# Descriptive Statistics in $\mathbf{R}$ 

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## Basic Data Descriptions

To find out about a dataset in R we can run a names command on the particular dataframe (dataset). Let's return to our example dataset, first loading it into R:

```
library(rio)
D<-import("https://jan-rovny.squarespace.com/s/France.dta")
```

Let's explore our data:

```
names(D)
```

| [1] | "dpt" | "female" | "age" |
| :--- | :--- | :--- | :--- |
| [5] "inc" | "urban" | "educ" |  |
| [9] "lr" | "redist" | "religion" | "religiosity" |
| [13] "adopt_homo" | "anti_vax" | "gilets" | "pro_immig" |
| [17] "sov_eu" | "str_lead" | "milit" | "plit_oppose_rur" |
| [21] "prvt_PS" | "prvt_EELV" | "prvt_LREM" | "prvt_LR" |
| [25] "prvt_FN" | "prvt_RE" | "vote1" |  |

This produces a list of all the variable names in the dataset. Alternatively, we can ask to receive both variable names and some basic summary statistics:

```
summary(D)
\begin{tabular}{llllll}
\multicolumn{2}{c}{ dpt } & \multicolumn{2}{c}{ female } & \multicolumn{2}{c}{ age } \\
Min. \(: 1.00\) & Min. \(: 0.0000\) & Min. \(: 18.00\) & Min. \(: 0.00\) \\
1st Qu. \(: 33.00\) & 1st Qu. \(: 0.0000\) & 1st Qu. \(: 27.00\) & 1st Qu. \(: 4.00\) \\
Median \(: 59.00\) & Median \(: 1.0000\) & Median \(: 39.00\) & Median \(: 6.00\) \\
Mean \(: 53.93\) & Mean \(: 0.5331\) & Mean \(: 44.03\) & Mean \(: 5.39\)
\end{tabular}
```



| _RE | vote1 |
| :---: | :---: |
| Min. : 1.000 | Min. $: 1.000$ |
| 1st Qu.: 1.000 | 1st Qu.:1.000 |
| Median : 1.000 | Median :3.000 |
| Mean : 2.406 | Mean :2.939 |
| 3rd Qu.: 3.000 | 3rd Qu.:5.000 |
| Max. : 11.000 | Max. :6.000 |
| NA's :63 | NA's :575 |

We can also ask about the nature of each variable by typing:

```
is.character(D$vote1)
```

[1] FALSE

```
is.numeric(D$age)
```

[1] TRUE

```
is.factor(D$religion)
```

[1] FALSE

```
is.integer(D$female)
```

[1] FALSE

```
is.vector(D$lr)
```


## [1] FALSE

R answers TRUE or FALSE.

## Descriptive Statistics

Next, we should run some descriptive statistics on our data. Descriptive statistics do not test any hypotheses and do not try to infer any general rules from the data. They simply describe the data we have in front of us. The most basic descriptive statistics are measures of central tendency, such as mean, mode and median, and measures of dispersion, such as variance and standard deviation.

| Measure | Calculation | Description |
| :--- | :--- | :--- |
| Mean | $\bar{X}=\mu=\frac{\sum x_{i}}{N}$ | the arithmetic mean <br> the most frequently <br> occurring value |
| Mode | $\sigma^{2}=\frac{\sum\left(x_{i} i \bar{X}\right)^{2}}{N-1}$ | the central value <br> square deviation from <br> mean |
| Median | deviation from mean |  |
| Variance |  |  |
| Standard Deviation | $\sigma=\sqrt{\frac{\sum\left(x_{i}-\bar{X}\right)^{2}}{N-1}}$ |  |

In R, we can easily obtain these measures:

```
summary(D$age)
```

| Min. | 1st Qu. | Median | Mean | 3rd Qu. | Max. |
| ---: | ---: | ---: | ---: | ---: | ---: |
| 18.00 | 27.00 | 39.00 | 44.03 | 59.00 | 93.00 |

This gives us the minimum, maximum, mean and median values of age. If we want particular statistics, we can (at any point, even within other commands) ask $R$ to produce them by issuing the following commands:

```
mean(D$age, na.rm=T)
```

[1] 44.02613

```
median(D$age, na.rm=T)
```

[1] 39

```
var(D$age, na.rm=T)
```

[1] 376.66

```
sd(D$age, na.rm=T)
```

[1] 19.40773

```
min(D$age, na.rm=T)
```

[1] 18

```
max(D$age, na.rm=T)
```

[1] 93

```
range(D$age, na.rm=T)
```

[1] 1893

The mode of a vector is a little harder to obtain. To get the mode of vector $x$, you can get it like this:

```
names(sort(-table(D$age))) [1]
```

[1] "35"

This creates a table of the frequencies of each value, multipling by -1 and sorting puts the largest frequency first, and 'names()[1]' extracts the name of the first element, which is the sample mode. You may need to then use 'as.numeric()' on the result if you want a number.

## Statistics Summary

There is a useful package for summarizing data, called 'modelsummary'. We can look at all our continuous variables by specifying

```
library(modelsummary)
```

datasummary_skim(D)

|  | Unique (\#) | Missing (\%) | Mean | SD | Min | Median | Max |
| :--- | ---: | ---: | ---: | ---: | ---: | ---: | ---: |
| dpt | 95 | 0 | 53.9 | 26.5 | 1.0 | 59.0 | 95.0 |
| female | 3 | 0 | 0.5 | 0.5 | 0.0 | 1.0 | 2.0 |
| age | 76 | 0 | 44.0 | 19.4 | 18.0 | 39.0 | 93.0 |
| educ | 9 | 0 | 5.4 | 1.9 | 0.0 | 6.0 | 8.0 |
| inc | 14 | 8 | 7.9 | 2.6 | 1.0 | 8.0 | 13.0 |
| urban | 5 | 1 | 1.9 | 0.9 | 1.0 | 2.0 | 4.0 |
| religion | 8 | 3 | 4.2 | 2.8 | 1.0 | 4.0 | 7.0 |
| religiosity | 6 | 49 | 1.6 | 1.1 | 0.0 | 1.0 | 4.0 |
| lr | 6 | 5 | 2.9 | 1.0 | 1.0 | 3.0 | 5.0 |
| redist | 5 | 3 | 2.3 | 1.0 | 1.0 | 2.0 | 4.0 |
| feminism | 5 | 4 | 2.7 | 1.1 | 1.0 | 3.0 | 4.0 |
| pro_immig | 5 | 5 | 2.7 | 1.1 | 1.0 | 3.0 | 4.0 |
| adopt_homo | 5 | 3 | 2.1 | 1.0 | 0.0 | 2.0 | 3.0 |
| anti_vax | 4 | 3 | 0.6 | 0.9 | 0.0 | 0.0 | 2.0 |
| gilets | 4 | 3 | 0.8 | 0.9 | 0.0 | 0.0 | 2.0 |
| elit_oppose_rur | 5 | 13 | 1.4 | 1.0 | 0.0 | 1.0 | 3.0 |
| sov_eu | 5 | 8 | 2.5 | 1.0 | 1.0 | 3.0 | 4.0 |
| str_lead | 5 | 4 | 0.6 | 0.8 | 0.0 | 0.0 | 3.0 |
| milit_ | 5 | 54 | 0.5 | 0.8 | 0.0 | 0.0 | 3.0 |
| prvt_LFI | 12 | 5 | 5.1 | 3.6 | 1.0 | 5.0 | 11.0 |
| prvt_PS | 12 | 6 | 4.8 | 2.9 | 1.0 | 5.0 | 11.0 |
| prvt_EELV | 12 | 4 | 5.6 | 3.0 | 1.0 | 6.0 | 11.0 |
| prvt_LREM | 12 | 6 | 5.3 | 3.3 | 1.0 | 6.0 | 11.0 |
| prvt_LR | 12 | 7 | 4.6 | 2.9 | 1.0 | 5.0 | 11.0 |
| prvt_FN | 12 | 5 | 3.9 | 3.6 | 1.0 | 1.0 | 11.0 |
| prvt_RE | 12 | 4 | 2.4 | 2.7 | 1.0 | 1.0 | 11.0 |
| vote1 | 7 | 33 | 2.9 | 1.7 | 1.0 | 3.0 | 6.0 |

## Basic plots

The subsequent step in learning about our data should be the plotting of the data. Mean and variance give us a good idea as to the central tendency and dispersion of a variable, but it is even more interesting to see the frequency distribution across its values. To see a distribution of of a variable we first need to create the distribution density function:

```
den<-density(D$lr, na.rm=T)
```

Now we can plot d to see the distribution:

```
plot(den)
```

density.default( $x=\mathrm{D} \$ \mathrm{I}$, na.rm = T )


Density functions are, however, only meaningful for continuous data. In the cases of categorical or ordinal data it is more meaningful to look at a histogram. To plot a histogram in R, we simply say:

```
hist(D$religiosity)
```

Histogram of D\$religiosity


Another useful descriptive tool is a boxplot. A boxplot shows us the median, the quartiles, and the maximum and minimum of a variable. In R, say:

```
boxplot(D$prvt_LREM)
```



Boxplots are particularly useful for comparing the distributions of certain subsets of a given variable. Say that we are interested in seeing the different income distributions of men and women. We can do this by looking at a boxplot of income by gender:

```
boxplot(D$inc ~ D$female)
```



## Nicer plots

$R$ is famous for being able to create pretty graphics. One of the most commonly used packages for this is 'ggplot2.' Let's see what we can do with it:

```
library(ggplot2) #call up the package
```

Now, let's create some nicer descriptive graphics. Let's look again at the distribution of leftright preferences:

```
ggplot(D,aes(lr)) +
    geom_histogram(binwidth = 1, color="blue", fill="blue")+ #determines type, arguments def
    xlab("left-right") #label x axis
```

Warning: Removed 78 rows containing non-finite values (`stat_bin()`).


Let's consider again income and gender:

```
ggplot(D,aes(y=as.numeric(inc), x=as.factor(female), fill=as.factor(female)))+ \#define axe
    geom_violin()+ \#define violin plot
    xlab("Gender")+ylab("Income")+ \#label axes
    scale_fill_discrete(name="Gender", labels=c("male","female")) \#label fill title and labe
```

Warning: Removed 140 rows containing non-finite values (`stat_ydensity()`).
Warning: Groups with fewer than two data points have been dropped.


Next, let us look at the propensity of men and women to vote for the Green (EELV) party:

```
ggplot(D,aes(x=prvt_EELV, fill=as.factor(female)))+ #need to specify 'femal' as factor
    geom_density(alpha=0.3)+ #allows transparency, alpha defines level of opacity
    xlim(0,10)+ #defines range of x axis
    xlab("Propensity to vote for EELV")+ #x label
    scale_fill_discrete(name="Gender", labels=c("male","female", "neither")) #name and label
```

```
Warning: Removed 176 rows containing non-finite values (`stat_density()`).
Warning: Groups with fewer than two data points have been dropped.
Warning in max(ids, na.rm = TRUE): no non-missing arguments to max; returning
-Inf
```



Note that women are quite more likely to support the Greens.

## Tables

Finally, it is very useful to organize our data into a table. A two-way table arranges the values of one variable by the values of another. Such organization is of course only meaningful for categorical or ordinal data, not for continuous variables. Let's make a table summarizing the vote for different candidates by gender (note, we are working with the variable vote created in the previous lesson dealing with Operations in R!):

```
table(D$female, D$vote)
```

|  | Melenchon | Jadot | Macron | Peceresse | Le | Pen | Zemmour |
| ---: | ---: | ---: | ---: | ---: | ---: | ---: | ---: |
| 0 | 180 | 28 | 149 | 25 | 110 | 39 |  |
| 1 | 204 | 42 | 168 | 25 | 145 | 31 |  |
| 2 | 1 | 0 | 0 | 0 | 0 | 0 |  |

This, however, creates a table with raw numbers, which is not very useful. To do this comparison meaningfully, we must compare proportional data. In R we first create a raw table of vote by rich:

```
cand.table<-table(D$female,D$vote)
```

Now we use the prop.table command to create proportions:

```
prop.table(cand.table) # gives us the proportions by all cells
    Melenchon Jadot Macron Peceresse Le Pen
0 0.1569311247 0.0244115083 0.1299040976 0.0217959895 0.0959023540
1 0.1778552746 0.0366172624 0.1464690497 0.0217959895 0.1264167393
2 0.0008718396 0.0000000000 0.0000000000 0.0000000000 0.0000000000
    Zemmour
0 0.0340017437
1 0.0270270270
2 0.0000000000
prop.table(cand.table,1) #gives us the proportions by rows
\begin{tabular}{lrrrrrr} 
& Melenchon & Jadot & Macron & Peceresse & Le Pen & Zemmour \\
0 & 0.33898305 & 0.05273070 & 0.28060264 & 0.04708098 & 0.20715631 & 0.07344633 \\
1 & 0.33170732 & 0.06829268 & 0.27317073 & 0.04065041 & 0.23577236 & 0.05040650 \\
2 & 1.00000000 & 0.00000000 & 0.00000000 & 0.00000000 & 0.00000000 & 0.00000000
\end{tabular}
prop.table(cand.table,2) #gives us the proportions by columns
```

|  | Melenchon | Jadot | Macron | Peceresse | Le Pen | Zemmour |
| :--- | ---: | ---: | ---: | ---: | ---: | ---: |
| 0 | 0.467532468 | 0.400000000 | 0.470031546 | 0.500000000 | 0.431372549 | 0.557142857 |
| 1 | 0.529870130 | 0.600000000 | 0.529968454 | 0.500000000 | 0.568627451 | 0.442857143 |
| 2 | 0.002597403 | 0.000000000 | 0.000000000 | 0.000000000 | 0.000000000 | 0.000000000 |

In order to test whether there is a difference gender support across parties, we can ask R to provide the $\chi^{2}$ test:

```
library(MASS) #load the appropriate library
chisq.test(cand.table) #perform the test
```

```
Warning in chisq.test(cand.table): Chi-squared approximation may be incorrect
```

```
    Pearson's Chi-squared test
data: cand.table
X-squared = 7.0122, df = 10, p-value = 0.7243
```

Given the low p-value, we reject the hypothesis that there is no difference between men's and women's party support. Gender seems to map onto party preferences.

A very nice way to create cross-tabulations is to go back to the 'modelsummary' package:

```
library(modelsummary)
datasummary_crosstab(female ~ vote, data = D, statistic = 1 ~ 1 + N + Percent("col"))
```

| female |  | Melenchon | Jadot | Macron | Peceresse | Le Pen | Zemmour | All |
| :--- | ---: | ---: | ---: | ---: | ---: | ---: | ---: | ---: |
| 0 | N | 180 | 28 | 149 | 25 | 110 | 39 | 805 |
|  | $\% \mathrm{col}$ | 46.8 | 40.0 | 47.0 | 50.0 | 43.1 | 55.7 | 46.7 |
| 1 | N | 204 | 42 | 168 | 25 | 145 | 31 | 916 |
|  | $\% \mathrm{col}$ | 53.0 | 60.0 | 53.0 | 50.0 | 56.9 | 44.3 | 53.2 |
| 2 | N | 1 | 0 | 0 | 0 | 0 | 0 | 1 |
|  | $\% \mathrm{col}$ | 0.3 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.1 |
| All | N | 385 | 70 | 317 | 50 | 255 | 70 | 1722 |
|  | $\% \mathrm{col}$ | 100.0 | 100.0 | 100.0 | 100.0 | 100.0 | 100.0 | 100.0 |

This shows the same results as earlier, but in a much nicer format!

