

# How\_to\_use\_EFGLmh

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## Introduction

This will walk through the functions in the `EFGLmh` package. This package was written as a replacement for IDFGEN mainly motivated by the need to work with microhaps. It has been written to function for any codominant diploid marker, but is written and tested with SNPs and microhaps (SNPs are really just a subcategory of microhaps) in mind.

If you want to see all the options for a function, the manual has this information in a quicker-to-find format than this vignette.

One of the main differences between IDFGEN and `EFGLmh` is that IDFGEN keeps data in a separate environment, as if the data is somewhere in the ether until using an IDFGEN function to access it. This (mostly) prevents users from accidentally modifying things, but it also causes some bugginess, makes it hard for users to purposefully modify objects, and can cause some issues when loading in data from multiple data files. `EFGLmh` instead holds data as objects of a new class, called `EFGLdata`. As such, your dataset will have a variable name associated with it.

Now, let's walk through the functions in the package.

## Getting data into EFGLmh

First, install if needed, and load the package.

```
# install tidyverse if you haven't already
install.packages("tidyverse")

# install the package if needed
devtools::install_github("delomast/EFGLmh")

# and Load the package
library(EFGLmh)

# and Load the tidyverse for the examples here
library(tidyverse)

options(tibble.max_extra_cols = 10) # one of my preferred options for tidyverse
```

## Loading in data

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Now, let's first load in our data. We can either read our data into as a dataframe, matrix, or tibble, perhaps do some modifications, and then hand it over to `EFGLmh`, or we can load it directly from a tab separated file into `EFGLmh`.

If we read it in separately, the dataframe, matrix, or tibble (below, variable `exampleData`) must have a column of population (pedigree) names, a column of unique individual names, optional metadata columns, and then

genotype columns in a two column per call format. The pedigree and individual names can be anywhere, if their locations are specified. The genotype columns must be consecutive and on the right hand side. The start of the genotype columns can be specified, but if not, it will look for the first column with a column name ending in ".A1", ".a1", "-A1", or "-a1". Locus names are pulled from the first column for each locus.

```
# example of loading from file outside of EFGLmh
exampleData <- readr::read_tsv("example_snp_mh.txt", guess_max = 1e4)
```

```
print(exampleData)
#> # A tibble: 4,881 x 744
#>   Pedigree Individual Nam~ Gender DateSampled LengthFork1 FieldID1 GenMa GenPa
#>   <chr>      <chr>          <chr> <date>          <dbl> <chr>    <chr> <chr>
#> 1 OmyOXB0~ OmyOXB019S_0001 F    2019-03-11      710 0001    <NA> <NA>
#> 2 OmyOXB0~ OmyOXB019S_0002 F    2019-03-11      680 0002    OmyO~ OmyO~
#> 3 OmyOXB0~ OmyOXB019S_0003 F    2019-03-11      690 0003    OmyO~ OmyO~
#> 4 OmyOXB0~ OmyOXB019S_0004 F    2019-03-11      700 0004    OmyO~ OmyO~
#> 5 OmyOXB0~ OmyOXB019S_0005 F    2019-03-11      700 0005    <NA> <NA>
#> 6 OmyOXB0~ OmyOXB019S_0006 F    2019-03-11      680 0006    OmyO~ OmyO~
#> 7 OmyOXB0~ OmyOXB019S_0007 F    2019-03-11      650 0007    OmyO~ OmyO~
#> 8 OmyOXB0~ OmyOXB019S_0008 F    2019-03-11      730 0008    OmyO~ OmyO~
#> 9 OmyOXB0~ OmyOXB019S_0009 F    2019-03-11      660 0009    <NA> <NA>
#> 10 OmyOXB0~ OmyOXB019S_0010 F    2019-03-14      740 0010    OmyO~ OmyO~
#> # ... with 4,871 more rows, and 736 more variables: `OMS00039_mh-A1` <chr>,
#> #   `OMS00039_mh-A2` <chr>, `OMS00052_mh-A1` <chr>, `OMS00052_mh-A2` <chr>,
#> #   `OMS00077_mh-A1` <chr>, `OMS00077_mh-A2` <chr>, `OMS00101_mh-A1` <chr>,
#> #   `OMS00101_mh-A2` <chr>, `OMS00116_mh-A1` <chr>, `OMS00116_mh-A2` <chr>, ...
# example of modifying in r, here we are just selecting a few populations
t1 <- exampleData %>% filter(Pedigree %in% c("OmyOXB019S", "OmyEFSW19S"))
# or, without dplyr:
# t1 <- t[t$Pedigree %in% c("OmyOXB019S", "OmyEFSW19S"),]

# and now we pass the data to EFGLmh
data1 <- readInData(t1)
```

If we want to read data directly from a file, we just specify the file name as the first argument. The file must have the same structure as described above: a column of population (pedigree) names, a column of unique individual names, optional metadata columns, and then genotype columns in a two column per call format. The pedigree and individual names can be anywhere, if their locations are specified. The genotype columns must be consecutive and on the right hand side. The start of the genotype columns can be specified, but if not, it will look for the first column with a column name ending in ".A1", ".a1", "-A1", or "-a1". Locus names are pulled from the first column for each locus. This has been chosen to work directly with Progeny outputs.

```
data_direct_from_file <- readInData("example_snp_mh.txt")
# metadata columns with lots of blanks can give parsing errors.
# this can usually be solved with a larger number for the guess_max argument:
# data_direct_from_file <- readInData("example_snp_mh.txt", guess_max = 1e5)
```

There are many optional arguments for `readInData`:

- `genotypeStart`: you can specify the first genotype column if you don't want it to be auto-detected.
- `pedigreeColumn`: The column number that contains population (pedigree) names. Default is 1
- `nameColumn`: The column number that contains individual names. Default is 2

- `convertNames`: TRUE to convert genotype and pedigree names in the same way that IDFGEN does (remove special characters from both and remove "." from genotype names). Default is TRUE
- `convertMetaDataNames`: TRUE to remove special characters and spaces from metadata column names. This makes accessing them easier. Default is TRUE
- `missingAlleles`: a vector of values to treat as missing alleles. Default is `c("0", "00", "000")`
- `guess_max`: when reading from a file, this is passed to `read_tsv`. Parsing errors due to column data types can sometimes be fixed by increasing this. Default is 1e4

The `readInData` function creates object of class `EFGLdata`. When we print them, we just a list of the population names and the number of loci.

```
data1
#> Populations:
#> [1] "OmyEFSW19S" "OmyOXB019S"
#>
#> 368 Loci
```

## Structure of EFGLdata objects

The underlying structure of an `EFGLdata` object is just a list of two tibbles. The first entry is named "genotypes" and contains... metadata! No, it contains population names, individual names, and genotypes in a two column per call format (missing genotype is NA). The second entry is named "metadata" and contains population names, individual names, and metadata.

```
names(data1)
#> [1] "genotypes" "metadata"
data1$genotypes
#> # A tibble: 501 x 738
#>   Pop   Ind   OMS00039_mh.A1 OMS00039_mh.A2 OMS00052_mh.A1 OMS00052_mh.A2
#>   <chr> <chr> <chr>          <chr>          <chr>          <chr>
#> 1 OmyE~ OmyE~ GGC          GGC          GG           TG
#> 2 OmyE~ OmyE~ GAC          GAC          GG           GA
#> 3 OmyE~ OmyE~ GGC          GGC          GG           TG
#> 4 OmyE~ OmyE~ GGC          GAC          GG           GA
#> 5 OmyE~ OmyE~ GGC          GAC          GG           GA
#> 6 OmyE~ OmyE~ GGC          GAC          GG           GG
#> 7 OmyE~ OmyE~ GGC          GAC          GG           TG
#> 8 OmyE~ OmyE~ GGC          GAC          GG           TG
#> 9 OmyE~ OmyE~ GGC          GAC          TG           TG
#> 10 OmyE~ OmyE~ GGC          GGC          GG           GG
#> # ... with 491 more rows, and 732 more variables: OMS00077_mh.A1 <chr>,
#> #   OMS00077_mh.A2 <chr>, OMS00101_mh.A1 <chr>, OMS00101_mh.A2 <chr>,
#> #   OMS00116_mh.A1 <chr>, OMS00116_mh.A2 <chr>, OMS00118_mh.A1 <chr>,
#> #   OMS00118_mh.A2 <chr>, OMS00120_mh.A1 <chr>, OMS00120_mh.A2 <chr>, ...
data1$metadata
#> # A tibble: 501 x 8
#>   Pop   Ind   Gender DateSampled LengthFork1 FieldID1 GenMa   GenPa
#>   <chr> <chr>   <chr>   <date>         <dbl>   <chr>   <chr>   <chr>
#> 1 OmyEFS~ OmyEFSW1~ F      2019-04-07      710 0001   <NA>   <NA>
#> 2 OmyEFS~ OmyEFSW1~ M      2019-04-07      570 0003   <NA>   <NA>
#> 3 OmyEFS~ OmyEFSW1~ M      2019-04-10      640 0004   <NA>   <NA>
#> 4 OmyEFS~ OmyEFSW1~ F      2019-04-12      680 0007   OmyEFSW1~ OmyEFSW1~
```

```
#> 5 OmyEFS~ OmyEFSW1~ M      2019-04-12      520 0011      OmyEFSW1~ OmyEFSW1~
#> 6 OmyEFS~ OmyEFSW1~ M      2019-04-15      610 0016      OmyEFSW1~ OmyEFSW1~
#> 7 OmyEFS~ OmyEFSW1~ F      2019-04-15      710 0017      OmyEFSW1~ OmyEFSW1~
#> 8 OmyEFS~ OmyEFSW1~ F      2019-04-15      570 0018      OmyEFSW1~ OmyEFSW1~
#> 9 OmyEFS~ OmyEFSW1~ M      2019-04-17      760 0020      OmyEFSW1~ OmyEFSW1~
#> 10 OmyEFS~ OmyEFSW1~ M     2019-04-20      580 0022      OmyEFSW1~ OmyEFSW1~
#> # ... with 491 more rows
```

This (hopefully) makes it simple for you to pull out or modify data manually if there is not a specially written function in the package addressing what you want to accomplish. Simply refer to `data1$genotypes` or `data1$metadata` and treat it as you would treat any dataframe or tibble. One thing to remember if you modify things manually: the genotypes and metadata tibbles in an `EFGLdata` object should have the same individuals in the same order. You can check that you haven't messed things up by using the `construct_EFGLdata` function.

```
# do some modification on data1
# ...
# and then run some error checking
data1 <- construct_EFGLdata(data1)
```

## Summarizing data

There are some common data summaries you may want from your data that `EFGLmh` has special functions to address. We'll walk through them here.

### Just accessing data

Get the names of all populations in an `EFGLdata` object

```
pop_names <- getPops(data1)
pop_names
#> [1] "OmyEFSW19S" "OmyOXB019S"
```

Get the names of all individuals, or all individuals in a subset of populations

```
# all inds in data1
all_inds <- getInds(data1)
# just look at first 20
all_inds[1:20]
#> [1] "OmyEFSW19S_0001" "OmyEFSW19S_0003" "OmyEFSW19S_0004" "OmyEFSW19S_0007"
#> [5] "OmyEFSW19S_0011" "OmyEFSW19S_0016" "OmyEFSW19S_0017" "OmyEFSW19S_0018"
#> [9] "OmyEFSW19S_0020" "OmyEFSW19S_0022" "OmyEFSW19S_0023" "OmyEFSW19S_0024"
#> [13] "OmyEFSW19S_0026" "OmyEFSW19S_0032" "OmyEFSW19S_0034" "OmyEFSW19S_0035"
#> [17] "OmyEFSW19S_0042" "OmyEFSW19S_0052" "OmyEFSW19S_0053" "OmyEFSW19S_0054"

# only inds in one pop
subset_inds <- getInds(data1, pops = c("OmyOXB019S"))
# looking at first 20
subset_inds[1:20]
#> [1] "OmyOXB019S_0001" "OmyOXB019S_0002" "OmyOXB019S_0003" "OmyOXB019S_0004"
```

```
#> [5] "OmyOXB019S_0005" "OmyOXB019S_0006" "OmyOXB019S_0007" "OmyOXB019S_0008"
#> [9] "OmyOXB019S_0009" "OmyOXB019S_0010" "OmyOXB019S_0011" "OmyOXB019S_0012"
#> [13] "OmyOXB019S_0013" "OmyOXB019S_0014" "OmyOXB019S_0015" "OmyOXB019S_0016"
#> [17] "OmyOXB019S_0017" "OmyOXB019S_0018" "OmyOXB019S_0019" "OmyOXB019S_0020"
```

## Get the locus names

```
loci <- getLocci(data1)
# Looking at first 20
loci[1:20]
#> [1] "OMS00039_mh"      "OMS00052_mh"      "OMS00077_mh"      "OMS00101_mh"
#> [5] "OMS00116_mh"      "OMS00118_mh"      "OMS00120_mh"      "OMS00128_mh"
#> [9] "OMS00129_mh"      "OMS00143_mh"      "OMS00149_mh"      "OMS00151_mh"
#> [13] "OMS00175_mh"      "Omy_101832195_mh" "Omy_102867443_mh" "Omy_104519624_mh"
#> [17] "Omy_107336170_mh" "Omy_108007193_mh" "Omy_109243222_mh" "Omy_110201359_mh"
```

## Get the metadata column names

```
meta_names <- getMeta(data1)
meta_names
#> [1] "Gender"      "DateSampled" "LengthFork1" "FieldID1"    "GenMa"
#> [6] "GenPa"
```

## Get the number of individuals in all, or a subset of populations

```
countInds <- numInds(data1)
countInds
#> OmyEFSW19S OmyOXB019S
#>          25          476
countInds_1 <- numInds(data1, pops = c("OmyOXB019S"))
countInds_1
#> OmyOXB019S
#>          476
```

dumpTable from IDFGEN is also included, as it is commonly used

```
dumpTable(geno_success, "genotyping_success.txt")
```

## some common calculations

Calculate allelic richness. I recommend doing this if you load in a dataset of just SNPs to make sure every locus has  $\leq 2$  alleles, as expected.

```
allele_rich <- aRich(data1)
# this returns a tibble
allele_rich
#> # A tibble: 343 x 2
#>   locus      aRich
#>   <chr>      <int>
```

```
#> 1 M09AAC055      2
#> 2 M09AAD076      2
#> 3 M09AAE082      2
#> 4 M09AAJ163      2
#> 5 OcL_gshpx357    1
#> 6 OMGH1PROM1SNP1  2
#> 7 OMS00002        2
#> 8 OMS00003        2
#> 9 OMS00006        2
#> 10 OMS00008       2
#> # ... with 333 more rows
# if you want to see counts of loci by allelic richness
allele_rich %>% count(aRich)
#> # A tibble: 5 x 2
#>   aRich     n
#>   <int> <int>
#> 1     1     8
#> 2     2    262
#> 3     3     54
#> 4     4     18
#> 5     5      1
# same thing, without tidyverse
table(allele_rich$aRich)
#>
#>    1    2    3    4    5
#>    8 262   54   18    1
```

### Genotyping success of loci, as a proportion

```
loci_success <- lociSuccess(data1)
loci_success
#> # A tibble: 368 x 2
#>   Locus      success
#>   <chr>      <dbl>
#> 1 M09AAC055    0.964
#> 2 M09AAD076    0.952
#> 3 M09AAE082    0.962
#> 4 M09AAJ163    0.904
#> 5 OcL_gshpx357 0.962
#> 6 OMGH1PROM1SNP1 0.958
#> 7 OMS00002      0.902
#> 8 OMS00003      0.768
#> 9 OMS00006      0.964
#> 10 OMS00008     0.878
#> # ... with 358 more rows
```

### Genotyping success of individuals (more about removing failed individuals later)

```
geno_success <- genoSuccess(data1)
# this returns a tibble with both success as a proportion, and as the number of missing genotypes
geno_success
#> # A tibble: 501 x 4
#>   Pop      Ind      success numFail
```

```

#>   <chr>      <chr>      <dbl> <int>
#> 1 OmyEFSW19S OmyEFSW19S_0001 0.910 33
#> 2 OmyEFSW19S OmyEFSW19S_0003 0.880 44
#> 3 OmyEFSW19S OmyEFSW19S_0004 0.918 30
#> 4 OmyEFSW19S OmyEFSW19S_0007 0.916 31
#> 5 OmyEFSW19S OmyEFSW19S_0011 0.924 28
#> 6 OmyEFSW19S OmyEFSW19S_0016 0.932 25
#> 7 OmyEFSW19S OmyEFSW19S_0017 0.913 32
#> 8 OmyEFSW19S OmyEFSW19S_0018 0.916 31
#> 9 OmyEFSW19S OmyEFSW19S_0020 0.916 31
#> 10 OmyEFSW19S OmyEFSW19S_0022 0.913 32
#> # ... with 491 more rows
# or with just a subset of Loci
subsetLoci <- getLoci(data1)
subsetLoci <- subsetLoci[!grepl("SEX", subsetLoci)]
geno_success_noSDY <- genoSuccess(data1, loci = subsetLoci)
geno_success_noSDY
#> # A tibble: 501 x 4
#>   Pop      Ind      success numFail
#>   <chr>    <chr>    <dbl> <int>
#> 1 OmyEFSW19S OmyEFSW19S_0001 0.910 33
#> 2 OmyEFSW19S OmyEFSW19S_0003 0.880 44
#> 3 OmyEFSW19S OmyEFSW19S_0004 0.918 30
#> 4 OmyEFSW19S OmyEFSW19S_0007 0.916 31
#> 5 OmyEFSW19S OmyEFSW19S_0011 0.924 28
#> 6 OmyEFSW19S OmyEFSW19S_0016 0.932 25
#> 7 OmyEFSW19S OmyEFSW19S_0017 0.913 32
#> 8 OmyEFSW19S OmyEFSW19S_0018 0.916 31
#> 9 OmyEFSW19S OmyEFSW19S_0020 0.916 31
#> 10 OmyEFSW19S OmyEFSW19S_0022 0.913 32
#> # ... with 491 more rows

```

Calculate observed and expected heterozygosity within each population

```

heterozygosity <- calcHet(data1)
heterozygosity
#> # A tibble: 686 x 4
#>   Pop      Locus      expHet obsHet
#>   <chr>    <chr>    <dbl> <dbl>
#> 1 OmyEFSW19S M09AAC055 0.147 0.08
#> 2 OmyEFSW19S M09AAD076 0.471 0.52
#> 3 OmyEFSW19S M09AAE082 0.241 0.28
#> 4 OmyEFSW19S M09AAJ163 0.5 0.5
#> 5 OmyEFSW19S OcL_gshpx357 0 0
#> 6 OmyEFSW19S OMGH1PROM1SNP1 0.269 0.24
#> 7 OmyEFSW19S OMS00002 0.493 0.48
#> 8 OmyEFSW19S OMS00003 0.340 0.348
#> 9 OmyEFSW19S OMS00006 0.493 0.32
#> 10 OmyEFSW19S OMS00008 0.147 0.16
#> # ... with 676 more rows

```

# manipulating EFGLdata objects

These functions handle some common operations we perform on our datasets.

Combining EFGLdata objects. Let's say we have two data files to read in (e.g. one mixture and one baseline, or multiple PBT baselines). We then want to combine them for filtering, analysis, export, etc.

```
# creating a second input datafile
t2 <- exampleData %>% filter(!(Pedigree %in% c("OmyOXBO19S", "OmyEFSW19S")))

# and now creating a second EFGLdata object
data2 <- readInData(t2)

data2
#> Populations:
#> [1] "OmyDWOR19S" "OmyLSCR19S" "OmyLYON19S" "OmyPAHH19S" "OmySAWT19S"
#> [6] "OmyWALL19S"
#>
#> 368 Loci
data1
#> Populations:
#> [1] "OmyEFSW19S" "OmyOXBO19S"
#>
#> 368 Loci
```

So we have two EFGLdata objects, one with 6 populations and one with 2. Now, we combine them:

```
all_data <- combineEFGLdata(data1, data2, genoComb = "intersect", metaComb = "intersect")
all_data
#> Populations:
#> [1] "OmyDWOR19S" "OmyEFSW19S" "OmyLSCR19S" "OmyLYON19S" "OmyOXBO19S"
#> [6] "OmyPAHH19S" "OmySAWT19S" "OmyWALL19S"
#>
#> 368 Loci
```

We've now created a third EFGLdata object with all 8 populations. The arguments `genoComb` and `metaComb` tell the function how to combine loci and metadata if they are different. Options are "intersect" to only keep the loci or metadata that are in both, or "union" to keep the loci or metadata that are in either (missing loci/metadata will be given values of NA). Note that you can combine an unlimited number of EFGLdata objects in one command. For example, for four objects: `all_data <- combineEFGLdata(data1, data2, data3, data4, genoComb = "intersect", metaComb = "intersect")`. Having many EFGLdata objects can use a lot of memory if you have large numbers of individuals/loci. So, if you are done with the original EFGLdata objects, you can remove them to free up some memory:

```
rm(data1)
rm(data2)
```

Moving all individuals in a subset of populations to a different (new or existing) population.

```
# say we want to combine OmyDWOR19S and OmyEFSW19S, and call it "newPop"
all_data <- movePops(all_data, pops = c("OmyDWOR19S", "OmyEFSW19S"), newName = "newPop")
all_data
#> Populations:
#> [1] "newPop" "OmyLSCR19S" "OmyLYON19S" "OmyOXBO19S" "OmyPAHH19S"
```



```
#> [6] "OmySAWT19S" "OmyWALL19S"
#>
#> 368 Loci
```

## Moving a subset of individuals to a different (new or existing) population

```
numInds(all_data)
#>      newPop OmyLSCR19S OmyLYON19S OmyOXB019S OmyPAHH19S OmySAWT19S OmyWALL19S
#>      1395      126      87      476      1278      864      655
toMove <- c("OmyWALL19S_0696", "OmyWALL19S_0697", "OmyWALL19S_0698")
all_data <- moveInds(all_data, inds = toMove, newName = "specialInds")
numInds(all_data)
#>      newPop OmyLSCR19S OmyLYON19S OmyOXB019S OmyPAHH19S OmySAWT19S
#>      1395      126      87      476      1278      864
#> OmyWALL19S specialInds
#>      652      3
```

## Remove loci

```
toRemove <- c("OMS00079", "Omy_Omyclmk43896")
all_data <- removeLoci(all_data, lociRemove = toRemove)
all_data
#> Populations:
#> [1] "newPop"      "OmyLSCR19S"  "OmyLYON19S"  "OmyOXB019S"  "OmyPAHH19S"
#> [6] "OmySAWT19S"  "OmyWALL19S"  "specialInds"
#>
#> 366 Loci
```

## Remove individuals

```
numInds(all_data)
#>      newPop OmyLSCR19S OmyLYON19S OmyOXB019S OmyPAHH19S OmySAWT19S
#>      1395      126      87      476      1278      864
#> OmyWALL19S specialInds
#>      652      3
toRemove <- c("OmyWALL19S_0001", "OmyWALL19S_0002")
all_data <- removeInds(all_data, inds = toRemove)
numInds(all_data)
#>      newPop OmyLSCR19S OmyLYON19S OmyOXB019S OmyPAHH19S OmySAWT19S
#>      1395      126      87      476      1278      864
#> OmyWALL19S specialInds
#>      650      3
```

## Remove populations

```
all_data
#> Populations:
#> [1] "newPop"      "OmyLSCR19S"  "OmyLYON19S"  "OmyOXB019S"  "OmyPAHH19S"
#> [6] "OmySAWT19S"  "OmyWALL19S"  "specialInds"
#>
#> 366 Loci
```

```
all_data <- removePops(all_data, pops = c("OmyLSCR19S", "OmySAWT19S"))
all_data
#> Populations:
#> [1] "newPop"      "OmyLYON19S"  "OmyOXB019S"  "OmyPAHH19S"  "OmyWALL19S"
#> [6] "specialInds"
#>
#> 366 Loci
```

## exporting data

These functions export data in formats used by other packages and programs. They are listed here mainly so you can have a list of the export functions in one place and see an example. For a full explanation of the options within each of these functions, consult the manual.

A rubias baseline

```
gsi_baseline <- exportRubias_baseline(all_data, pops = c("OmyOXB019S", "newPop"),
                                     repunit = "Pop", collection = "Pop", loci = NULL)
```

A rubias mixture

```
gsi_mixture <- exportRubias_mixture(all_data, pops = c("OmyLYON19S", "specialInds"),
                                    collection = "Pop", loci = NULL)
```

A gRandma baseline or mixture

```
# baseline
gma_baseline <- exportGrandma(all_data, pops = c("OmyOXB019S", "newPop"), loci = NULL,
                              baseline = TRUE)

# mixture
gma_mixture <- exportGrandma(all_data, pops = c("OmyLYON19S", "specialInds"), loci = NULL,
                              baseline = FALSE)
```

In addition to exporting gRandma inputs, there is also a function to remove loci for gRandma inputs that either failed for all individuals, or have no variation.

```
# this creates a list with baseline and mixture
cleanInput <- cleanGrandma(baseline = gma_baseline, mixture = gma_mixture)
#> Removing Locus Ocl_gshpx357 for no variation.
#> Removing Locus Omy_myclarp404111 for no variation.
#> Removing Locus Omy_BAMBI4238 for no variation.
#> Removing Locus Omy_G3PD_2246 for no variation.
#> Removing Locus Omy_RAD103335945 for no variation.
gma_baseline <- cleanInput$baseline
gma_mixture <- cleanInput$mixture
```

A hierfstat input dataframe

```
hfstat_in <- exportHierFstat(all_data)
```

Write a GenePop file

```
exportGenePop(all_data, "genepop.txt", useIndNames = TRUE)
```

Write a GenAlEx file

```
exportGenAlEx(all_data, "genalexInput.txt")
```

Write a SNPPIT input file

```
exportSNPPIT(all_data, "snppitInput.txt", baseline = c("OmyOXB019S", "newPop"),
             mixture = c("OmyLYON19S", "specialInds"), errorRate = .005)
```

# examples of common steps in data analysis

## remove poorly genotyping individuals

First, we determine genotyping success. We're using all loci, but remember `genoSuccess` can also use just a subset of loci if you input a vector of locus names.

```
geno_success <- genoSuccess(all_data)
geno_success
#> # A tibble: 3,889 x 4
#>   Pop      Ind      success numFail
#>   <chr> <chr>      <dbl>   <int>
#> 1 newPop OmyDWOR19S_0001 0.962     14
#> 2 newPop OmyDWOR19S_0002 0.995      2
#> 3 newPop OmyDWOR19S_0003 0.978      8
#> 4 newPop OmyDWOR19S_0004 0.995      2
#> 5 newPop OmyDWOR19S_0005 0.989      4
#> 6 newPop OmyDWOR19S_0006 0.992      3
#> 7 newPop OmyDWOR19S_0007 0.992      3
#> 8 newPop OmyDWOR19S_0008 0.989      4
#> 9 newPop OmyDWOR19S_0009 0.997      1
#> 10 newPop OmyDWOR19S_0010 0.989      4
#> # ... with 3,879 more rows
```

Now we get a list of individual names to remove and then use the `removeInds` function. We can filter by the proportion success or by the number of missing loci.

```
# identify any under 90%
failedInds <- geno_success %>% filter(success < .9) %>% pull(Ind)
# example of code to filter by number of missing loci
# (remove any with more than 37 genotypes missing)
# failedInds <- geno_success %>% filter(numFail < 37) %>% pull(Ind)
# and remove
```

```
sum(numInds(all_data))
#> [1] 3889
all_data <- removeInds(all_data, inds = failedInds)
sum(numInds(all_data))
#> [1] 3448
```

And perhaps we want to save a list of the failed individuals and their populations

```
removeTable <- geno_success %>% filter(Ind %in% failedInds)
dumpTable(removeTable, "failed_inds.txt")
# or, to efficiently do it all in the tidyverse:
# geno_success %>% filter(Ind %in% failedInds) %>% dumpTable("failed_inds.txt")
```

## removing duplicates (with some outside help)

Just as we use GSI\_sim to quickly identify duplicate samples, we can use rubias.

```
rubiasIn <- exportRubias_baseline(all_data, pops = c("OmyPAHH19S", "specialInds"),
                                repunit = "Pop", collection = "Pop")
# require 70% genotypes successful in both (but we've already filtered), and
# require 95% of genotypes to be the same
library(rubias)
dupTable <- close_matching_samples(rubiasIn, gen_start_col = 5, min_frac_non_miss = .7,
                                   min_frac_matching = .95)
#> Summary Statistics:
#>
#> 1009 Individuals in Sample
#>
#> 366 Loci: M09AAC055.A1, M09AAD076.A1, M09AAE082.A1, M09AAJ163.A1, Ocl_gshpx357.A1,
  OMGH1PROM1SNP1.A1, OMS00002.A1, OMS00003.A1, OMS00006.A1, OMS00008.A1, OMS00013.A1,
  OMS00014.A1, OMS00015.A1, OMS00017.A1, OMS00018.A1, OMS00024.A1, OMS00030.A1,
  OMS00039_mh.A1, OMS00041.A1, OMS00048.A1, OMS00052_mh.A1, OMS00053.A1, OMS00056.A1,
  OMS00057.A1, OMS00058.A1, OMS00061.A1, OMS00062.A1, OMS00064.A1, OMS00068.A1, OMS00070.A1,
  OMS00071.A1, OMS00072.A1, OMS00074.A1, OMS00077_mh.A1, OMS00078.A1, OMS00087.A1,
  OMS00089.A1, OMS00090.A1, OMS00092.A1, OMS00095.A1, OMS00096.A1, OMS00101_mh.A1,
  OMS00103.A1, OMS00105.A1, OMS00106.A1, OMS00111.A1, OMS00112.A1, OMS00114.A1,
  OMS00116_mh.A1, OMS00118_mh.A1, OMS00119.A1, OMS00120_mh.A1, OMS00121.A1, OMS00127.A1,
  OMS00128_mh.A1, OMS00129_mh.A1, OMS00132.A1, OMS00133.A1, OMS00134.A1, OMS00138.A1,
  OMS00143_mh.A1, OMS00149_mh.A1, OMS00151_mh.A1, OMS00153.A1, OMS00154.A1, OMS00156.A1,
  OMS00164.A1, OMS00169.A1, OMS00173.A1, OMS00174.A1, OMS00175_mh.A1, OMS00176.A1,
  OMS00179.A1, OMS00180.A1, Omy_1004.A1, Omy_101554306.A1, Omy_101832195_mh.A1,
  Omy_101993189.A1, Omy_102505102.A1, Omy_102867443_mh.A1, Omy_103705558.A1,
  Omy_104519624_mh.A1, Omy_104569114.A1, Omy_105075162.A1, Omy_105105448.A1, Omy_105385406.A1,
  Omy_105714265.A1, Omy_107031704.A1, Omy_10728569.A1, Omy_107336170_mh.A1, Omy_10780634.A1,
  Omy_108007193_mh.A1, Omy_109243222_mh.A1, Omy_109525403.A1, Omy_109894185.A1,
  Omy_110064419.A1, Omy_110201359_mh.A1, Omy_110362585.A1, Omy_110689148.A1, Omy_111084526.A1,
  Omy_11138351_mh.A1, Omy_111666301.A1, Omy_112301202_mh.A1, Omy_11282082_mh.A1,
  Omy_113490159.A1, Omy_114315438.A1, Omy_114587480.A1, Omy_114976223.A1, Omy_116733349.A1,
  Omy_116938264.A1, Omy_117286374.A1, Omy_117370400.A1, Omy_117540259_mh.A1, Omy_11781581.A1,
  Omy_118175396.A1, Omy_118205116.A1, Omy_11865491.A1, Omy_120255332_mh.A1, Omy_128693455.A1,
  Omy_128923433_mh.A1, Omy_128996481.A1, Omy_129870756.A1, Omy_130524160_mh.A1,
  Omy_131460646_mh.A1, Omy_187760385_mh.A1, Omy_96222125_mh.A1, Omy_9707773_mh.A1,
  Omy_97660230.A1, Omy_97865196.A1, Omy_97954618_mh.A1, Omy_98683165.A1, Omy_99300202_mh.A1,
  Omy_ada1071.A1, Omy_anp17_mh.A1, Omy_aromat280_mh.A1, Omy_arp630.A1, Omy_aspAT123_mh.A1,
  Omy_b1266.A1, Omy_b9164.A1, Omy_BACB4324.A1, Omy_BACF5284_mh.A1, Omy_BAMBI2312.A1,
  Omy_BAMBI4238.A1, Omy_bcAKaLa380rd.A1, Omy_ca05064_mh.A1, Omy_carban1264_mh.A1,
  Omy_cd28130.A1, Omy_cd59206.A1, Omy_cd59b112.A1, Omy_cin172.A1, Omy_cox1221.A1,
  Omy_cox2335_mh.A1, Omy_crb106.A1, Omy_cyp17153_mh.A1, Omy_e1147_mh.A1, Omy_ftzf1217.A1,
  Omy_a1103.A1, Omy_a1282_mh.A1, Omy_G3PD_2246.A1, Omy_G3PD_2371.A1, Omy_aadd45332.A1,
```

```
Omy_gdh271.A1, Omy_GH1P1_2.A1, Omy_gh475.A1, Omy_GHSR121_mh.A1, Omy_gluR79.A1,
Omy_GREB1_05.A1, Omy_GREB1_09.A1, Omy_hsc71580_mh.A1, Omy_hsf1b241.A1, Omy_hsf2146.A1,
Omy_hsp4786.A1, Omy_hsp70aPro329.A1, Omy_hsp90BA193.A1, Omy_hus152.A1, Omy_IL17185.A1,
Omy_IL1b_028.A1, Omy_IL1b163_mh.A1, Omy_IL6320.A1, Omy_impa155.A1, Omy_inos97.A1,
Omy_LDHB1_i2.A1, Omy_LDHB2_e5.A1, Omy_LDHB2_i6.A1, Omy_lpl220_mh.A1, Omy_mapK3103.A1,
Omy_mcsf268_mh.A1, Omy_metA161_mh.A1, Omy_metB138_mh.A1, Omy_MYC_2_mh.A1,
Omy_myclarp404111.A1, Omy_myod178.A1, Omy_nach200_mh.A1, Omy_NaKATPa350.A1, Omy_ndk152.A1,
Omy_nips299.A1, Omy_nkef241_mh.A1, Omy_ntl27.A1, Omy_nxt2273_mh.A1, Omy_Ogo4212.A1,
Omy_OmyP9180.A1, Omy_Ots249227.A1, Omy_oxct85_mh.A1, Omy_p53262.A1, Omy_pad196_mh.A1,
Omy_ppie232_mh.A1, Omy_RAD10335945.A1, Omy_RAD1073310.A1, Omy_RAD11659.A1, Omy_RAD118659.A1,
Omy_RAD1243964.A1, Omy_RAD1256614.A1, Omy_RAD1303467.A1, Omy_RAD1307316.A1,
Omy_RAD1349913.A1, Omy_RAD1403346.A1, Omy_RAD1570953.A1, Omy_RAD1610420_mh.A1,
Omy_RAD1763223.A1, Omy_RAD1784916.A1, Omy_RAD1890348_mh.A1, Omy_RAD191922.A1,
Omy_RAD1934024.A1, Omy_RAD1957859.A1, Omy_RAD2091711.A1, Omy_RAD2212369.A1,
Omy_RAD2357743.A1, Omy_RAD2389458_mh.A1, Omy_RAD2428774.A1, Omy_RAD2504268.A1,
Omy_RAD25678_mh.A1, Omy_RAD2608069_mh.A1, Omy_RAD2669136_mh.A1, Omy_RAD2774055.A1,
Omy_RAD2823638.A1, Omy_RAD2970018_mh.A1, Omy_RAD297626_mh.A1, Omy_RAD3039217.A1,
Omy_RAD3061961.A1, Omy_RAD3140867.A1, Omy_RAD320910.A1, Omy_RAD3213958.A1,
Omy_RAD3312247.A1, Omy_RAD3379824.A1, Omy_RAD3500513.A1, Omy_RAD351499.A1, Omy_RAD354179.A1,
Omy_RAD365148.A1, Omy_RAD3667.A1, Omy_RAD368487.A1, Omy_RAD3695253.A1, Omy_RAD3781668.A1,
Omy_RAD3840619.A1, Omy_RAD3915633.A1, Omy_RAD392622_mh.A1, Omy_RAD4013255.A1,
Omy_RAD4052048.A1, Omy_RAD4064158.A1, Omy_RAD4159434.A1, Omy_RAD4246532.A1,
Omy_RAD4279359.A1, Omy_RAD4357337.A1, Omy_RAD4361242_mh.A1, Omy_RAD4369441.A1,
Omy_RAD4510418.A1, Omy_RAD4631435.A1, Omy_RAD4645251.A1, Omy_RAD4667227.A1,
Omy_RAD4708054.A1, Omy_RAD4744453_mh.A1, Omy_RAD4795551.A1, Omy_RAD484814.A1,
Omy_RAD4879969.A1, Omy_RAD4911135_mh.A1, Omy_RAD5063221.A1, Omy_RAD5245817_mh.A1,
Omy_RAD5281228_mh.A1, Omy_RAD537456_mh.A1, Omy_RAD5540454.A1, Omy_RAD5599710.A1,
Omy_RAD5791629.A1, Omy_RAD5821370_mh.A1, Omy_RAD5883515_mh.A1, Omy_RAD5975841.A1,
Omy_RAD5995044.A1, Omy_RAD6013512.A1, Omy_RAD61959.A1, Omy_RAD6259638.A1, Omy_RAD6580868.A1,
Omy_RAD6595969.A1, Omy_RAD6640236.A1, Omy_RAD6683417.A1, Omy_RAD6863440.A1,
Omy_RAD701631_mh.A1, Omy_RAD72108_mh.A1, Omy_RAD7252844_mh.A1, Omy_RAD7320463_mh.A1,
Omy_RAD738450_mh.A1, Omy_RAD73959.A1, Omy_RAD7396373_mh.A1, Omy_RAD7606020.A1,
Omy_RAD7657062_mh.A1, Omy_RAD7778954.A1, Omy_RAD7814727.A1, Omy_RAD7850257.A1,
Omy_RAD7877610.A1, Omy_RAD7931458_mh.A1, Omy_RAD8513135.A1, Omy_RAD8670672_mh.A1,
Omy_RAD880287.A1, Omy_RAD8812232.A1, Omy_RAD900413_mh.A1, Omy_RAD9248564_mh.A1,
Omy_RAD9358037.A1, Omy_RAD9871553.A1, Omy_rapd167.A1, Omy_rbm4b203.A1, Omy_redd1410.A1,
Omy_sast264_mh.A1, Omy_SECC22b88_mh.A1, Omy_srp0937.A1, Omy_sSOD1.A1, Omy_star206.A1,
Omy_stat3273.A1, Omy_sys1188_mh.A1, Omy_tlr3377.A1, Omy_tlr5205_mh.A1, Omy_txnlp343_mh.A1,
Omy_u0779166.A1, Omy_u0953469.A1, Omy_u0954311.A1, Omy_u0956119_mh.A1, Omy_u0961043.A1,
Omy_U11_2b154_mh.A1, Omy_UBA3b.A1, Omy_UT16_2173.A1, Omy_vamp5303.A1, Omy_vatf406.A1,
Omy_zg5791.A1, Omy1011SNP.A1, Omy25_61284413.A1, Omy25_61285646.A1, Omy25_61286316.A1,
Omy25_61287415.A1, Omy25_61294400.A1, Omy25_61316270.A1, Omy25_61317685.A1,
Omy25_61317777.A1, Omy25_61318852.A1, Omy25_61322413.A1, Omy28_11607954.A1,
Omy28_11625241.A1, Omy28_11632591.A1, Omy28_11658853.A1, Omy28_11667578.A1,
Omy28_11671116.A1, Omy28_11676622.A1, Omy28_11683204.A1, Omy28_11773194.A1, OmyR14589.A1,
OmyR19198.A1, OmyR24370.A1, OmyR33562.A1, OmyR40252.A1, OmyR40319.A1, OmyY1_2SEXY.A1
```

```
#>
#> 2 Reporting Units: OmyPAHH19S, specialInds
#>
#> 2 Collections: OmyPAHH19S, specialInds
#>
#> 8.85% of allelic data identified as missing
dupTable
#> # A tibble: 2 x 10
#>   num_non_miss num_match indiv_1 indiv_2 collection_1 collection_2 sample_type_1
#>   <int>      <int> <chr>   <chr>   <chr>         <chr>         <chr>
#> 1      335      335 OmyPAH~ OmyPAH~ OmyPAHH19S   OmyPAHH19S   reference
#> 2      336      336 OmyPAH~ OmyPAH~ OmyPAHH19S   OmyPAHH19S   reference
#> # ... with 3 more variables: repunit_1 <chr>, sample_type_2 <chr>,
#> #   repunit_2 <chr>
```

So we've found two pairs of duplicates, now we want to keep the ones with more genotypes. We can use the genotyping success calculated earlier to choose which one to remove. There is a special function to identify the one with lower genotyping success.

```
toRemove <- whichLower(dupTable, geno_success)
all_data <- removeInds(all_data, inds = toRemove)
```

And let's write a table of the duplicates

```
dupTable %>% select(1:6) %>% dumpTable("duplicates.txt")
```