

# TutorialImputingMissingData

## Tutorial on Missing Data Imputation

We follow the tutorial on R packages for missing data imputation by MANISH SARASWAT which can be found [here](#), but discuss the mi package first:

### mi

mi is the package by Dr. Gelman, maintained by Dr. Goodrich and uses predictive mean matching (pmm). predictive mean matching is explained well here, by Paul Allison on Statistical Horizon with statistical background and pitfalls, referencing also (Morris 2014).

```
library(mi)
library(missForest)
```

```
data("iris")
```

```
# seed missing values ( 10% )
iris.mis <- prodNA(iris, noNA = 0.1)
summary(iris.mis)
```

```
##   Sepal.Length   Sepal.Width   Petal.Length   Petal.Width
##   Min.    :4.400   Min.    :2.000   Min.    :1.000   Min.    :0.100
##   1st Qu.:5.100   1st Qu.:2.800   1st Qu.:1.600   1st Qu.:0.300
##   Median :5.700   Median :3.000   Median :4.400   Median :1.300
##   Mean   :5.799   Mean   :3.062   Mean   :3.838   Mean   :1.196
##   3rd Qu.:6.400   3rd Qu.:3.350   3rd Qu.:5.100   3rd Qu.:1.800
##   Max.   :7.900   Max.   :4.400   Max.   :6.900   Max.   :2.500
##   NA's    :19     NA's    :11     NA's    :14     NA's    :15
##           Species
##   setosa    :44
##   versicolor:42
##   virginica :48
##   NA's      :16
##
##
##
```

```
# imputing missing value with mi
mi_data <- mi(iris.mis, seed = 335)
summary(mi_data)
```

```
## $Sepal.Length
## $Sepal.Length$is_missing
## missing
## FALSE TRUE
##   131    19
##
## $Sepal.Length$imputed
##   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
## -1.6110 -0.2304  0.2033  0.1184  0.4818  1.2290
```

```

##
## $Sepal.Length$observed
##      Min.   1st Qu.   Median     Mean  3rd Qu.     Max.
## -0.87930 -0.43940 -0.06236  0.00000  0.37750  1.32000
##
##
## $Sepal.Width
## $Sepal.Width$is_missing
## missing
## FALSE  TRUE
##    139    11
##
## $Sepal.Width$imputed
##      Min.   1st Qu.   Median     Mean  3rd Qu.     Max.
## -1.50400 -0.37170 -0.01112 -0.01717  0.33670  0.93960
##
## $Sepal.Width$observed
##      Min.   1st Qu.   Median     Mean  3rd Qu.     Max.
## -1.23600 -0.30490 -0.07204  0.00000  0.39370  1.55800
##
##
## $Petal.Length
## $Petal.Length$is_missing
## missing
## FALSE  TRUE
##    136    14
##
## $Petal.Length$imputed
##      Min.   1st Qu.   Median     Mean  3rd Qu.     Max.
## -0.9199 -0.7391 -0.5747 -0.2510  0.3358  0.8095
##
## $Petal.Length$observed
##      Min.   1st Qu.   Median     Mean  3rd Qu.     Max.
## -0.8118 -0.6402  0.1607  0.0000  0.3609  0.8757
##
##
## $Petal.Width
## $Petal.Width$is_missing
## missing
## FALSE  TRUE
##    135    15
##
## $Petal.Width$imputed
##      Min.   1st Qu.   Median     Mean  3rd Qu.     Max.
## -0.8620 -0.5160  0.1088  0.0147  0.5229  0.8280
##
## $Petal.Width$observed
##      Min.   1st Qu.   Median     Mean  3rd Qu.     Max.
## -0.73390 -0.60000  0.06943  0.00000  0.40420  0.87280
##
##
## $Species
## $Species$crosstab
##

```

```
##           observed imputed
##   setosa      176      37
##   versicolor  168      20
##   virginica   192       7
```

## MICE Package

```
library(missForest)
library(mice)
library(VIM)
```

```
data <- iris
```

### Generate Missing Data with missForest

Generate 10% missing values at Random using the missForest package

```
iris.mis <- prodNA(iris, noNA = 0.1)
summary(iris.mis)
```

```
##   Sepal.Length   Sepal.Width   Petal.Length   Petal.Width
##   Min.    :4.300   Min.    :2.000   Min.    :1.000   Min.    :0.100
##   1st Qu.:5.100   1st Qu.:2.800   1st Qu.:1.600   1st Qu.:0.300
##   Median :5.800   Median :3.000   Median :4.400   Median :1.300
##   Mean   :5.859   Mean   :3.057   Mean   :3.794   Mean   :1.197
##   3rd Qu.:6.400   3rd Qu.:3.300   3rd Qu.:5.100   3rd Qu.:1.800
##   Max.    :7.700   Max.    :4.400   Max.    :6.900   Max.    :2.500
##   NA's    :27     NA's    :14     NA's    :12     NA's    :8
##   Species
##   setosa    :44
##   versicolor:49
##   virginica :43
##   NA's      :14
##
##
##
```

### Remove categorical variables and focus on continuous variables

```
iris.mis <- subset(iris.mis, select = -c(Species))
summary(iris.mis)
```

```
##   Sepal.Length   Sepal.Width   Petal.Length   Petal.Width
##   Min.    :4.300   Min.    :2.000   Min.    :1.000   Min.    :0.100
##   1st Qu.:5.100   1st Qu.:2.800   1st Qu.:1.600   1st Qu.:0.300
##   Median :5.800   Median :3.000   Median :4.400   Median :1.300
##   Mean   :5.859   Mean   :3.057   Mean   :3.794   Mean   :1.197
##   3rd Qu.:6.400   3rd Qu.:3.300   3rd Qu.:5.100   3rd Qu.:1.800
##   Max.    :7.700   Max.    :4.400   Max.    :6.900   Max.    :2.500
##   NA's    :27     NA's    :14     NA's    :12     NA's    :8
```

## Inspect Missing Pattern with MICE

```
md.pattern(iris.mis)
```

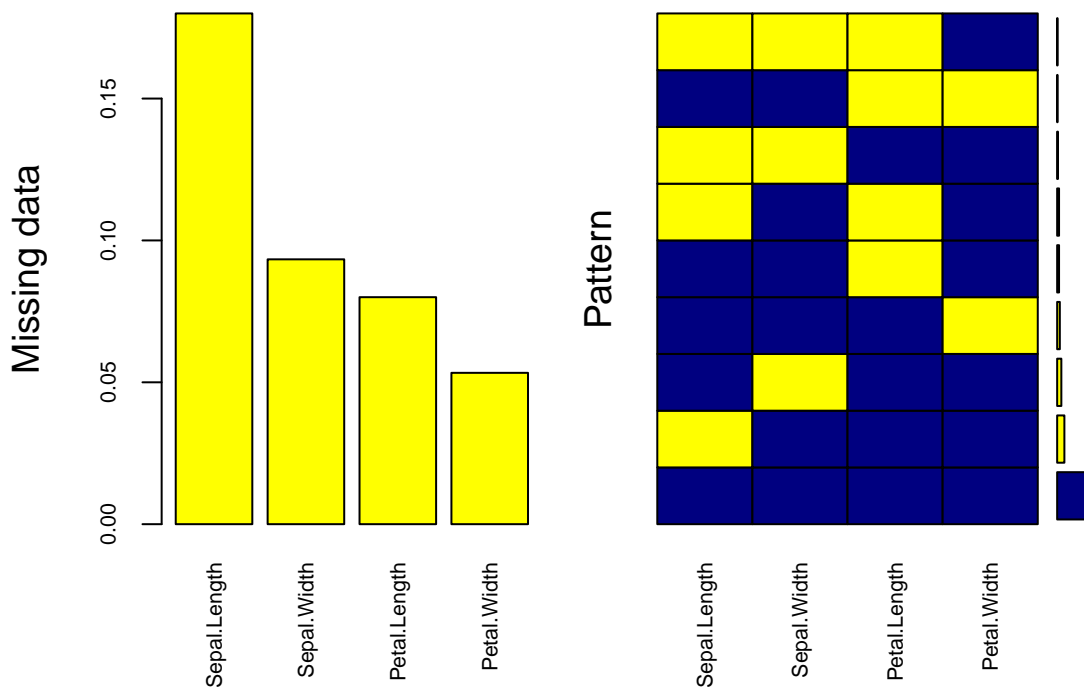
```
##      Petal.Width Petal.Length Sepal.Width Sepal.Length
## 99           1           1           1           1  0
## 19           1           1           1           0  1
## 11           1           1           0           1  1
##  5           1           0           1           1  1
##  7           0           1           1           1  1
##  2           1           1           0           0  2
##  5           1           0           1           0  2
##  1           0           0           1           1  2
##  1           1           0           0           0  3
##              8          12          14          27 61
```

```
md.pattern(iris.mis)
```

```
##      Petal.Width Petal.Length Sepal.Width Sepal.Length
## 99           1           1           1           1  0
## 19           1           1           1           0  1
## 11           1           1           0           1  1
##  5           1           0           1           1  1
##  7           0           1           1           1  1
##  2           1           1           0           0  2
##  5           1           0           1           0  2
##  1           0           0           1           1  2
##  1           1           0           0           0  3
##              8          12          14          27 61
```

## Visual Inspection of Missing Pattern with VIM

```
mice_plot <- aggr(iris.mis, col=c('navyblue','yellow'),
                    numbers=TRUE, sortVars=TRUE,
                    labels=names(iris.mis), cex.axis=.7,
                    gap=3, ylab=c("Missing data", "Pattern"))
```



```
##
## Variables sorted by number of missings:
##   Variable      Count
## Sepal.Length 0.18000000
## Sepal.Width  0.09333333
## Petal.Length 0.08000000
## Petal.Width  0.05333333
```

## Imputing the missing data with MICE

```
imputed_Data <- mice(iris.mis, m=5, maxit = 50, method = 'pmm', seed = 500)
```

```
summary(imputed_Data)
```

```
## Multiply imputed data set
## Call:
## mice(data = iris.mis, m = 5, method = "pmm", maxit = 50, seed = 500)
## Number of multiple imputations: 5
## Missing cells per column:
## Sepal.Length Sepal.Width Petal.Length Petal.Width
##           27           14           12            8
## Imputation methods:
## Sepal.Length Sepal.Width Petal.Length Petal.Width
##           "pmm"           "pmm"           "pmm"           "pmm"
## VisitSequence:
## Sepal.Length Sepal.Width Petal.Length Petal.Width
##           1           2           3           4
## PredictorMatrix:
```

```
##           Sepal.Length Sepal.Width Petal.Length Petal.Width
## Sepal.Length           0           1           1           1
## Sepal.Width            1           0           1           1
## Petal.Length           1           1           0           1
## Petal.Width            1           1           1           0
## Random generator seed value: 500
```

```
#check imputed values
imputed_Data$imp$Sepal.Width
```

```
##      1  2  3  4  5
## 7  3.0 3.0 2.9 3.1 3.2
## 8  3.3 3.8 3.8 3.2 3.1
## 31 3.1 3.0 3.6 2.8 3.9
## 34 3.7 3.4 3.4 3.4 4.4
## 43 3.4 3.0 3.0 3.2 3.0
## 46 3.0 3.2 3.7 3.1 3.6
## 81 2.7 2.4 3.0 2.5 3.0
## 83 3.0 3.4 2.5 2.9 2.8
## 84 2.7 3.3 2.9 2.8 2.0
## 86 2.6 3.3 3.1 3.0 3.2
## 109 2.3 2.8 2.8 3.0 2.5
## 116 2.8 3.1 3.0 3.3 3.8
## 121 2.8 3.4 3.0 2.8 2.7
## 147 2.6 2.8 2.6 2.9 2.6
```

```
#get complete data ( 2nd out of 5)
completeData <- complete(imputed_Data,2)
```

## Build a model using the imputed data

```
#build predictive model
#Caveat I deviate from the Tutorial by using imputed_Data instead of iris.mis, because it otherwise thr
fit <- with(data = imputed_Data, exp = lm(Sepal.Width ~ Sepal.Length + Petal.Width))

#combine results of all 5 models
combine <- pool(fit)
summary(combine)
```

```
##           est           se           t           df      Pr(>|t|)
## (Intercept)  2.0545050 0.34950151  5.878387  80.46665 9.007068e-08
## Sepal.Length 0.2613735 0.07049808  3.707526  97.07369 3.484152e-04
## Petal.Width -0.4377542 0.07219741 -6.063295 142.33757 1.138309e-08
##           lo 95      hi 95 nmis      fmi      lambda
## (Intercept)  1.3590367  2.7499732  NA 0.15445611 0.13369807
## Sepal.Length 0.1214556  0.4012913  27 0.12031921 0.10238003
## Petal.Width -0.5804720 -0.2950365   8 0.02642488 0.01284051
```

## Build a model without imputation to compare

```
raw.data <- iris
poor_fit <- fit <- with(data = raw.data, exp = lm(Sepal.Width ~ Sepal.Length + Petal.Width))
summary(poor_fit)
```

```
##
## Call:
## lm(formula = Sepal.Width ~ Sepal.Length + Petal.Width)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.99563 -0.24690 -0.00503  0.23354  1.01131
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)   1.92632    0.32094   6.002 1.45e-08 ***
## Sepal.Length  0.28929    0.06605   4.380 2.24e-05 ***
## Petal.Width  -0.46641    0.07175  -6.501 1.17e-09 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.3841 on 147 degrees of freedom
## Multiple R-squared:  0.234, Adjusted R-squared:  0.2236
## F-statistic: 22.46 on 2 and 147 DF, p-value: 3.091e-09
```

The point estimates of the `poor_fit` regression summary (without imputation) differ from the regression coefficients based on the imputed data; the latter also have wider confidence bands expressing the increased uncertainty due to imputation.

## AMELIA package

```
rm(list = setdiff(ls(), lsf.str())) # uses setdiff to identify all objects that are NOT functions.
# and removes them
# lsf.str() finds all functions

library(Amelia)
library(missForest)
```

## Seed 10% missing values

```
data("iris")
iris.mis <- prodNA(iris, noNA = 0.1)
summary(iris.mis)
```

| ## | Sepal.Length  | Sepal.Width   | Petal.Length  | Petal.Width   |
|----|---------------|---------------|---------------|---------------|
| ## | Min. :4.300   | Min. :2.200   | Min. :1.000   | Min. :0.100   |
| ## | 1st Qu.:5.100 | 1st Qu.:2.800 | 1st Qu.:1.525 | 1st Qu.:0.300 |
| ## | Median :5.800 | Median :3.000 | Median :4.400 | Median :1.300 |
| ## | Mean :5.836   | Mean :3.078   | Mean :3.808   | Mean :1.216   |
| ## | 3rd Qu.:6.400 | 3rd Qu.:3.400 | 3rd Qu.:5.100 | 3rd Qu.:1.800 |
| ## | Max. :7.900   | Max. :4.400   | Max. :6.900   | Max. :2.500   |
| ## | NA's :12      | NA's :15      | NA's :16      | NA's :16      |
| ## | Species       |               |               |               |
| ## | setosa :45    |               |               |               |
| ## | versicolor:45 |               |               |               |
| ## | virginica :44 |               |               |               |
| ## | NA's :16      |               |               |               |

```
##
##
##
```

## Specify columns and run amelia

```
amelia_fit <- amelia(iris.mis, m=5, parallel = "multicore", noms = "Species")
```

```
## -- Imputation 1 --
##
## 1 2 3 4 5 6
##
## -- Imputation 2 --
##
## 1 2 3 4 5 6
##
## -- Imputation 3 --
##
## 1 2 3 4 5 6
##
## -- Imputation 4 --
##
## 1 2 3 4 5 6
##
## -- Imputation 5 --
##
## 1 2 3 4 5 6 7 8
```

```
# access imputed outputs
amelia_fit$imputations[[1]]
```

| ##    | Sepal.Length | Sepal.Width | Petal.Length | Petal.Width | Species |
|-------|--------------|-------------|--------------|-------------|---------|
| ## 1  | 5.100000     | 3.330577    | 1.400000     | 0.39988457  | setosa  |
| ## 2  | 4.900000     | 3.000000    | 1.400000     | 0.20000000  | setosa  |
| ## 3  | 4.700000     | 3.200000    | 1.300000     | 0.20000000  | setosa  |
| ## 4  | 4.600000     | 3.100000    | 1.500000     | 0.20000000  | setosa  |
| ## 5  | 5.000000     | 3.600000    | 1.400000     | 0.20000000  | setosa  |
| ## 6  | 5.400000     | 3.900000    | 1.700000     | 0.40000000  | setosa  |
| ## 7  | 4.600000     | 3.400000    | 1.400000     | 0.30000000  | setosa  |
| ## 8  | 5.000000     | 3.400000    | 1.500000     | 0.20000000  | setosa  |
| ## 9  | 4.400000     | 2.900000    | 1.400000     | 0.23935405  | setosa  |
| ## 10 | 4.900000     | 3.100000    | 1.500000     | 0.10000000  | setosa  |
| ## 11 | 5.400000     | 3.700000    | 1.500000     | 0.20000000  | setosa  |
| ## 12 | 4.800000     | 3.400000    | 1.177967     | 0.20000000  | setosa  |
| ## 13 | 4.800000     | 3.000000    | 1.400000     | 0.10000000  | setosa  |
| ## 14 | 4.300000     | 3.000000    | 1.292697     | 0.10000000  | setosa  |
| ## 15 | 5.800000     | 4.000000    | 1.200000     | 0.20000000  | setosa  |
| ## 16 | 5.700000     | 4.400000    | 1.500000     | 0.40000000  | setosa  |
| ## 17 | 5.400000     | 3.900000    | 1.964659     | 0.42279760  | setosa  |
| ## 18 | 5.100000     | 4.072374    | 1.400000     | 0.30000000  | setosa  |
| ## 19 | 5.700000     | 3.800000    | 1.700000     | 0.30000000  | setosa  |
| ## 20 | 5.100000     | 3.800000    | 1.264734     | 0.30000000  | setosa  |
| ## 21 | 5.400000     | 3.400000    | 1.989505     | 0.20000000  | setosa  |
| ## 22 | 5.100000     | 3.700000    | 1.500000     | 0.40000000  | setosa  |



|       |          |          |          |             |            |
|-------|----------|----------|----------|-------------|------------|
| ## 23 | 4.600000 | 3.600000 | 1.000000 | 0.20000000  | setosa     |
| ## 24 | 5.100000 | 3.300000 | 1.700000 | 0.50000000  | setosa     |
| ## 25 | 4.800000 | 3.400000 | 1.900000 | 0.20000000  | setosa     |
| ## 26 | 5.000000 | 3.000000 | 1.600000 | 0.20000000  | setosa     |
| ## 27 | 5.000000 | 3.400000 | 1.600000 | 0.40000000  | setosa     |
| ## 28 | 5.200000 | 3.500000 | 1.500000 | 0.44604599  | setosa     |
| ## 29 | 5.200000 | 3.400000 | 1.400000 | 0.20000000  | setosa     |
| ## 30 | 4.700000 | 3.507064 | 1.086849 | -0.03636943 | setosa     |
| ## 31 | 4.980361 | 3.100000 | 1.600000 | 0.20000000  | versicolor |
| ## 32 | 5.400000 | 3.400000 | 1.500000 | 0.40000000  | setosa     |
| ## 33 | 5.200000 | 4.100000 | 1.500000 | 0.10000000  | setosa     |
| ## 34 | 5.500000 | 4.200000 | 1.400000 | 0.20000000  | setosa     |
| ## 35 | 4.900000 | 3.219927 | 1.500000 | 0.20000000  | setosa     |
| ## 36 | 5.007234 | 3.202944 | 1.200000 | 0.20000000  | setosa     |
| ## 37 | 5.500000 | 3.500000 | 1.300000 | 0.20000000  | setosa     |
| ## 38 | 4.900000 | 3.600000 | 1.400000 | 0.10000000  | setosa     |
| ## 39 | 4.400000 | 3.000000 | 1.300000 | 0.20000000  | setosa     |
| ## 40 | 5.100000 | 3.400000 | 1.500000 | 0.20000000  | setosa     |
| ## 41 | 5.000000 | 3.500000 | 1.300000 | 0.30000000  | setosa     |
| ## 42 | 4.500000 | 2.300000 | 1.300000 | 0.30000000  | setosa     |
| ## 43 | 4.400000 | 3.200000 | 1.300000 | 0.60060704  | setosa     |
| ## 44 | 5.000000 | 3.500000 | 1.600000 | 0.05965278  | setosa     |
| ## 45 | 5.100000 | 3.800000 | 1.615997 | 0.40000000  | virginica  |
| ## 46 | 4.800000 | 3.000000 | 1.400000 | 0.30000000  | setosa     |
| ## 47 | 5.004813 | 3.800000 | 1.600000 | 0.25853418  | setosa     |
| ## 48 | 4.600000 | 3.200000 | 1.400000 | 0.20000000  | setosa     |
| ## 49 | 5.300000 | 3.700000 | 1.500000 | 0.20000000  | setosa     |
| ## 50 | 5.000000 | 3.300000 | 1.400000 | 0.20000000  | setosa     |
| ## 51 | 7.000000 | 3.200000 | 4.700000 | 1.40000000  | versicolor |
| ## 52 | 6.400000 | 3.200000 | 4.500000 | 1.50000000  | versicolor |
| ## 53 | 6.900000 | 3.100000 | 4.900000 | 1.50000000  | versicolor |
| ## 54 | 5.500000 | 2.300000 | 4.000000 | 1.30000000  | versicolor |
| ## 55 | 6.500000 | 2.800000 | 4.600000 | 1.50000000  | versicolor |
| ## 56 | 5.700000 | 2.800000 | 4.081530 | 1.22805684  | versicolor |
| ## 57 | 6.300000 | 3.300000 | 4.700000 | 1.60000000  | versicolor |
| ## 58 | 4.900000 | 2.400000 | 3.300000 | 1.00000000  | versicolor |
| ## 59 | 6.600000 | 2.900000 | 4.728998 | 1.30000000  | versicolor |
| ## 60 | 5.200000 | 2.599399 | 3.900000 | 1.40000000  | versicolor |
| ## 61 | 5.000000 | 2.228232 | 3.500000 | 1.00000000  | versicolor |
| ## 62 | 5.900000 | 3.000000 | 4.200000 | 1.50000000  | versicolor |
| ## 63 | 6.000000 | 2.200000 | 3.993515 | 1.00000000  | versicolor |
| ## 64 | 6.100000 | 2.900000 | 4.700000 | 1.40000000  | versicolor |
| ## 65 | 5.373604 | 2.900000 | 3.600000 | 1.30000000  | versicolor |
| ## 66 | 6.700000 | 3.100000 | 4.400000 | 1.40000000  | versicolor |
| ## 67 | 6.108290 | 3.000000 | 4.500000 | 1.50000000  | versicolor |
| ## 68 | 5.800000 | 2.700000 | 4.100000 | 1.00000000  | versicolor |
| ## 69 | 6.200000 | 2.200000 | 4.500000 | 1.50000000  | versicolor |
| ## 70 | 5.600000 | 2.500000 | 3.900000 | 1.10000000  | virginica  |
| ## 71 | 5.900000 | 3.200000 | 4.800000 | 1.80000000  | versicolor |
| ## 72 | 6.100000 | 2.800000 | 4.000000 | 1.30000000  | versicolor |
| ## 73 | 6.300000 | 3.154109 | 4.900000 | 1.50000000  | versicolor |
| ## 74 | 6.100000 | 2.800000 | 4.700000 | 1.20000000  | versicolor |
| ## 75 | 6.400000 | 2.900000 | 4.300000 | 1.30000000  | versicolor |
| ## 76 | 6.600000 | 3.000000 | 4.400000 | 1.40000000  | versicolor |

|        |          |          |          |            |            |
|--------|----------|----------|----------|------------|------------|
| ## 77  | 6.800000 | 2.800000 | 4.800000 | 1.40000000 | versicolor |
| ## 78  | 6.700000 | 3.000000 | 5.000000 | 1.70000000 | versicolor |
| ## 79  | 6.000000 | 2.900000 | 4.500000 | 1.50000000 | versicolor |
| ## 80  | 5.113774 | 2.600000 | 3.500000 | 1.32383482 | versicolor |
| ## 81  | 5.500000 | 2.400000 | 3.800000 | 1.10000000 | versicolor |
| ## 82  | 4.847074 | 2.698750 | 3.700000 | 1.00000000 | versicolor |
| ## 83  | 5.800000 | 2.700000 | 3.900000 | 1.20000000 | versicolor |
| ## 84  | 6.000000 | 2.584889 | 5.100000 | 1.60000000 | versicolor |
| ## 85  | 5.400000 | 3.000000 | 4.500000 | 1.50000000 | versicolor |
| ## 86  | 6.000000 | 3.400000 | 4.500000 | 1.60000000 | versicolor |
| ## 87  | 6.700000 | 3.100000 | 4.700000 | 1.50000000 | versicolor |
| ## 88  | 6.300000 | 2.300000 | 4.400000 | 1.30000000 | versicolor |
| ## 89  | 5.600000 | 3.000000 | 4.100000 | 1.30000000 | versicolor |
| ## 90  | 5.500000 | 2.500000 | 4.044402 | 1.30000000 | versicolor |
| ## 91  | 5.500000 | 2.566176 | 4.400000 | 1.20000000 | versicolor |
| ## 92  | 6.100000 | 3.000000 | 4.600000 | 1.40000000 | versicolor |
| ## 93  | 5.800000 | 2.600000 | 3.939241 | 1.20000000 | versicolor |
| ## 94  | 5.000000 | 2.300000 | 3.300000 | 1.00000000 | versicolor |
| ## 95  | 5.600000 | 2.700000 | 4.200000 | 1.30000000 | versicolor |
| ## 96  | 5.700000 | 3.000000 | 4.200000 | 1.20000000 | versicolor |
| ## 97  | 5.700000 | 2.900000 | 4.238714 | 1.30000000 | versicolor |
| ## 98  | 6.200000 | 2.900000 | 4.300000 | 1.30000000 | versicolor |
| ## 99  | 5.100000 | 2.500000 | 3.000000 | 1.10000000 | versicolor |
| ## 100 | 5.700000 | 2.800000 | 4.100000 | 1.30000000 | versicolor |
| ## 101 | 6.300000 | 3.300000 | 6.000000 | 2.50000000 | virginica  |
| ## 102 | 5.800000 | 2.700000 | 5.100000 | 1.90000000 | virginica  |
| ## 103 | 7.100000 | 3.000000 | 5.900000 | 2.10000000 | virginica  |
| ## 104 | 6.300000 | 2.900000 | 5.600000 | 1.80000000 | virginica  |
| ## 105 | 6.500000 | 3.000000 | 5.800000 | 2.20000000 | virginica  |
| ## 106 | 7.600000 | 3.000000 | 6.600000 | 2.10000000 | virginica  |
| ## 107 | 4.900000 | 2.500000 | 4.500000 | 1.70000000 | virginica  |
| ## 108 | 7.300000 | 2.750850 | 6.300000 | 1.80000000 | virginica  |
| ## 109 | 6.700000 | 2.500000 | 5.800000 | 1.80000000 | virginica  |
| ## 110 | 7.200000 | 3.600000 | 6.100000 | 2.50000000 | virginica  |
| ## 111 | 6.500000 | 3.200000 | 5.100000 | 2.00000000 | virginica  |
| ## 112 | 6.022868 | 2.700000 | 5.300000 | 1.76363897 | virginica  |
| ## 113 | 6.800000 | 3.000000 | 5.500000 | 2.10000000 | virginica  |
| ## 114 | 5.700000 | 2.500000 | 5.000000 | 2.00000000 | virginica  |
| ## 115 | 5.800000 | 2.800000 | 5.100000 | 2.40000000 | virginica  |
| ## 116 | 6.400000 | 3.200000 | 5.300000 | 2.30000000 | virginica  |
| ## 117 | 6.500000 | 3.000000 | 5.500000 | 1.80000000 | virginica  |
| ## 118 | 7.700000 | 3.800000 | 6.700000 | 2.20000000 | virginica  |
| ## 119 | 7.700000 | 2.600000 | 6.900000 | 2.30000000 | virginica  |
| ## 120 | 6.000000 | 2.200000 | 5.000000 | 1.50000000 | virginica  |
| ## 121 | 6.900000 | 3.200000 | 5.700000 | 2.30000000 | virginica  |
| ## 122 | 5.600000 | 2.800000 | 4.900000 | 2.00000000 | virginica  |
| ## 123 | 7.700000 | 3.125382 | 6.700000 | 2.00000000 | virginica  |
| ## 124 | 6.300000 | 2.700000 | 4.900000 | 1.80000000 | virginica  |
| ## 125 | 6.700000 | 3.300000 | 5.700000 | 2.08762104 | virginica  |
| ## 126 | 7.396717 | 2.859290 | 6.000000 | 1.80000000 | virginica  |
| ## 127 | 6.200000 | 2.800000 | 4.800000 | 1.80000000 | virginica  |
| ## 128 | 6.100000 | 3.000000 | 4.900000 | 1.80000000 | virginica  |
| ## 129 | 6.880215 | 3.041143 | 5.814224 | 2.10000000 | virginica  |
| ## 130 | 7.070717 | 3.000000 | 5.800000 | 1.60000000 | virginica  |

```
## 131      7.400000      2.800000      6.346632  1.90000000 virginica
## 132      7.900000      3.800000      6.400000  2.00000000 virginica
## 133      6.400000      2.800000      5.600000  2.20000000 virginica
## 134      6.300000      2.800000      5.100000  1.50000000 virginica
## 135      6.100000      2.600000      5.600000  1.40000000 virginica
## 136      7.700000      3.000000      6.100000  1.93107089 virginica
## 137      6.300000      3.400000      5.600000  2.40000000 virginica
## 138      6.400000      3.100000      5.500000  1.99954423 virginica
## 139      6.000000      3.000000      4.800000  1.80000000 virginica
## 140      6.900000      3.100000      5.400000  2.08780234 virginica
## 141      6.700000      3.100000      5.600000  2.40000000 versicolor
## 142      6.900000      3.100000      5.100000  2.30000000 virginica
## 143      5.800000      2.700000      5.100000  1.90000000 virginica
## 144      6.800000      3.200000      5.900000  2.30000000 virginica
## 145      6.700000      3.300000      5.898961  2.50000000 virginica
## 146      6.218693      3.000000      5.200000  2.04898523 virginica
## 147      6.300000      2.500000      5.000000  1.90000000 virginica
## 148      6.500000      3.000000      5.200000  2.00000000 virginica
## 149      6.200000      3.400000      5.400000  2.30000000 virginica
## 150      5.900000      3.000000      5.100000  1.80000000 virginica
# ...
```

## missForest package

```
#missForest
library(missForest)

#load data
data("iris")

#seed 10% missing values
iris.mis <- prodNA(iris, noNA = 0.1)
summary(iris.mis)
```

```
##      Sepal.Length      Sepal.Width      Petal.Length      Petal.Width
## Min.      :4.300      Min.      :2.00      Min.      :1.000      Min.      :0.100
## 1st Qu.:5.100      1st Qu.:2.80      1st Qu.:1.600      1st Qu.:0.300
## Median :5.800      Median :3.00      Median :4.400      Median :1.300
## Mean   :5.832      Mean   :3.07      Mean   :3.847      Mean   :1.179
## 3rd Qu.:6.400      3rd Qu.:3.40      3rd Qu.:5.100      3rd Qu.:1.800
## Max.    :7.900      Max.    :4.40      Max.    :6.900      Max.    :2.500
## NA's    :11        NA's    :18        NA's    :15        NA's    :16
##      Species
## setosa      :44
## versicolor:46
## virginica   :45
## NA's        :15
##
##
##
```

## **Hmisc**

another package discussed but which I did not explore so far.