reads (`forward.fq`) and one for the reverse reads (`reverse.fq`). Both files are required to be in FASTQ format. If docker or singularity are installed no further setup is requirement, because all dependencies and packages are installed and run from the containers on any given environment. Besides the individual output files, recording the process of the respective program, all programs write the assembly products in to files called `output.fa` in FASTA format. For the quantitative and consistency measurements the singularity containers were run on the Julia HPC-Cluster of the University of Würzburg using the SLURM workload manager *Jette*, *Yoo*, and *Grondona*, 2002. All runs for all assemblies were set with a time limit of

48h. This was necessary because some assemblers e.g. `IOGA`, if not finishing after at least 12 hours appear to continue in some kind of loop and never finish.

1.2.2 Data

Three different data sets were used for this study. (i) Simulated data from *A. thaliana* chloroplasts. (ii) real data with known reference chloroplast to rate the success of the assemblies. (iii) Novel data sets from NCBI's SRA without a know reference chloroplast to apply the gained knowledge for the *de novo* assembly of more than 100 chloroplasts.

Simulated

For first steps in any benchmarking process it is always useful to start with simulated data, where the investigators have full control over all the parameters involved. In the case of the present study the data's input parameters thought to be influential on the outcome where: The read length, the ratio between chloroplast and core genome reads. The simulations were based on data from the TAIR10 genome *Berardini* et al., 2015 and performed using `seqkit` *Shen* et al., 2016. Ratios simulated were: 0:1, 1:10, 1:1000 and 1:1000, with read length of 150 and 250 bp. The simulated data consisted either of 2 million read pairs or the full data available. The simulation process is documented and the code and the data is available on github and zenodo *Ankenbrand* and *Förster*, 2019

Real data set

Real data was selected from the SRA database table 1.1 lists the search terms that had to be met according to the aforementioned search terms.

TABLE 1.1: Data selection criteria for real data sets from SRA

choice	option	explanation
green plants	Organism	include only photosynthetic plants e.g. no algae
wgs	Strategy	only data from wgs projects included
Illumina	Platform	include only paired-en Illumina reads
biomol DNA	Properties	include only biomol. DNA samples (e.g. no RNA)
paired	Layout	exclude single-end reads
random	Selection	
public	Access	Only publicly available data included

In total this resulted in 369 data sets representing a broad variety of the plant kingdom with many different families and genera included.

Novel data sets

To assess the performance on assemblies without a published chloroplast on `CpBase` *CpBase* 105 data sets were selected from SRA, it was emphasized that such data sets were selected, with the next relatives with a reference chloroplast as distantly related as possible in taxonomic terms according to NCBI *NCBI Taxonomy*

1.2.3 Evaluation

Quantitative

Each assembly from each assembler was compared to their respective reference genome by alignment using minimap2 *Li*, 2018 and based on those alignments scores were calculated following equation 1.1 from 0 to 100 with 100 being a perfect score. Four different metrics contributed equally to the final score. (i) The coverage of the assembled genome compared to the reference genome cov_{ref} as an estimate for the completeness. (ii) The vice versa case cov_{qry} as a measure for the correctness of the assembly. (iii) The success of resolving the IR correct,

estimated from the size difference from the reference and the newly assembled genome is: $min\left\{\frac{cov_{qry}}{cov_{ref}}, \frac{cov_{ref}}{cov_{qry}}\right\}$. (iv) The number of total contigs were weighted as $\frac{1}{n_{contigs}}$ giving a chloroplast with 1 contig the optimal score.

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

While it is difficulty to assess the success or failure of assemblies on a continuous scale, equation 1.1 allows for objective and unbiased measurements. SNPs or other small variants do not influence the outcome of the score, because it much more likely that there are due to in-species variation of the plastid's genome and not caused be the assembly, and even if the latter is true it would be difficult to evaluate that.

Consistency

In any given bioinformatical application consistency is a desired trait. All software (exceptions excluded) should given repeatedly the same input provide the same output. The same obviously or even more so holds true for assembly tools. To evaluate the reproducibility of the the 7 tools. All the 369 real data sets described in section 1.2.2 has been used twice for assembly with each assembler and scored twice with equation 1.1. The correlation between the first and the second scores and runs was used the measure for the robustness of a program.

1.3 Results

1.3.1 Quantitative

Simulated data

The simulated data was assembled and scored with all the tools as described above. Figure 1.3 shows as a tile plot the results for all data sets and assemblers. While at first sight there is no clear correlation with the input data sets. It is obvious that there are grave differences between the assemblers. Two programs namely `Chloroplast assembly protocol` and `IOGA` failed to correctly assemble a single chloroplast genome. `IOGA`even fails to provide output at all for the majority of the data sets. While those two stand out as a negative example `Fast-Plast`and `GetOrganelle`stand out as a positive example perfectly or nearly perfectly assembling all the data sets, with `GetOrganelle`surpassing the performance of `Fast-Plast`. In the middle of the filed are `chloroExtractor`, `ORG.Asm`and `NOVOPlasty`performing reasonably well, but sometimes lacking to solve the IRs and the circular structure.

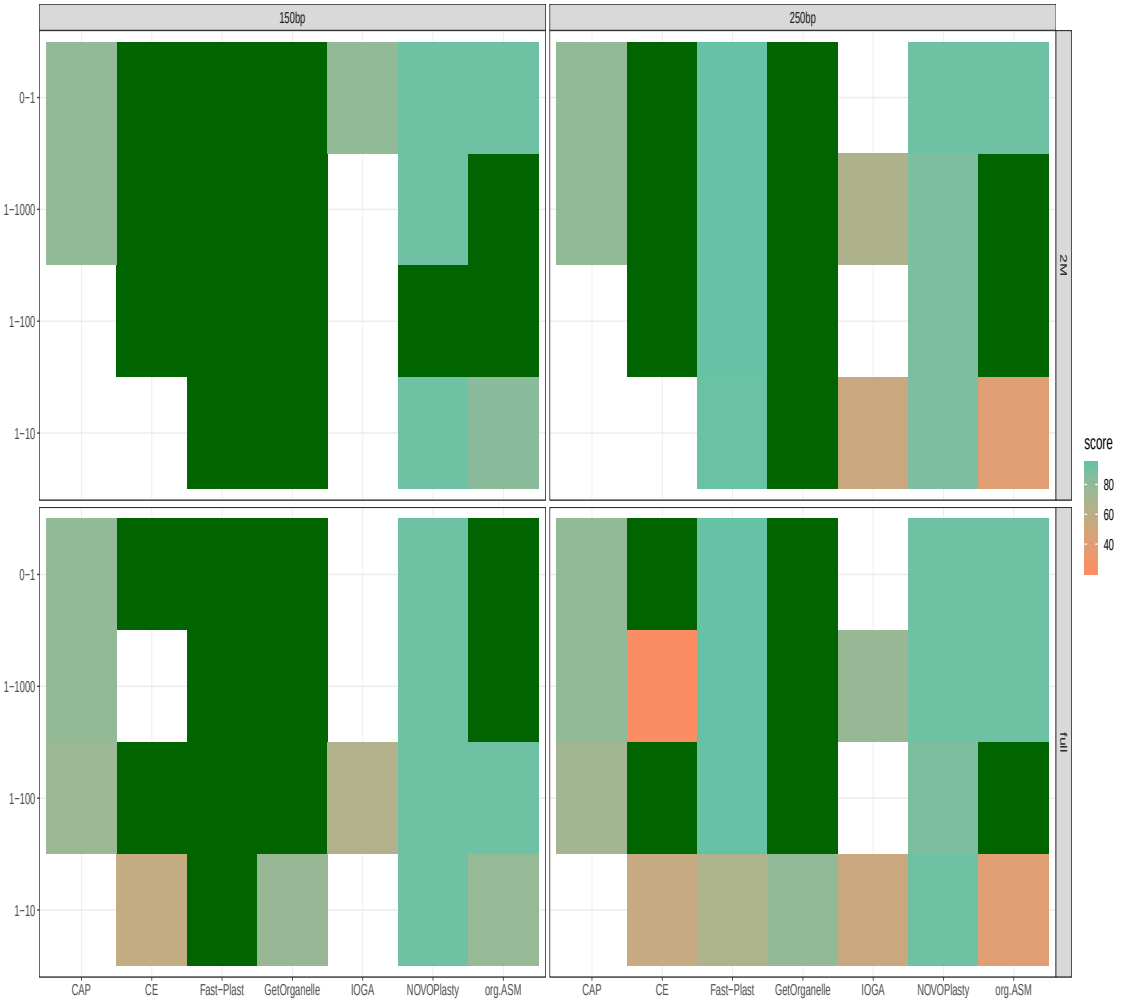


FIGURE 1.3: Results of assemblies executed with simulated data sets.

While there is a significant difference between the assemblers the same is not necessarily true in general for the other varying parameters. While `Fast-Plast`deals with the shorter reads of 150 bp much better than with the longer reads of 250 bp. The outcome of the other assemblies does not seem to be influenced by that. There is no difference between the full and the subsampled data sets. And while all assemblers appear to be more challenge by low chloroplast to core genome ratios of 1:10 larger rations do not affect the quality of the result as expected. Table 1.2 shows all the individual results for all data sets and assemblers. For the fields with no entry the respective assembler failed to provide an output.

TABLE 1.2: Scores of assemblies of simulated data

	data set	CAP	CE	Fast-Plast	GetOrganelle	IOGA	NOVOPlasty	org.ASM
1	sim_150bp.0-1	79.10	100.00	99.48	100.00		91.52	100.00
2	sim_150bp.0-1.2M	79.10	100.00	99.72	100.00	79.10	91.52	91.50
3	sim_150bp.1-10		56.44	100.00	76.98		91.52	78.00
4	sim_150bp.1-10.2M			99.97	100.00		91.52	82.72
5	sim_150bp.1-100	75.72	100.00	99.48	100.00	66.09	91.52	91.50
6	sim_150bp.1-100.2M		100.00	99.47	100.00		100.00	100.00
7	sim_150bp.1-1000	79.10		99.72	100.00		91.52	100.00
8	sim_150bp.1-1000.2M	79.10	100.00	99.72	100.00		91.52	100.00
9	sim_250bp.0-1	79.10	100.00	93.82	100.00		91.52	91.50
10	sim_250bp.0-1.2M	79.10	100.00	93.83	100.00		91.52	91.50
11	sim_250bp.1-10		54.98	68.45	78.89	52.71	91.52	40.20
12	sim_250bp.1-10.2M			93.00	100.00	52.67	87.40	40.20
13	sim_250bp.1-100	72.81	100.00	93.82	100.00		87.40	100.00
14	sim_250bp.1-100.2M		100.00	93.83	100.00		87.40	100.00
15	sim_250bp.1-1000	79.10	21.30	93.83	100.00	76.96	91.52	91.50
16	sim_250bp.1-1000.2M	79.10	100.00	93.83	100.00	67.55	87.40	100.00

Real data sets

Table 1.3 gives the results from the assemblies of 369 data sets with 7 assemblers. Similar to the results of the previous section there is a significant difference between the tools. Likewise `GetOrganelle`is the most successful assembler by a large margin with 210 of 369 perfectly assembled chloroplast genomes, failing to provide output for only 9 data sets, resulting in a media score > 99. Contrary to `GetOrganelle`, `Chloroplast assembly protocol`and `IOGA`fail to completely assemble a single genome. The performance of `Fast-Plast`could be considered reasonably well, completing approximately half as many genomes as `GetOrganelle`and being the only other tool whose average score is larger than 90. Similar to the trials with the simulated data in chapter 1.3.1 in the middle of the field are `chloroExtractor`, `NOVOPlasty` and `ORG.Asm`.

TABLE 1.3: 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 1.4 emphasizes the large differences between the assemblers shown in table 1.3. The swarm plots show some distinct bands for some assemblers e.g. `NOVOPlasty`and `ORG.Asm`, suggesting that multiple assemblies fail to be solved into a single contig genome at a certain point. As thoroughly discussed in section 1.4 just from this swarm plot it is debatable if all the tools could be recommended for the purpose they were designed for.

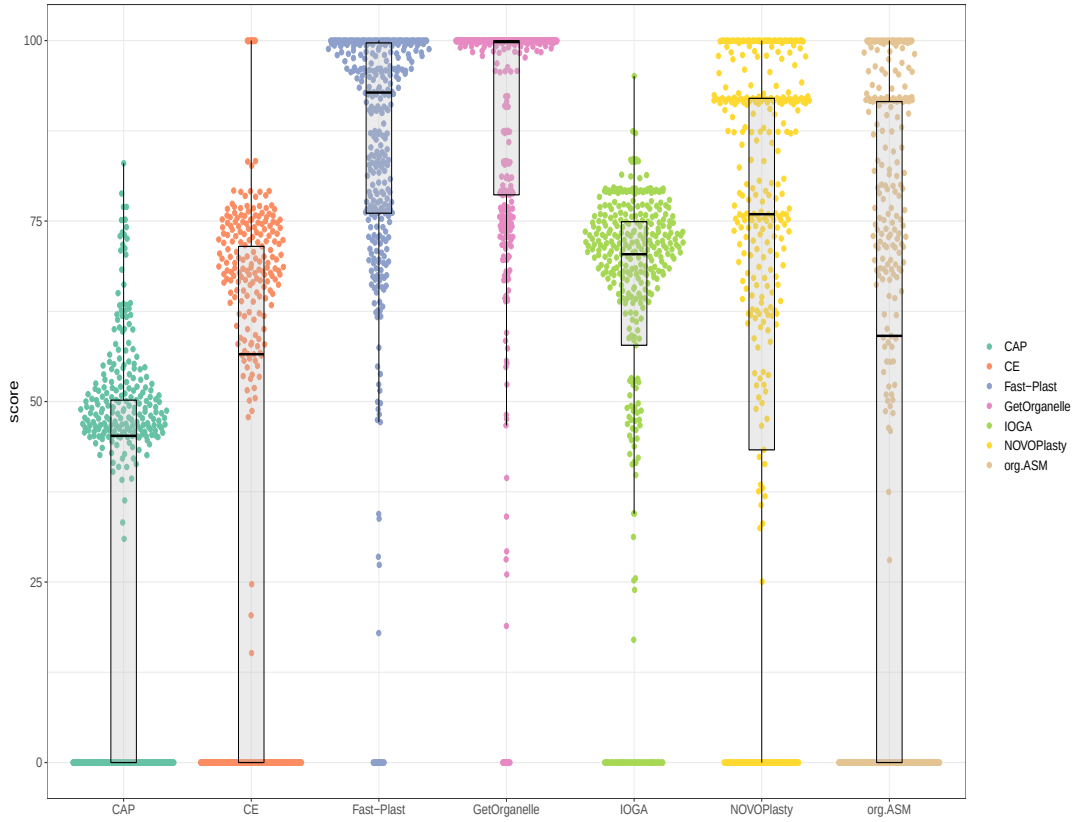


FIGURE 1.4: Box and swarm plots depict the results from the scoring shown in 1.1

Consistency

Consistency testing was done by re-running every assembly for the real data sets twice and comparing the scores. `chloroExtractor`was the only tool that was 100 % consistent over 2 runs. Followed by `Fast-Plast`and `NOVOPlasty`. The consistency plot figure 1.5 for both of them results in an arrowhead shaped plot. With the main differences between the first and second run in the best scores. All other assemblers appear to produce the same output in the two runs except if the fail to complete the assembly at all. This is less pronounced for `Chloroplast assembly protocol`and `GetOrganelle`and is a grave issue for `ORG.Asm`and `IOGA`.

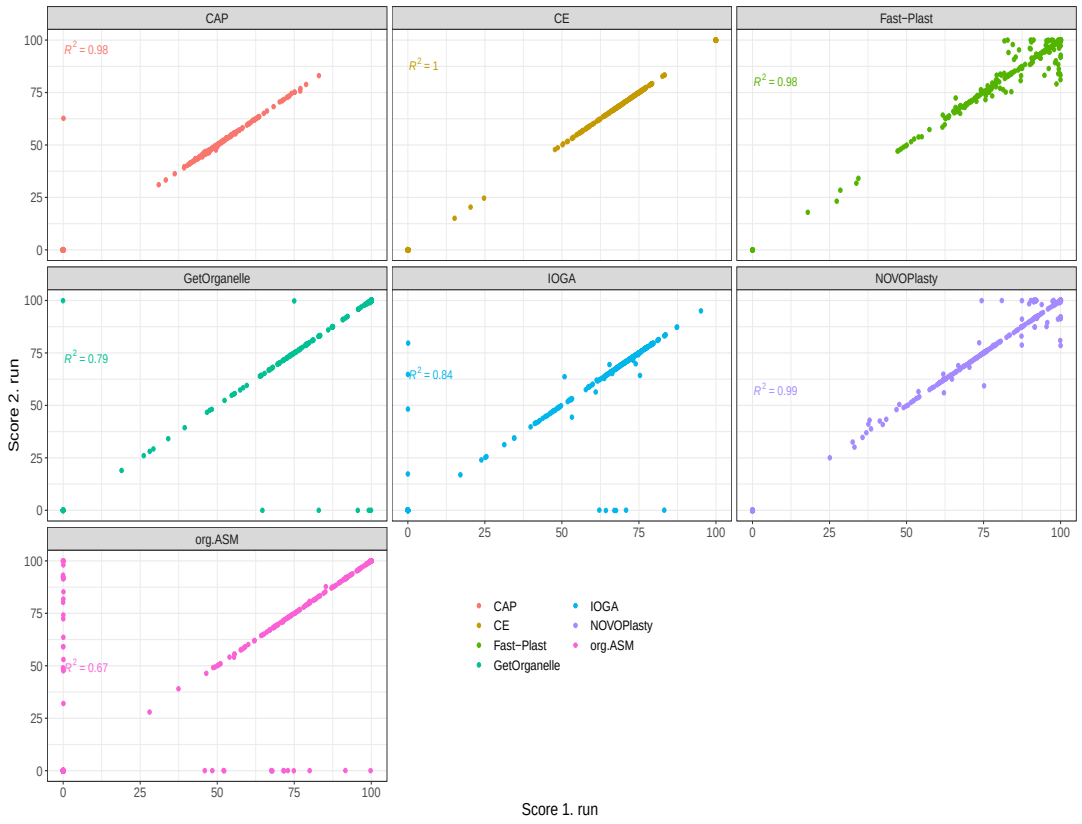


FIGURE 1.5: Swarm plots depict the results from the scoring shown in 1.1 for two independent runs for each assembler on each of the data sets

Novel

The final assessment in the scope of the study was to test the assemblers on novel data sets without a published chloroplast. This step is important for two reasons. (i) There could be the possibility that certain tools perform well on known chloroplasts because they somehow of knowledge over those and simply apply it during those assemblies and therefore the previous results will not be able to generalize on unknown data. (ii) To apply and test the gained insights in the hope of providing the scientific community with a larger variety of published chloroplast genomes. Again the most successful assembler was `GetOrganelle`, with 49 out of 105 data sets completely assembled. Lacking a reference genome the success had to be defined differently and equation 1.1 was not suitable to evaluate the novel

assemblies. Metrics influencing the score of the novel assemblies were the number of contigs, solving the IRs and the size of the SSC and LSC. This known to the authors might be very biased and not true for all chloroplast and assumes that all chloroplast genomes follow the general structure for their genomes described in chapter 1.1. Figure 1.6 compares the results for the assemblies with at least one successful assembly.

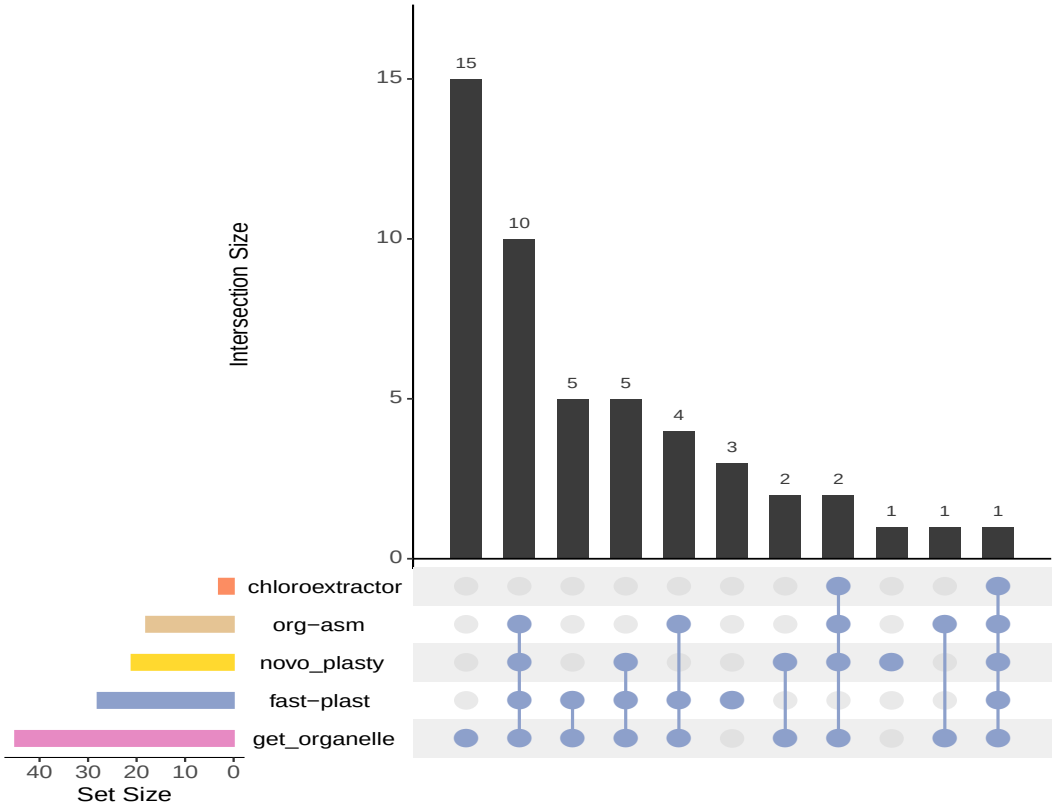


FIGURE 1.6: Upset plot comparing the success rates of the different assemblers

1.4 Discussion

The study compromised of two goals. (i) to assess the overall performance of a variety of tools designed specifically for the assembly of circular chloroplast genomes from paired-end Illumina data and (ii) to *de novo* assemble a variety of yet unpublished chloroplast genomes from existing data. To accomplish the

first goal 16 simulated and 369 simulated data sets were used adding up to a total of 5166 assemblies for the real data sets and 112 for the simulated data, along 735 assemblies for the novel data sets, thus underlying the statistical powers of this benchmarking study. The most successful tools were `GetOrganelle` and `Fast-Plast` which are recommended to be used complementary, because as shown in figure 1.7 they succeed for the most data sets compared to other assemblers and accomplish to satisfactory assemble chloroplast genomes where the other fails. If both of them fail it might be worthwhile to repeat the runs because other results could be expected as shown in the scatter plots of figure 1.5, especially `Fast-Plast`might be able to improve the previously achieved sore. Only if both of them fail it might, even though improbable, that `NOVOPlasty`might lead to a successful assembly. The other assemblers should be used with caution. While `chloroExtractor`might be good for a quick overview due to its relatively low demand in computational time *Freudenthal* et al., 2019b; `Chloroplast assembly protocol`, `ORG.Asm`and `IOGA`are not be recommended to used as the primary tools in organelle genome assembly projects, as used in this study.

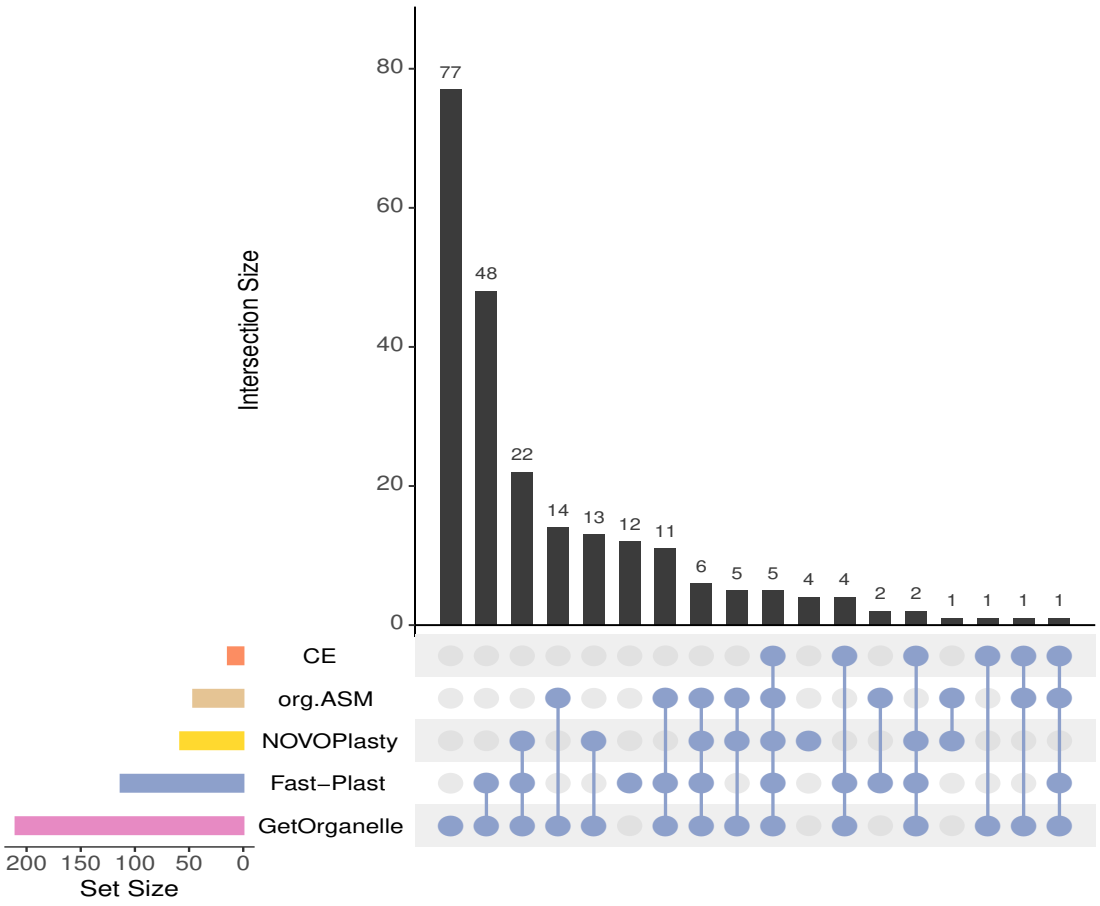


FIGURE 1.7: Upset plot showing the intersections of success rates between assemblers. A successful assembly was defined with a score > 99 according to equation 1.1. The colored, horizontal barplot indicates the total number of successful assemblies for an individual tool. The black, vertical barplot gives the magnitude of the intersection between the assemblers indicated with the dot. Therefore there first bar is to be interpreted as follows: 77 data sets were only successfully assembled by `chloroExtractor`, likewise 48 genomes were assembled completely by `GetOrganelle` and `Fast-Plast` and so on.

It might be possible that overall performance of a specify tool might change significantly by fine tuning the input parameters of the tool, which was purposely not done in the scope of the present study, because this study was designed to

mimic the behavior have end-users and not developers of such tools and the assumption is proposed that end-users with little experience in bioinformatics would be inclined to use the basic configurations of such a tool.

While there is a huge differences for all assemblers they are presented with the same challenges and the bottlenecks are similar for each of them, the success rate of passing those differs however. Figure 1.8 shows the alignment of the 7 chloroplast genomes of *Oryza brachyantha* a grass distantly related to cultivated rice *Orayza sativa* and the respective reference genome. For the need of a linear representation of the circular genome the convention is to present chloroplast genomes in the order LSC - IRa - SSC -IRb. *O. brachyantha* was chosen because multiple tools successfully or at least almost assembled the full genome. Only `Chloroplast assembly protocol`is singled out, which only managed to assemble a few fragments on the SCC and the IRs on many contigs. A common mistake is to return 3 contigs as `IOGA` did. They represent the LSC the SSC and one IR but failed to resolve those regions into a one circular contig. `GetOrganelle` and `Fast-Plast` were able to reproduce the structure of the reference, while `chloroExtractor` flipped the LSC and `NOVOPlasty`and `ORG.Asm` were not able to construct the single contig into the conventional structure. All of this are common mistakes appearing more or less rare in all the assemblers. This could be a good starting point for the developers to further improve their tools. In this example all but `Chloroplast assembly protocol` were able to construct all the parts of the chloroplast's genome, and the main mistake was to resolve the structure of the genome into a circular, one contig version.

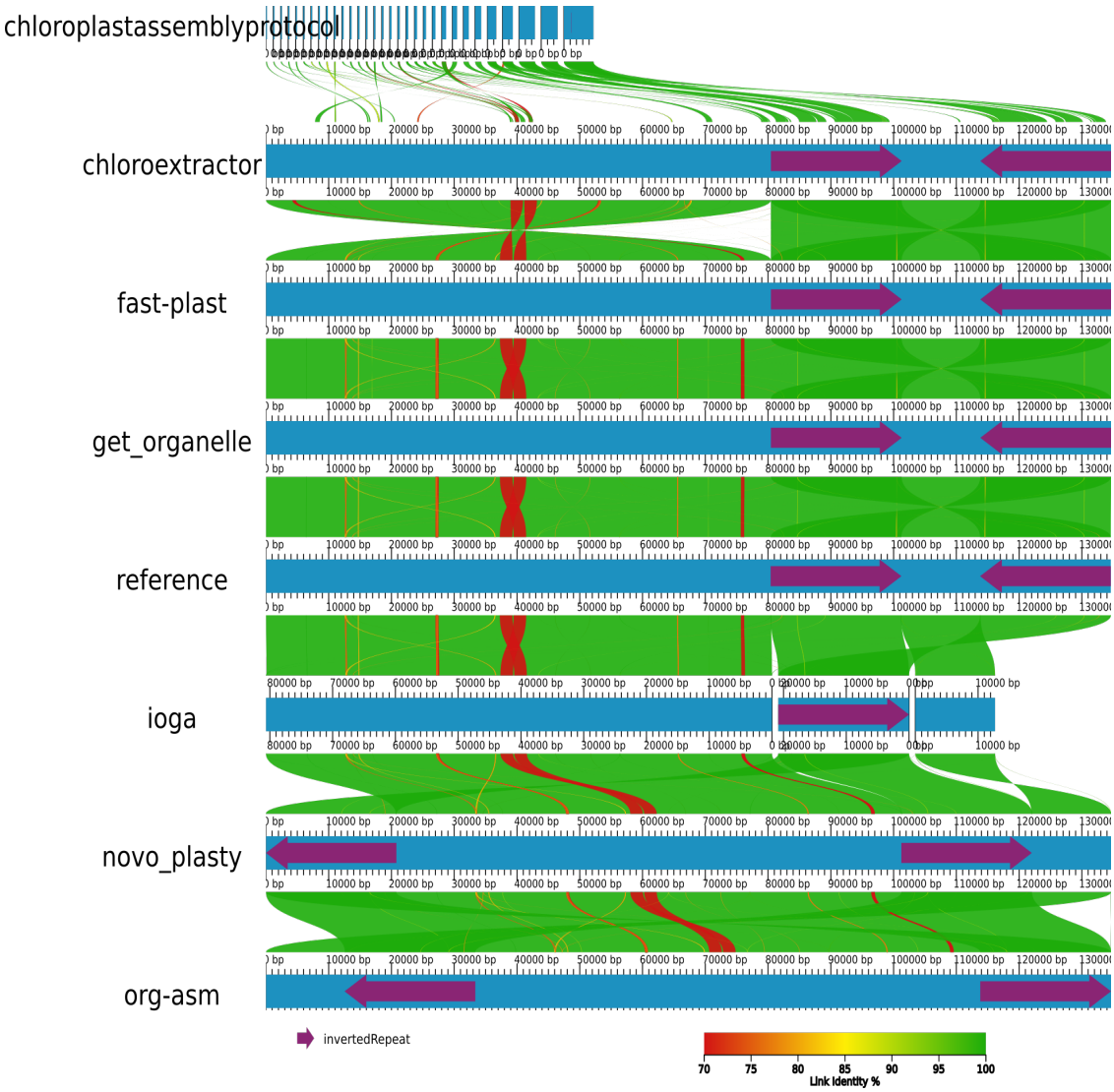


FIGURE 1.8: AliTV plot *Ankenbrand* et al., 2017 from *Freudenthal* et al., 2019b showing the alignments of *Oryza brachyantha* chloroplast genomes fro all 7 assemblers. Regions in adjacent assemblies are connected with colored ribbons for similar regions in alignment with the identity coded as described in the legend. The purple arrows indicate the IR regions

1.5 Conclusion & outlook

Organelle genomics is promising field in plant genetics. As described in section 1.1 chloroplast genomes are well-suited for applications in evolutionary sciences, taxonomy and barcoding applications. Alike its mother branch genomics

for comparative chloroplast genomics its just as crucial to obtain high quality genomes. And the quality is mainly influenced by two major factors: the quality of the genome sequencing protocol and the quality of the assembly. As shown the latter varies massively between tools and not all tools are recommend equally from the conclusions drawn for the above experiments. All tools have room for improvement, this is meant to criticize the respectable work of the developers, but to encourage them to further develop tools and publish them under terms of liberal software licenses for the greater benefit of the entire scientific community.

Chapter 2

Understanding the haplotype structure of Arabidopisis thaliana

2.1 Introduction

Recombination and LD in *A. thaliana Kim* et al., 2007 LD in *A. thaliana Nordborg* et al., 2002 Evolution of selfing *Tang* et al., 2007 Evolution and genetic differentiation among relatives of Arabidopsis thaliana *Koch* and *Matschinger*, 2007 FLC haplotypes *Li* et al., 2014

2.2 Haplotyping of A. thaliana

2.3 Results

2.4 Disucssion

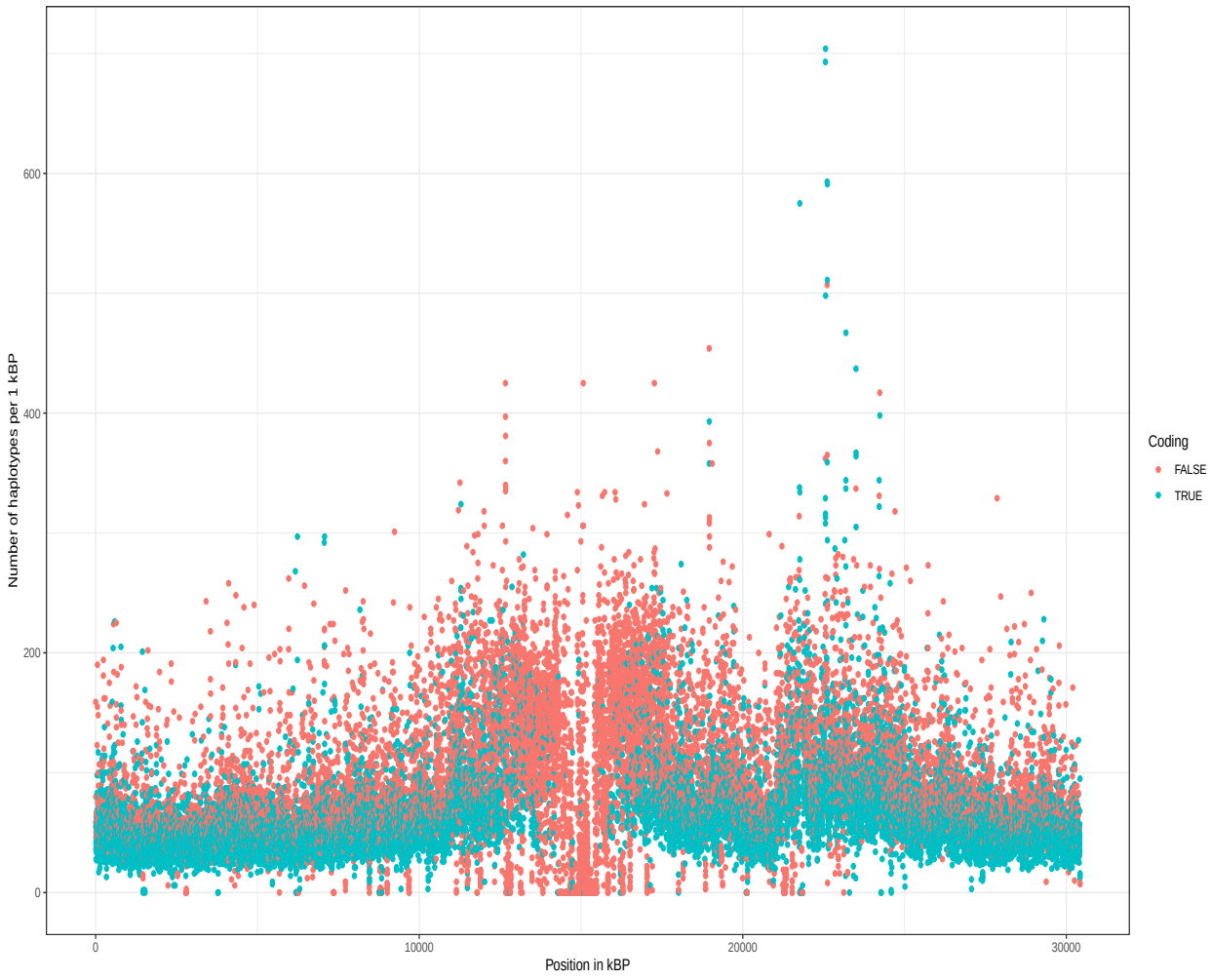


FIGURE 2.1: The number of segregating haplotypes with a polymorphism in at least one position over a stretch of 1 kBP.

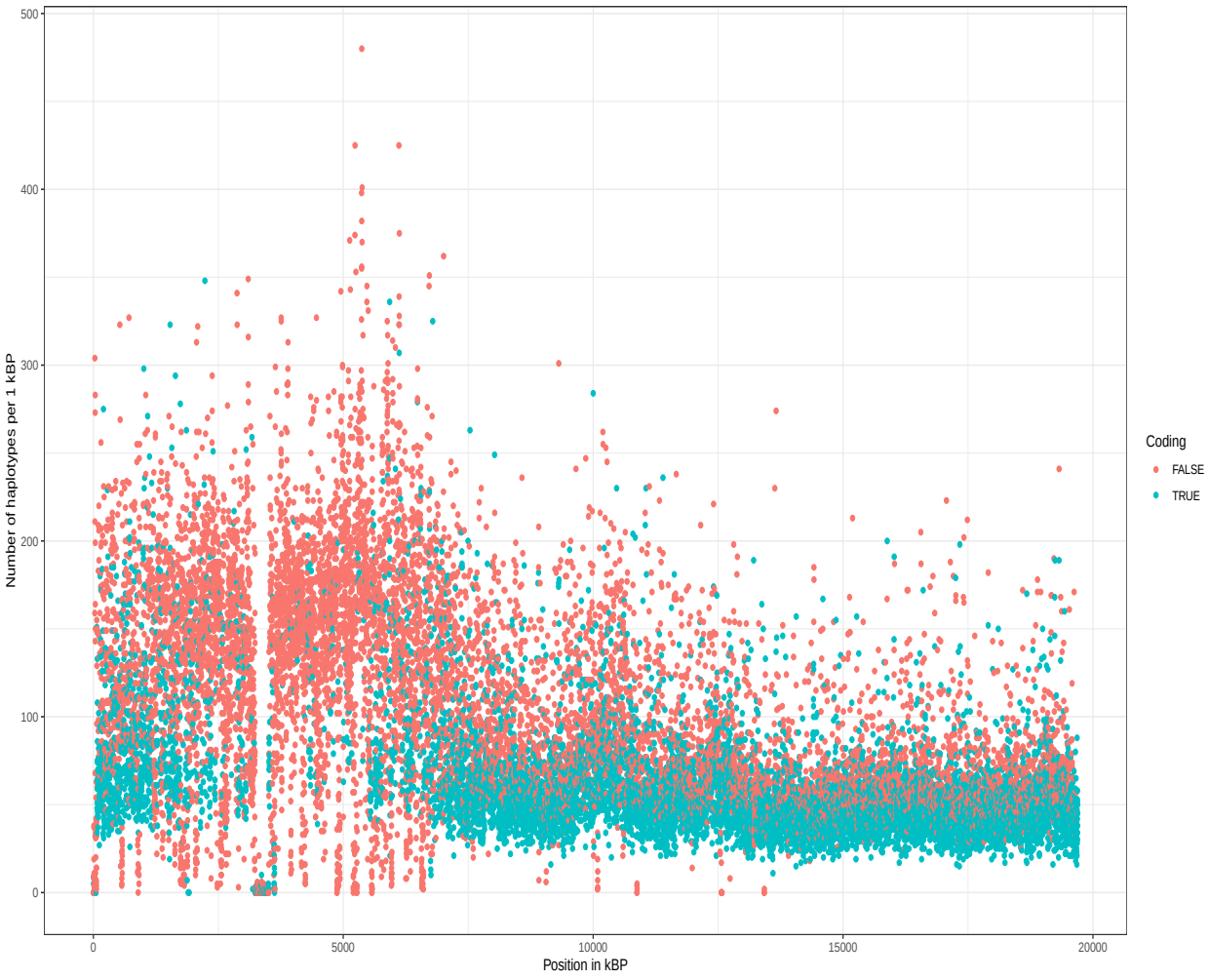


FIGURE 2.2: Number of segregating haplotypes with a polymorphism in at least one position over a stretch of 1 kBP.

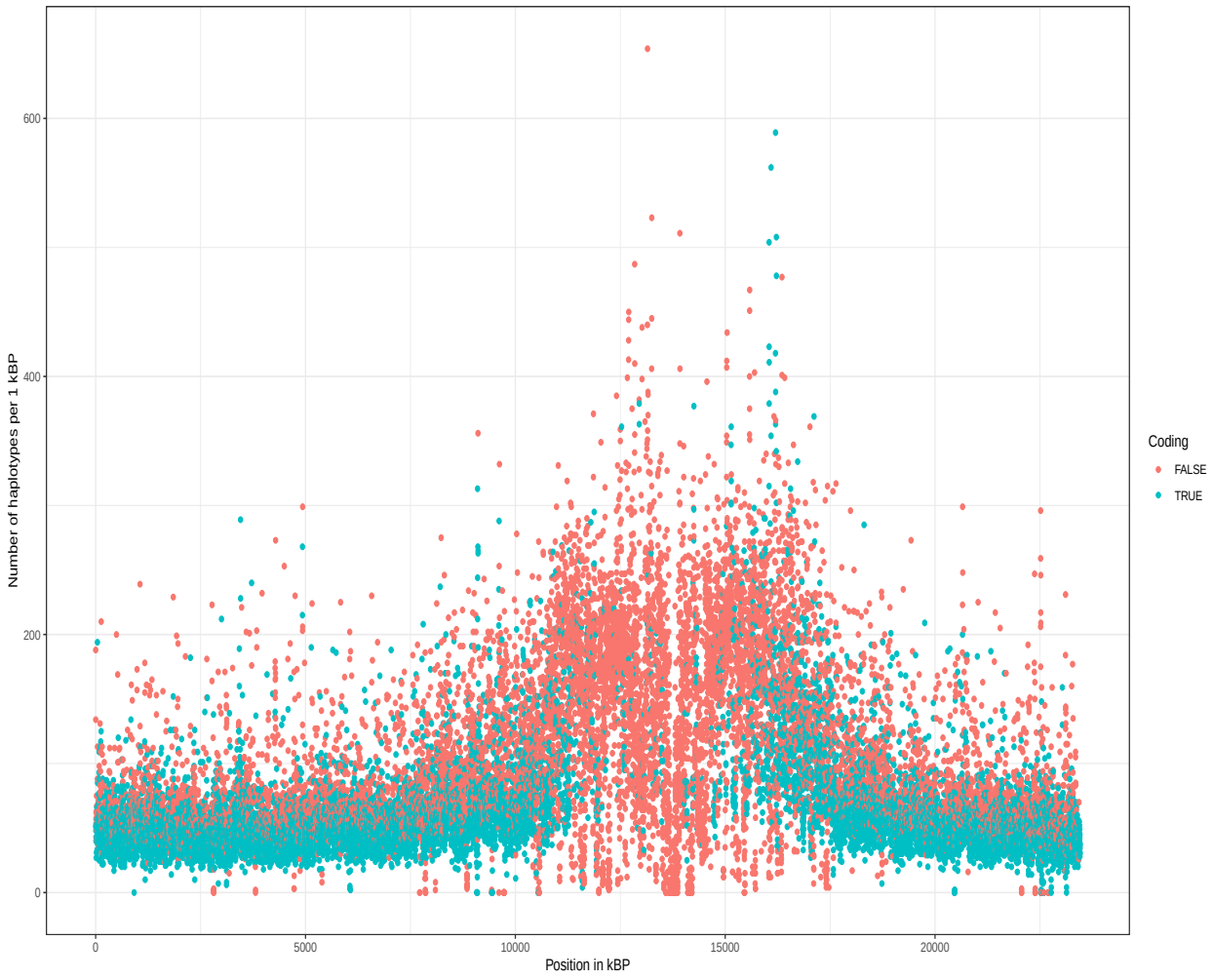


FIGURE 2.3: Number of segregating haplotypes with a polymorphism in at least one position over a stretch of 1 kBP.

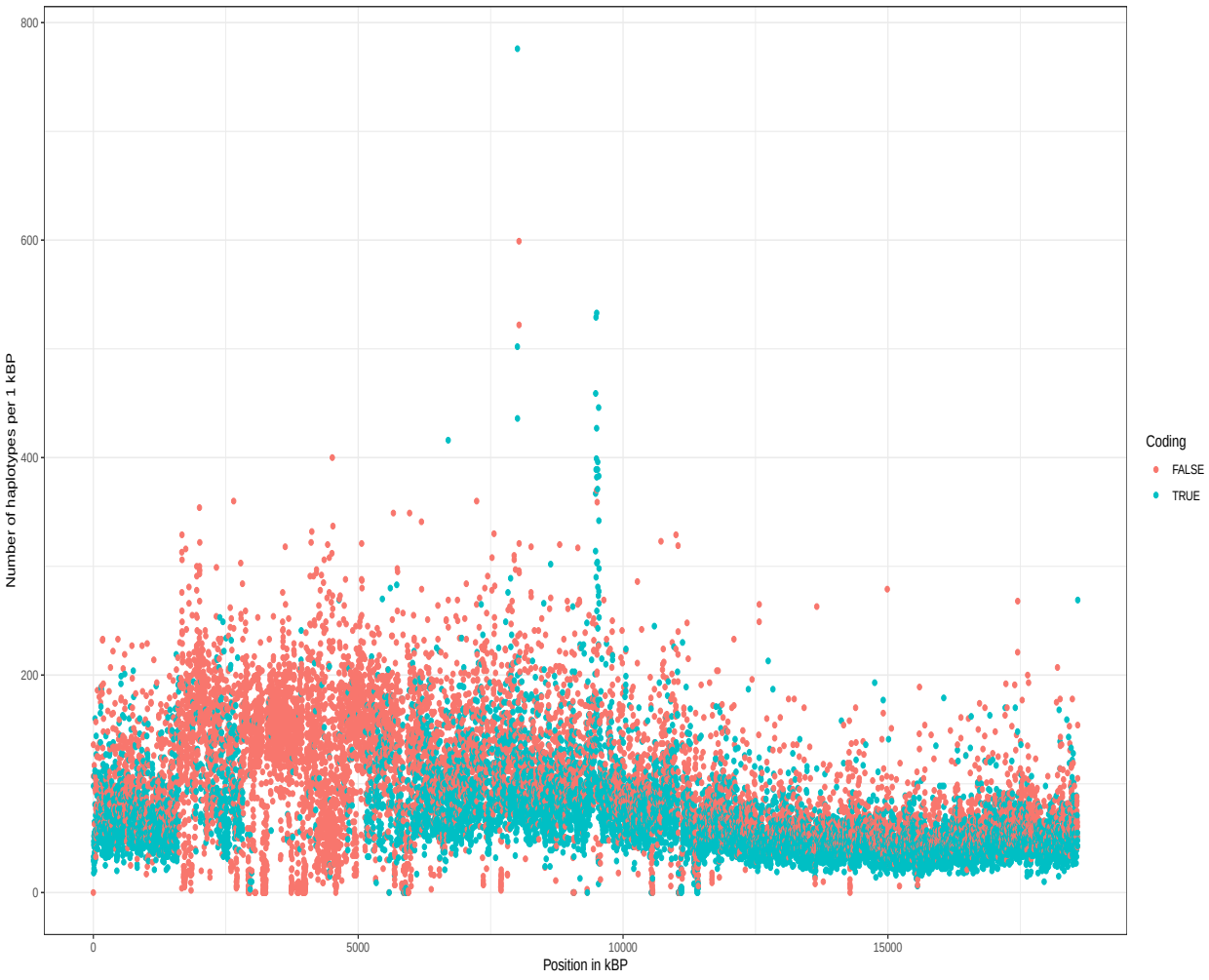


FIGURE 2.4: Number of segregating haplotypes with a polymorphism in at least one position over a stretch of 1 kBP.

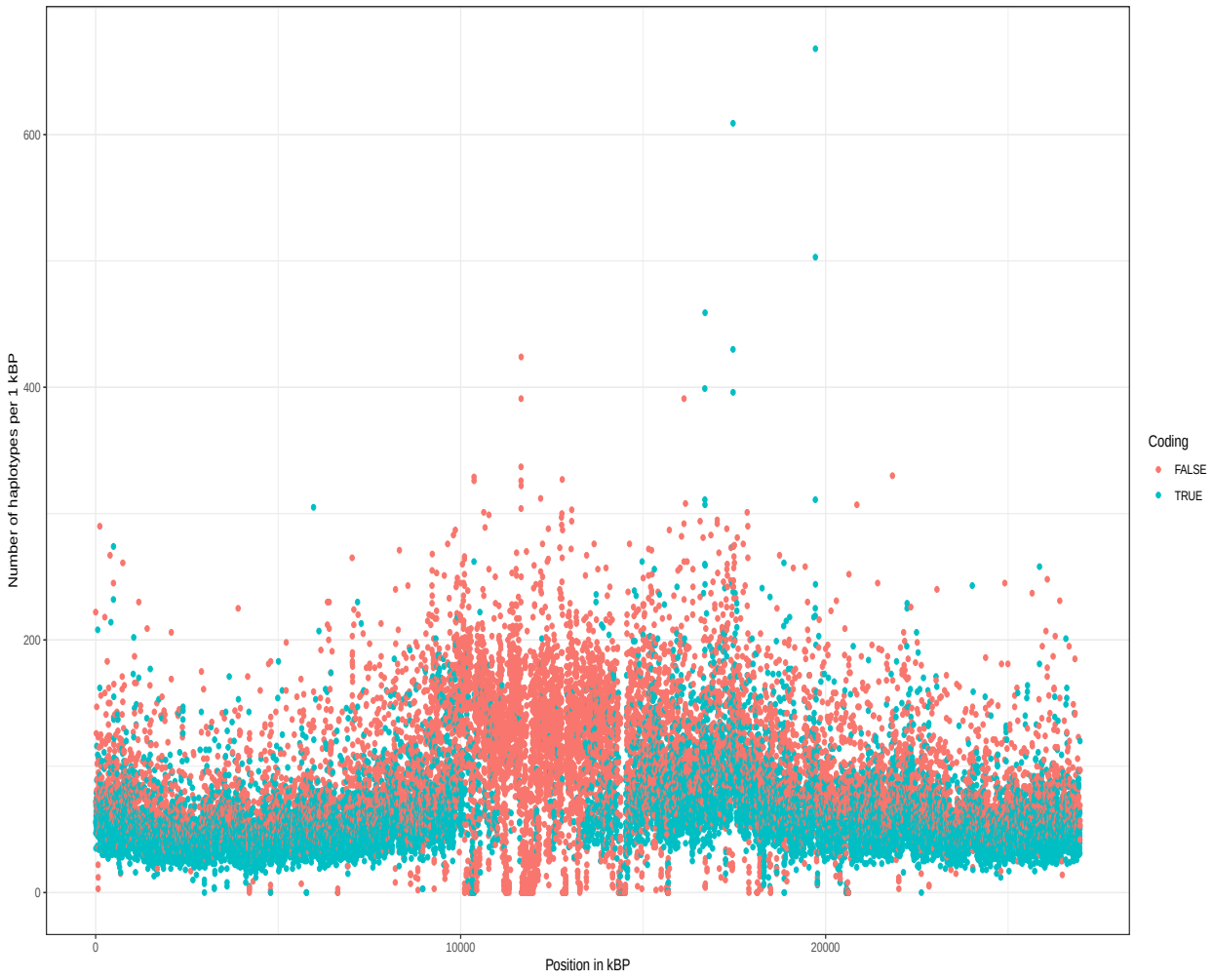


FIGURE 2.5: Number of segregating haplotypes with a polymorphism in at least one position over a stretch of 1 kBP.

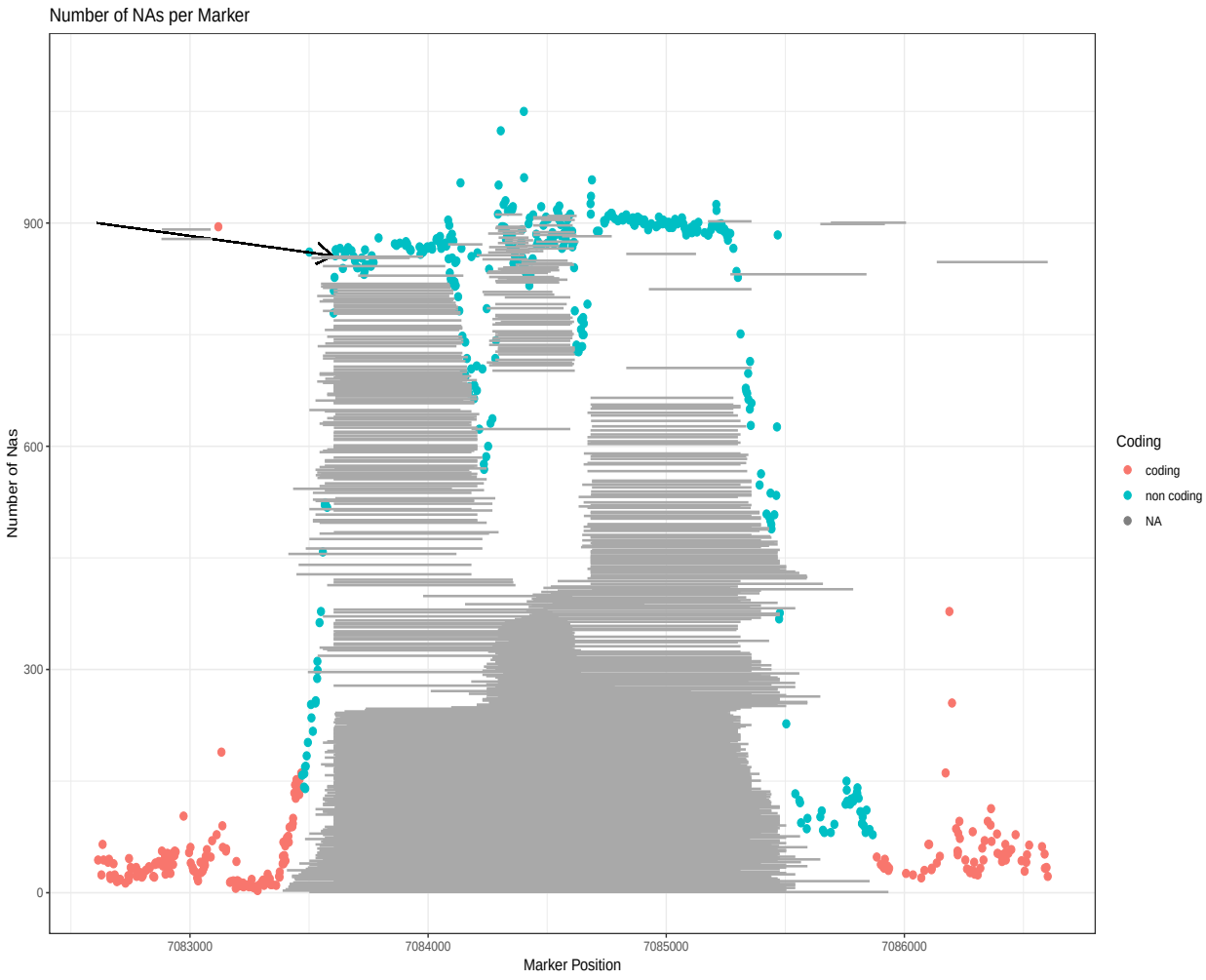


FIGURE 2.6: Number of segregating haplotypes with a polymorphism in at least one position over a stretch of 1 kBP.

Chapter 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 bioχiv 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 posses 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:

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

From this LMM the residual sum of squares for marker i are calcucated as descirebed in 3.2

$$RSS_i = \sum Y - (X_i\beta_0 + I_i\beta_1) \tag{3.2}$$

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:

$$F = \frac{RSS_{env} - R1_{full}}{\frac{R1_{full}}{n-3}} \tag{3.3}$$

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 permuation-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 then *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.

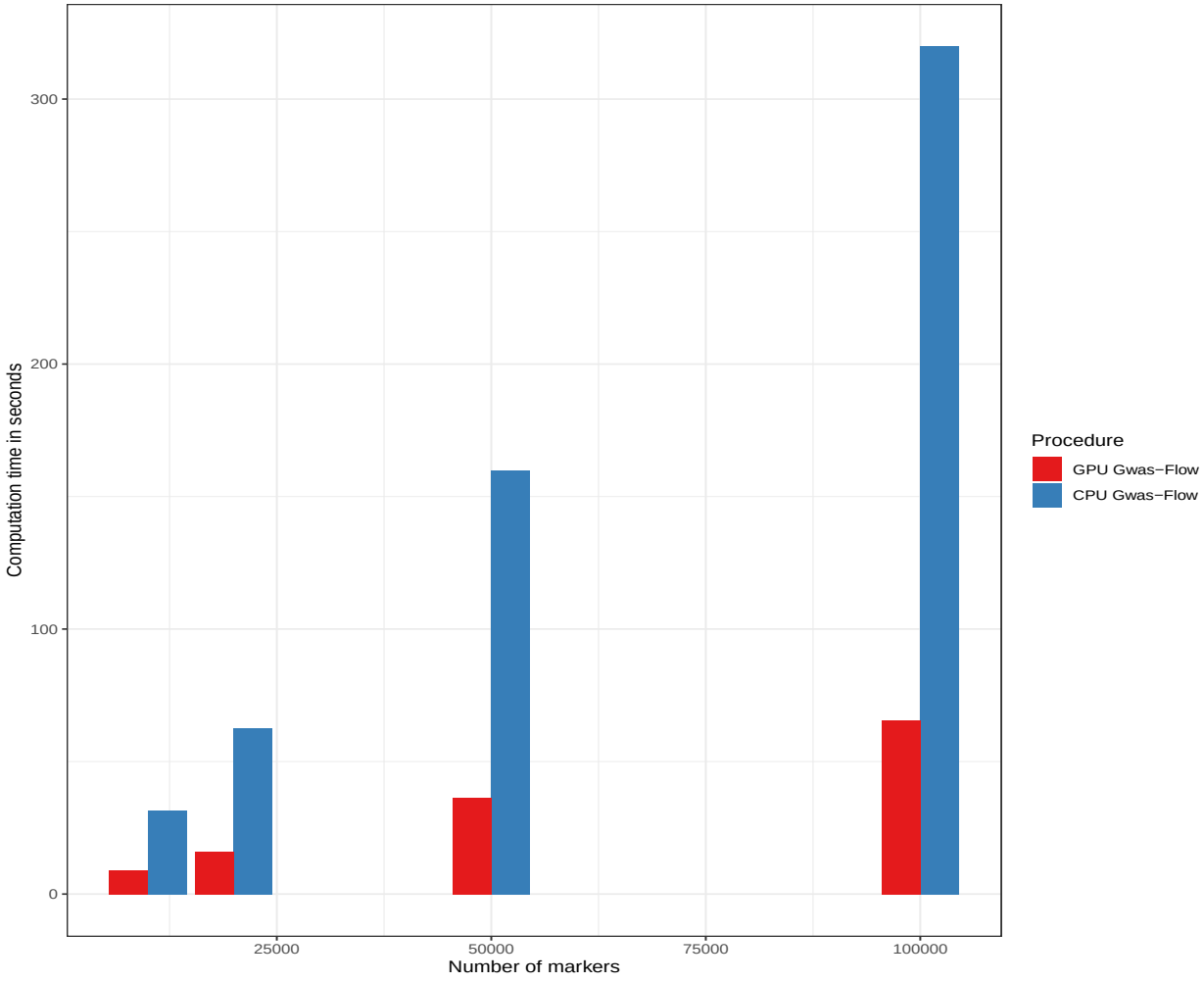


FIGURE 3.1: Computational time as a function of the number of genetic markers with constantly 2000 accessions for both `GWAS-Flow` versions

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

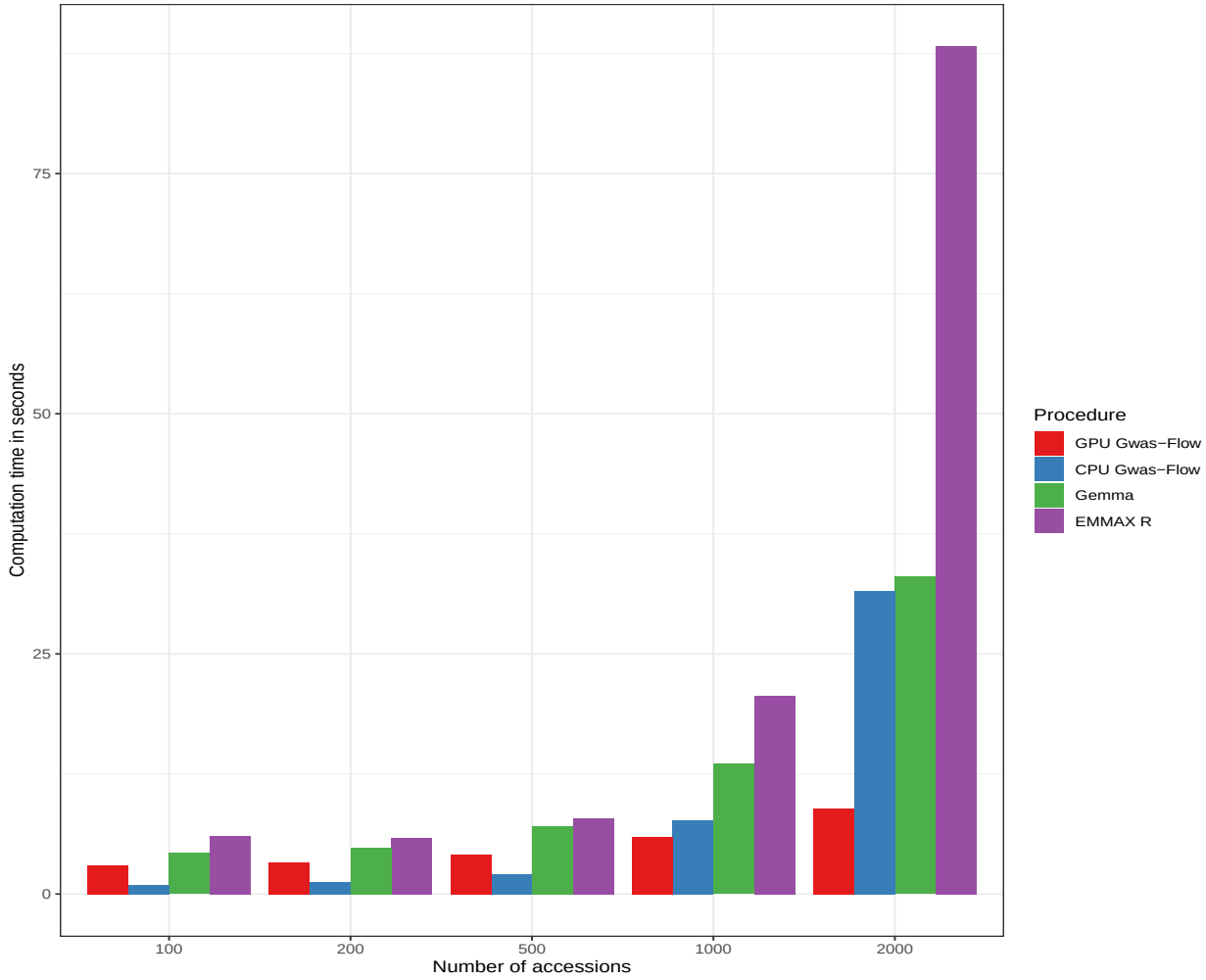


FIGURE 3.2: Computational time as a function of the number of accessions with 10000 markers each.

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 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.

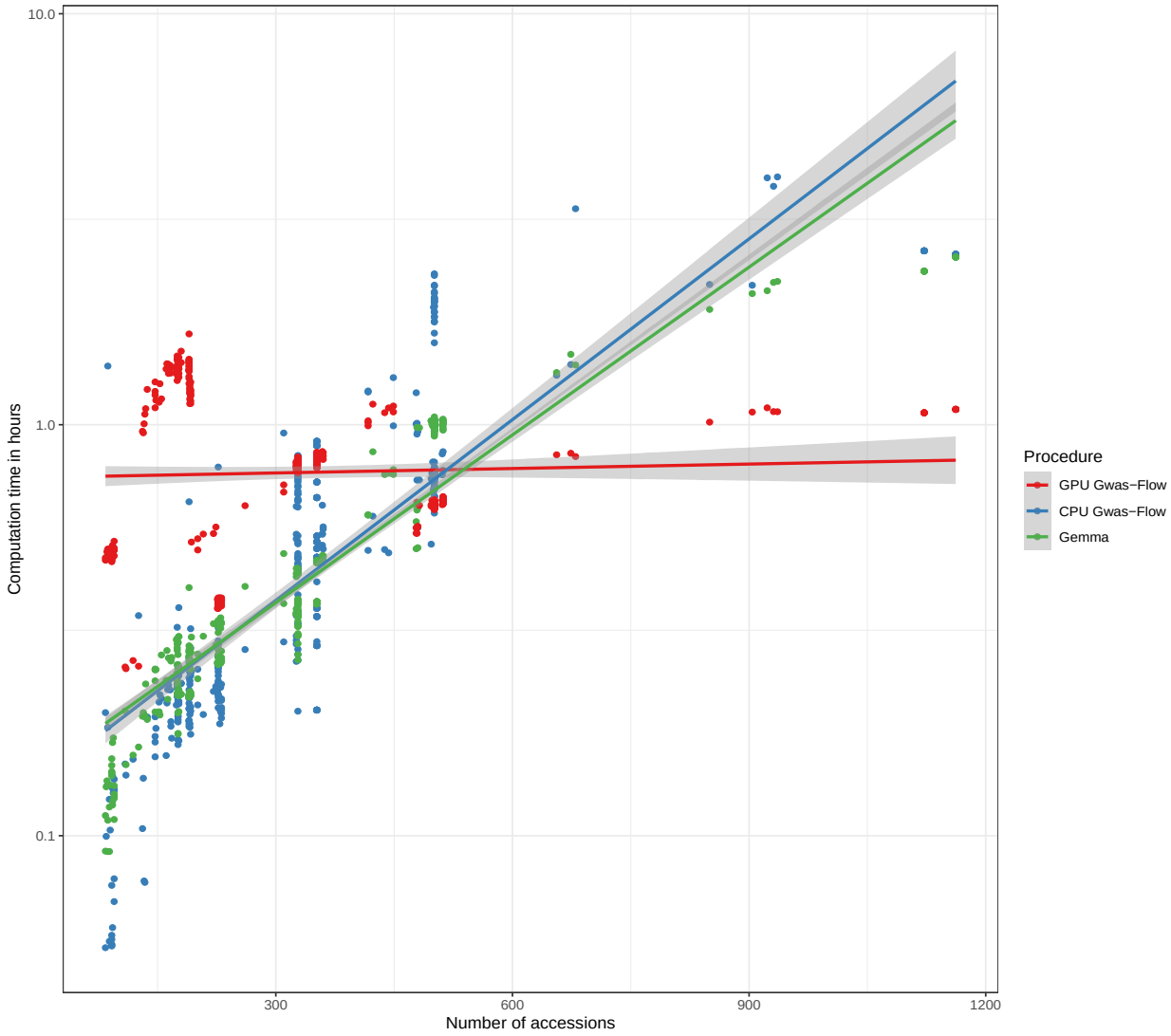


FIGURE 3.3: Comparison of the computational time for the analyses of $>$ 200 phenotypes from *Arabidopsis thaliana* as a function of the number of accessions for *GEMMA* and the CPU- and GPU-based version of `GWAS-Flow`. GWAS was performed with a fully imputed genotype matrix containing 10.7 M markers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

Chapter 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.

This basic perceptron, which contrary to perceptrons used nowadays does not have an embedded activation function, takes n binary inputs $x_1, x_2....x_n$ 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 $w_1, w_2...w_n$. The output y is determined by the weighted sum of the weights and biases $\sum_i w_i x_i$.

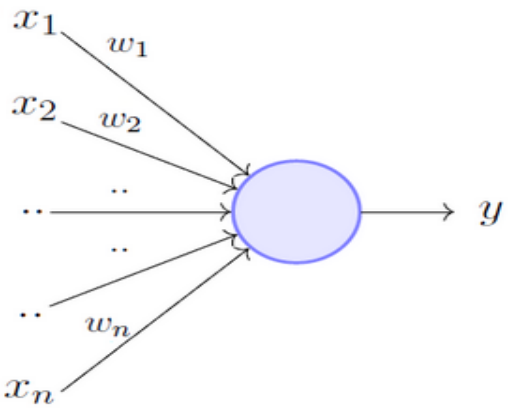


FIGURE 4.1: Basic perceptron model as proposed by Rosenblatt

If a certain threshold value is met the neuron is either activated and outputs 1 or not activated resulting in and output of 0. This is algebraically represented in equation 4.1:

$$0 = \text{if} \sum_{i}^{n} w_j x_i - \theta \leq 0 \tag{4.1a}$$

$$1 = \text{if} \sum_{i}^{n} w_i x_i - \theta > 0 \tag{4.1b}$$

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 and per definition is a negative value. A single perceptron is a linear classifier and can only be trained on linearly separable functions and can 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 let to a near stillstance 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 the 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 harboring 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.

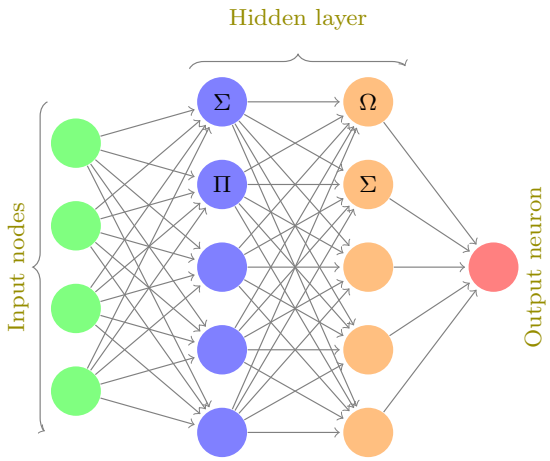


FIGURE 4.2: Schematic layout of a simple multi-layer perceptron

In the sample layout of figure 4.2 the neurons in the first column weigh the inputs and pass those the the neurons in 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. There are also layers were neurons in the previous layer are only connected with neighboring neurons in the succeeding layers. Those are known as locally-connected layers (LCL) or related to

them are convolutional layers which shared weights between selected neurons, building convolutional neural networks (CNN) *LeCun* et al., 1999 .

Activation functions

The neurons discussed so far are only capable of outputting binary results. Either 0 or 1, depending on whether threshold values are being reached 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 provide more sophisticated rules for the output in accordance to their inputs *Žilinskas*, 2006.

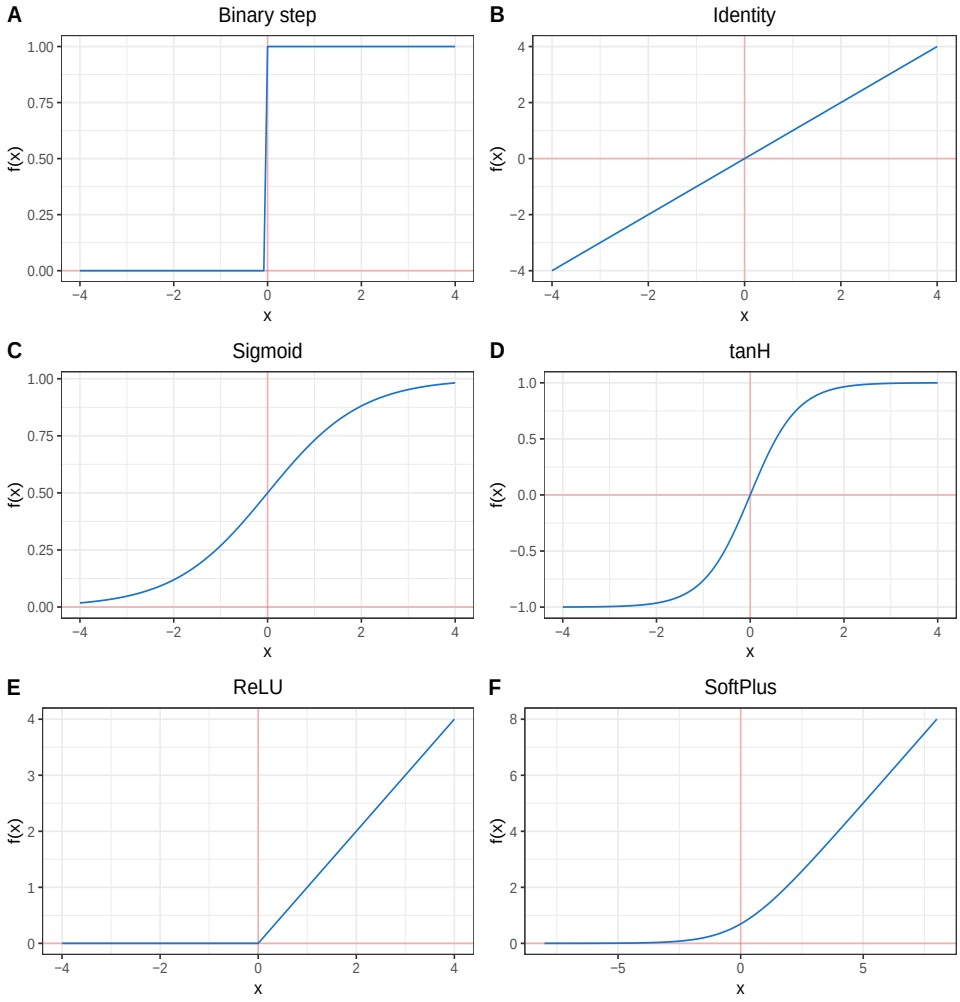


FIGURE 4.3: Popular activation functions used in neural networks. **A** Binary step activation function. **B** Identity activation function. **C** Sigmoid or logistic activation function. **D** tangens hyperbolicus activation function. **E** rectified linear units activation function . **F** SoftPlus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

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

around 0.

$$f(x) = \sigma(x) = \begin{cases} 0 \; for \; x < 0 \\ 1 \; for \; x \geq 0 \end{cases} \tag{4.2}$$

$$f(x) = \sigma(x) = x \tag{4.3}$$

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

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

$$f(x) = \sigma(x) = \begin{cases} 0 \; for \; x < 0 \\ x \; for \; x \geq 0 \end{cases} \tag{4.6}$$

$$f(x) = ln(1 + e^{x}) \tag{4.7}$$

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 many deep-learning applications over 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 at start, 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 $x_1 \dots x_4$ 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 and RMSE 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 are regression problems, that use MSE as their loss function, this will be the only loss function used.

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

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.

$$L(w,b) = \frac{1}{2n}\sum_{x}\|y(x) - \widetilde{y}\|^2. \tag{4.9}$$

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 $L(w,b) \to 0$ 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 fine 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.

$$\Delta L = \frac{\partial L}{\partial w}\Delta w + \frac{\partial L}{\partial b}\Delta b \tag{4.10}$$

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

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

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

$$\Delta C = \nabla L * \Delta d \tag{4.12}$$

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

$$\Delta d = -\eta \nabla L \tag{4.13}$$

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.

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

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 iterational update of the network is often called epoch or training epoch.

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

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

$$\tag{4.15c}$$

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

$$w = w_i - \eta \nabla L \tag{4.16}$$

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 ind 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 stochastical 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*, *Williams*, et al., 1988.

$$w = w_i - \eta \nabla L + \alpha \Delta w \tag{4.17}$$

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 two small the GD will not be able to overcome local minima and if α is two 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*, *Taylor*, et al., 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 widespread 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*, *Williams*, et al., 1988

Regularization parameters

When applying the combined aforementioned algorithms and optimizers to find global minima of a loss function of a neural network the problem of overfitting

arises, because optimizers like Adam work "too" well. This issue 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 $L(w, b) \to 0$ the initially drawn conclusion could mislead to assuming that 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.

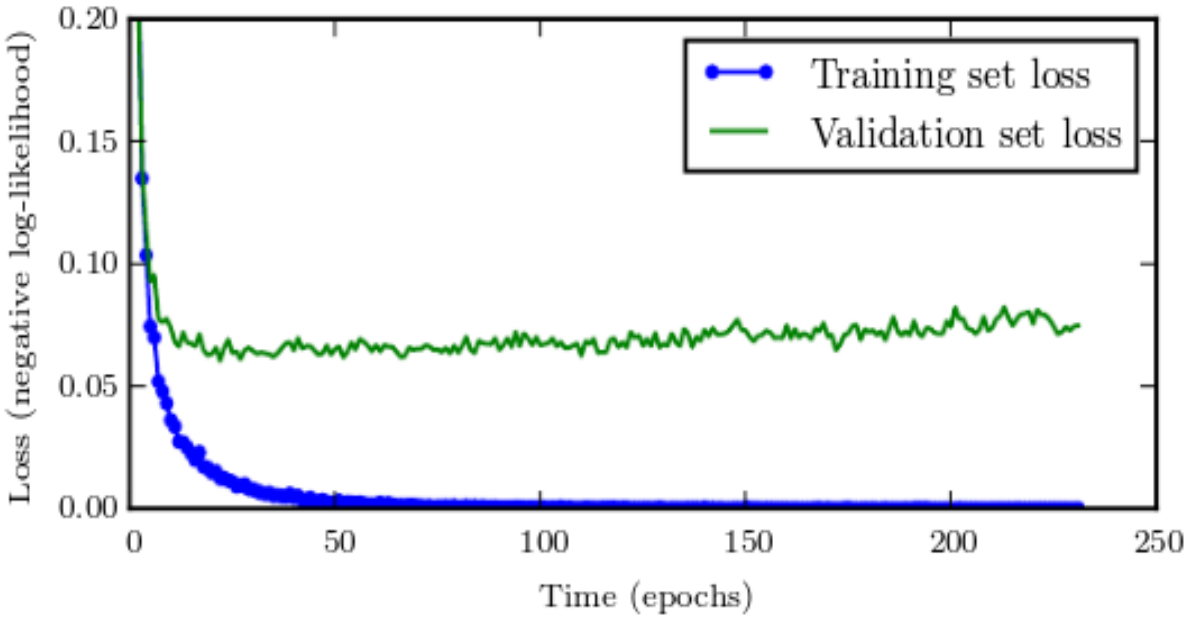


FIGURE 4.4: Learning curves showing how a loss function changes during training in the loss and validation data set. While the training loss approaches 0 the validation loss starts increasing after hitting a minimum. This effect is due to overfitting on the training data set. Figure from *Goodfellow*,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

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

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 form 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 sè* 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 in 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.

$$\sigma_P = \sigma_G + \sigma_E \tag{4.19}$$

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 σ_{GxE} 4.20 , *Lynch*, *Walsh*, et al., 1998, *Walsh* and *Lynch*, 2018b.

$$\sigma_P = \sigma_G + \sigma_E + \sigma_{GxE} \tag{4.20}$$

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

$$\sigma_G = \sigma_A + \sigma_D + \sigma_I \tag{4.21}$$

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.

$$\sigma_I = \sigma_{AxA} + \sigma_{DxD} + \sigma_{AxD} \tag{4.22}$$

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 one 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.

$$H^2 = \frac{\sigma_A + \sigma_D + \sigma_I}{\sigma_P} \tag{4.23}$$

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 import 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 a 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*, 2018b.

$$h^2 = \frac{\sigma_A}{\sigma_P} \tag{4.24}$$

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

Introduction to genomic selection

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 olearacea spp*) *Thorwarth*, *Yousef*, and *Schmid*, 2018. Cotton (*Gossiypium spp.*) *Gapare* et al., 2018. Maze (*Zea mays*) *Moeinizade* 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; *Rincent* 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 cerale*) *Auinger* et al., 2016; *Bernal-Vasquez* et al., 2014; *Wang* et al., 2014; *Bernal-Vasquez* et al., 2017; *Marulanda* et al., 2016. Sugar beet (*Beta vulgaris*),*Würschum* et al., 2013; *Biscarini* et al., 2014. Sugar cane (*Saccharum officinarum*) *Gouy* et al., 2013 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.

Even though GS finds broad application in plant breeding it has been originally developed for the use in animal breeding *Hayes* and *Goddard*, 2010; *Goddard*, *Hayes*, and *Meuwissen*, 2011. The gold standard is a method known as genomic

BLUP *VanRaden*, 2008 which utilizes a relationship matrix based on the co-occurrence of genetic markers. This method is derived from the pre-genomic era in animal breeding where the relationship matrix was constructed after pedigrees according to the best linear unbiased predictors based linear mixed models developed by *Henderson*, 1975. GBLUP accounts only for additive-genetic effects *VanRaden*, 2008. There are other methods that are able to account for more complex genomic effects that are non-additive. Popular among those are reproducing Kernel Hilbert Spaces (RKHS) *Gianola* and *Kaam*, 2008. Alternatively to linear mixed models a variety of different Bayesian methods became popular, basically differing in the degree of shrinkage of the assumed marker distribution *Hayes*, *Goddard*, et al., 2001; *Gianola* et al., 2009; *Habier* et al., 2011; *Gianola*, 2013; *Crossa* et al., 2017; *Azodi* et al., 2019.

Genomic selection in recurrent selection and the breeders equation

While the quantitative genetic methods breeders utilize are complex their goals can be defined in one sentence: To genetically improve plant germplasms for agriculture. The breeding process started at the same time as farming was first practiced 10.000 BC in the region between the Euphrat and Tigris rivers known as the fertile crescent. This changed the phenotypic appearance of the early crops dramatically to the point that they share little external traits with their wild ancestors. Those changes have also been deeply carved into the genomes, that underwent serious alterations, including hybridization, duplications etc. Leading to most crop plants not having any wild ancestors with whom they could naturally mate. For example wheat (*Triticum aestivum*), one of the three most important sources of food on a global scale underwent multiple hybridization steps *Ozkan*, *Levy*, and *Feldman*, 2001. Wheat is a hybrid from either the diploid emmer (*T. diccoides*) or durum wheat (*T. durum*) and *Aegilops tauschii*, while emmer and durum are hybrids derived from wild emmer which is a hybrid of wild grass of the genus of *Aegilops* and *T. urata Friebe* et al., 2000; *Feldman* and *Levy*, 2012. While

being ignorant of modern genetics early "plant breeders" must have had an intuitive, yet naive, understanding of the general concept of heritability in a way that they must have established that offsprings share properties of their parent generation, which lead to regrowing individuals with desired traits generations after generation. This lead to many changes including that artificial selected plants are commonly largely inbred. This process could be considered an early form of recurrent truncation selection. Truncation selection on a normal distributed phenotype is shown in figure 4.5.

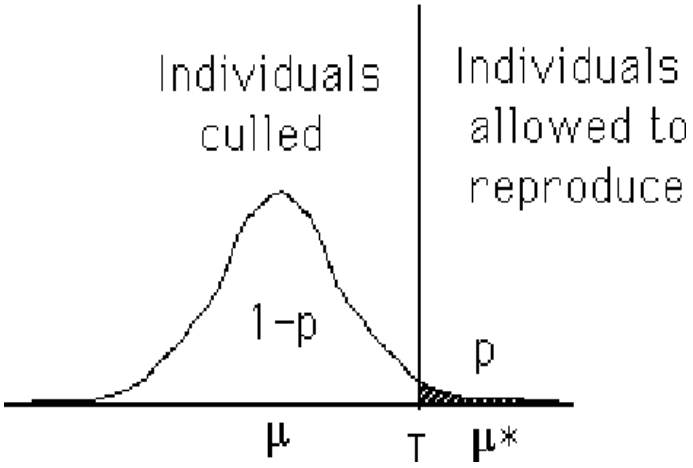


FIGURE 4.5: Truncation selection from a normal distributed phenotype with a threshold value of T, μ as the mean of the total population and μ^* as the mean of the selected phenotypes. Graphic from *Walsh* and *Lynch*, 2018a

Like the early breeders modern breeders of to determine the selection threshold T to divide the total population with the mean μ into two groups: the individuals culled and the ones allowed to reproduce with the mean μ^*. The difference between those two is the selection differential S:

$$S = \mu^* - \mu \tag{4.25}$$

which in the case of normal distributed data as depicted in figure **??** can be expressed as:

$$S = \varphi(\frac{T-\mu}{\sigma})\frac{\sigma}{p} \tag{4.26}$$

From which we can obtain the selection intensity i, which makes i solely a function of p

$$i = \frac{S}{\sigma} = \frac{\varphi(z_{|1-p|})}{p} \tag{4.27}$$

With recurrent truncation selection over many generations the population mean of the trait μ will change (hopefully in the desired direction), if the heritability (in this case the narrow sense heritability) $h^2 > 0$. It is impossible to breed for traits that do not contain any genetic components in its architecture *Walsh* and *Lynch*, 2018b. Next to i the intensity and h^2 the additive portion of the heritability the accuracy of the selection r_{uA} is important for the success of a breeding program. Those three terms can be applied to compute the gain of selection R over one generation (equation 4.28). Due to its importance in the evaluation of breeding schemes it is known as the breeder's equation *Mousseau* and *Roff*, 1987; *Falconer* and *Mackay*, 1996; *Kingsolver* et al., 2001.

$$R = ir_{uA}\sigma_A \tag{4.28}$$

The accuracy r_{uA} of equation 4.28 in cases only phenotypic selection is conducted the heritability and in cases where the selection process is aided by genomic prediction it is the prediction accuracy. According to breeder's equation there are three parameters which can be influenced through genomic prediction. (i) The prediction accuracy, which is usually smaller than the heritability, varies for different prediction equations and an increase in the accuracy will lead to an proportional increase in R the gain per generation cycle. For this reasons since 2001 in quantitative genetics one very active field of research was and still is to find new algorithms that are superior to others as presented in the next chapter

(4.1.3. As later evaluated on more than 150 phenotypes in chapter **??** h^2 is always larger than r_{uA}. Which if it was the only variable factor in equation 4.28 make genomic selection inferior to phenotypic selection. Which from a certain point of view it is. Phenotypic trials are better approximation for phenotypic appearance as GEBVs. However as the cost of genotyping have decreased dramatically in the last 20 years. Phenotyping in the field remains tedious, laborious and mostly vastly expensive. Taking into account that field trials have to be repeated in several years and locations to produce reliable accounts it becomes clear that genotyping 10th of thousands of accessions is much cheaper than conducting field trials with 1000 of them.

(ii) The selection intensity can much stricter if the total population that is selected from is larger and in genomic prediction settings they are, because it allows selection from two pools. The first the pool of plants with known phenotyped and known genotype and from those were just genomic data is available. When selecting from a pool of 1000 with $p = 0.05$ with the goal to keep 50 plants in the next breeding cycle, the same goal can be reached when genomically selecting from a pool of 10000 with and intensity of $p = 0.05$.

(iii) The decreased time per generation is probably the largest advantage of genomic selection when applied to breeding. While in field trials it is only possible to have one generation per year. Genomic selection does not require the plants to be grown in the field. For selection it is only necessary to grow enough so that DNA can be extracted from the tissue and evaluated. After selection only the ones above the threshold are grown until they bear seats (or any other reproductive organ) and be used for the next selection cycle, allowing up to ten generations per year. This development hast lead to the rise to a new branch of breeding: speed breeding *Ghosh* et al., 2018; *Watson* et al., 2018. In practical, company-level genomic prediction as largely contributed to an increase by a factor of 2 of the gain in selection in recent years (personal communication with breeding company employees).

The last term in equation 4.28 the additive genetic variance σ_A is not directly yet heavily influenced by the described breeding scheme. Artificial selection has similar effects on the genetic variance as bottlenecks in natural selection have: it decreases, thus making it harder to increase R in later selection cycles *Walsh* and *Lynch*, 2018b.

Genomic BLUP and Bayesian methods

All methods share a common statistical obstacle which is commonly referred to as the $n >> p$ problematic, which arises because the number n marker is usually significantly larger than the number of observations p. In practical applications it is not uncommon the have more than 100k markers while the number of phenotypes is no larger than 100. This does not allow to obtain genomic estimated breeding values (GEBV) by single marker regression as done by GWAS, which have highly inflated over all SNP-effects *Korte* and *Farlow*, 2013. One possible is to include effect sizes as random effects and make prior assumptions about their distribution. The difference in prior distribution is the main distinction between the methods of the Bayesian alphabet *Gianola*, 2013.

Genomic BLUP

In the early years of research on genomic prediction algorithms they were not solely benchmarked against each other, but had to compete with the previously popular pedigree methods. Quickly in the course of the first decade of this millennium the superiority of the genomic method became elucidated in livestock and plant breeding *Habier*, *Fernando*, and *Dekkers*, 2007; *VanRaden*, 2008; *VanRaden* et al., 2008; *Harris*, *Johnson*, *Spelman*, et al., 2009. While the genomic methods are superior to non-genomic methods, there is no clear evidence that either of the genomic methods are superior to each other and there is lack of empirical evidence that the Bayesian methods generally outperform GBLUP *Moser* et al., 2009 ; *Bernardo*, 2010; *Azodi* et al., 2019. Alike in the pedigree BLUP in genomic

BLUP the co-variance between related individuals is used for the prediction. In the later case it is constructed from marker information. In the GWAS terminology the relationship matrix is referred to as K for kinship in GWAS literature, while in GS circumstances it is also called GRM (genomic relationship matrix) or simply abbreviated as G. This study will remain consistent with the circumstantial literature and therefore purposely inconsistent within itself. In the chapter addressing GWAS the it will be called K for kinship matrix and it the following chapter elucidating GBLUP it will be referred to as G. The general genomic prediction model 4.29 is derived from the mixed model *Henderson*, 1975; *VanRaden*, 2008 and implemented as:

$$Y = X\beta + Zu + \varepsilon \tag{4.29}$$

where Y is and $nx1$ vector of phenotypic observations, X the matrix of the fixed effects and β the vector of the fixed effects. Z the incidence matrix for the combined marker effects and u a $(nx1)$ vector of the additive genetic effect the vector of the residuals ε. To construct the model lets assume a matrix of size (nxm) with n individuals and m loci M containing marker information for 3 individuals on 4 loci, thus being of size $3x4$. The 4 markers of matrix 4.30 can take values of -1, 0 and 1 translating into minor allele, heterozygous locus and major allele. The following example calculation has been adapted from *Isik*, 2013.

$$M = \begin{pmatrix} -1 & 0 & 1 & -1 \\ -1 & 0 & 0 & 0 \\ 0 & 1 & 1 & -1 \end{pmatrix} \tag{4.30}$$

The M matrix contains all the information that is necessary for the computation of the K matrix and other viable genetic parameters. The MM' matrix of size nxn (**??**) bears additional parameters.

$$MM' = \begin{pmatrix} 3 & 1 & 2 \\ -1 & 1 & 0 \\ 2 & 0 & 3 \end{pmatrix} \tag{4.31}$$

The diagonal show the number of homozygous loci per individual, while the other elements of the matrix indicate the number of markers shared by related individuals and is an indicator for the distance of the relationship as defined by identity-by-descent *VanRaden*, 2008; *Misztal* et al., 2013. While matrix 4.31 calculates the metrics per individual the $M'M$ matrix (4.32) counts those metrics per marker. Likewise the diagonal contains the number of homozygous individuals per marker.

$$M'M = \begin{pmatrix} 3 & -1 & 0 & 0 \\ -1 & 1 & 1 & 1 \\ 0 & 1 & 2 & 1 \\ 0 & 1 & 1 & 2 \end{pmatrix} \tag{4.32}$$

The next step is to obtain a matrix of the allele frequencies at each locus of the size (nxm) as matrix M. For the design of matrix P (4.33) let the minor allele frequencies $p_1 \dots p_4$ be $\{0.3, 0.2, 0.1, 0.15\}$. The allele frequency of the i^{th} column of P is expressed, according the ,th marker of matrix M as $P_i = 2(p_i - 0.5)$ resulting in:

$$P = \begin{pmatrix} -0.4 & -0.6 & -0.8 & -0.7 \\ -0.4 & -0.6 & -0.8 & -0.7 \\ -0.4 & -0.6 & -0.8 & -0.7 \end{pmatrix} \tag{4.33}$$

The allele frequencies as in this simulated example should be taken from the entire population and not the subsample used in this calculation *VanRaden*, 2008. The final step to obtain the Z matrix of equation 4.29 is to subtract the P matrix from the M matrix $Z = M - P$ resulting in:

$$Z = \begin{pmatrix} 1.4 & 0.6 & 1.8 & -0.3 \\ -0.6 & 0.6 & 0.8 & 0.7 \\ 0.4 & 1.6 & 1.8 & -0.3 \end{pmatrix} \tag{4.34}$$

In Z the mean values of the allele effects are set to 0 and the subtraction of P emphasizes the effect of rare variants *VanRaden*, 2008. There is a large variety of methods to generate the genomic relationship matrices and here lies the major difference between different genomic BLUP methods. But they all have in common that K is always of size nxn.

(i) The naive is approach to iterate over each individual and count the common markers with every other individual. This approach is not uncommon and suited for inbred or doubled-haploid populations, less so for outcrossed populations with high degrees of heterozygosity because in the sample implementation it does only account for homozygous loci. This method becomes computationally intense when the data sets grow larger as common today (personal observation).

(ii) Probably the most popular method in GS is to obtain K as proposed by *VanRaden*, 2008 designed after Wright's *Wright*, 1922 equations for the covariance in structured populations, as described by equation 4.35 with Z as in 4.34.

$$G = \frac{ZZ'}{2\Sigma p_i(1-p_i)} \tag{4.35}$$

(iii) The unified additive relationship G_{UAR} according to *Yang* et al., 2010 and equation 4.36

$$G_{UAR} = A_{jk} = \frac{1}{N}\Sigma_i A_{ijk} = \begin{cases} \frac{1}{N}\Sigma_i \frac{(x_{ij}-2p_i)(x_{ik}-2p_i)}{2p_i(1-p_i)}, j \neq k \\ 1 + \frac{1}{N}\Sigma_i \frac{x_{ij}^2(1+2p_i)x_{ij}+2p_i^2}{2p_i(1-p_i)}, j = k \end{cases} \tag{4.36}$$

where p_i is the allele frequency at locus i and x_{ij} the genotype for the j^{th} individual at the i^th locus. Another method also proposed by *Yang* et al., 2010 is to adjust G_{UAR} with β as in equation **??**

$$G_{UARadj} = \begin{cases} \beta A_{jk}, & j \neq k \\ 1 + \beta(A_{jk} - 1), & j = k \end{cases} \tag{4.37}$$

(iv) Another approach is to weigh marker by the reciprocals of their expected variance according to the model 4.38 originally designed to investigate population structures in human data *Leutenegger* et al., 2003; *Amin, Van Duijn*, and *Aulchenko*, 2007.

$$\begin{aligned} G &= ZDZ', with \\ D_{ii} &= \frac{1}{m|2p_i(1-p_i)|} \end{aligned} \tag{4.38}$$

(v) Other methods like the gaussian kernel compute kinship between individuals by the euclidean distance between the respective genotypes *Morota* and *Gianola*, 2014.

$$\begin{aligned} K(x_i, x_j) &= exp(-\theta d_{ij}^2) \\ &= \prod_{k=1}^{m} exp(-\theta(x_{ik} - x_{jk})^2) \end{aligned} \tag{4.39}$$

with $d_{ij} = \sqrt{(x_{i1} - x_{j1})^2 + \cdots + (x_{ik} - x_{jk})^2 + \cdots + (x_{im} - x_{j,a})^2}$ and $x_{ik}(i, j = 1, \ldots, n, k = 1, \ldots, m)$ and x_{ik} as the i^{th} individual at SNP k.

The linear model in equation 4.29 $Y = X\beta + Zu + \varepsilon$ with β as the vector fixed effects and u as the vector of additive genetic effects. The mixed model can be solved to obtain genomic estimated breeding values as:

$$\begin{pmatrix} X'X & X'Z & 0 \\ Z'X & Z'Z + G^{11} & G^{12} \\ 0 & G^{21} & G^{22} \end{pmatrix} \begin{pmatrix} \hat{b} \\ \hat{y}_1 \\ \hat{y}_2 \end{pmatrix} = \begin{pmatrix} X'y \\ Z'y \\ 0 \end{pmatrix} \tag{4.40}$$

with G^{12} as the part of G^{-1} containing individuals with phenotypic data. with G^{22} as the part of G^{-1} containing individuals without phenotypic data and just SNP information.

The GEBV of the unknown phenotypes $\hat{y}_2$ can thus be predicted as:

$$\hat{y}_2 = -\left(G^{22}\right)^{-1} G^{21}\hat{y}_1 \tag{4.41}$$

GBLUP is fairly easy compared to more complex Bayesian methods and be quickly implemented in any programming language capable of solving liner equations. Computational as the the number of phenotypes in the study increases in numbers the timed demand grows exponentially, because the kinship matrix quadruples in size and it becomes more complicated to compute the inverse of G (personal observations).

Bayesian methods

Next to the universal GBLUP a set of related algorithms became popular for solving the mixed models involved in genomic selection, known as the Bayesian alphabet *Gianola* et al., 2009; *Gianola*, 2013. They are all based on Bayes' fundamental theorem in equation 4.42

$$P(\theta|y) = \frac{P(\theta)P(y|\theta)}{P(y)} \tag{4.42}$$

with $P(\theta)$ as the prior distribution, $P(y|\theta)$ as the likelihood and $P(y)$ as the marginal density of y. The prior distribution in GS assume that y was drawn from a certain distribution. Infinitesimal models assume that the genetic effects

follow a normal distribution *Legarra*, *Lourenco*, and *Vitezica*, 2018. The Bayesian frameworks however will assume non-normal distributed marker effects. This can be explained by a two-step hierarchical distribution. Stage one assumes that every marker has *a priori* a different variance *Legarra*, *Lourenco*, and *Vitezica*, 2018.

$$p(a_i|\sigma^2_{ai}) = N(0, \sigma^1_{ai}) \tag{4.43}$$

The second stage assumes prior distributions for the variances.

$$p(a_i|variable) = P(\dots) \tag{4.44}$$

with *variable* standing for the large variety of prior distribution. In total there are more than >20 different Bayesian models known to the authors with unknown number of different methods proposed. Their main difference "simply" lies in the a priori assumptions. This change can make some methods mathematically much more advanced then others. And as shown in later chapters none of the methods is completely superior over others in terms of prediction accuracy. Approximation to the solution of the linear equations is usually performed by Gibb's sampling using Markov Chain Monte Carlo (MCMC) simulations *De Los Campos* et al., 2009; *Campos* and *Rodriguez*, 2016. Table 4.1 summarizes commonly applied Bayesian methods for genomic prediction indicating the key differences between them.

TABLE 4.1: Overview of properties of a variety of commonly applied Bayesian methods for genomic prediction. Table altered after *Kärkkäinen* and *Sillanpää*, 2012

Name	Reference	Prior	Indicator	Hierarchy	Hyperprior	Estimation
BayesA	*Hayes*, *Goddard*, et al., 2001	Student	No	Yes	No	MCMC
BayesB	*Hayes*, *Goddard*, et al., 2001	Student	Yes	Yes	No	MCMC
BayesC	*Verbyla* et al., 2009	Student	Yes	Yes	No	MCMC
BL	*Xu*, 2010	Laplace	No	Yes	No	EM
BayesDπ	*Habier* et al., 2011	Student	Yes	Yes	Yes	MCMC

The name is given by the author. The prior column tells which shrinkage prior is used.

cross validation

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., 2017 as well as in medical applications, since it was first reported *Hayes*, *Goddard*, et al., 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., 2017. 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 usefull in some cases the when the whole genome regression is performed by neural nets 1 While every new method is a valuable addition to the tool-kits for genomic selection, some fundamental problems remain unsolved, of which the n»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 issue 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 problems 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 EG-BLUP, 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* et al., 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*, *Goddard*, et al., 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 an 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 4.2 provides also the possible genotypes that can be derived by two bi-allelic markers $G_1 \ldots G_4$ 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 4.2: Simple simulated phenotypes and genotypes for genomic prediction with genotypes $G_1 \ldots G_4$, 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 base on epistatic effects σ_I generated by passing the markers M_1 and M_2 through their respective logic gates. This theoretically in 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 4.3.

TABLE 4.3: Results of genomic prediction from phenotypes and genotypes in table 4.2

	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 a 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 be interactions my 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

Two different data sets were used for the genomic prediction trials. A set of maze doubled-haploid (DH) populations, derived from MAZE landraces. And *A. thaliana* data sets, with genomic data procured along the 1001 genomic project *Alonso-Blanco* et al., 2016 and various phenotypic trials.

4.3.1 DH populations derived from maize landraces

The DH populations were produced, propagated and phenotyped in the scope of the MAZE project phase I, funded by the Federal Ministry of Education and Research (BMBF) (Funding ID: 031B0195, project "MAZE") as well as the KWS SAAT SE, by various project partners at the Technical University of Munich, University of Hohenheim and the KWS. A thorough description of the germplasm selection and phenotyping was recently published by *Hölker* et al., 2019.
Modern maize cultivars are almost exclusively high-performing hybrids from two inbreed lines from different heterotic pools. Commonly hybrids are derived from the cross European Flint x American Dent *Santos Dias* et al., 2004; *Brauner* et al., 2019. Before hybrid breeding became the predominant method in maze breeding in the 1960s landraces were grown by farmers. Landraces are dynamic, open-pollinated, locally highly-adapted populations. That did not derive from modern breeding but from locally confined selection and adaption by farmers to often very specific needs *Arteaga* et al., 2016. They hybrids grown today are derived from just a few landraces as founder lines, while the majority of landraces has been nearly forgotten. This and high intensity selection over many generation has led to a loss of genetic diversity σ_G in modern maize cultivars.

Therefore the landrace germplasm present a important, essential stock of genetic variability for continuous success in maize breeding. The utilization of those germplasms would be impossible without the invaluable work of institutions as the IPK Gartersleben whose goal as genebanks is to maintain and store genetic material for long time periods. Of those landraces three, representing large phenotypic heterogentiy were chosen: (i) Kemater Landmais Gelb (KE, Austria), Petkuser Ferdinand Rot (PE, Germany) and Lalin (LL, Spain). They represent 95 % of the molecular variance if a set of 35 landraces analyzed in a preceding project by *Mayer* et al., 2017.
In total 1015 DH lines (516 KE, 432 PE, 67 LL) were produced with *in vivo* haploid induction with an inducer line as described in *Roeber*, *Gordillo*, and *Geiger*, 2005.

Genomic maize data

(The genomic data was provided by the TUM as described by *Hölker* et al., 2019)
Genotyping was performed with the 600k Affymetrix® Axiom® Maize array *Unterseer* et al., 2014. The markers were quality filters and missing values were imputed individually for each landrace population using Beagle 5.0 *Browning* and *Browning*, 2007; *Browning*, *Zhou*, and *Browning*, 2018. After LD pruning and further quality control 29833 markers remained for 471 Kemater and 403 PE DHs. LL was excluded from further analyses due to insufficient amounts of genotypes.

Phenotypic maze data

(The phenotype data was provided by the TUM as described by *Hölker* et al., 2019)
The traits were evaluated with lattice design in 7 different locations across Europe. Those traits were: Early Vigor (EV) at three different stages (V3, V4, V6); Plant height (PH) at two stages (V4,V6) and the final plant height (PH_final), as well as male and female flowering time (Days till Tasseling (DtTAS) and Days till Silking (DtSILK)) and root lodging (RL). To account for GxE best linear unbiased

estimators were calculated according to Henderson's model *Henderson*, 1975 and use for further prediction.

4.3.2 A. thaliana

Genomic data

The genomic data was generated during the course of the 1001 genome project of *A. thaliana Alonso-Blanco* et al., 2016 producing completed sequenced and assembled genomes from 1035 genomes, along 600k marker data for 1307 accessions with a small overlap between those groups resulting in a total of 2029 genotyped accessions. With more than 10 mio. SNPs and Indels on the 5 chromosomes of e *A. thaliana*. Imputation of missing data and upsampling of the 600k subsets was performed with Beagle3 *Browning* and *Browning*, 2007. For every one of the 164 phenotypes used for prediction subsets were sampled, LD pruned and MAF filtered. LD pruning was executed with the R-package SNPRelate *Zheng*, 2013 with a relatively strict LD threshold of 0.65 and $MAF > 10$. This resulted in data sets with approximately 150.000 markers for each phenotype.

Phenotypic data

A complete list of the phenotypes used can be found in Appendix B with the according study references. The phenotypic trials ranged from 100 to more than 1000 accessions per data set *Atwell* et al., 2010; *Li* et al., 2010; *Strauch* et al., 2015; *Meijó* et al., 2014.

4.4 Methods

The theoretical backgrounds of the methods used for genomic prediction were described in section 4.1.1 for the ANNs and section4.1.3 for the Bayesian methods

and GBLUP. The next sections are devoted to explaining who those methods were adapted and implemented for the prediction of maize and *Arabidopsis* traits.

CV

4.4.1 ANN

The scripts for ANN based GS were written in python using the lower level API TensorFlow *Abadi* et al., 2016 and the higher level API Keras *Chollet* et al., 2015. Both are very versatile, well-documented and are capable of performing a large variety of machine learning applications. For those reasons they are the most used ML libraries. Another advantage is that they work well on GPUs, which allows ML algorithms to run a reasonable amount of time compared to CPU-based calculations. Prior to training the data was split into TRN and TST. The markers of TRN served as the input layer for the network while the phenotypes were trained upon in the output layer, which in the present cases consisted of only one node, because GS in the cases applied here is a regression problem. Preliminary trials showed Adam is the superior optimizer for GS and hence was the only one further used. Likewise relu was the activation of choice being superior to sigmoid or other non rectifiers. All the weights and the biases of the kernel were initialized with truncated normal distributed values. The loss function used was always MSE.

Having a few hyperparameters fixed, the other ones were optimized via grid search. For each TRN multiple networks were trained to fine tune the input parameters. Those were the number of layers, the nodes per layer, the magnitude of the dropout, the type of dropout used, whether the first layer was locally-connected for fully-connected and the duration of training via the training epochs. This amount to a total of a little shy of 260000 trained networks for the 146 *A. thaliana* data sets alone.

After another set preliminary runs LCL as the first layer seamed to result in

higher accuracies then FLC as the first layer and where henceforth exclusively used and applied with a stride length of 7. The stride length determines how many node of the input layer, in this case markers, where combined in the first hidden layer. The type of drop out used (alpha dropout, Gaussian noise or normal dropout) did not show an effect therefore the normal dropout function was used. The network training was iterated over the different number epochs, architecture, drop out values the the cross validation cycles, thus explaining the tremendous amount of total networks trained. Epochs from 5 to 60 in steps 5 and several 1, 2 or 3 Layer architectures following the locally-connected layer.

4.4.2 GBLUP

The evaluation of the genomic BLUP was performed with the R-package BGLR *Campos* and *Rodriguez*, 2016. To allow pairwise comparison of the individual validation runs the same validation scheme as for the ANNs was used with the same TST and TRN sets.

4.5 Results

Results of *A. thaliana* prediction

C.3

Phenotype	GBLUP	ANN	Architecture	Epochs
YEL	0.9259	0.891	20, 10	20
FT16	0.8237	0.8215	100	10
2W	0.8156	0.8205	50, 30	35
FT10	0.8249	0.8191	48	50
LD	0.8128	0.8159	150	30
DTF sweden 2009 (1st experiment)	0.8063	0.8141	48	30
DTF sweden 2009 (2nd experiment)	0.8035	0.8091	50, 30	20
DTF sweden 2008 (2nd experiment)	0.7986	0.8057	150	25
4W	0.795	0.8052	50, 35, 15	30
FT22	0.8009	0.8043	150	15
DTF spain 2008 (2nd experiment)	0.7975	0.8032	150	40
LN16	0.7996	0.7999	50, 30	20
DTF spain 2009 (2nd experiment)	0.7917	0.7988	150	55
LDV	0.8158	0.7975	150	15
0W GH FT	0.7873	0.7942	50, 30	15

DTFmainEffect2009	0.7794	0.7855	50, 35, 15	35
SD	0.7905	0.7848	48	30
DTFplantingSummer2008	0.75	0.7746	50, 30	20
FT GH	0.7693	0.7702	50, 30	15
DTFlocSweden2009	0.7595	0.7626	50, 30	60
DTFplantingSummer2009	0.7521	0.7584	50, 30	50
0W	0.7488	0.7473	48	40
DTF spain 2009 (1st experiment)	0.7691	0.7425	48	40
DTF sweden 2008 (1st experiment)	0.727	0.728	50, 30	20
DTFlocSweden2008	0.7161	0.7271	50, 30	55
Seed Dormancy	0.7014	0.7241	50, 30	35
DTFmainEffect2008	0.7102	0.7142	50, 30	20
8W	0.7259	0.7083	150	50
LN22	0.7004	0.7069	50, 30	20
Size sweden 2009 (1st experiment)	0.6905	0.6994	48	50
LN10	0.6934	0.698	50, 30	20
DTF spain 2008 (1st experiment)	0.6944	0.677	150	25
SDV	0.6775	0.6728	150	15
8W GH FT	0.7001	0.6546	48	40
0W GH LN	0.6568	0.654	50, 30	20
Storage 7 days	0.6496	0.65	50, 30	25
Storage 28 days	0.6627	0.6483	50, 30	55
8W GH LN	0.671	0.6434	48	70
Size sweden 2009 (2nd experiment)	0.6114	0.6268	48	50
SizeLocSweden2009	0.6144	0.619	150	35
FLC	0.6118	0.6161	50, 30	30
LFS GH	0.6178	0.6136	150	35
FT Field	0.7324	0.6112	150	60
LY	0.6072	0.6088	150	60
Storage 56 days	0.6085	0.5788	150	15
LES	0.56	0.5764	150	50
M216T665	0.5155	0.5674	50, 30	50
LC Duration GH	0.5799	0.5664	150	55
M172T666	0.5165	0.5487	150	60
Trichome avg JA	0.588	0.5343	150	55
Secondary Dormancy	0.5184	0.5264	150	30
SizeMainEffect2009	0.52	0.5171	48	50
DSDS50	0.4754	0.5006	50, 30	60
avrPphB	0.5054	0.4942	150	60
Hypocotyl length	0.4934	0.4807	150	50
Size spain 2009 (1st experiment)	0.5121	0.4751	150	50
Yield spain 2009 (1st experiment)	0.5205	0.4719	50, 30	50
Leaf serr 10	0.4636	0.4683	150	55
Size spain 2009 (2nd experiment)	0.471	0.4623	48	50
Trichome avg C	0.4617	0.4385	48	40
Germ in dark	0.4447	0.4382	150	15
YieldMainEffect2009	0.505	0.4345	150	30

FT Diameter Field	0.5004	0.4274	150	15
Bacterial titer	0.5406	0.417	150	55
FRI	0.4011	0.4119	48	30
Rosette Erect 22	0.3973	0.3934	48	30
Area sweden 2009 (1st experiment)	0.4203	0.3895	50, 35, 15	30
Width 10	0.3932	0.3784	50, 30	60
Silique 22	0.4339	0.377	50, 30	50
avrRpt2	0.3757	0.3737	50, 30	30
M130T666	0.4381	0.3733	150	60
SizePlantingSummer2009	0.3769	0.3615	150	5
Area sweden 2009 (2nd experiment)	0.359	0.3542	48	45
FW	0.3397	0.3522	50, 30	25
P31	0.3632	0.3419	50, 30	45
MT GH	0.4016	0.3397	150	50
avrB	0.3304	0.3384	50, 30	30
avrRpm1	0.361	0.3368	50, 30	20
Seed bank 133-91	0.3446	0.3334	150	5
Mg25	0.5321	0.3288	50, 30	60
Leaf roll 10	0.3558	0.3272	48	40
Yield spain 2009 (2nd experiment)	0.4184	0.3197	20, 10	40
Noco2	0.3051	0.3174	48	30
Emwa1	0.3226	0.3124	50, 30	30
FT Duration GH	0.2659	0.3123	48	5
Leaf serr 22	0.3021	0.3108	150	60
Anthocyanin 10	0.3198	0.3107	50, 35, 15	60
Cd114	0.3345	0.3069	50, 30	50
Leaf serr 16	0.2895	0.3011	48	40
Fe56	0.2802	0.3006	150	35
YieldLocSweden2009	0.3431	0.2993	150	60
Width 16	0.3463	0.2983	150	50
Co59	0.2738	0.2953	50, 35, 15	25
K39	0.3036	0.2952	50, 30	60
Leaf roll 16	0.3072	0.2886	150	15
DTFplantingLoc2008	0.2971	0.275	50, 30	5
SizePlantingSummerLocSweden2009	0.2803	0.2704	50, 30	60
Mn55	0.2775	0.2662	50, 30	20
Anthocyanin 22	0.2731	0.2635	150	15
As75	0.254	0.2619	50, 30	35
Na23	0.2564	0.2598	50, 30	15
Ni60	0.2894	0.2539	150	25
Mo98	0.2765	0.2537	50, 30	35
Chlorosis 22	0.2622	0.2453	50, 35, 15	10
Hiks1	0.2441	0.2452	20, 10	20
Zn66	0.2553	0.2444	150	35
B11	0.2891	0.2392	48	40
Germ 16	0.2987	0.2356	50, 30	41
At2	0.2147	0.216	150	15

Emco5	0.166	0.2101	150, 30	20
Se82	0.2192	0.2075	150	25
Mature cell length	0.1987	0.2052	150	45
DW	0.2878	0.2048	50, 30	60
Yield sweden 2009 (1st experiment)	0.2274	0.2033	150	55
As2	0.1774	0.1962	150	15
Meristem zone length	0.1976	0.195	150	50
Germ 10	0.2073	0.1873	20, 10	40
Anthocyanin 16	0.2433	0.1867	20, 10	10
Width 22	0.2224	0.1856	50, 30	50
YieldPlantingSummerLocSweden2009	0.2146	0.18	150	55
DTFplantingSummerLocSweden2009	0.2032	0.1775	150	55
Bs	0.2161	0.1656	50, 30	60
Bs CFU2	0.1672	0.1584	50, 35, 15	15
Germ 22	0.1267	0.1533	50, 30	35
Leaf roll 22	0.1135	0.1511	48	45
RP GH	0.1755	0.1458	150	15
Cu65	0.1543	0.1315	150	5
Li7	0.1611	0.1297	150	60
As	0.1089	0.1227	100	20
At1	0.1473	0.1197	48	40
S34	0.1045	0.11	50, 30	60
YieldPlantingSummer2009	0.1265	0.0984	150	50
Silique 16	0.2366	0.0884	50, 30	60
Chlorosis 10	0.0243	0.088	50, 35, 15	55
Ca43	0.3333	0.0732	50, 35, 15	55
Seedling Growth	0.0813	0.0636	48	30
Vern Growth	-0.0096	0.0422	150	15
At2 CFU2	0.0694	0.0378	150	25
Yield sweden 2009 (2nd experiment)	0.0536	0.0355	150	25
As CFU2	0.0312	0.035	150	5
At1 CFU2	0.0818	0.0319	50, 30	50
Aphid number	-0.0246	0.029	50, 35, 15	10
After Vern Growth	-0.1433	0.0057	50, 35, 15	5
Chlorosis 16	-0.0313	-0.0121	150	5
As2 CFU2	0.0504	-0.0325	50, 30	60

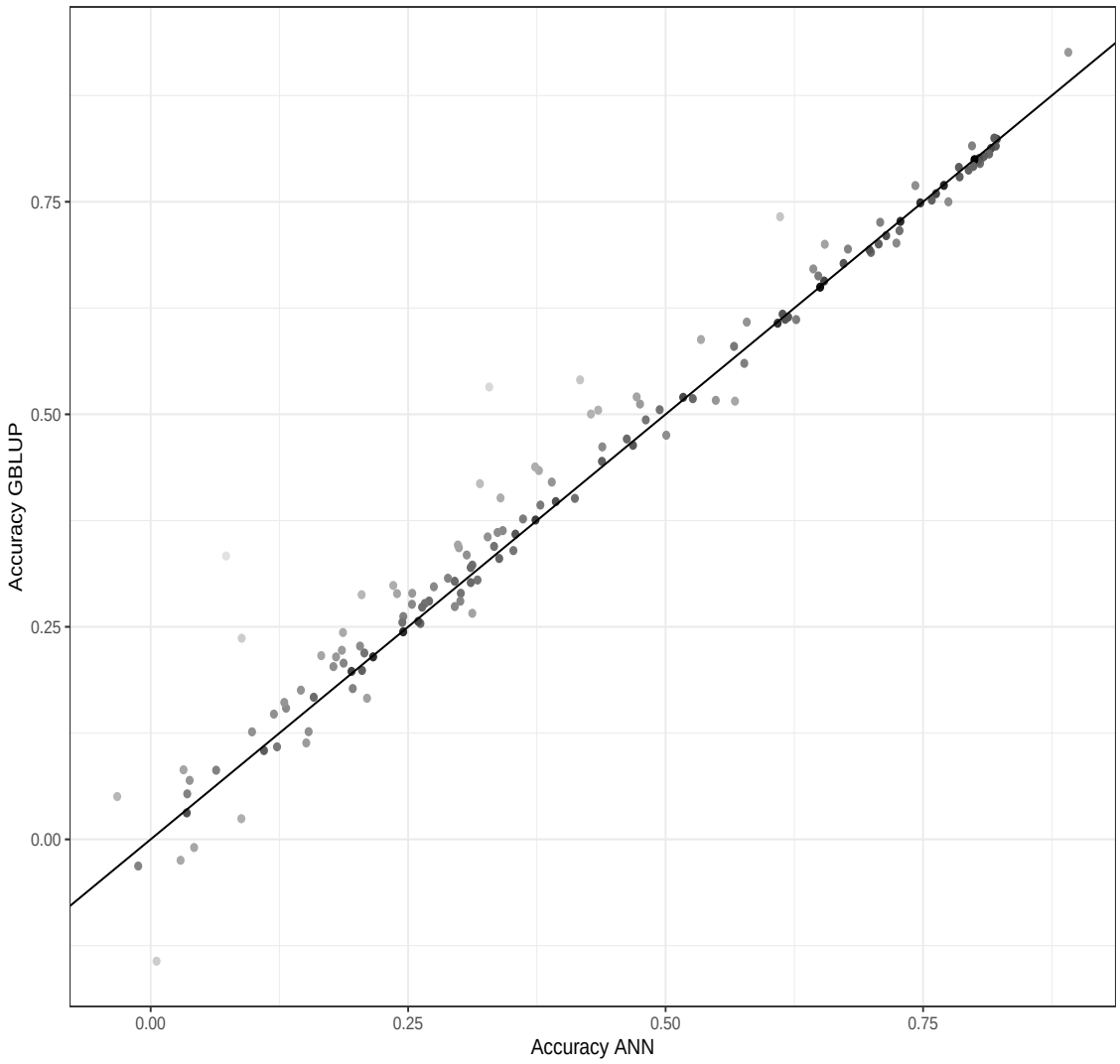


FIGURE 4.6: Scatterplot comparing prediction accuaracies of ANN and GBLUP in *A. thaliana*. Greyscale indicates the magnitude of the difference between the methods

4.5.1 Results of maize prediction

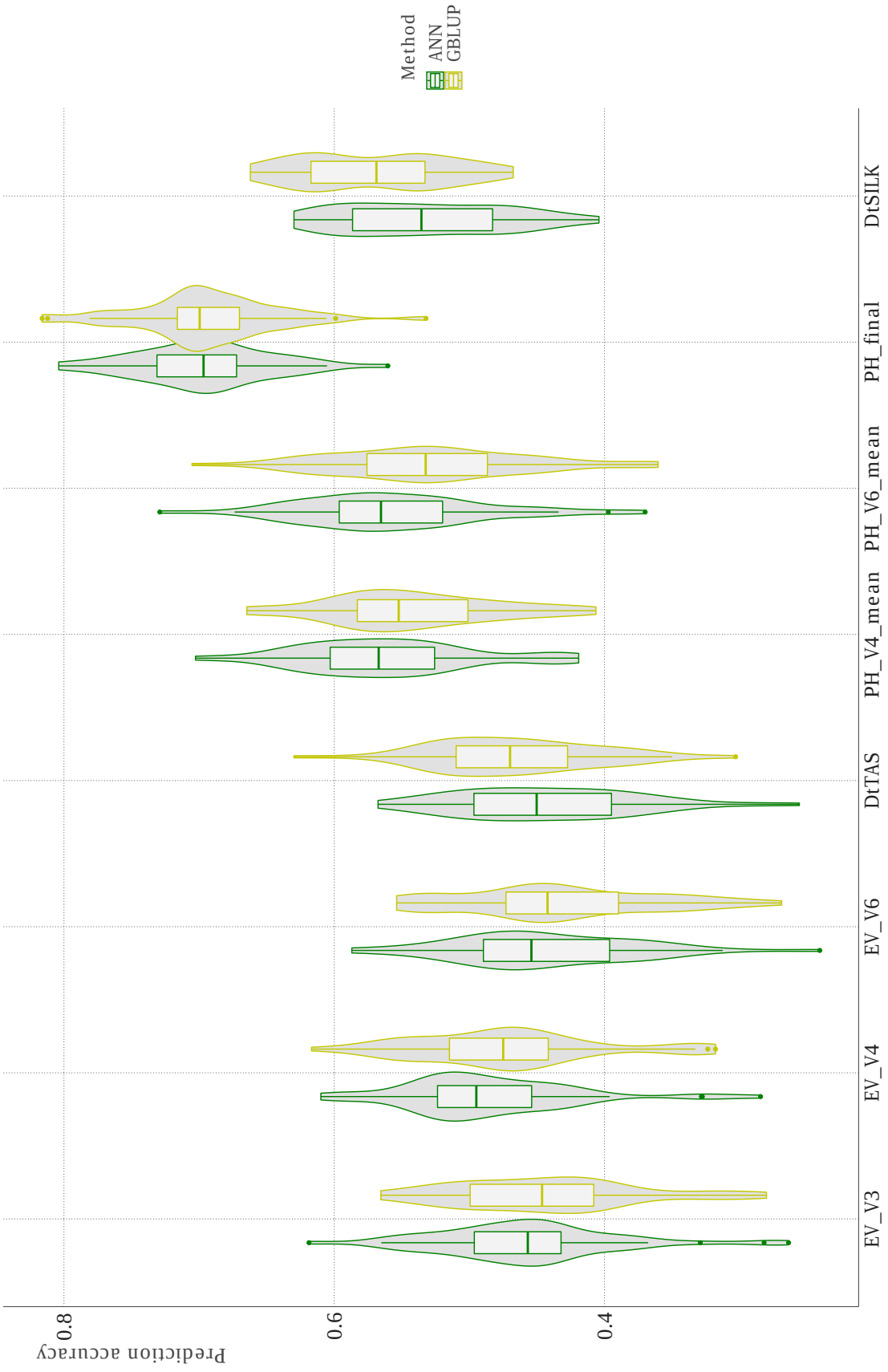


FIGURE 4.7: Violinplot comparing the results for GP in the DH population Kemater for ANN and GBLUP

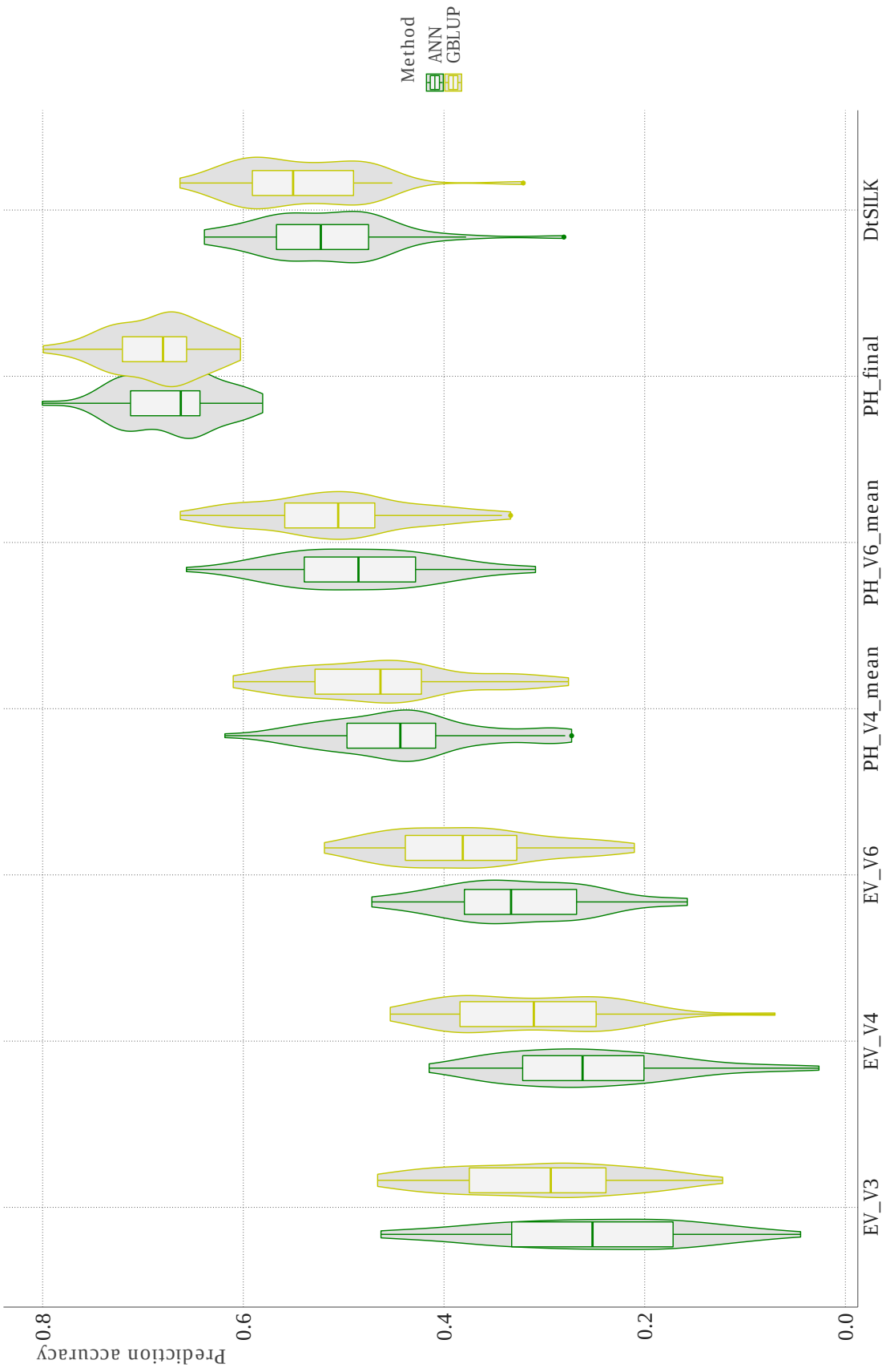


FIGURE 4.8: Violinplot comparing the results for GP in the DH population Petkuser for ANN and GBLUP

	Kemater		Petkuser	
Phenotype	GBLUP	ANN	GBLUP	ANN
EV_V3	0.44	0.46	0.31	0.25
EV_V4	0.47	0.49	0.31	0.25
EV_V6	0.43	0.44	0.38	0.33
DtTAS	0.47	0.44		
PH_V4_mean	0.54	0.56	0.46	0.44
PH_V6_mean	0.53	0.56	0.51	0.48
PH_final	0.69	0.70	0.68	0.67
DtSILK	0.57	0.53	0.54	0.52

4.6 Discussion

TABLE 4.5: ANN architectures resulting in highest prediction accuracies, with number of hidden layer (HL) and the total count (n)

LCL	Architecture	HL	n
True	150	2	56
True	50, 30	3	47
True	48	2	23
True	50, 35, 15	4	11
True	20, 10	3	5
True	100	2	2
True	150, 30	3	1

Chapter 5

GWAS

5.1 Introduction

Chapter 2 or 3 introduced a new framework for high throughout GWAS. GWAS-Flow enables to execute GWAS analysis on GPU and thus gains an incredible performance advantage compared to other state of the art GWAS technologies. This enabled the research group of evolutionary genomics at the CCTB to evaluate 462 (oder so) data sets from Arapheno with the full 10 mio data set originally imputed with Beagle version 3. Those GWAS have been repeated 100 times with shuffled phenotypes to estimate permutation based thresholds. Additionally all phenotypes were re-evaluated with a recently generated data set which based the imputation on the more recent Beagle version 5, which supposingly is more accurate (Pook et al). In the scope of this chapter it will be assessed if this does influence the outcome of the GWAS. Furthermore was GWAS-Flow used to evaluate some of the common practices in GWAS, that a prior do not seam relevant to the author. Sometimes yet uncommon in the literature it is recommend to use transformations for the pheonotypic values prior to performing GWAS to account for non-normal distributed data, transformations or calculated with the log, square root or boxcox. Another common practice is to use principal components from PCA to account for population structure. This however should have been cover sufficiently by the K matrix which is part of basically any mixed linear model based GWAS approach

5.2 Reevalulation of 463 phenotypes from the AraPheno database

5.2.1 Introduction

5.2.2 Material and Methods

5.2.3 Results

5.2.4 Results

5.2.5 Disucssion

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

5.3.1 Introduction

5.3.2 Material and Methods

5.3.3 Results

5.3.4 Results

5.3.5 Disucssion

Appendix A

Source code

A.1 GBLUP example

```
M <-  matrix(c(1,-1,0,0,0,1,1,0,1,-1,0,-1),nrow=3)
MtM  <- M %*% t(M)
MtM
       [,1] [,2] [,3]
[1,]    3   -1    2
[2,]   -1    1    0
[3,]    2    0    3
tMM  <- t(M) %*% t(M)
tMM
     [,1] [,2] [,3] [,4]
[1,]    2    0    1   -1
[2,]    0    1    1   -1
[3,]    1    1    2   -2
[4,]   -1   -1   -2    2

P = matrix(rep(2*(mafs - 0.5),3),nrow=3,byrow=T)
P
     [,1] [,2] [,3] [,4]
[1,] -0.4 -0.6 -0.8 -0.7
[2,] -0.4 -0.6 -0.8 -0.7
[3,] -0.4 -0.6 -0.8 -0.7
```

A.2 gwas.py

```
import os
```

```
import sys
import time
import numpy as np
import pandas as pd
import main
import h5py

# set defaults
mac_min = 1
batch_size =  500000
out_file = "results.csv"
m = 'phenotype_value'
perm = 1
mac_min= 6

X_file = 'gwas_sample_data/AT_geno.hdf5'
Y_file = 'gwas_sample_data/phenotype.csv'
K_file = 'gwas_sample_data/kinship_ibs_binary_mac5.h5py'



for i in range (1,len(sys.argv),2):
    if sys.argv[i] == "-x" or sys.argv[i] == "--genotype":
        X_file = sys.argv[i+1]
    elif sys.argv[i] == "-y" or sys.argv[i] == "--phenotype":
        Y_file = sys.argv[i+1]
    elif sys.argv[i] == "-k" or sys.argv[i] == "--kinship":
        K_file = sys.argv[i+1]
    elif sys.argv[i] == "-m":
        m = sys.argv[i+1]
    elif sys.argv[i] == "-a" or sys.argv[i] == "--mac_min":
        mac_min = int(sys.argv[i+1])
    elif sys.argv[i] == "-bs" or sys.argv[i] == "--batch-size":
        batch_size = int(sys.argv[i+1])
    elif sys.argv[i] == "-p" or sys.argv[i] == "--perm":
        perm  = int(sys.argv[i+1])
    elif sys.argv[i] == "-o" or sys.argv[i] == "--out":
        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 csv or hdf5 format of size")
42          print("-y , --phenotype: file container phenotype
    information in csv format"  )
43          print("-k , --kinship : file containing kinship matrix of
    size k X k in csv or hdf5 format")
44          print("-m : name of columnn containing the phenotype :
    default m = phenotype_value")
45          print("-a , --mac_min : integer specifying the minimum
    minor allele count necessary for a marker to be included.
    Default a = 1" )
46          print("-bs, --batch-size : integer specifying the number of
     markers processed at once. Default -bs 500000" )
47          print("-p , --perm : single integer specifying the number
    of permutations. Default 1 == no perm ")
48          print("-o , --out : name of output file. Default -o results
    .csv  ")
49          print("-h , --help : prints help and command line options")
50          quit()
51      else:
52          print('unknown option ' + str(sys.argv[i]))
53          quit()
54
55
56
57  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("- "),
   markers_used)))
74     else:
75         chr_reg = h5py.File(X_file,'r')['positions'].attrs['
   chr_regions']
76         mk_index= np.array(range(len(markers)),dtype=int)[macs >=
   mac_min]
77         chr_pos = np.array([list(map(lambda x: sum(x > chr_reg
   [:,1]) + 1, mk_index)), markers_used]).T
78         my_time = np.repeat((time.time()-start),len(chr_pos))
79     pd.DataFrame({
80         'chr' : chr_pos[:,0] ,
81         'pos' : chr_pos[:,1] ,
82         'pval': output[:,0] ,
83         'mac' : np.array(macs[macs >= mac_min],dtype=np.int) ,
84         'eff_size': output[:,1] ,
85         'SE' : output[:,2]}).to_csv(out_file,index=False)
86 elif perm > 1:
87     min_pval = []
88     perm_seeds = []
89     my_time = []
90     for i in range(perm):
91         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({
```

```
        'time': my_time ,
        'seed': perm_seeds ,
        'min_p': min_pval }).to_csv(out_file,index=False)

print("done")

end = time.time()
eltime = np.round(end -start,2)

if eltime <= 59:
    print("Total time elapsed",  eltime, "seconds")
elif eltime > 59 and eltime <= 3600:
    print("Total time elapsed",  np.round(eltime / 60,2) , "minutes
    ")
elif eltime > 3600 :
    print("Total time elapsed",  np.round(eltime / 60 / 60,2), "
    hours")


```

A.3 main.py

```
    import pandas as pd
    import numpy as np
    from scipy.stats import f
    import tensorflow as tf
    import limix
    import herit
    import h5py
    import limix
    import multiprocessing as mlt

    def load_and_prepare_data(X_file,Y_file,K_file,m):
    type_K = K_file.split(".")[-1]
    type_X = X_file.split(".")[-1]

    ## load and preprocess genotype matrix
```

```
16      Y = pd.read_csv(Y_file,engine='python').sort_values(['
    accession_id']).groupby('accession_id').mean()
17      Y = pd.DataFrame({'accession_id' :  Y.index, 'phenotype_value'
    : Y[m]})
18      if type_X == 'hdf5' or type_X == 'h5py'  :
19          SNP = h5py.File(X_file,'r')
20          markers= np.asarray(SNP['positions'])
21          acc_X =  np.asarray(SNP['accessions'][:],dtype=np.int)
22      elif type_X == 'csv' :
23          X = pd.read_csv(X_file,index_col=0)
24          markers = X.columns.values
25          acc_X = X.index
26          X = np.asarray(X,dtype=np.float32)/2
27      else :
28          sys.exit("Only hdf5, h5py and csv files are supported")
29
30      if type_K == 'hdf5' or type_K == 'h5py':
31          k = h5py.File(K_file,'r')
32          acc_K = np.asarray(k['accessions'][:],dtype=np.int)
33      elif type_K == 'csv':
34          k = pd.read_csv(K_file,index_col=0)
35          acc_K = k.index
36          k = np.array(k, dtype=np.float32)
37
38      acc_Y =  np.asarray(Y[['accession_id']]).flatten()
39      acc_isec = [isec for isec in acc_X if isec in acc_Y]
40
41      idx_acc = list(map(lambda x: x in acc_isec, acc_X))
42      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      if type_X == 'hdf5' or type_X == 'h5py' :
48          X = np.asarray(SNP['snps'][0:(len(SNP['snps'])+1),],dtype=
    np.float32)[:,idx_acc].T
49          X = X[np.argsort(acc_X[idx_acc]),:]
```

```
50          k1 = np.asarray(k['kinship'][:])[idk_acc,:]
51          K  = k1[:,idk_acc]
52          K = K[np.argsort(acc_X[idx_acc]),:]
53          K = K[:,np.argsort(acc_X[idx_acc])]
54      else:
55          X  = X[idx_acc,:]
56          k1 = k[idk_acc,:]
57          K  = k1[:,idk_acc]
58
59
60      print("data has been imported")
61      return X,K,Y_,markers
62
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)
        * K
77      vg, delta, ve  = herit.estimate(Y,"normal",K_stand,verbose =
       False)
78      print(" Pseudo-heritability is " , vg / (ve + vg + delta))
79      print(" Performing GWAS on ", n , " phenotypes and ", n_marker
       ,"markers")
80      ## Transform kinship-matrix, phenotypes and estimate intercpt
81      Xo = np.ones(K.shape[0]).flatten()
82      M = np.transpose(np.linalg.inv(np.linalg.cholesky(vg * K_stand
       + ve  * np.identity(n)))).astype(np.float32)
```

```
83      Y_t = np.sum(np.multiply(np.transpose(M),Y),axis=1).astype(np.
    float32)
84      int_t = np.sum(np.multiply(np.transpose(M),np.ones(n)),axis=1).
    astype(np.float32)
85      ## EMMAX Scan
86      RSS_env = (np.linalg.lstsq(np.reshape(int_t,(n,-1)) , np.
    reshape(Y_t,(n,-1)))[1]).astype(np.float32)
87      ## calculate betas and se of betas
88      def stderr(a,M,Y_t2d,int_t):
89          x = tf.stack((int_t,tf.squeeze(tf.matmul(M.T,tf.reshape(a
    ,(n,-1))))),axis=1)
90          coeff = tf.matmul(tf.matmul(tf.linalg.inv(tf.matmul(tf.
    transpose(x),x)),tf.transpose(x)),Y_t2d)
91          SSE = tf.reduce_sum(tf.math.square(tf.math.subtract(Y_t,tf
    .math.add(tf.math.multiply(x[:,1],coeff[0,0]),tf.math.multiply(x
    [:,1],coeff[1,0])))))
92          SE = tf.math.sqrt(SSE/(471-(1+2)))
93          StdERR = tf.sqrt(tf.linalg.diag_part(tf.math.multiply(SE ,
     tf.linalg.inv(tf.matmul(tf.transpose(x),x))))[1]
94          return tf.stack((coeff[1,0],StdERR))
95      ## calculate residual sum squares
96      def rss(a,M,y,int_t):
97          x_t = tf.reduce_sum(tf.math.multiply(M.T,a),axis=1)
98          lm_res = tf.linalg.lstsq(tf.transpose(tf.stack((int_t,x_t)
    ,axis=0)),Y_t2d)
99          lm_x = tf.concat((tf.squeeze(lm_res),x_t),axis=0)
100         return tf.reduce_sum(tf.math.square(tf.math.subtract(tf.
    squeeze(Y_t2d),tf.math.add(tf.math.multiply(lm_x[1],lm_x[2:]),
    tf.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.4 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 GLMMExpFam
6      from glimix_core.lmm import LMM
7      from limix._data._assert import assert_likelihood
8      from limix._data import normalize_likelihood, conform_dataset
9      from limix.qtl._assert import assert_finite
10     from limix._display import session_block, session_line
11     lik = normalize_likelihood(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             data = conform_dataset(y, M=M, K=K)
16         y = data["y"]
17         M = data["M"]
18         K = data["K"]
19         assert_finite(y, M, K)
20         if K is not None:
21            # K = K / diag(K).mean()
22             QS = economic_qs(K)
23         else:
24             QS = None
25         if lik_name == "normal":
26             method = LMM(y.values, M.values, QS, restricted=True)
27             method.fit(verbose=verbose)
28         else:
29             method = GLMMExpFam(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
```

Appendix B

A. thaliana phenotypic data

ID	Phenotype name	doi	Reference
1	FT Diameter Field	10.21958/phenotype:1	*Atwell* et al., 2010
2	At2 CFU2	10.21958/phenotype:2	*Atwell* et al., 2010
3	Leaf serr 16	10.21958/phenotype:3	*Atwell* et al., 2010
4	Seed bank 133-91	10.21958/phenotype:4	*Atwell* et al., 2010
5	Na23	10.21958/phenotype:5	*Atwell* et al., 2010
6	Leaf serr 10	10.21958/phenotype:6	*Atwell* et al., 2010
7	Emco5	10.21958/phenotype:7	*Atwell* et al., 2010
8	Leaf roll 16	10.21958/phenotype:8	*Atwell* et al., 2010
9	Leaf roll 10	10.21958/phenotype:9	*Atwell* et al., 2010
10	Bs	10.21958/phenotype:10	*Atwell* et al., 2010
11	2W	10.21958/phenotype:11	*Atwell* et al., 2010
12	Rosette Erect 22	10.21958/phenotype:12	*Atwell* et al., 2010
13	Cd114	10.21958/phenotype:13	*Atwell* et al., 2010
14	Width 16	10.21958/phenotype:14	*Atwell* et al., 2010
15	Storage 28 days	10.21958/phenotype:15	*Atwell* et al., 2010
16	LY	10.21958/phenotype:16	*Atwell* et al., 2010
17	avrRpm1	10.21958/phenotype:17	*Atwell* et al., 2010
18	Width 10	10.21958/phenotype:18	*Atwell* et al., 2010
19	Chlorosis 22	10.21958/phenotype:19	*Atwell* et al., 2010

20	Storage 7 days	10.21958/phenotype:20	*Atwell* et al., 2010
21	As2 CFU2	10.21958/phenotype:21	*Atwell* et al., 2010
22	Co59	10.21958/phenotype:22	*Atwell* et al., 2010
23	FW	10.21958/phenotype:23	*Atwell* et al., 2010
24	Cu65	10.21958/phenotype:24	*Atwell* et al., 2010
25	Bacterial titer	10.21958/phenotype:25	*Atwell* et al., 2010
26	Width 22	10.21958/phenotype:26	*Atwell* et al., 2010
27	Storage 56 days	10.21958/phenotype:27	*Atwell* et al., 2010
28	YEL	10.21958/phenotype:28	*Atwell* et al., 2010
29	FLC	10.21958/phenotype:29	*Atwell* et al., 2010
30	FT16	10.21958/phenotype:30	*Atwell* et al., 2010
31	FT10	10.21958/phenotype:31	*Atwell* et al., 2010
32	FT Duration GH	10.21958/phenotype:32	*Atwell* et al., 2010
33	Se82	10.21958/phenotype:33	*Atwell* et al., 2010
34	LDV	10.21958/phenotype:34	*Atwell* et al., 2010
35	Noco2	10.21958/phenotype:35	*Atwell* et al., 2010
36	8W GH LN	10.21958/phenotype:36	*Atwell* et al., 2010
37	0W	10.21958/phenotype:37	*Atwell* et al., 2010
38	MT GH	10.21958/phenotype:38	*Atwell* et al., 2010
39	After Vern Growth	10.21958/phenotype:39	*Atwell* et al., 2010
40	Aphid number	10.21958/phenotype:40	*Atwell* et al., 2010
41	LN22	10.21958/phenotype:41	*Atwell* et al., 2010
42	Bs CFU2	10.21958/phenotype:42	*Atwell* et al., 2010
43	avrRpt2	10.21958/phenotype:43	*Atwell* et al., 2010
44	Hypocotyl length	10.21958/phenotype:44	*Atwell* et al., 2010
45	Germ 22	10.21958/phenotype:45	*Atwell* et al., 2010
46	Leaf roll 22	10.21958/phenotype:46	*Atwell* et al., 2010
47	SD	10.21958/phenotype:47	*Atwell* et al., 2010

48	8W	10.21958/phenotype:48	*Atwell* et al., 2010
49	FT GH	10.21958/phenotype:49	*Atwell* et al., 2010
50	DSDS50	10.21958/phenotype:50	*Atwell* et al., 2010
51	Ca43	10.21958/phenotype:51	*Atwell* et al., 2010
52	LC Duration GH	10.21958/phenotype:52	*Atwell* et al., 2010
53	0W GH FT	10.21958/phenotype:53	*Atwell* et al., 2010
54	B11	10.21958/phenotype:54	*Atwell* et al., 2010
55	Chlorosis 10	10.21958/phenotype:55	*Atwell* et al., 2010
56	RP GH	10.21958/phenotype:56	*Atwell* et al., 2010
57	Chlorosis 16	10.21958/phenotype:57	*Atwell* et al., 2010
58	LFS GH	10.21958/phenotype:58	*Atwell* et al., 2010
59	Germ 10	10.21958/phenotype:59	*Atwell* et al., 2010
60	Germ 16	10.21958/phenotype:60	*Atwell* et al., 2010
61	Anthocyanin 16	10.21958/phenotype:61	*Atwell* et al., 2010
62	Anthocyanin 10	10.21958/phenotype:62	*Atwell* et al., 2010
63	At1 CFU2	10.21958/phenotype:63	*Atwell* et al., 2010
64	Ni60	10.21958/phenotype:64	*Atwell* et al., 2010
65	P31	10.21958/phenotype:65	*Atwell* et al., 2010
66	Emwa1	10.21958/phenotype:66	*Atwell* et al., 2010
67	As75	10.21958/phenotype:67	*Atwell* et al., 2010
68	Germ in dark	10.21958/phenotype:68	*Atwell* et al., 2010
69	FRI	10.21958/phenotype:69	*Atwell* et al., 2010
70	As CFU2	10.21958/phenotype:70	*Atwell* et al., 2010
71	Trichome avg C	10.21958/phenotype:71	*Atwell* et al., 2010
72	Vern Growth	10.21958/phenotype:72	*Atwell* et al., 2010
73	Mo98	10.21958/phenotype:73	*Atwell* et al., 2010
74	Hiks1	10.21958/phenotype:74	*Atwell* et al., 2010
75	Anthocyanin 22	10.21958/phenotype:75	*Atwell* et al., 2010

76	Zn66	10.21958/phenotype:76	*Atwell* et al., 2010
77	Trichome avg JA	10.21958/phenotype:77	*Atwell* et al., 2010
78	LES	10.21958/phenotype:78	*Atwell* et al., 2010
79	Silique 16	10.21958/phenotype:79	*Atwell* et al., 2010
80	Emoy*	10.21958/phenotype:80	*Atwell* et al., 2010
81	K39	10.21958/phenotype:81	*Atwell* et al., 2010
82	0W GH LN	10.21958/phenotype:82	*Atwell* et al., 2010
83	At2	10.21958/phenotype:83	*Atwell* et al., 2010
84	At1	10.21958/phenotype:84	*Atwell* et al., 2010
85	LN10	10.21958/phenotype:85	*Atwell* et al., 2010
86	FT Field	10.21958/phenotype:86	*Atwell* et al., 2010
87	LN16	10.21958/phenotype:87	*Atwell* et al., 2010
88	avrB	10.21958/phenotype:88	*Atwell* et al., 2010
89	LD	10.21958/phenotype:89	*Atwell* et al., 2010
90	Seedling Growth	10.21958/phenotype:90	*Atwell* et al., 2010
91	S34	10.21958/phenotype:91	*Atwell* et al., 2010
92	Leaf serr 22	10.21958/phenotype:92	*Atwell* et al., 2010
93	DW	10.21958/phenotype:93	*Atwell* et al., 2010
94	Seed Dormancy	10.21958/phenotype:94	*Atwell* et al., 2010
95	Mn55	10.21958/phenotype:95	*Atwell* et al., 2010
96	Silique 22	10.21958/phenotype:96	*Atwell* et al., 2010
97	avrPphB	10.21958/phenotype:97	*Atwell* et al., 2010
98	Fe56	10.21958/phenotype:98	*Atwell* et al., 2010
99	8W GH FT	10.21958/phenotype:99	*Atwell* et al., 2010
100	4W	10.21958/phenotype:100	*Atwell* et al., 2010
101	Li7	10.21958/phenotype:101	*Atwell* et al., 2010
102	FT22	10.21958/phenotype:102	*Atwell* et al., 2010
103	As2	10.21958/phenotype:103	*Atwell* et al., 2010

104	SDV	10.21958/phenotype:104	*Atwell* et al., 2010
105	Mg25	10.21958/phenotype:105	*Atwell* et al., 2010
106	Secondary Dormancy	10.21958/phenotype:106	*Atwell* et al., 2010
107	As	10.21958/phenotype:107	*Atwell* et al., 2010
108	Area Sweden 2009 (1st experiment)	10.21958/phenotype:108	*Li* et al., 2010
109	Size Planting Summer 2009	10.21958/phenotype:109	*Li* et al., 2010
110	Size Sweden 2009 (2nd experiment)	10.21958/phenotype:110	*Li* et al., 2010
111	Size Planting Summer Loc Sweden 2009	10.21958/phenotype:111	*Li* et al., 2010
112	Area Sweden 2009 (2nd experiment)	10.21958/phenotype:112	*Li* et al., 2010
113	DTF Sweden 2008 (1st experiment)	10.21958/phenotype:113	*Li* et al., 2010
114	Yield Sweden 2009 (2nd experiment)	10.21958/phenotype:114	*Li* et al., 2010
115	Size Loc Sweden 2009	10.21958/phenotype:115	*Li* et al., 2010
116	DTF planting Summer Loc Sweden 2009	10.21958/phenotype:116	*Li* et al., 2010
117	DTF loc Sweden 2008	10.21958/phenotype:117	*Li* et al., 2010
118	DTF loc Sweden 2009	10.21958/phenotype:118	*Li* et al., 2010
119	DTF Spain 2009 (1st experiment)	10.21958/phenotype:119	*Li* et al., 2010
120	DTF planting Loc 2008	10.21958/phenotype:120	*Li* et al., 2010
121	DTF Spain 2009 (2nd experiment)	10.21958/phenotype:121	*Li* et al., 2010

122	Yield Spain 2009 (2nd experiment)	10.21958/phenotype:122	*Li* et al., 2010
123	Size Sweden 2009 (1st experiment)	10.21958/phenotype:123	*Li* et al., 2010
124	Yield Spain 2009 (1st experiment)	10.21958/phenotype:124	*Li* et al., 2010
125	DTF main Effect 2009	10.21958/phenotype:125	*Li* et al., 2010
126	DTF main Effect 2008	10.21958/phenotype:126	*Li* et al., 2010
127	Size Spain 2009 (2nd experiment)	10.21958/phenotype:127	*Li* et al., 2010
128	Size Spain 2009 (1st experiment)	10.21958/phenotype:128	*Li* et al., 2010
129	DTF planting Summer 2009	10.21958/phenotype:129	*Li* et al., 2010
130	DTF planting Summer 2008	10.21958/phenotype:130	*Li* et al., 2010
131	Size Main Effect 2009	10.21958/phenotype:131	*Li* et al., 2010
132	DTF Spain 2008 (1st experiment)	10.21958/phenotype:132	*Li* et al., 2010
133	Yield Planting Summer 2009	10.21958/phenotype:133	*Li* et al., 2010
134	DTF Sweden 2009 (1st experiment)	10.21958/phenotype:134	*Li* et al., 2010
135	Yield Loc Sweden 2009	10.21958/phenotype:135	*Li* et al., 2010
136	DTF Spain 2008 (2nd experiment)	10.21958/phenotype:136	*Li* et al., 2010
137	Yield Main Effect 2009	10.21958/phenotype:137	*Li* et al., 2010
138	Yield Planting Summer Loc Sweden 009	10.21958/phenotype:138	*Li* et al., 2010

139	Yield Sweden 2009 (1st experiment)	10.21958/phenotype:139	*Li* et al., 2010
140	DTF Sweden 2009 (2nd experiment)	10.21958/phenotype:140	*Li* et al., 2010
141	DTF Sweden 2008 (2nd experiment)	10.21958/phenotype:141	*Li* et al., 2010
142	Mature cell length	10.21958/phenotype:142	*Meijó* et al., 2014
143	Meristem zone length	10.21958/phenotype:143	*Meijó* et al., 2014
144	M216T665	10.21958/phenotype:144	*Strauch* et al., 2015
145	M130T666	10.21958/phenotype:145	*Strauch* et al., 2015
146	M172T666	10.21958/phenotype:146	*Strauch* et al., 2015
261	FT10	10.21958/phenotype:261	*Alonso-Blanco* et al., 2016
262	FT16	10.21958/phenotype:262	*Alonso-Blanco* et al., 2016
269	Li7	10.21958/phenotype:269	*Forsberg* et al., 2015
270	B11	10.21958/phenotype:270	*Forsberg* et al., 2015
271	Na23	10.21958/phenotype:271	*Forsberg* et al., 2015
272	Mg25	10.21958/phenotype:272	*Forsberg* et al., 2015
273	P31	10.21958/phenotype:273	*Forsberg* et al., 2015
274	S34	10.21958/phenotype:274	*Forsberg* et al., 2015
275	K39	10.21958/phenotype:275	*Forsberg* et al., 2015
276	Ca43	10.21958/phenotype:276	*Forsberg* et al., 2015
277	Mn55	10.21958/phenotype:277	*Forsberg* et al., 2015
279	Co59	10.21958/phenotype:279	*Forsberg* et al., 2015
280	Ni60	10.21958/phenotype:280	*Forsberg* et al., 2015
281	Cu65	10.21958/phenotype:281	*Forsberg* et al., 2015
282	Zn66	10.21958/phenotype:282	*Forsberg* et al., 2015
283	As75	10.21958/phenotype:283	*Forsberg* et al., 2015
284	Se82	10.21958/phenotype:284	*Forsberg* et al., 2015

Appendix C

Genomic prediction

C.1 GP ANN

```
1
2   import os,sys,gc
3 import pandas as pd
4 import numpy as np
5 import timeit
6 from datetime import datetime
7 import keras
8 import tensorflow as tf
9 from keras import backend as K
10 from keras import layers
11 from keras.models import Sequential
12 from keras.layers import Dense, Dropout, GaussianNoise,
     AlphaDropout, Reshape
13 from keras.layers import Flatten, LocallyConnected1D,
     LocallyConnected2D
14 from keras.optimizers import Adam, Adagrad, Adadelta
15 from keras.backend.tensorflow_backend import set_session
16
17 ##set default values
18
19 learning_rate = 0.01
20 JobID = 1
21 ps = 25
22 optim = "adam"
23 X_file = "KE.geno.csv"
```

```
Y_file = "KE_pheno.csv"
CV_file = "KE_cv_pw.csv"
label = "DtSILK"
start_time = timeit.default_timer()
act="relu"
drop_rate = str('0.5,0.5,0.5')
arc = str('63,63')
DG = 'D,D,D,D,D,G'
LC = True
training_epochs = 25
hyp = False

### parse command line arguments

for i in range (1,len(sys.argv),2):
    if sys.argv[i] == "-x":
        X_file = sys.argv[i+1]
    elif sys.argv[i] == "-y":
        Y_file = sys.argv[i+1]
    elif sys.argv[i] == "-cv":
        CV_file = sys.argv[i+1]
    elif sys.argv[i] == "-JobID":
        JobID = int(sys.argv[i+1])
    elif sys.argv[i] == "-label":
        label = sys.argv[i+1]
    elif sys.argv[i] == "-act":
        act = str(sys.argv[i+1])
    elif sys.argv[i] == "-epochs":
        training_epochs = int(sys.argv[i+1])
    elif sys.argv[i] == "-lr":
        learning_rate = float(sys.argv[i+1])
    elif sys.argv[i] == "-arc":
        arc = sys.argv[i+1]
    elif sys.argv[i] == "-ps":
        ps = int(sys.argv[i+1])
    elif sys.argv[i] == "-dr":
        drop_rate=str(sys.argv[i+1])
    elif sys.argv[i] == "-LC":
```

```
62          LC = bool(sys.argv[i+1])
63      elif sys.argv[i] == "hyp":
64          hyp = bool(sys.argv[i+1])
65      else:
66          print('unknown option ' + str(sys.argv[i]))
67          quit()
68
69
70
71  ## change dir to data location
72
73
74  #os.chdir('/home/jaf81qa/jan_storage/tens')
75  x = pd.read_csv(X_file, index_col = 0)
76  #os.chdir("/storage/full-share/genoPred/maze")
77  y = pd.read_csv(Y_file, index_col = 0)
78  cv_folds = pd.read_csv(CV_file,index_col=0)
79
80  ## select column of phenotype file via columnname
81
82  y = y[[label]]
83  ## activity_regularizer=regularizers.l1(0.01)))
84
85  def build_network(arc,drop_rate,LC,DG):
86      def add_drops(model,drop_out,k):
87          if DG[k].upper() == 'D':
88              model.add(Dropout(drop_out[0]))
89          elif DG[k].upper() == 'G':
90              model.add(GaussianNoise(drop_out[k]))
91          elif DG[k].upper() == "A":
92              model.add(AlphaDropout(drop_out[k]))
93          else:
94              pass
95          return model
96      DG = DG.strip().split(",")
97      arc = arc.strip().split(",")
98      archit = []
99      for layer in  arc:
```

```
100         archit.append(int(layer))
101     layer_number = len(archit)
102     drop_rate = drop_rate.strip().split(",")
103     drop_out = []
104     for drops in drop_rate:
105         drop_out.append(float(drops))
106     model = Sequential()
107     if LC == True:
108         model.add(Reshape(input_shape=(x_train.shape[1],),
    target_shape=(x_train.shape[1],1)))
109         model.add(LocallyConnected1D(1,10,strides=7,input_shape=(
    x_train.shape[1],1)))
110         model.add(Flatten())
111         start = 0
112         model = add_drops(model,drop_out,start)
113     elif LC == False:
114         model.add(Dense(archit[0], kernel_initializer='
    truncated_normal', activation=act, input_shape=(x_train.shape
    [1],)))
115         model = add_drops(model,drop_out,start)
116     start = 1
117     for k in range(start,len(archit)):
118         model.add(Dense(archit[k], kernel_initializer='
    truncated_normal', activation=act))
119         model = add_drops(model,drop_out,k)
120     model.add(Dense(1, kernel_initializer='truncated_normal'))
121     return(model)
122
123
124 config = tf.ConfigProto()
125 #config.gpu_options.per_process_gpu_memory_fraction = 0.1
126 config.gpu_options.allow_growth = True
127 set_session(tf.Session(config=config))
128
129
130 if not os.path.isfile("RESULTScv50.txt"):
131     out2 = open("RESULTScv50.txt",'w')
```

```
132     out2.write('DateTime\tCompTime\tDF\tGenos\tPhenos\tCV_fold\
    tArchit\tConv\tActFun\tEpochs\tdrop_rate\tAccuracy\n' )
133
134
135 for k in range(1,51):
136     print("Training on cv fold "+ str(k))
137     cv = cv_folds['cv_' + str(k)]
138     num_cvs = np.ptp(cv) + 1
139
140     i = 1
141     x_train = x[cv != i]
142     x_test = x[cv == i]
143     y_train = y[cv != i]
144     y_test = y[cv == i]
145
146     yhat = np.zeros(shape = y_test.shape)
147
148     model = build_network(arc,drop_rate,LC,DG)
149     model.compile(loss='mse', optimizer=Adam(lr=0.01,decay = 0.001)
    ,metrics=['accuracy'])
150     model.fit(x_train,y_train, epochs=training_epochs , verbose=0)
151 #     score = model.evaluate(x_test, y_test, verbose=0)
152     bla = model.predict(x_test)
153     y_sub= y[np.asarray(cv == i)]
154
155     print(model.summary())
156     print('\n')
157     print(label)
158
159     comp_time = int(round(timeit.default_timer() - start_time,0))
160
161     DateTime = datetime.now().strftime('%Y-%m-%d %H:%M:%S')
162     acc = np.corrcoef(bla[:,0],np.asarray(y_sub)[:,0])[0,1]
163
164     out2 = open("RESULTScv50.txt", 'a')
165     out2.write('%s\t%i\t%s\t%s\t%s\t%i\t%s\t%s\t%s\t%i\t%s\t%0.5f\n
    ' % (
```

```
        DateTime, comp_time, label, X_file, Y_file, int(k), arc, LC
    ,  act,int(training_epochs), drop_rate, round(acc,4)))

    del model,bla, x_train, x_test, y_train, y_test
    K.clear_session()
    gc.collect()

    config = tf.ConfigProto()
    #config.gpu_options.per_process_gpu_memory_fraction = 0.1
    config.gpu_options.allow_growth = True
    set_session(tf.Session(config=config))
```

C.2 GBLUP script

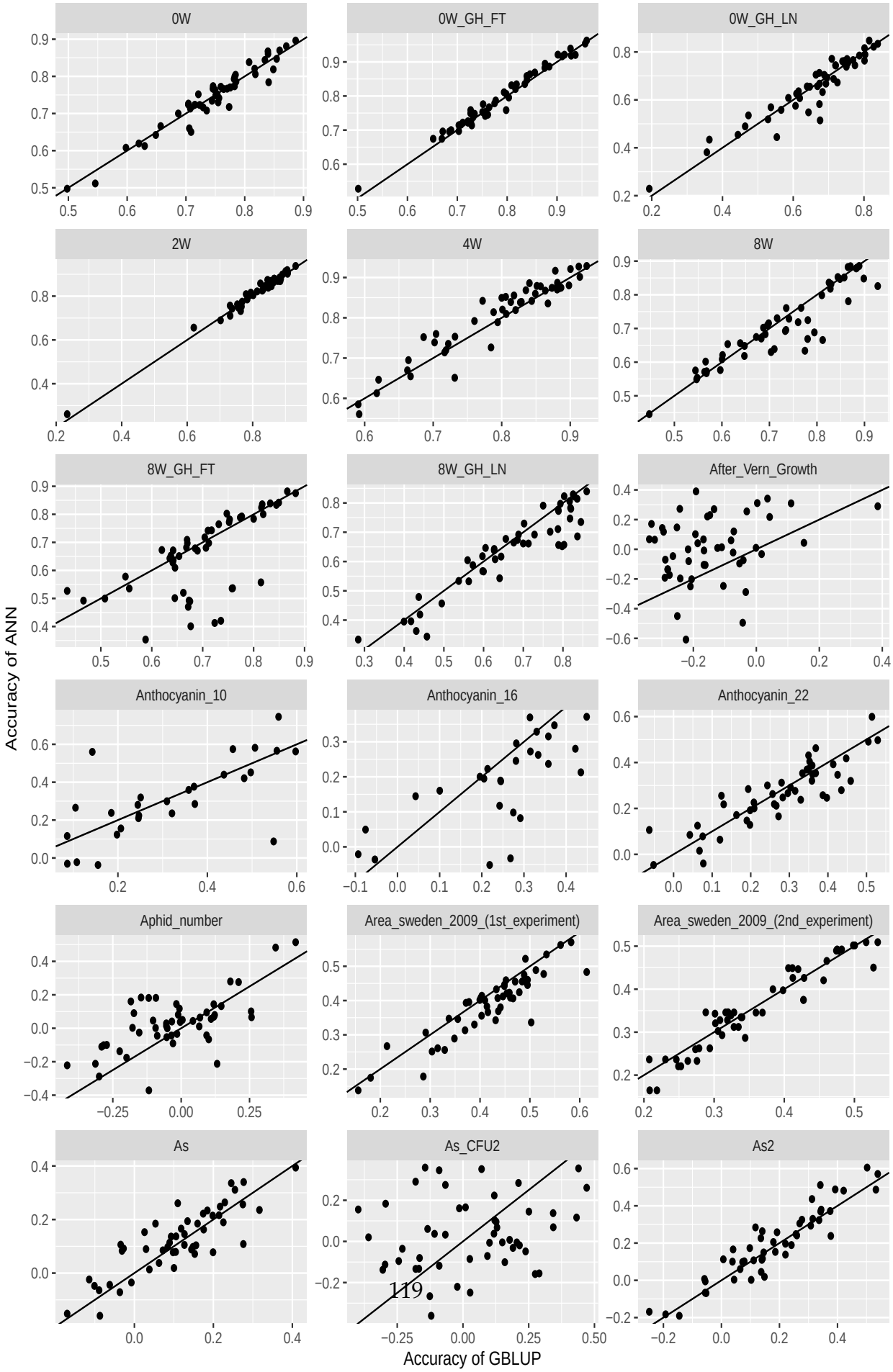
```
    geno_pred <- function(phenocsv,genocsv,cvfcsv,cvf=1,mod = "BRR"
    ,label,phe)
{
    my_phe <- phe
    depends<- c("BGLR","doBy","doParallel",'R.utils',"BBmisc","
    dplyr")
    foo <- sapply(depends,
                  function(X){if(!suppressPackageStartupMessages(
    require(X,character.only = T))){install.packages(X)}})
    foo <- sapply(depends,function(X){
    suppressPackageStartupMessages(library(X,character.only=TRUE))})
    rm(foo)


    maze <- read.csv(genocsv, row.names = 1)
    phe <- read.csv(phenocsv, row.names = 1)
    cvffolds <- read.csv(cvfcsv,row.names=1)

    X <- scale(maze)
    y <- phe[[label]]
    if(any(is.na(y))){
        rms <- which(is.na(y))
        y <- y[-rms]
        X <- X[-rms,]
```

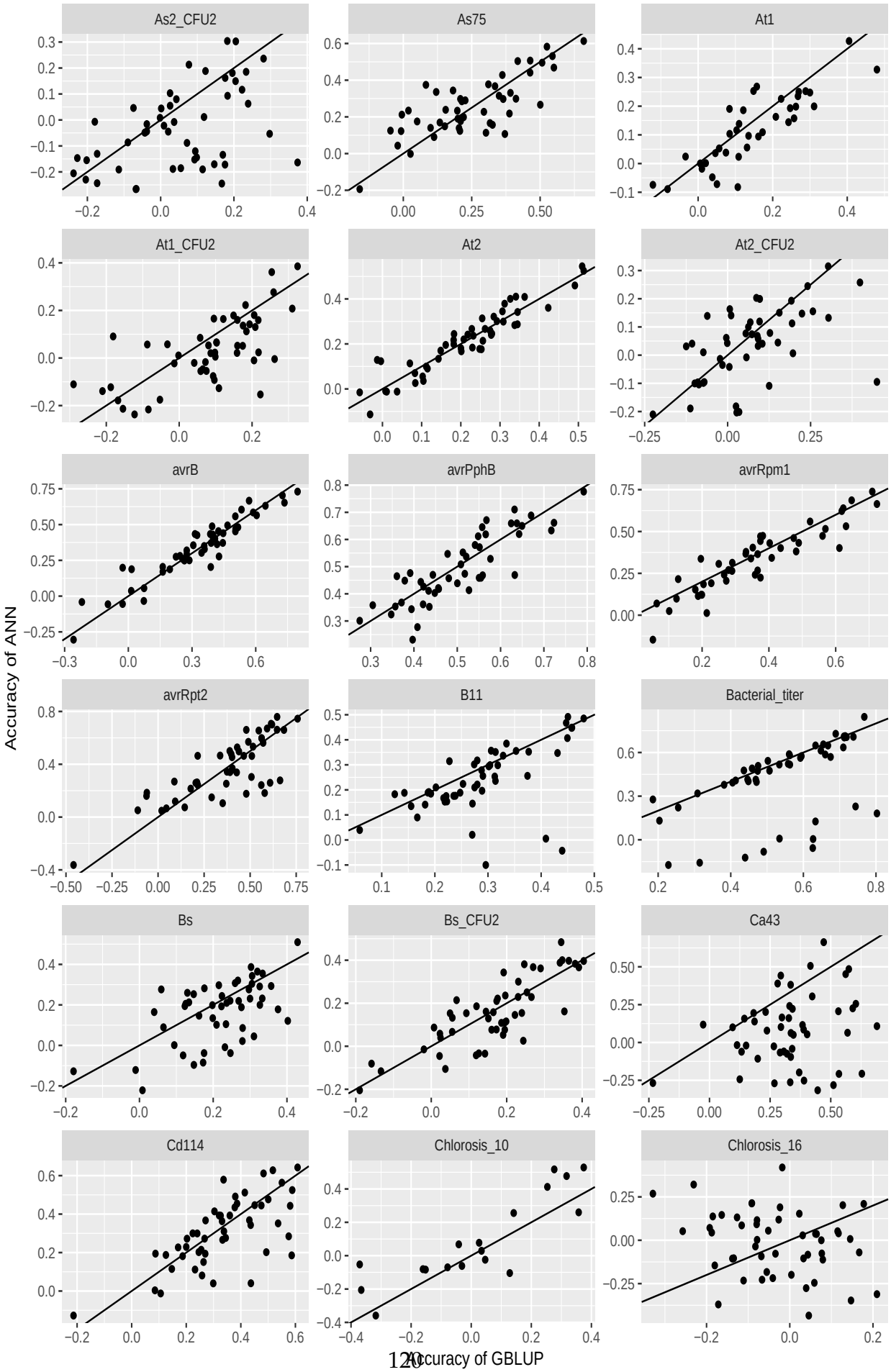
```
21    }
22    for(i in 1:50){
23        cvf = i
24        n=length(y)
25        seed <- sample(1:100,1)
26                                        #set.seed(seed)
27                                        #folds=sample(1:cvf,size=n,
    replace=T)
28        folds = cvffolds[,cvf]
29        yHatCV=rep(NA,n)
30
31        for(i in 1:max(folds)){
32            cat("Predicting cv-fold ",i," of ", max(folds))
33            tst=which(folds==i)
34            yNA=y
35            yNA[tst]=NA
36            fm=BGLR(y=yNA,ETA=list(list(X=X,model=mod)),verbose =F
    ,nIter=7000,burnIn=1000)
37            yHatCV[tst]=fm$yHat[tst]
38            cat("    done\n")
39        }
40
41        my_cor <- cor(yHatCV,y,use = "complete.obs")
42        print(c("Corrleation of GP", mod, my_cor))
43        filename = paste0(my_phe,"_gp_results.csv")
44        print(filename)
45        if(!any(dir() == filename)){
46            res <- matrix(ncol=8, nrow = 1) %>%
47                setColNames(c("geno","pheno","cv_folds","seed","
    label", "cor","method","nmark"))
48            res[1,] <- c(as.character(genocsv),as.character(
    phenocsv),as.character(cvf),as.character(seed),
49                         as.character(label),as.character(my_cor),
    as.character(mod),dim(X)[2])
50            print("#################")
51       print(res)
52       print("#############")
53            write.csv(res,filename)
```

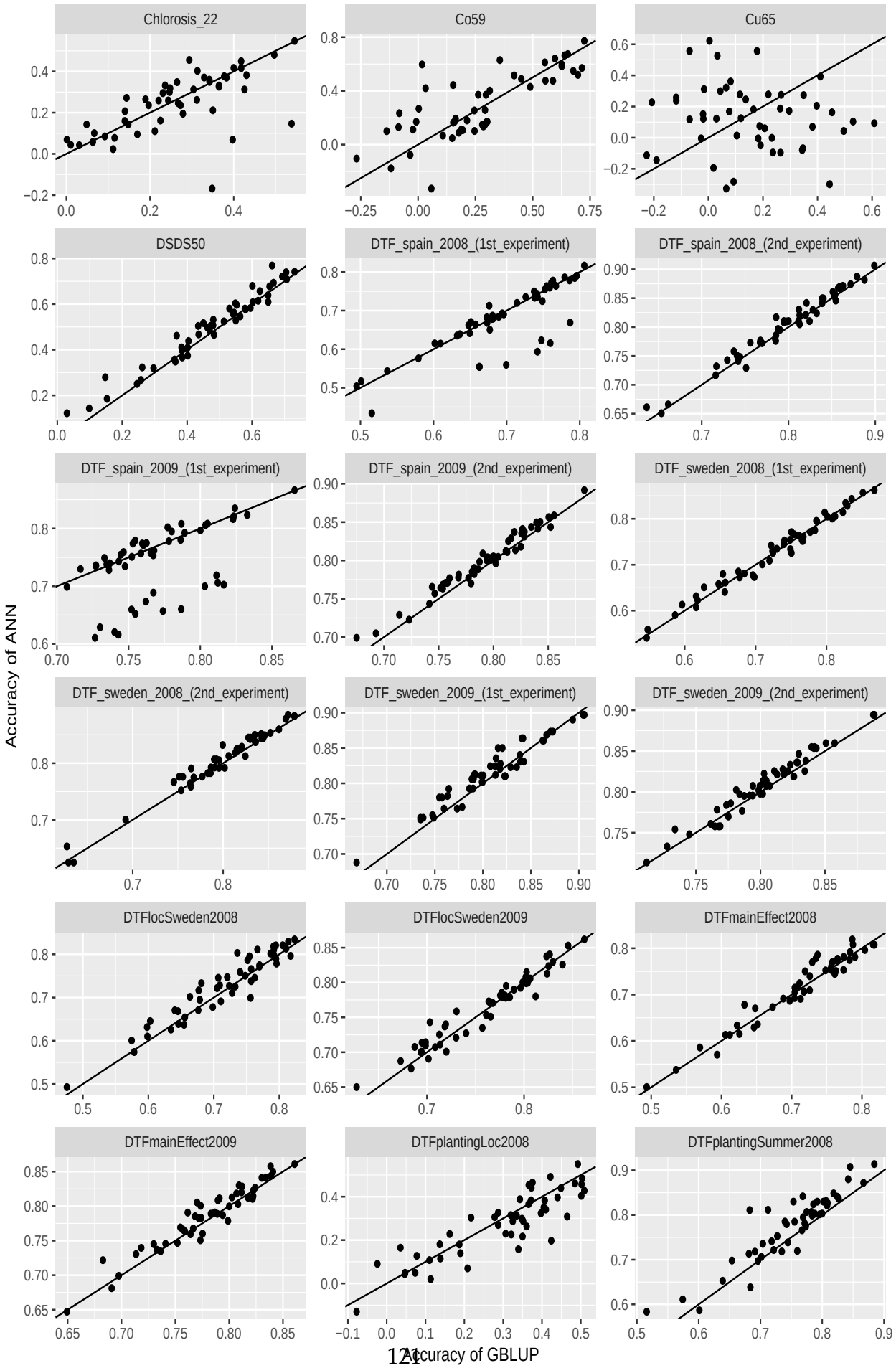
```
54          }else{
55              res <- read.csv(filename,row.names = 1)
56              for(i in 1:7){
57                  res[,i] <- as.character(res[,i])
58              }
59              res[dim(res)[1]+1,] <- c(as.character(genocsv),phenocsv
    ,cvf,seed,as.character(label),my_cor,mod,dim(X)[2])
60              write.csv(res,filename)
61          }
62      }
63
64    }
65 ## execute this script with: Rscript ex.gblup.r -x genofile -y
    phenofile -c cv file
66 source("~/PHD/Projects/gblup/bglr.r")
67
68
69 my.args <- commandArgs(trailingOnly = TRUE)
70 #my.args <- c("-x", "gent_geno.csv","-y" , "gent_pheno.csv")
71 ### set defaults
72 #cvf.name = NA
73
74 ## parsing the command line options
75 all.opts <- c("-x","-y","-label","-h","-cv","-phe")
76 for(i in 1:length(my.args)){
77      if( i %% 2 == 1){
78          if(!my.args[i] %in%  all.opts){
79              cat("unknown option", my.args[i], "Use only", all.opts
    , "\n")
80              cat("use -h for help \n")
81              quit()
82          }
83      }
84      if(my.args[i] == "-x"){
85          geno.name <- as.character(my.args[i+1])
86      } else if(my.args[i] == "-y") {
87          pheno.name <- as.character(my.args[i+1])
88      } else if(my.args[i] == "-label") {
```

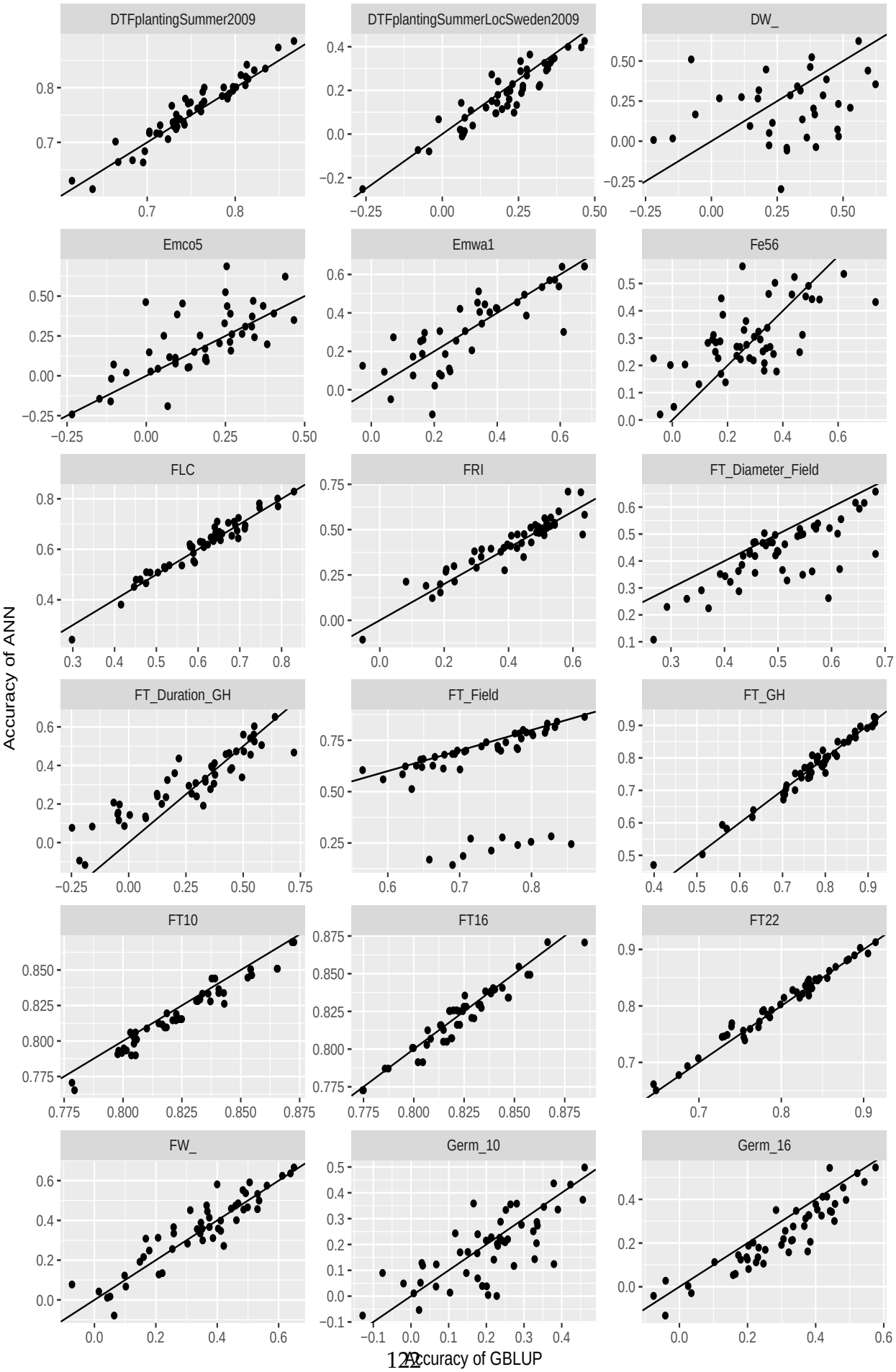
```
89          my_ph <- as.character(my.args[i+1])
90      } else if(my.args[i] == "-cv"){
91          cv.name = as.character(my.args[i+1])
92      } else if(my.args[i] == "-phe"){
93          my_phe <- as.character(my.args[i+1])
94      } else if(my.args[i] == "-h") {
95          print(" This script takes as a minimum two intputs\n")
96          print(" -x genotypefile")
97          print(" -y phenotypefile ")
98          print(" -cv cross-valiadtion file : is optional if none is
    specified random 5 fold cv will be used")
99          print(" -JobID : specify column number to use in your cross
     validation file")
100         print(" -label : use header of phenotype file column you
    want to use")
101         quit()
102     }
103 }
104
105
106 #pheno.name <- my.args[1]
107 #geno.name <- my.args[2]
108 #cvf.name <- my.args[3]
109
110 geno_pred(phenocsv = pheno.name,genocsv=geno.name, cvfcsv = cv.name
    , label=my_ph,mod = "BRR", phe =my_phe)
```

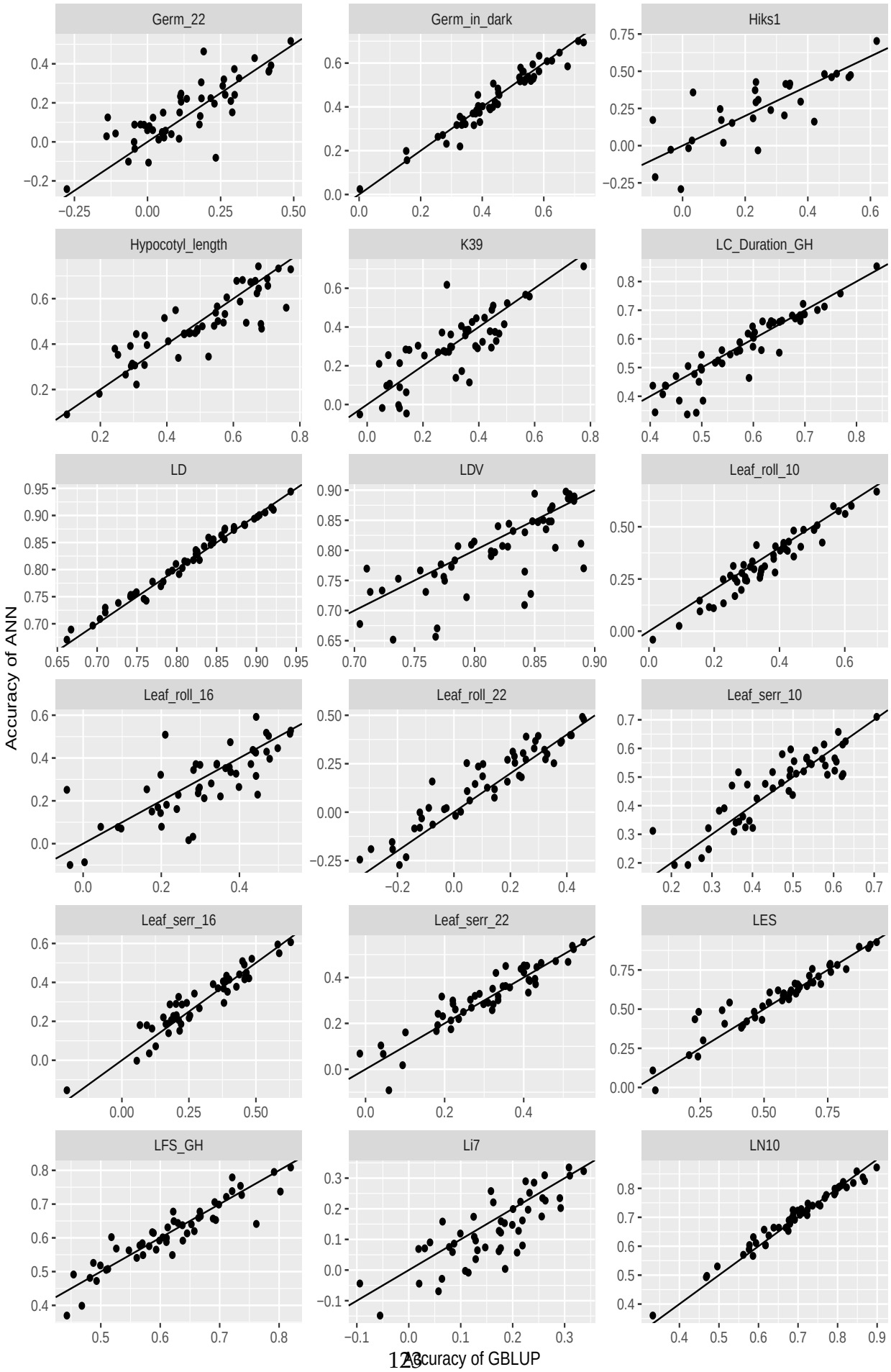
C.3 Results of GP

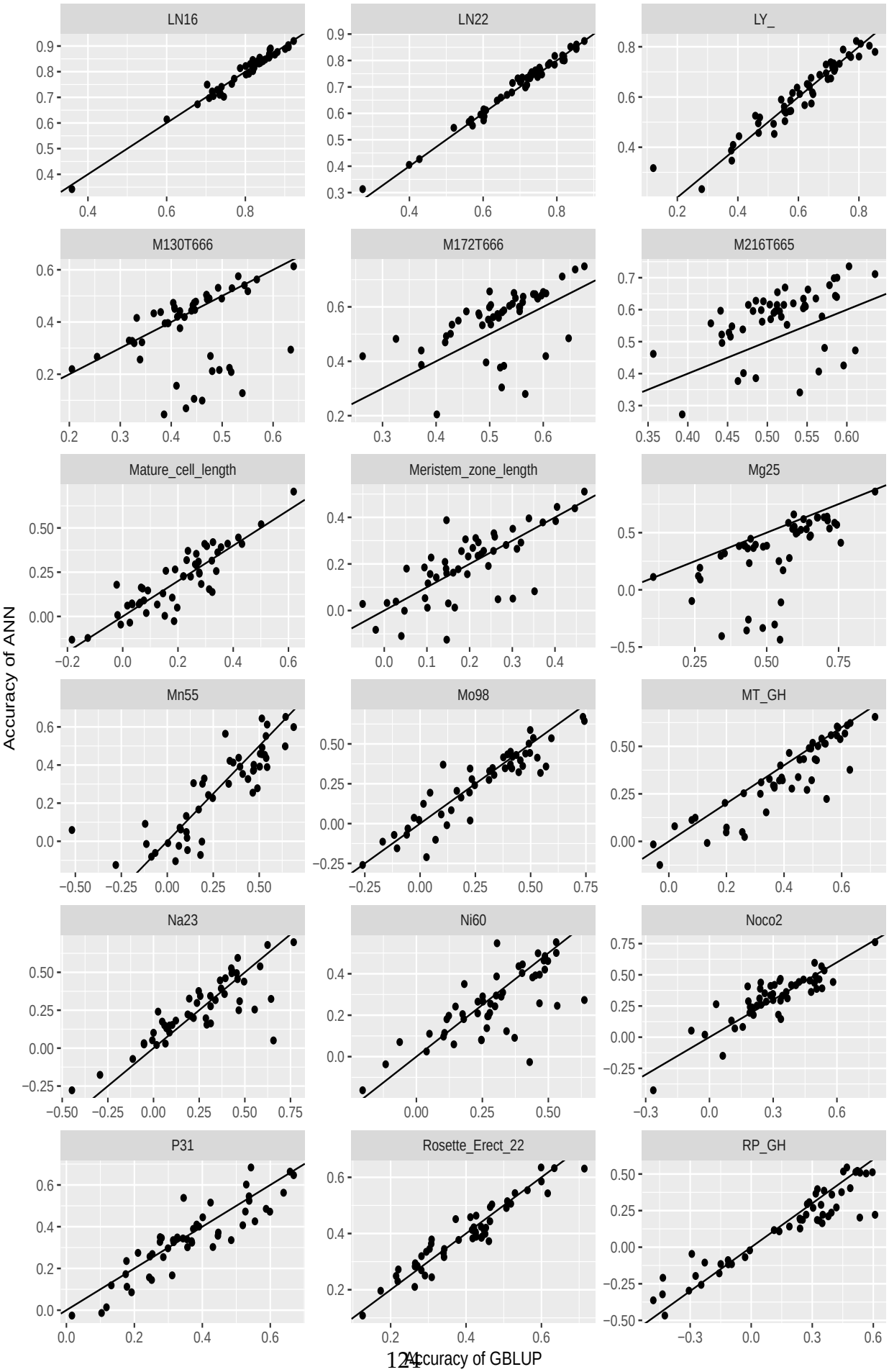


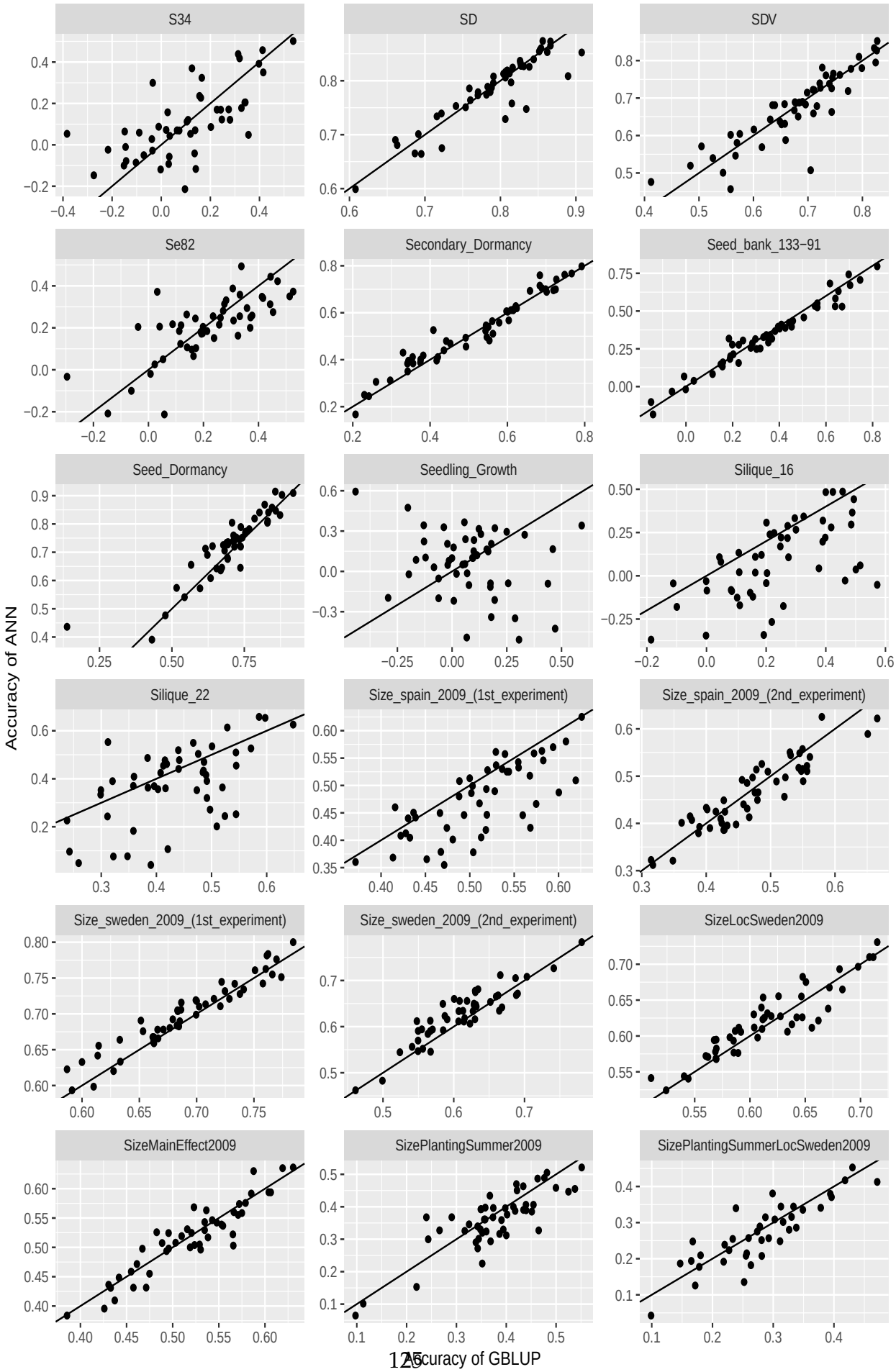

As2_CFU2
As75
At1
At1_CFU2
At2
At2_CFU2
avrB
avrPphB
avrRpm1
avrRpt2
B11
Bacterial_titer
Bs
Bs_CFU2
Ca43
Cd114
Chlorosis_10
Chlorosis_16
Accuracy of ANN
Accuracy of GBLUP

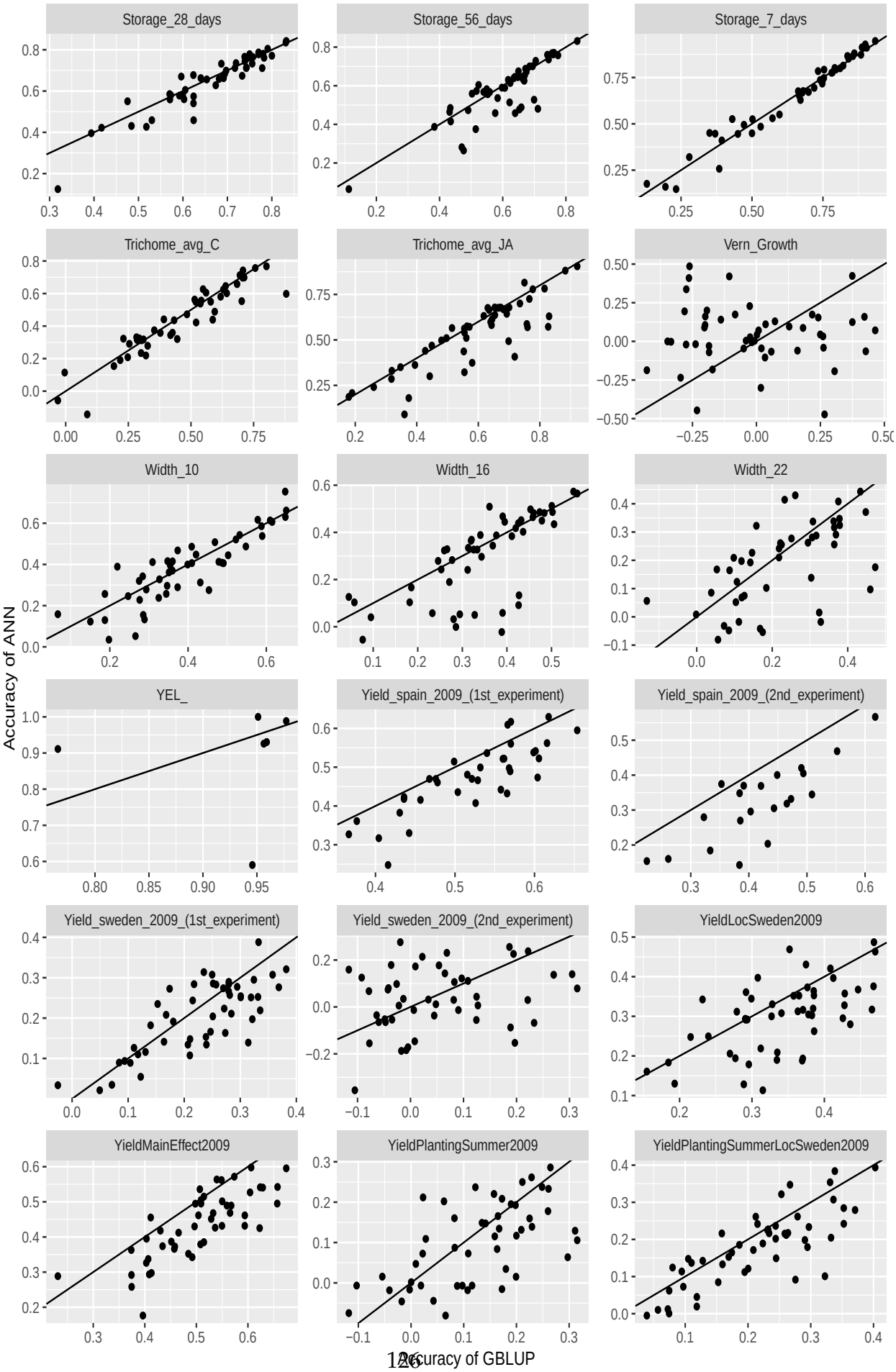

Chlorosis_22
Co59
Cu65
DSDS50
DTF_spain_2008_(1st_experiment)
DTF_spain_2008_(2nd_experiment)
DTF_spain_2009_(1st_experiment)
DTF_spain_2009_(2nd_experiment)
DTF_sweden_2008_(1st_experiment)
DTF_sweden_2008_(2nd_experiment)
DTF_sweden_2009_(1st_experiment)
DTF_sweden_2009_(2nd_experiment)
DTFlocSweden2008
DTFlocSweden2009
DTFmainEffect2008
DTFmainEffect2009
DTFplantingLoc2008
DTFplantingSummer2008
Accuracy of ANN
Accuracy of GBLUP

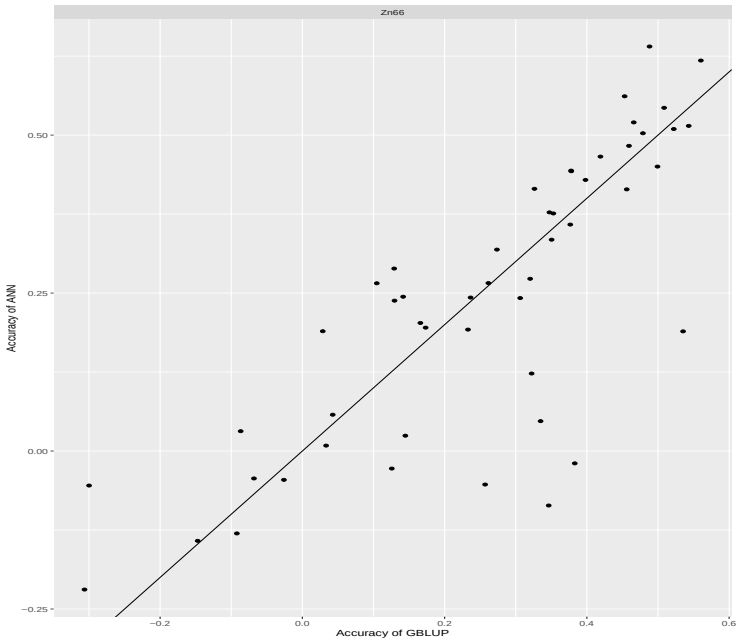

DTFplantingSummer2009
DTFplantingSummerLocSweden2009
DW_
Emco5
Emwa1
Fe56
FLC
FRI
FT_Diameter_Field
FT_Duration_GH
FT_Field
FT_GH
FT10
FT16
FT22
FW_
Germ_10
Germ_16
Accuracy of ANN
Accuracy of GBLUP


Germ_22
Germ_in_dark
Hiks1
Hypocotyl_length
K39
LC_Duration_GH
LD
LDV
Leaf_roll_10
Leaf_roll_16
Leaf_roll_22
Leaf_serr_10
Leaf_serr_16
Leaf_serr_22
LES
LFS_GH
Li7
LN10
Accuracy of ANN
Accuracy of GBLUP


LN16
LN22
LY_
M130T666
M172T666
M216T665
Mature_cell_length
Meristem_zone_length
Mg25
Mn55
Mo98
MT_GH
Na23
Ni60
Noco2
P31
Rosette_Erect_22
RP_GH
Accuracy of ANN
Accuracy of GBLUP


S34
SD
SDV
Se82
Secondary_Dormancy
Seed_bank_133−91
Seed_Dormancy
Seedling_Growth
Silique_16
Silique_22
Size_spain_2009_(1st_experiment)
Size_spain_2009_(2nd_experiment)
Size_sweden_2009_(1st_experiment)
Size_sweden_2009_(2nd_experiment)
SizeLocSweden2009
SizeMainEffect2009
SizePlantingSummer2009
SizePlantingSummerLocSweden2009
Accuracy of ANN
Accuracy of GBLUP


Storage_28_days
Storage_56_days
Storage_7_days
Trichome_avg_C
Trichome_avg_JA
Vern_Growth
Width_10
Width_16
Width_22
YEL_
Yield_spain_2009_(1st_experiment)
Yield_spain_2009_(2nd_experiment)
Yield_sweden_2009_(1st_experiment)
Yield_sweden_2009_(2nd_experiment)
YieldLocSweden2009
YieldMainEffect2009
YieldPlantingSummer2009
YieldPlantingSummerLocSweden2009
Accuracy of ANN
Accuracy of GBLUP


Zn66
Accuracy of ANN
Accuracy of GBLUP
0.50
0.25
0.00
−0.25
−0.2
0.0
0.2
0.4
0.6

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