

R programming

Dr. Umesh Ghoshdastider
ETH Zurich

R

Visualization

Open source



Data science

Platform agnostic

**Computational
statistics**

R

R is a powerful, extensible environment. It has a wide range of statistics and general data analysis and visualization capabilities.

Data handling, wrangling, and storage

Wide array of statistical methods and graphical techniques available

Easy to install on any platform and use (and it's free!)

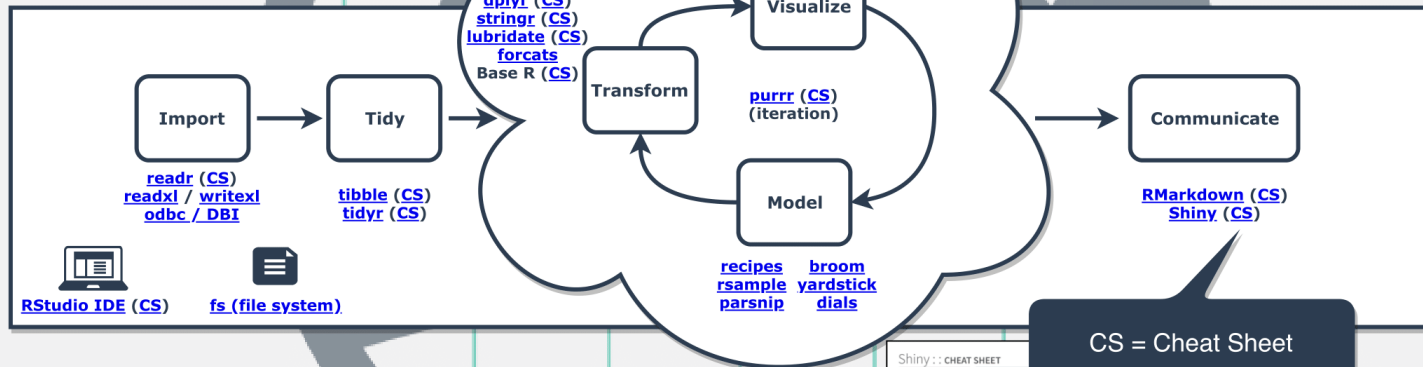
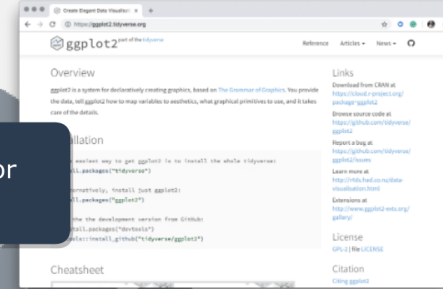
Open source with a large and growing community of peers

Data Science with R Workflow

The Data Science With R Workflow is available in the book: [R For Data Science](#). If you want to learn R and this workflow *for business*, take the [R For Business Analysis \(DS4B 101-R\) course](#) through Business Science University.



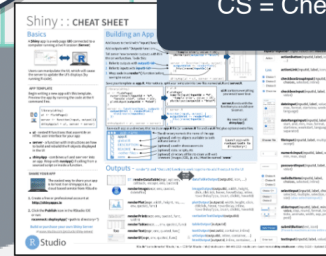
Click the links for Documentation



Important Resources

- R For Data Science Book: <http://r4ds.had.co.nz/>
- Rmarkdown Book: <https://bookdown.org/yihui/rmarkdown/>
- Data Visualization Book: <https://rkabacoff.github.io/datavis/>
- More Cheatsheets: <https://www.rstudio.com/resources/cheatsheets/>
- tidyverse packages: <https://www.tidyverse.org/>
- Connecting to databases: <https://db.rstudio.com/>
- RMarkdown website: <https://rmarkdown.rstudio.com/>
- Shiny web applications website: <http://shiny.rstudio.com/>
- Jenny Bryan's purrr tutorial: <https://jennybryan.org/>

"Business Science University:
Enterprise-Grade Data Science Education"



Business Science University
university.business-science.io



RStudio is freely available open-source Integrated Development Environment (IDE).

RStudio provides an environment with many features to make using R easier and is a great alternative to working on R in the terminal.

R Studio

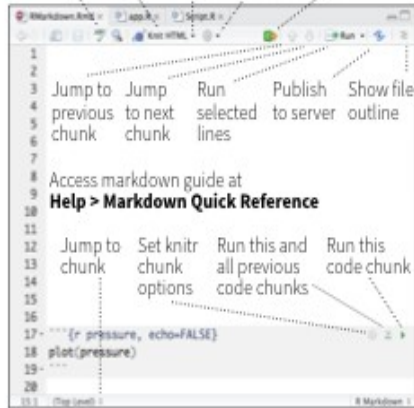
RStudio IDE : : CHEAT SHEET

Documents and Apps

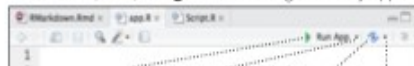


Open Shiny, R Markdown, knitr, Sweave, LaTeX, .Rd files and more in Source Pane

Check spelling
Render output
Choose output format
Choose output location
Insert code chunk

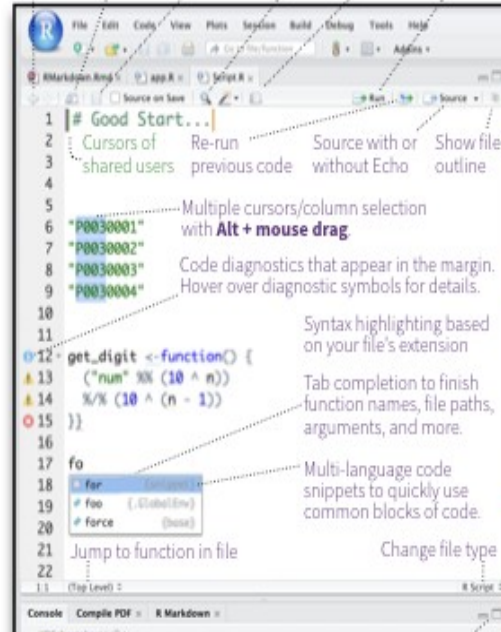


RStudio recognizes that files named **app.R**, **server.R**, **ui.R**, and **global.R** belong to a shiny app



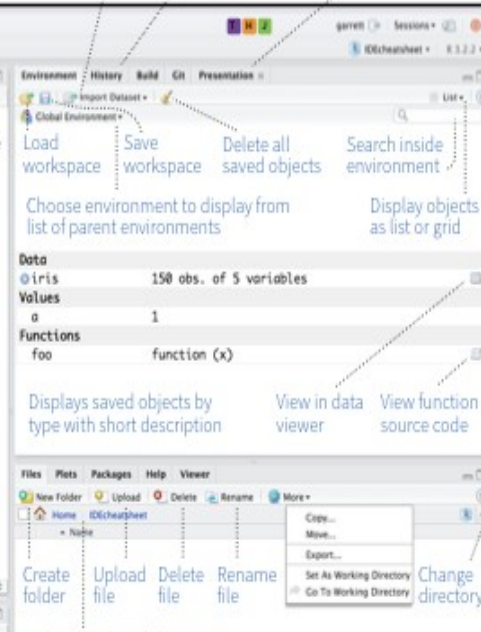
Write Code

Navigate tabs
Open in new window
Save
Find and replace
Compile as notebook
Run selected code



R Support

Import data with wizard
History of past commands to run/copy
Display .RPres slideshows
File > New File > R Presentation



Pro Features

Share Project with Collaborators
Active shared collaborators

Start new R Session in current project

Close R Session in project

Select R Version

PROJECT SYSTEM

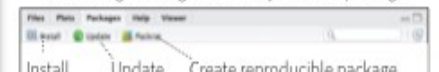
File > New Project

RStudio saves the call history, workspace, and working directory associated with a project. It reloads each when you re-open a project.

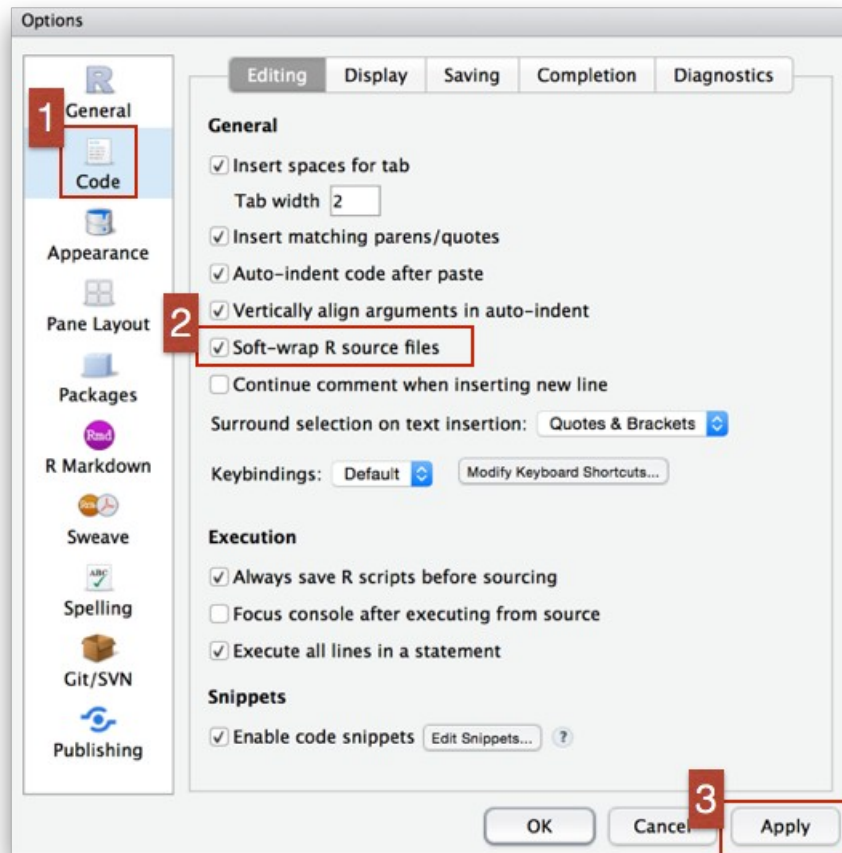
RStudio opens plots in a dedicated Plots pane



GUI Package manager lists every installed package

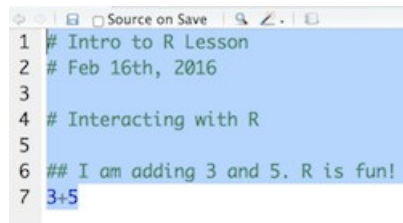


Rstudio





The Rstudio script editor allows you to 'send' the current line or the currently highlighted text to the R console by clicking on the Run button in the upper-right hand corner of the script editor. Alternatively, you can run by simply pressing the Ctrl and Enter keys at the same time as a shortcut.

A screenshot of the RStudio script editor window. The window has a title bar with 'Source on Save' and search icons. The script content is as follows:

```
1 # Intro to R Lesson
2 # Feb 16th, 2016
3
4 # Interacting with R
5
6 ## I am adding 3 and 5. R is fun!
7 3+5
```

The text on lines 1 through 6 is highlighted in light blue. Line 7 is not highlighted.

Getting Help

Accessing the help files

?mean

Get help of a particular function.

help.search('weighted mean')

Search the help files for a word or phrase.

help(package = 'dplyr')

Find help for a package.

More about an object

str(iris)

Get a summary of an object's structure.

class(iris)

Find the class an object belongs to.

Using Packages

install.packages('dplyr')

Download and install a package from CRAN.

library(dplyr)

Load the package into the session, making all its functions available to use.

dplyr::select

Use a particular function from a package.

data(iris)

Load a built-in dataset into the environment.

Working Directory

getwd()

Find the current working directory (where inputs are found and outputs are sent).

setwd('C://file/path')

Change the current working directory.

Use projects in RStudio to set the working directory to the folder you are working in.

Variable Names

Variables can be given almost any name, such as `x`, `current_temperature`, or `subject_id`. However, there are some rules / suggestions you should keep in mind:

- Make your names explicit and not too long.
- Avoid names starting with a number (`2x` is not valid but `x2` is)
- Avoid names of fundamental functions in R (e.g., `if`, `else`, `for`, see here for a complete list). In general, even if it's allowed, it's best to not use other function names (e.g., `c`, `T`, `mean`, `data`) as variable names. When in doubt check the help to see if the name is already in use.
- Avoid dots (`.`) within a variable name as in `my.dataset`. There are many functions in R with dots in their names for historical reasons, but because dots have a special meaning in R (for methods) and other programming languages, it's best to avoid them.
- Use nouns for object names and verbs for function names
- Keep in mind that R is case sensitive (e.g., `genome_length` is different from `Genome_length`)
- Be consistent with the styling of your code (where you put spaces, how you name variable, etc.). In R, two popular style guides are Hadley Wickham's style guide and Google's.

Data Types

Variables can contain values of specific types within R. The six data types that R uses include:

"numeric" for any numerical value

"character" for text values, denoted by using quotes (") around value

"integer" for integer numbers (e.g., 2L, the L indicates to R that it's an integer)

"logical" for TRUE and FALSE (the Boolean data type)

"complex" to represent complex numbers with real and imaginary parts (e.g., 1+4i)

and that's all we're going to say about them

"raw" that we won't discuss further

The table below provides examples of each of the commonly used data types:

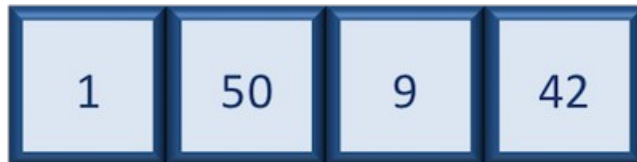
Data Type	Examples
Numeric:	1, 1.5, 20, pi
Character:	"anytext", "5", "TRUE"
Integer:	2L, 500L, -17L
Logical:	TRUE, FALSE, T, F

Data Structures

vectors (c),
factors (factor),
matrices (matrix),
data frames (data.frame)
lists (list).

Vectors

A vector is the most common and basic data structure in R, and is pretty much the workhorse of R. It's basically just a collection of values, mainly either numbers, All must be same data types.



Vectors

Creating Vectors

<code>c(2, 4, 6)</code>	2 4 6	Join elements into a vector
<code>2:6</code>	2 3 4 5 6	An integer sequence
<code>seq(2, 3, by=0.5)</code>	2.0 2.5 3.0	A complex sequence
<code>rep(1:2, times=3)</code>	1 2 1 2 1 2	Repeat a vector
<code>rep(1:2, each=3)</code>	1 1 1 2 2 2	Repeat elements of a vector

Vector Functions

sort(x)

Return x sorted.

table(x)

See counts of values.

rev(x)

Return x reversed.

unique(x)

See unique values.

Selecting Vector Elements

By Position

`x[4]` The fourth element.

`x[-4]` All but the fourth.

`x[2:4]` Elements two to four.

`x[-(2:4)]` All elements except two to four.

`x[c(1, 5)]` Elements one and five.

By Value

`x[x == 10]` Elements which are equal to 10.

`x[x < 0]` All elements less than zero.

`x[x %in% c(1, 2, 5)]` Elements in the set 1, 2, 5.

Named Vectors

`x['apple']` Element with name 'apple'.

Factors

A factor is a special type of vector that is used to store categorical data. Each unique category is referred to as a factor level (i.e. category = level). Factors are built on top of integer vectors such that each factor level is assigned an integer value, creating value-label pairs.

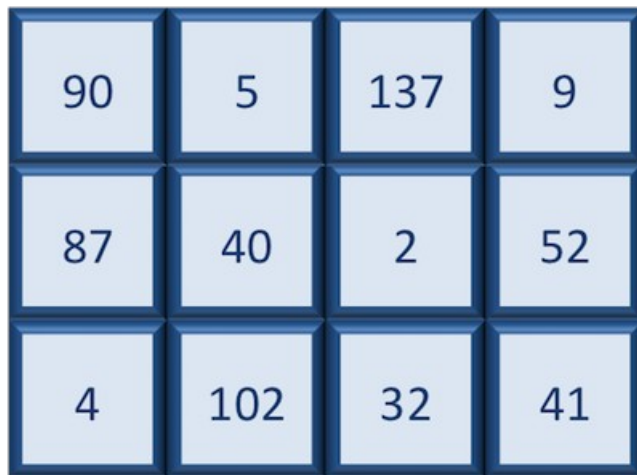
```
expr <- c("l", "h", "m", "h", "l", "m", "h")  
expression <- factor(expr)
```

Values	
expr	chr [1:7] "l" "h" "m" "h" "l" "m" "h"
expression	Factor w/ 3 levels "h","l","m": 2 1 3 1 2 3 1
y	2

Matrix

A matrix in R is a collection of vectors of same length and identical datatype. Vectors can be combined as columns in the matrix or by row, to create a 2-dimensional structure.

Matrices are used commonly as part of the mathematical machinery of statistics. They are usually of numeric datatype and used in computational algorithms to serve as a checkpoint. For example, if input data is not of identical data type (numeric, character, etc.), the `matrix()` function will throw an error and stop any downstream code execution.



A 3x4 matrix of numbers, displayed as a grid of light blue squares with dark blue borders. The numbers are arranged in three rows and four columns.

90	5	137	9
87	40	2	52
4	102	32	41

Data Frame

A `data.frame` is the de facto data structure for most tabular data and what we use for statistics and plotting. A `data.frame` is similar to a matrix in that it's a collection of vectors of the same length and each vector represents a column. However, in a `dataframe` each vector can be of a different data type (e.g., characters, integers, factors).

A data frame is the most common way of storing data in R, and if used systematically makes data analysis easier.

We can create a `dataframe` by bringing vectors together to form the columns. We do this using the `data.frame()` function, and giving the function the different vectors we would like to bind together. This function will only work for vectors of the same length.

Also see the
dplyr package.

Data Frames

```
df <- data.frame(x = 1:3, y = c('a', 'b', 'c'))
```

A special case of a list where all elements are the same length.

x	y
1	a
2	b
3	c

List subsetting



Understanding a data frame

View(df)

See the full data frame.

head(df)

See the first 6 rows.

Matrix subsetting

df[, 2]



df[2,]



df[2, 2]



nrow(df)

Number of rows.

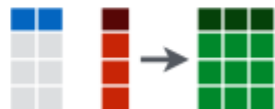
ncol(df)

Number of columns.

dim(df)

Number of columns and rows.

cbind - Bind columns.

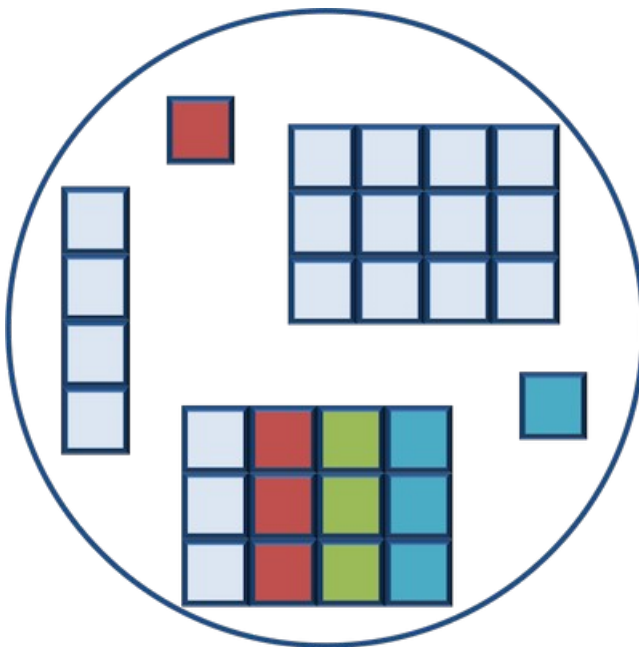


rbind - Bind rows.



Lists

Lists are a data structure in R that can be perhaps a bit daunting at first, but soon become amazingly useful. A list is a data structure that can hold any number of any types of other data structures. If you have variables of different data structures you wish to combine, you can put all of those into one list object by using the `list()` function and placing all the items you wish to combine within parentheses:



Lists

```
list1 <- list(species, df, number)
```

Print out the list to screen to take a look at the components:

```
list1
```

```
[[1]]
```

```
[1] "ecoli" "human" "corn"
```

```
[[2]]
```

```
species glengths
```

```
1  ecoli    4.6
```

```
2  human  3000.0
```

```
3  corn 50000.0
```

```
[[3]]
```

```
[1] 5
```

Matrices

```
m <- matrix(x, nrow = 3, ncol = 3)
```

Create a matrix from x.



`m[2,]` - Select a row



`m[, 1]` - Select a column



`m[2, 3]` - Select an element

`t(m)`

Transpose

`m %*% n`

Matrix Multiplication

`solve(m, n)`

Find x in: $m \cdot x = n$

Lists

```
l <- list(x = 1:5, y = c('a', 'b'))
```

A list is a collection of elements which can be of different types.

`l[[2]]`

Second element
of l.

`l[1]`

New list with
only the first
element.

`l$x`

Element named
x.

`l['y']`

New list with
only element
named y.

Functions

A key feature of R is functions. Functions are "self contained" modules of code that accomplish a specific task. Functions usually take in some sort of data structure (value, vector, dataframe etc.), process it, and return a result.

```
sqrt(100)
```

```
Round(3.333,3)
```

Package Source

A key feature of R is functions. Functions are "self contained" modules of



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[abc.data](#)
[abcdeFBA](#)
[ABCOptim](#)
[ABCp2](#)
[ahcrf](#)

Available CRAN Packages By Name

[A](#)[B](#)[C](#)[D](#)[E](#)[F](#)[G](#)[H](#)[I](#)[J](#)[K](#)[L](#)[M](#)[N](#)[O](#)[P](#)[Q](#)[R](#)[S](#)[T](#)[U](#)[V](#)[W](#)[X](#)[Y](#)[Z](#)

Accurate, Adaptable, and Accessible Error Metrics for Predictive Models
Access to Abbyy Optical Character Recognition (OCR) API
Tools for Approximate Bayesian Computation (ABC)
Computed ABC Analysis
Data Only: Tools for Approximate Bayesian Computation (ABC)
ABCDE_FBA: A-Biologist-Can-Do-Everything of Flux Balance Analysis with this package
Implementation of Artificial Bee Colony (ABC) Optimization
Approximate Bayesian Computational Model for Estimating P2
Approximate Bayesian Computation via Random Forests



Package Source

```
install.packages("ggplot2")
```

```
install.packages("BiocManager")
```

```
library(BiocManager)
```

```
install("DESeq2")
```

```
install.packages("~/Downloads/ggplot2_1.0.1.tar.gz", type="source",  
repos=NULL)
```

```
library(ggplot2)
```

```
sessionInfo()
```


Save Session

```
save(iris, file="/tmp/iris.Rdata")
```

```
some_data <- load(file="~/Downloads/iris.RData")
```

Programming

For Loop

```
for (variable in sequence){  
  Do something  
}
```

Example

```
for (i in 1:4){  
  j <- i + 10  
  print(j)  
}
```

While Loop

```
while (condition){  
  Do something  
}
```

Example

```
while (i < 5){  
  print(i)  
  i <- i + 1  
}
```

If Statements

```
if (condition){  
  Do something  
} else {  
  Do something different  
}
```

Example

```
if (i > 3){  
  print('Yes')  
} else {  
  print('No')  
}
```

Functions

```
function_name <- function(var){  
  Do something  
  return(new_variable)  
}
```

Example

```
square <- function(x){  
  squared <- x*x  
  return(squared)  
}
```

Reading and Writing Data

Also see the **readr** package.

Input	Output	Description
<code>df <- read.table('file.txt')</code>	<code>write.table(df, 'file.txt')</code>	Read and write a delimited text file.
<code>df <- read.csv('file.csv')</code>	<code>write.csv(df, 'file.csv')</code>	Read and write a comma separated value file. This is a special case of read.table/write.table.
<code>load('file.RData')</code>	<code>save(df, file = 'file.Rdata')</code>	Read and write an R data file, a file type special for R.

Conditions

<code>a == b</code>	Are equal	<code>a > b</code>	Greater than	<code>a >= b</code>	Greater than or equal to	<code>is.na(a)</code>	Is missing
<code>a != b</code>	Not equal	<code>a < b</code>	Less than	<code>a <= b</code>	Less than or equal to	<code>is.null(a)</code>	Is null

Strings

Also see the **stringr** package.

<code>paste(x, y, sep = ' ')</code>	Join multiple vectors together.
<code>paste(x, collapse = ' ')</code>	Join elements of a vector together.
<code>grep(pattern, x)</code>	Find regular expression matches in x.
<code>gsub(pattern, replace, x)</code>	Replace matches in x with a string.
<code>toupper(x)</code>	Convert to uppercase.
<code>tolower(x)</code>	Convert to lowercase.
<code>nchar(x)</code>	Number of characters in a string.

Factors

<code>factor(x)</code> Turn a vector into a factor. Can set the levels of the factor and the order.	<code>cut(x, breaks = 4)</code> Turn a numeric vector into a factor by 'cutting' into sections.
---	---

Read Tabular Data - These functions share the common arguments:

```
read_* (file, col_names = TRUE, col_types = NULL, locale = default_locale(), na = c("", "NA"),
        quoted_na = TRUE, comment = "", trim_ws = TRUE, skip = 0, n_max = Inf, guess_max = min(1000,
        n_max), progress = interactive())
```

a,b,c
1,2,3
4,5,NA



A	B	C
1	2	3
4	5	NA

Comma Delimited Files

read_csv("file.csv")

To make file.csv run:

write_file(x = "a,b,c\n1,2,3\n4,5,NA", path = "file.csv")

a;b;c
1;2;3
4;5;NA



A	B	C
1	2	3
4	5	NA

Semi-colon Delimited Files

read_csv2("file2.csv")

write_file(x = "a;b;c\n1;2;3\n4;5;NA", path = "file2.csv")

a|b|c
1|2|3
4|5|NA



A	B	C
1	2	3
4	5	NA

Files with Any Delimiter

read_delim("file.txt", delim = "|")

write_file(x = "a|b|c\n1|2|3\n4|5|NA", path = "file.txt")

a b c
1 2 3
4 5 NA



A	B	C
1	2	3
4	5	NA

Fixed Width Files

read_fwf("file.fwf", col_positions = c(1, 3, 5))

write_file(x = "a b c\n1 2 3\n4 5 NA", path = "file.fwf")

Tab Delimited Files

read_tsv("file.tsv") Also **read_table()**.

write_file(x = "a\tb\tc\n1\t2\t3\n4\t5\tNA", path = "file.tsv")

USEFUL ARGUMENTS

a,b,c
1,2,3
4,5,NA

Example file

write_file("a,b,c\n1,2,3\n4,5,NA","file.csv")
f <- "file.csv"

1	2	3
4	5	NA

Skip lines

read_csv(f, skip = 1)

A	B	C
1	2	3
4	5	NA

No header

read_csv(f, col_names = FALSE)

A	B	C
1	2	3

Read in a subset

read_csv(f, n_max = 1)

x	y	z
A	B	C
1	2	3
4	5	NA

Provide header

read_csv(f, col_names = c("x", "y", "z"))

A	B	C
NA	2	3
4	5	NA

Missing Values

read_csv(f, na = c("1", "."))

Data Inspection

We already saw how the functions `head()` and `str()` can be useful to check the content and the structure of a `data.frame`. Here is a non-exhaustive list of functions to get a sense of the content/structure of data.

All data structures - content display:

`str()`: compact display of data contents (env.)

`class()`: data type (e.g. character, numeric, etc.) of vectors and data structure of dataframes, matrices, and lists.

`summary()`: detailed display, including descriptive statistics, frequencies

`head()`: will print the beginning entries for the variable

`tail()`: will print the end entries for the variable

Vector and factor variables:

`length()`: returns the number of elements in the vector or factor

Dataframe and matrix variables:

`dim()`: returns dimensions of the dataset

`nrow()`: returns the number of rows in the dataset

`ncol()`: returns the number of columns in the dataset

`rownames()`: returns the row names in the dataset

`colnames()`: returns the column names in the dataset

Save Session

```
save(iris, file="/tmp/iris.Rdata")
```

```
some_data <- load(file="~/Downloads/iris.RData")
```

The tidyverse

Components



The tidyverse is a collection of R packages that share common philosophies and are designed to work together. This site is a work-in-progress guide to the tidyverse and its packages.

dplyr

The most useful tool in the tidyverse is dplyr. It's a swiss-army knife for data wrangling. dplyr has many handy functions that we recommend incorporating into your analysis:

`select()` extracts columns and returns a tibble.

`arrange()` changes the ordering of the rows.

`filter()` picks cases based on their values.

`mutate()` adds new variables that are functions of existing variables.

`rename()` easily changes the name of a column(s)

`summarise()` reduces multiple values down to a single summary.

`pull()` extracts a single column as a vector.

`_join()` group of functions that merge two data frames together, includes (`inner_join()`, `left_join()`, `right_join()`, and `full_join()`).

dplyr

`select()`

To extract columns from a tibble we can use the `select()` function.

```
# Convert the res_tableOE data frame to a tibble
```

```
res_tableOE <- res_tableOE %>%  
  rownames_to_column(var="gene") %>%  
  as_tibble()
```

```
# extract selected columns from res_tableOE
```

```
res_tableOE %>%  
  select(gene, baseMean, log2FoldChange, padj)
```

Conversely, you can remove columns you don't want with negative selection.

```
res_tableOE %>%  
  select(-c(lfcSE, stat, pvalue))
```

dplyr

```
## # A tibble: 23,368 x 4
##   gene   baseMean log2FoldChange   padj
##   <chr>   <dbl>       <dbl>     <dbl>
## 1 1/2-SBSRNA4 45.6520399  0.266586547 2.708964e-01
## 2   A1BG 61.0931017  0.208057615 3.638671e-01
## 3 A1BG-AS1 175.6658069 -0.051825739 7.837586e-01
## 4   A1CF 0.2376919  0.012557390      NA
## 5  A2LD1 89.6179845  0.343006364 7.652553e-02
## 6   A2M 5.8600841 -0.270449534 2.318666e-01
## 7  A2ML1 2.4240553  0.236041349      NA
## 8  A2MP1 1.3203237  0.079525469      NA
## 9  A4GALT 64.5409534  0.795049160 2.875565e-05
## 10 A4GNT 0.1912781  0.009458374      NA
## # ... with 23,358 more rows
```

Let's save that tibble as a new variable called sub_res:

```
sub_res <- res_tableOE %>%
  select(-c(lfcSE, stat, pvalue))
```

dplyr

```
arrange(sub_res, padj)
## # A tibble: 23,368 x 4
##   gene  baseMean log2FoldChange    padj
##   <chr>    <dbl>      <dbl>    <dbl>
## 1  MOV10 21681.7998    4.7695983 0.0000000e+00
## 2   H1F0 7881.0811    1.5250811 2.007733e-162
## 3  HSPA6 168.2522     4.4993734 1.969313e-134
## 4 HIST1H1C 1741.3830    1.4868361 5.116720e-101
## 5  TXNIP 5133.7486    1.3868320 4.882246e-90
## 6  NEAT1 21973.7061     0.9087853 2.269464e-83
## 7  KLF10 1694.2109    1.2093969 9.257431e-78
## 8  INSIG1 11872.5106    1.2260848 8.853278e-70
## 9  NR1D1 969.9119     1.5236259 1.376753e-64
## 10 WDFY1 1422.7361     1.0629160 1.298076e-61
## # ... with 23,358 more rows
```

dplyr

filter()

Let's keep only genes that are expressed (baseMean above 0) with an adjusted P value below 0.01. You can perform multiple filter() operations together in a single command.

```
sub_res %>%
```

```
  filter(baseMean > 0 & padj < 0.01)
```

```
## # A tibble: 4,959 x 4
```

```
##   gene      baseMean log2FoldChange   padj
```

```
##   <chr>      <dbl>      <dbl>   <dbl>
```

```
## 1 A4GALT      64.5        0.798 2.40e- 5
```

```
## 2 AAGAB     2614.        -0.390 1.68e-11
```

```
## 3 AAMP      3157.        -0.380 9.11e-13
```

```
## 4 AARS      3690.         0.167 2.10e- 3
```

```
## 5 AARS2     2255.        -0.204 3.77e- 4
```

```
## 6 AASDHPPT  3561.         -0.293 3.79e- 7
```

```
## 7 AASS      1018.         0.347 7.94e- 5
```

```
## 8 AATF      2613.        -0.290 1.97e- 7
```

```
## 9 ABAT       384.         0.384 1.99e- 4
```

```
## 10 ABCA1     108.         0.833 4.19e- 7
```

```
## # ... with 4,949 more rows
```

dplyr

mutate()

mutate() enables you to create a new column from an existing column.

Let's generate log10 calculations of our baseMeans for each gene.

```
sub_res %>%
```

```
  mutate(log10BaseMean = log10(baseMean)) %>%
```

```
  select(gene, baseMean, log10BaseMean)
```

```
## # A tibble: 23,368 x 3
```

```
##   gene      baseMean log10BaseMean
```

```
##   <chr>      <dbl>      <dbl>
```

```
## 1 1/2-SBSRNA4  45.7        1.66
```

```
## 2 A1BG        61.1        1.79
```

```
## 3 A1BG-AS1    176.         2.24
```

```
## 4 A1CF        0.238       -0.624
```

```
## 5 A2LD1       89.6        1.95
```

```
## 6 A2M         5.86        0.768
```

```
## 7 A2ML1       2.42        0.385
```

```
## 8 A2MP1       1.32        0.121
```

```
## 9 A4GALT      64.5        1.81
```

```
## 10 A4GNT      0.191       -0.718
```

```
## # ... with 23,358 more rows
```

dplyr

rename()

You can quickly rename an existing column with rename(). The syntax is new_name = old_name.

```
sub_res %>%
```

```
  rename(symbol = gene)
```

```
## # A tibble: 23,368 x 4
```

```
##   symbol      baseMean log2FoldChange      padj
```

```
##   <chr>      <dbl>      <dbl>      <dbl>
```

```
## 1 1/2-SBSRNA4 45.7        0.268    0.264
```

```
## 2 A1BG       61.1        0.209    0.357
```

```
## 3 A1BG-AS1   176.        -0.0519  0.781
```

```
## 4 A1CF       0.238        0.0130  NA
```

```
## 5 A2LD1      89.6        0.345    0.0722
```

```
## 6 A2M        5.86       -0.274    0.226
```

```
## 7 A2ML1      2.42        0.240    NA
```

```
## 8 A2MP1      1.32        0.0811  NA
```

```
## 9 A4GALT     64.5        0.798    0.0000240
```

```
## 10 A4GNT     0.191       0.00952  NA
```

```
## # ... with 23,358 more rows
```

dplyr

`pull()`

In the recent dplyr 0.7 update, `pull()` was added as a quick way to access column data as a vector. This is very handy in chain operations with the pipe operator.

```
# Extract first 10 values from the gene column  
pull(sub_res, gene) %>% head()
```


dplyr

`_join()`

Dplyr has a powerful group of join operations, which join together a pair of data frames based on a variable or set of variables present in both data frames that uniquely identify all observations. These variables are called keys.

`inner_join`: Only the rows with keys present in both datasets will be joined together.

`left_join`: Keeps all the rows from the first dataset, regardless of whether in second dataset, and joins the rows of the second that have keys in the first.

`right_join`: Keeps all the rows from the second dataset, regardless of whether in first dataset, and joins the rows of the first that have keys in the second.

`full_join`: Keeps all rows in both datasets. Rows without matching keys will have NA values for those variables from the other dataset.

dplyr

```
ID <- c(546, 983, 042, 952, 853, 061)
diet <- c("veg", "pes", "omni", "omni", "omni", "omni")
exercise <- c("high", "low", "low", "low", "med", "high")
behavior <- data.frame(ID, diet, exercise)
```

Creating blood dataframe

```
ID <- c(983, 952, 704, 555, 853, 061, 042, 237, 145, 581, 249, 467, 841,
546)
blood_levels <- c(43543, 465, 4634, 94568, 134, 347, 2345, 5439, 850,
6840, 5483, 66452, 54371, 1347)
blood <- data.frame(ID, blood_levels)
```

dplyr

To join only the IDs present in both data frames, we could use the `inner_join()` function:

```
# Inner join
```

```
inner_join(blood, behavior)
```

Alternatively, if we wanted to return all blood IDs, but include only the behavior IDs that match, we could use the `left_join()` function:

```
# Left join
```

```
left_join(blood, behavior)
```

We could also do the same thing but return all behavior IDs and matching blood IDs using `right_join()`:

```
# Right join
```

```
right_join(blood, behavior)
```

Finally, we could return all IDs from both data frames regardless whether there is a matching key (ID):

```
# Full join
```

```
full_join(blood, behavior)
```