

# vignette

```
library(hlacoloc)
```

## Introduction

HLA-coloc performs colocalization in two steps, as described in the manuscript. These are:

1. HLA gene causal signature: this uses SuSiE to assign a posterior inclusion probability (PIP) to each HLA allele.
2. HLA PIP Bayesian regression: this uses stanR to perform Bayesian regression of the PIPs in each gene separately.

## Required inputs

The following dataframes are necessary to run it (for each of the two phenotypes):

1. The HLA association summary statistics. This is a dataframe with four columns:
  - **Name:** the name of the allele. These must be given in IMGT-HLA format, but can be of any field resolution though (as long as it's the same for both phenotypes).
  - **beta:** the beta of the associations.
  - **se:** the standard errors.
  - **N:** the sample sizes.
2. The LD matrix (can be either in dataframe or matrix format). This is a square matrix of R coefficient for the HLA alleles above. Importantly, the order of the alleles needs to be the same in the summary statistics dataframe and in the LD matrix here.

## Example

First, load the data:

```
data("ebna", "ms", "r_ebna", "r_ms")
```

Here's a snippet of the EBNA data:

```
head(ebna)
#>      Name      beta      se      N
#> 1 G*01:01:01 0.014137500 0.015906 7247
#> 2 G*01:04:04 0.076847400 0.070867 7247
#> 3 G*01:01:02 -0.017568100 0.018972 7247
```

```
#> 4 G*01:01:03 0.000931893 0.033494 7247
#> 5 G*01:05N -0.293138000 0.078049 7247
#> 6 G*01:06:01 0.002110380 0.035066 7247
r_ebna[1:5,1:5]
#>      G*01:01:01 G*01:04:04 G*01:01:02 G*01:01:03 G*01:05N
#> G*01:01:01 1.000000 -0.1573650 -0.5404320 -0.2478420 -0.0925080
#> G*01:04:04 -0.157365 1.0000000 -0.0359779 -0.0317737 -0.0171784
#> G*01:01:02 -0.540432 -0.0359779 1.0000000 -0.1419840 -0.0672568
#> G*01:01:03 -0.247842 -0.0317737 -0.1419840 1.0000000 -0.0257557
#> G*01:05N -0.092508 -0.0171784 -0.0672568 -0.0257557 1.0000000
```

And here's a snippet of the MS data:

```
head(ms)
#>      Name      beta      se      N
#> 1 G*01:01:01 -0.082764 0.032331 429822
#> 2 G*01:04:04 0.059263 0.144366 429822
#> 3 G*01:01:02 -0.050757 0.043057 429822
#> 4 G*01:01:03 0.120691 0.061987 429822
#> 5 G*01:05N -0.112573 0.158904 429822
#> 6 G*01:06:01 0.155703 0.059848 429822
r_ms[1:5,1:5]
#>      G*01:01:01 G*01:04:04 G*01:01:02 G*01:01:03 G*01:05N
#> G*01:01:01 1.0000000 -0.15260200 -0.5331010 -0.2476440 -0.09820330
#> G*01:04:04 -0.1526020 1.00000000 -0.0378230 -0.0167532 -0.00766048
#> G*01:01:02 -0.5331010 -0.03782300 1.0000000 -0.1369080 -0.05690370
#> G*01:01:03 -0.2476440 -0.01675320 -0.1369080 1.0000000 -0.02644930
#> G*01:05N -0.0982033 -0.00766048 -0.0569037 -0.0264493 1.00000000
```

Now we run coloc:

```
coloc_res<-hla_coloc(pheno1=ebna,
                    pheno1R=r_ebna,
                    pheno2=ms,
                    pheno2R=r_ms)
#> Joining, by = "Name"
#> Joining, by = "gene"
```

Results:

```
coloc_res[["hla_colocalization"]]
#> # A tibble: 9 x 5
#>   gene      susie_coloc_prob bayes_pd direction_of_correlat~1 hla_colocalization_p~2
#>   <chr>          <dbl>      <dbl> <chr>                                <dbl>
#> 1 DQB1          1.00          1 Correct                                1.00
#> 2 DRB1          0.990        0.918 Correct                                0.908
#> 3 DPB1          0.0856         1 Correct                                0.0856
#> 4 H            0.00349        0.994 Correct                                0.00347
#> 5 DQA1          0.00129        0.753 Correct                                0.000970
#> 6 B            0.000803       0.776 Incorrect                            0.000623
#> 7 C            0.000192       0.673 Incorrect                            0.000130
#> 8 A            0.000152       0.747 Correct                                0.000113
```

```
#> 9 G          0.00000352    0.514 Correct          0.00000181
#> # i abbreviated names: 1: direction_of_correlation,
#> #    2: hla_colocalization_probability
coloc_res[["plot"]]
```

