

# Data Analysis in R

## Data Cleaning

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Cleaning is always a chore...



But wouldn't you rather be a Dyson?



Or even better...



Get Started

## Getting Data in...

The first part of the process in uploading data into R.

But the biggest question is what kind of data do you have?



## Some Common Data Formats

- Delimited Files (fixed width, comma, tab, ...)
- Excel
- SPSS
- STATA
- Semi- structured (JSON, XML)

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Designed with interfaces to handle most files

Has some nice defaults that make it easier than some base packages

# Starting with CSVs

## Syntax

```
data <- read_csv("path_to_csv.csv")
```

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```
data <- read_csv("path_to_csv.csv")
```

## Options

- Specify column names
- Where data start
- Column types

## Other delimiters

### Tab Delimited Files

```
data <- read_tsv("path_to_csv.txt")
```

### Any other delimiter

```
data <- read_delim("path_to_csv.txt", delim = ";")
```

## Now to haven

The haven package can be used to read more proprietary data formats into R

### SAS

```
my_sas <- read_sas("myfile.sas7bdat")
```

### SPSS

```
my_sas <- read_spss("myfile.sav")
```

### STATA

```
my_sas <- read_dta("myfile.dta")
```

# Excel using readxl

And of course the most ubiquitous data form...

```
my_excel <- read_excel("my_excel_file.xlsx")
```

# Excel using readxl

And of course the most ubiquitous data form...

```
my_excel <- read_excel("my_excel_file.xlsx")
```

- Specify cell ranges
- Name columns
- etc



## And other formats

Json with `jsonlite`

XML with `xml2` or `XML` (*my preference is `xml2`*)

Now for cleaning

# Tidy data

Most of the tidyverse relies on the "tidy" paradigm of data

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Once data is in the format, visualisation and modeling becomes easier

## Wide to Narrow and Back Again

We will use the `tidyr` package to help move from wide data to narrow data to move to the tidy format

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## Key functions

`spread`

Narrow to Wide

`gather`

Wide to narrow

# Spread

## Syntax

```
spread(data = data,  
       key = "What You want to Be Columns",  
       value = "The value you want in the rows",  
       fill = "what you want to appear if there are no values")
```



# Spread

## Syntax

```
spread(data = data,  
       key = "What You want to Be Columns",  
       value = "The value you want in the rows",  
       fill = "what you want to appear if there are no values")
```

## Example

stocks

```
## # A tibble: 30 x 3  
##   time      stock price  
##   <date>    <chr>  <dbl>  
## 1 2010-01-01 X      0.892  
## 2 2010-01-02 X      1.09  
## 3 2010-01-03 X     -0.0525  
## 4 2010-01-04 X      0.899  
## 5 2010-01-05 X      0.326  
## 6 2010-01-06 X      1.82  
## 7 2010-01-07 X      0.0298  
## 8 2010-01-08 X      0.164  
## 9 2010-01-09 X      0.428  
## 10 2010-01-10 X     -0.475  
## # ... with 20 more rows
```

stocks %>%  
 spread(stock, price)

```
## # A tibble: 10 x 4  
##   time      X      Y      Z  
##   <date>    <dbl> <dbl> <dbl>  
## 1 2010-01-01 0.892 -0.0475 7.63  
## 2 2010-01-02 1.09  2.79 -1.78  
## 3 2010-01-03 -0.0525 1.72 -0.642  
## 4 2010-01-04 0.899  3.03 -1.26  
## 5 2010-01-05 0.326 -2.84  2.88  
## 6 2010-01-06 1.82  1.75  5.27  
## 7 2010-01-07 0.0298 1.22  4.13  
## 8 2010-01-08 0.164 -1.81  2.52  
## 9 2010-01-09 0.428 -1.43 -7.40  
## 10 2010-01-10 -0.475 -2.44 -3.41
```

# Gather

## Syntax

```
gather(data = data,  
       key = "new name of column",  
       value = "what you want to call value",  
       -"what you don't want grouped")
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       key = "new name of column",  
       value = "what you want to call value",  
       -"what you don't want grouped")
```

## Example

```
mini_iris
```

```
## # A tibble: 3 x 5  
##   Sepal.Length Sepal.Width Petal.Length Petal.Width Species  
## *      <dbl>      <dbl>      <dbl>      <dbl> <fct>  
## 1         5.1         3.5         1.4         0.2 setosa  
## 2         7         3.2         4.7         1.4 versicolor  
## 3         6.3         3.3         6         2.5 virginica
```

```
mini_iris %>%  
  gather(attribute, measurement, -Species)
```

```
## # A tibble: 12 x 3  
##   Species attribute measurement  
##   <fct>      <chr>      <dbl>  
## 1 setosa    Sepal.Length    5.1  
## 2 versicolor Sepal.Length    7  
## 3 virginica Sepal.Length    6.3  
## 4 setosa    Sepal.Width     3.5  
## 5 versicolor Sepal.Width     3.2  
## 6 virginica Sepal.Width     3.3  
## 7 setosa    Petal.Length    1.4  
## 8 versicolor Petal.Length    4.7  
## 9 virginica Petal.Length    6  
## 10 setosa    Petal.Width     0.2  
## 11 versicolor Petal.Width     1.4  
## 12 virginica Petal.Width     2.5
```

Now Let's Practice spread and gather

## Subset with `select`

Suppose you want to retain only a few columns.

This can be done with the `select` command from `dplyr`

```
iris %>%  
  select(Sepal.Length, Petal.Width)
```

```
## # A tibble: 150 x 2  
##   Sepal.Length Petal.Width  
##       <dbl>       <dbl>  
## 1         5.1         0.2  
## 2         4.9         0.2  
## 3         4.7         0.2  
## 4         4.6         0.2  
## 5          5         0.2  
## 6         5.4         0.4  
## 7         4.6         0.3  
## 8          5         0.2  
## 9         4.4         0.2  
## 10        4.9         0.1  
## # ... with 140 more rows
```

## Helpers for select

`starts_with("something")` selects those columns that start with a specified string

`contains("something")` selects those columns that have a string *anywhere* in the column name

`ends_with("something")` selects those columns that end with a specified string

`everything()` selects everything else that was not explicitly selected

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`starts_with("something")` selects those columns that start with a specified string

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`ends_with("something")` selects those columns that end with a specified string

`everything()` selects everything else that was not explicitly selected

```
iris %>%  
  select(starts_with("Sepal"))
```

```
## # A tibble: 150 x 2  
##   Sepal.Length Sepal.width  
##         <dbl>      <dbl>  
## 1         5.1        3.5  
## 2         4.9         3  
## 3         4.7        3.2  
## 4         4.6        3.1  
## 5          5         3.6  
## 6         5.4        3.9  
## 7         4.6        3.4  
## 8          5         3.4  
## 9         4.4        2.9  
## 10        4.9        3.1  
## # ... with 140 more rows
```

# unite and separate

**unite** is a function that allows you to join (paste together) two columns

## Syntax

```
unite(data = data, col = "new_column_name", sep = "separator",  
      remove = "T/F if you want to drop the columns", -column_you_dont_want_joined)
```



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**unite** is a function that allows you to join (paste together) two columns

## Syntax

```
unite(data = data, col = "new_column_name", sep = "separator",  
      remove = "T/F if you want to drop the columns", -column_you_dont_want_joined)
```

## Example

```
sample_df
```

```
## # A tibble: 3 x 3  
##   col1  col2 col3  
##   <chr> <dbl> <chr>  
## 1 A      1 X  
## 2 B      2 Y  
## 3 C      3 Z
```

```
sample_df %>%  
  unite(col = "united", sep = "_",  
        remove = FALSE, -col3)
```

```
## # A tibble: 3 x 4  
##   united col1  col2 col3  
##   <chr>  <chr> <dbl> <chr>  
## 1 A_1    A      1 X  
## 2 B_2    B      2 Y  
## 3 C_3    C      3 Z
```

# unite and separate

**separate** is a function that allows you to split a column into multiple columns

## Syntax

```
separate(data = data, col = "what to separate", into = "new columns",  
         sep = " what to separate by", remove = "T/F")
```

# unite and separate

**separate** is a function that allows you to split a column into multiple columns

## Syntax

```
separate(data = data, col = "what to separate", into = "new columns",  
         sep = " what to separate by", remove = "T/F")
```

## Example

```
sample_df
```

```
## # A tibble: 3 x 2  
##   united col3  
##   <chr> <chr>  
## 1 A_1   X  
## 2 B_2   Y  
## 3 C_3   Z
```

```
sample_df %>%  
  separate(col = united, into = c("col1", "col2"),  
          sep = "_", remove = TRUE)
```

```
## # A tibble: 3 x 3  
##   col1 col2 col3  
##   <chr> <chr> <chr>  
## 1 A     1     X  
## 2 B     2     Y  
## 3 C     3     Z
```

Now Let's Practice select, gather and unite

# Using filter

`filter` can be used to filter values to those ones that you would like

## Syntax

```
filter(data = data, condition to test)
```

# Using filter

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## Syntax

```
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```

## Example

```
table(iris[["Species"]])
```

```
##  
##      setosa versicolor  virginica  
##         50          50          50
```

```
iris %>%  
  filter(Species == "setosa") %>%  
  select(Species, contains("Sepal"))
```

```
## # A tibble: 50 x 3  
##   Species Sepal.Length Sepal.Width  
##   <fct>         <dbl>         <dbl>  
## 1 setosa         5.1           3.5  
## 2 setosa         4.9           3  
## 3 setosa         4.7           3.2  
## 4 setosa         4.6           3.1  
## 5 setosa         5           3.6  
## 6 setosa         5.4           3.9  
## 7 setosa         4.6           3.4  
## 8 setosa         5           3.4  
## 9 setosa         4.4           2.9  
## 10 setosa        4.9           3.1  
## # ... with 40 more rows
```

# Logical Operators

- `==` for testing equivalence
- `!=` not equal to
- `>` / `<` greater than or less than
- `>=` / `<=` greater than or less than or equal to
- `&` / `|` and and or allows for combining conditions (e.g. `Species == "Setosa" & Sepal.Length > 5`)

## rename for changing column names

**rename** can be used

### Syntax

```
rename(data = data, new_name = old_name)
```



# rename for changing column names

rename can be used

## Syntax

```
rename(data = data, new_name = old_name)
```

## Example

iris

```
## # A tibble: 150 x 5
##   Sepal.Length Sepal.Width Petal.Length Petal.Width Species
##   <dbl>         <dbl>         <dbl>         <dbl> <f
## 1         5.1         3.5         1.4         0.2 se
## 2         4.9         3         1.4         0.2 se
## 3         4.7         3.2         1.3         0.2 se
## 4         4.6         3.1         1.5         0.2 se
## 5         5         3.6         1.4         0.2 se
## 6         5.4         3.9         1.7         0.4 se
## 7         4.6         3.4         1.4         0.3 se
## 8         5         3.4         1.5         0.2 se
## 9         4.4         2.9         1.4         0.2 se
## 10        4.9         3.1         1.5         0.1 se
## # ... with 140 more rows
```

```
iris %>%
  rename(sepal_length = Sepal.Length) %>%
  select(sepal_length, ends_with("width"))
```

```
## # A tibble: 150 x 3
##   sepal_length Sepal.width Petal.width
##   <dbl>         <dbl>         <dbl>
## 1         5.1         3.5         0.2
## 2         4.9         3         0.2
## 3         4.7         3.2         0.2
## 4         4.6         3.1         0.2
## 5         5         3.6         0.2
## 6         5.4         3.9         0.4
## 7         4.6         3.4         0.3
## 8         5         3.4         0.2
## 9         4.4         2.9         0.2
## 10        4.9         3.1         0.1
## # ... with 140 more rows
```

## mutate to add new columns

**mutate** can be used to create a *derived* or *calculated* column

### Syntax

```
mutate(data = data, new_column = operation you want to do)
```

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## Syntax

```
mutate(data = data, new_column = operation you want to do)
```

## Example

mtcars

```
## # A tibble: 32 x 11
##   mpg   cyl  disp    hp  drat    wt   qsec    vs  a
##   * <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl>
## 1  21       6  160   110  3.9   2.62  16.5    0
## 2  21       6  160   110  3.9   2.88  17.0    0
## 3  22.8     4  108    93  3.85  2.32  18.6    1
## 4  21.4     6  258   110  3.08  3.22  19.4    1
## 5  18.7     8  360   175  3.15  3.44  17.0    0
## 6  18.1     6  225   105  2.76  3.46  20.2    1
## 7  14.3     8  360   245  3.21  3.57  15.8    0
## 8  24.4     4  147.    62  3.69  3.19  20      1
## 9  22.8     4  141.    95  3.92  3.15  22.9    1
## 10 19.2     6  168.   123  3.92  3.44  18.3    1
## # ... with 22 more rows
```

```
mtcars %>%
  mutate(mpg_per_wt = mpg / wt) %>%
  select(mpg, wt, mpg_per_wt)
```

```
## # A tibble: 32 x 3
##   mpg     wt mpg_per_wt
##   <dbl> <dbl>     <dbl>
## 1  21     2.62      8.02
## 2  21     2.88      7.30
## 3  22.8   2.32      9.83
## 4  21.4   3.22      6.66
## 5  18.7   3.44      5.44
## 6  18.1   3.46      5.23
## 7  14.3   3.57      4.01
## 8  24.4   3.19      7.65
## 9  22.8   3.15      7.24
## 10 19.2   3.44      5.58
## # ... with 22 more rows
```

# Group Operations

`group_by` allows for group-wise observations

You can then feed these groups to the `summarise/summarize` function to do group-wise calculations

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You can then feed these groups to the `summarise/summarize` function to do group-wise calculations

```
iris %>%  
  group_by(Species) %>%  
  summarise(mu_length = mean(Sepal.Length),  
            med_width = median(Sepal.Width))
```

```
## # A tibble: 3 x 3  
##   Species    mu_length med_width  
##   <fct>      <dbl>     <dbl>  
## 1 setosa      5.01        3.4  
## 2 versicolor 5.94        2.8  
## 3 virginica   6.59         3
```

## Add more groups with group\_by

```
mtcars %>%  
  group_by(cyl, am) %>%  
  summarise(avg_mpg = mean(mpg),  
            n = n(),  
            min_wt = min(wt),  
            max_wt = max(wt)) %>%  
  mutate(perc_of_group = n/sum(n)) %>%  
  ungroup() %>% # Needed to remove grouping  
  mutate(perc_total = n/sum(n))
```

```
## # A tibble: 6 x 8  
##   cyl    am avg_mpg     n min_wt max_wt perc_of_group perc_total  
##   <dbl> <dbl>   <dbl> <int> <dbl> <dbl>         <dbl>      <dbl>  
## 1     4     0    22.9     3  2.46  3.19         0.273     0.0938  
## 2     4     1    28.1     8  1.51  2.78         0.727     0.25  
## 3     6     0    19.1     4  3.22  3.46         0.571     0.125  
## 4     6     1    20.6     3  2.62  2.88         0.429     0.0938  
## 5     8     0    15.0    12  3.44  5.42         0.857     0.375  
## 6     8     1    15.4     2  3.17  3.57         0.143     0.0625
```

## To Recap

`gather` and `spread` to transform our data between wide and long forms

`select` to subset columns

`filter` to filter data to a specific condition

`unite` and `separate` to combine and separate columns

`rename` to rename our columns

`mutate` to add new derived or calculated columns

`group_by` for group-wise operations

`summarise` for summary functions on grouped variables

Thanks!