

# Package: RNaseqCovarImpute (via r-universe)

June 30, 2024

**Title** Impute Covariate Data in RNA Sequencing Studies

**Version** 1.3.0

**URL** <https://github.com/brennanhilton/RNaseqCovarImpute>

**BugReports** <https://github.com/brennanhilton/RNaseqCovarImpute/issues>

**Description** The RNaseqCovarImpute package makes linear model analysis for RNA sequencing read counts compatible with multiple imputation (MI) of missing covariates. A major problem with implementing MI in RNA sequencing studies is that the outcome data must be included in the imputation prediction models to avoid bias. This is difficult in omics studies with high-dimensional data. The first method we developed in the RNaseqCovarImpute package surmounts the problem of high-dimensional outcome data by binning genes into smaller groups to analyze pseudo-independently. This method implements covariate MI in gene expression studies by 1) randomly binning genes into smaller groups, 2) creating  $M$  imputed datasets separately within each bin, where the imputation predictor matrix includes all covariates and the log counts per million (CPM) for the genes within each bin, 3) estimating gene expression changes using `limma::voom` followed by `limma::lmFit` functions, separately on each  $M$  imputed dataset within each gene bin, 4) un-binning the gene sets and stacking the  $M$  sets of model results before applying the `limma::squeezeVar` function to apply a variance shrinking Bayesian procedure to each  $M$  set of model results, 5) pooling the results with Rubin's rules to produce combined coefficients, standard errors, and P-values, and 6) adjusting P-values for multiplicity to account for false discovery rate (FDR). A faster method uses principal component analysis (PCA) to avoid binning genes while still retaining outcome information in the MI models. Binning genes into smaller groups requires that the MI and limma-voom analysis is run many times (typically hundreds). The more computationally efficient MI PCA

method implements covariate MI in gene expression studies by 1) performing PCA on the log CPM values for all genes using the Bioconductor `PCAtools` package, 2) creating M imputed datasets where the imputation predictor matrix includes all covariates and the optimum number of PCs to retain (e.g., based on Horn's parallel analysis or the number of PCs that account for >80% explained variation), 3) conducting the standard limma-voom pipeline with the `voom` followed by `lmFit` followed by `eBayes` functions on each M imputed dataset, 4) pooling the results with Rubins' rules to produce combined coefficients, standard errors, and P-values, and 5) adjusting P-values for multiplicity to account for false discovery rate (FDR).

**License** GPL-3

**Encoding** UTF-8

**Roxygen** list(markdown = TRUE)

**RoxygenNote** 7.2.3

**VignetteBuilder** knitr

**biocViews** RNASeq, GeneExpression, DifferentialExpression, Sequencing

**Suggests** BiocStyle, knitr, PCAtools, rmarkdown, tidy, stringr, testthat (>= 3.0.0)

**Depends** R (>= 4.3.0)

**Imports** Biobase, BiocGenerics, BiocParallel, stats, limma, dplyr, magrittr, rlang, edgeR, foreach, mice

**Config/testthat/edition** 3

**Collate** 'RNAseqCovarImpute-package.R' 'combine\_rubins.R'  
 'combine\_rubins\_pca.R' 'example\_DGE.R' 'example\_data.R'  
 'get\_gene\_bin\_intervals.R' 'impute\_by\_gene\_bin\_helper.R'  
 'impute\_by\_gene\_bin.R' 'voom\_sx\_sy.R' 'lowess\_all\_gene\_bins.R'  
 'voom\_master\_lowess.R' 'limmavoom\_imputed\_data\_list\_helper.R'  
 'limmavoom\_imputed\_data\_list.R'  
 'limmavoom\_imputed\_data\_pca\_helper.R'  
 'limmavoom\_imputed\_data\_pca.R'

**Repository** <https://bioc.r-universe.dev>

**RemoteUrl** <https://github.com/bioc/RNAseqCovarImpute>

**RemoteRef** HEAD

**RemoteSha** 930fa0b1590173ef27ebb2b5ca8ce430c14d1b7d

## Contents

combine_rubins . . . . .	3
example_data . . . . .	4
example_DGE . . . . .	5
get_gene_bin_intervals . . . . .	6

<i>combine_rubins</i>	3
<i>impute_by_gene_bin</i> . . . . .	7
<i>limmavoom_imputed_data_list</i> . . . . .	8
<i>limmavoom_imputed_data_pca</i> . . . . .	9
<b>Index</b>	<b>11</b>

<i>combine_rubins</i>	<i>combine_rubins</i>
-----------------------	-----------------------

### Description

Combines results from each imputed dataset using Rubin's rules.

### Usage

```
combine_rubins(
  DGE,
  model_results,
  predictor,
  covariate = NULL,
  robust = FALSE,
  winsor.tail.p = c(0.05, 0.1)
)
```

### Arguments

<i>DGE</i>	A DGEList object.
<i>model_results</i>	Output from <i>limmavoom_imputed_data_list</i> .
<i>predictor</i>	Independent variable of interest, in the form of a linear model contrast. Must be a variable in <i>voom_formula</i> .
<i>covariate</i>	Arguments passed to <i>limma::squeezeVar</i> . If non-NULL, <i>var.prior</i> will depend on this numeric covariate. Otherwise, <i>var.prior</i> is constant.
<i>robust</i>	Arguments passed to <i>limma::squeezeVar</i> . Logical, should the estimation of <i>df.prior</i> and <i>var.prior</i> be robustified against outlier sample variances?
<i>winsor.tail.p</i>	Arguments passed to <i>limma::squeezeVar</i> . Numeric vector of length 1 or 2, giving left and right tail proportions of <i>x</i> to Winsorize. Used only when <i>robust=TRUE</i> .

### Value

Dataframe with one row per gene containing coefficients standard errors, degrees of freedom, t-statistics, P-Values, and adjusted P-values from the *limma-voom* pipeline.

<i>coef_combined</i>	combined logFCs across the multiple imputed datasets using Rubin's rules
<i>SE_P</i>	pooled standard error across the multiple imputed datasets using Rubin's rules

SE_P_bayes	pooled standard error across the multiple imputed datasets using Rubin's rules squeezed to global mean variance trend curve with limma-voom Bayesian procedure
df	limma-voom residual degrees of freedom adjusted for Rubin's rules
df_bayes	limma-voom residual degrees of freedom adjusted for Rubin's rules and Bayesian procedure
rubins_t	t-statistic = coef_combined divided by SE_p
rubins_t_bayes	t-statistic = coef_combined divided by SE_p_bayes
combined_p	p-value from two-sided t-distribution alpha = 0.05 using rubins_t
combined_p_bayes	p-value from two-sided t-distribution alpha = 0.05 using rubins_t_bayes
combined_p_adj	false discovery rate (FDR) adjusted combined_p
combined_p_adj_bayes	false discovery rate (FDR) adjusted combined_p_bayes

### Examples

```

data(example_data)
data(example_DGE)
intervals <- get_gene_bin_intervals(example_DGE, example_data, n = 10)
gene_bin_impute <- impute_by_gene_bin(example_data,
  intervals,
  example_DGE,
  m = 2
)
coef_se <- limmavoom_imputed_data_list(
  gene_intervals = intervals,
  DGE = example_DGE,
  imputed_data_list = gene_bin_impute,
  m = 2,
  voom_formula = "~x + y + z + a + b"
)

final_res <- combine_rubins(
  DGE = example_DGE,
  model_results = coef_se,
  predictor = "x"
)

```

**Description**

The exact code used to generate these data are found in the Example\_Data\_for\_RNAseqCovarImpute vignette. In short, `example_data` contains 500 rows with data for variables `x`, `y`, and `z`, which are continuous normally distributed, and `a` and `b`, which are binary variables. Missigness was simulated for all variables other than `x` such that a complete case analysis would drop 24.2% of participants. `example_DGE` contains random count data from the Poisson distribution for 500 made up genes, ENS1-ENS500

**Usage**

```
data(example_data)
```

**Format**

```
example_data:  
data frame with 500 rows and 5 variables  
x continuous normally distributed  
y continuous normally distributed  
z continuous normally distributed  
a binary  
b binary ...
```

**Value**

Tibble with 500 rows of data for variables `x`, `y`, and `z`

**Examples**

```
data(example_data)
```

---

example_DGE	<i>Simulated counts in DGE list</i>
-------------	-------------------------------------

---

**Description**

The exact code used to generate these data are found in the Example\_Data\_for\_RNAseqCovarImpute vignette. In short, `example_data` contains 500 rows with data for variables `x`, `y`, and `z`, which are continuous normally distributed, and `a` and `b`, which are binary variables. Missigness was simulated for all variables other than `x` such that a complete case analysis would drop 24.2% of participants. `example_DGE` contains random count data from the Poisson distribution for 500 made up genes, ENS1-ENS500

**Usage**

```
data(example_DGE)
```

**Format**

example\_DGE:  
A DGEList with 500 genes and 500 samples

**Value**

DGEList for 500 made up genes, ENS1-ENS500

**Examples**

```
data(example_DGE)
```

---

```
get_gene_bin_intervals  
get_gene_bin_intervals
```

---

**Description**

Creates gene bins. Input DGE list, sample data, and 'n' number of individuals per genes. By default, number of bins and genes per bin are set so that each bin has approximately 1 gene per 10 individuals in the data.

**Usage**

```
get_gene_bin_intervals(DGE, data, n = 10)
```

**Arguments**

DGE	A DGEList object.
data	Sample data with one row per sample. Sample row order should match the col order in the DGEList.
n	Genes per bin are set so that each bin has approximately 1 gene per n individuals in the data.

**Value**

Data frame with one row per gene bin. Columns indicate the start and end positions and the number of genes of each bin.

**Examples**

```

data(example_data)
data(example_DGE)
intervals <- get_gene_bin_intervals(example_DGE, example_data, n = 10)
gene_bin_impute <- impute_by_gene_bin(example_data,
  intervals,
  example_DGE,
  m = 2
)
coef_se <- limmvoom_imputed_data_list(
  gene_intervals = intervals,
  DGE = example_DGE,
  imputed_data_list = gene_bin_impute,
  m = 2,
  voom_formula = "~x + y + z + a + b"
)

final_res <- combine_rubins(
  DGE = example_DGE,
  model_results = coef_se,
  predictor = "x"
)

```

---

`impute_by_gene_bin`      *impute\_by\_gene\_bin*

---

**Description**

Loops through DGE list using the gene bin intervals from the "get\_gene\_bin\_intervals" function and makes imputed datasets. For instance, if  $n = 100$  and intervals contains 200 gene bin intervals, output will be a list of 200 sets of 100 imputed datasets. Each of the 200 sets are imputed using only the genes in one gene bin.

**Usage**

```
impute_by_gene_bin(data, intervals, DGE, m, maxit = 10, BPPARAM = bpparam())
```

**Arguments**

<code>data</code>	Sample data with one row per sample. Sample row order should match the col order in the DGEList.
<code>intervals</code>	Output from <code>get_gene_bin_intervals</code> function. A dataframe where each row contains the start (first col) and end (second col) values for each gene bin interval.
<code>DGE</code>	A DGEList object.
<code>m</code>	Number of imputed data sets.
<code>maxit</code>	Used by mice function.
<code>BPPARAM</code>	A BiocParallelParam object

**Value**

A list of sets of n imputed datasets, one per gene bin.

**Examples**

```
data(example_data)
data(example_DGE)
intervals <- get_gene_bin_intervals(example_DGE, example_data, n = 10)
gene_bin_impute <- impute_by_gene_bin(example_data,
  intervals,
  example_DGE,
  m = 2
)
coef_se <- limmavoom_imputed_data_list(
  gene_intervals = intervals,
  DGE = example_DGE,
  imputed_data_list = gene_bin_impute,
  m = 2,
  voom_formula = "~x + y + z + a + b"
)

final_res <- combine_rubins(
  DGE = example_DGE,
  model_results = coef_se,
  predictor = "x"
)
```

---

limmavoom\_imputed\_data\_list

*limmavoom\_imputed\_data\_list*

---

**Description**

Loops through the imputed data list (output from "impute\_by\_gene\_bin" function) and runs limmavoom RNA seq analysis.

**Usage**

```
limmavoom_imputed_data_list(
  gene_intervals,
  DGE,
  imputed_data_list,
  m,
  voom_formula,
  BPPARAM = bpparam()
)
```



**Arguments**

<code>gene_intervals</code>	Output from <code>get_gene_bin_intervals</code> function. A dataframe where each row contains the start (first col) and end (second col) values for each gene bin interval.
<code>DGE</code>	A <code>DGEList</code> object.
<code>imputed_data_list</code>	Output from <code>impute_by_gene_bin</code> .
<code>m</code>	Number of imputed data sets.
<code>voom_formula</code>	Formula for design matrix.
<code>BPPARAM</code>	A <code>BiocParallelParam</code> object

**Value**

A dataframe with coefficient, standard error, sigma, and residual degrees of freedom values from limma-voom gene expression analysis. One row per gene and one set of values per imputed dataset.

**Examples**

```
data(example_data)
data(example_DGE)
intervals <- get_gene_bin_intervals(example_DGE, example_data, n = 10)
gene_bin_impute <- impute_by_gene_bin(example_data,
  intervals,
  example_DGE,
  m = 2
)
coef_se <- limmavoom_imputed_data_list(
  gene_intervals = intervals,
  DGE = example_DGE,
  imputed_data_list = gene_bin_impute,
  m = 2,
  voom_formula = "~x + y + z + a + b"
)

final_res <- combine_rubins(
  DGE = example_DGE,
  model_results = coef_se,
  predictor = "x"
)
```

---

limmavoom\_imputed\_data\_pca

*limmavoom\_imputed\_data\_pca*

---

**Description**

Combines results from each imputed dataset using Rubin's rules.

**Usage**

```
limmavoom_imputed_data_pca(imp, DGE, voom_formula, BPPARAM = bpparam())
```

**Arguments**

<code>imp</code>	Imputed data from mice (mids object)
<code>DGE</code>	A DGEList object.
<code>voom_formula</code>	Formula for design matrix.
<code>BPPARAM</code>	A BiocParallelParam object

**Value**

Dataframe with one row per gene. Columns contain coefficients, standard errors, and p-values from the limma-voom pipeline.

**Examples**

```
data(example_data)
data(example_DGE)
pca_data = limma::voom(example_DGE)$E
p = PCAtools::pca(pca_data)
pcs = p$rotated[,1:78]
example_data = cbind(example_data, pcs)
imp = mice::mice(example_data, m=3)
mi_pca_res = limmavoom_imputed_data_pca(
  imp = imp,
  DGE = example_DGE,
  voom_formula = "~x + y + z + a + b"
)
```

# Index

## \* datasets

example\_data, [4](#)

example\_DGE, [5](#)

combine\_rubins, [3](#)

example\_data, [4](#)

example\_DGE, [5](#)

get\_gene\_bin\_intervals, [6](#)

impute\_by\_gene\_bin, [7](#)

limmavoom\_imputed\_data\_list, [8](#)

limmavoom\_imputed\_data\_pca, [9](#)