



Tidy work in Tidyverse

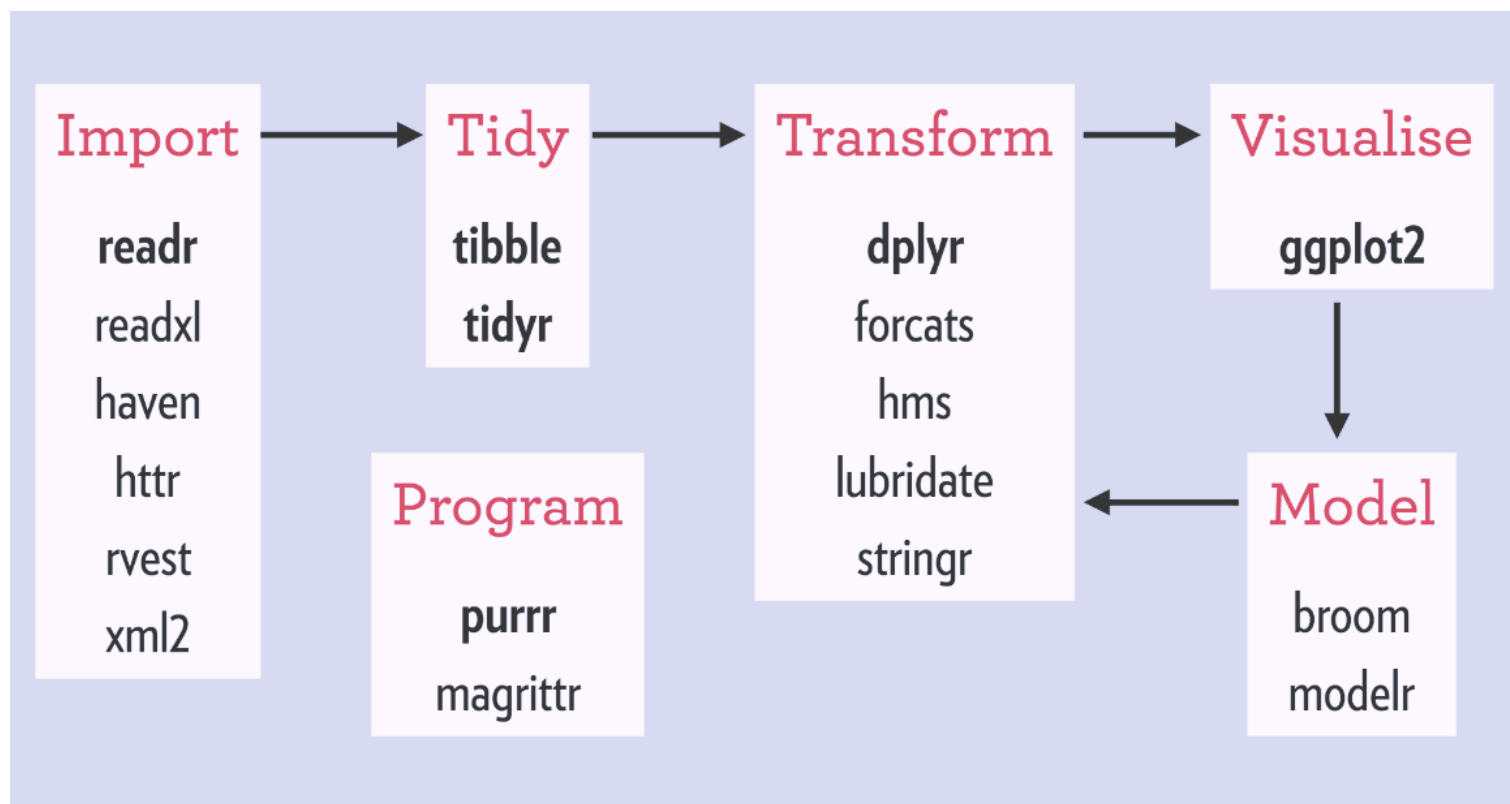
R Foundation for Life Scientists

Marcin Kierczak

Typical Tidyverse Workflow

The tidyverse curse?

Navigating the balance between base R and the tidyverse is a challenge to learn. -Robert A. Muenchen



source: <http://www.storybench.org/getting-started-with-tidyverse-in-r/>

Introduction to Pipes



Rene Magritt, *La trahison des images*, [Wikimedia Commons](#)



- Let the data flow.
- *Ceci n'est pas une pipe* -- `magrittr`
- The `%>%` pipe:
 - `x %>% f` \equiv `f(x)`
 - `x %>% f(y)` \equiv `f(x, y)`
 - `x %>% f %>% g %>% h` \equiv `h(g(f(x)))`

instead of writing this:

```
data <- iris
data <- head(data, n=3)
```

write this:

```
iris %>% head(n=3)
```

```
##   Sepal.Length Sepal.Width Petal.Length P
## 1         5.1         3.5         1.4
## 2         4.9         3.0         1.4
## 3         4.7         3.2         1.3
```

Tibbles



- `tibble` is one of the unifying features of tidyverse,
- it is a *better* `data.frame` realization,
- objects `data.frame` can be coerced to `tibble` using `as_tibble()`

```
head(as_tibble(iris))
```

```
## # A tibble: 6 × 5
##   Sepal.Length Sepal.Width Petal.Length P
##         <dbl>         <dbl>         <dbl>
## 1         5.1         3.5         1.4
## 2         4.9         3         1.4
## 3         4.7         3.2         1.3
## 4         4.6         3.1         1.5
## 5         5         3.6         1.4
## 6         5.4         3.9         1.7
```

```
tibble(
  x = 1,          # recycling
  y = runif(8),
  z = x + y^2,
  outcome = rnorm(8)
)
```

```
## # A tibble: 8 × 4
##       x     y     z outcome
##   <dbl> <dbl> <dbl>   <dbl>
## 1     1 0.590  1.35   2.12
## 2     1 0.367  1.13 -0.484
## 3     1 0.604  1.36 -1.42
## 4     1 0.735  1.54  0.464
## 5     1 0.572  1.33 -1.24
## 6     1 0.522  1.27 -2.73
## 7     1 0.545  1.30 -0.00577
## 8     1 0.815  1.66 -0.494
```

More on Tibbles

- When you print a `tibble`:
 - all columns that fit the screen are shown,
 - first 10 rows are shown,
 - data type for each column is shown.

```
as_tibble(cars) %>% print(n = 5)
```

```
## # A tibble: 50 × 2
##   speed  dist
##   <dbl> <dbl>
## 1     4     2
## 2     4    10
## 3     7     4
## 4     7    22
## 5     8    16
## # i 45 more rows
```

- `my_tibble %>% print(n = 50, width = Inf)`,
- `options(tibble.print_min = 15, tibble.print_max = 25)`,
- `options(dplyr.print_min = Inf)`,
- `options(tibble.width = Inf)`

Subsetting Tibbles

```
vehicles <- as_tibble(cars[1:5,])
```

```
vehicles[['speed']]
```

```
vehicles[[1]]
```

```
vehicles$speed
```

```
# Using placeholders
```

```
vehicles %>% .$dist
```

```
vehicles %>% .[['dist']]
```

```
vehicles %>% .[[2]]
```

```
## [1] 4 4 7 7 8
```

```
## [1] 4 4 7 7 8
```

```
## [1] 4 4 7 7 8
```

```
## [1] 2 10 4 22 16
```

```
## [1] 2 10 4 22 16
```

```
## [1] 2 10 4 22 16
```

Note! Not all old R functions work with tibbles, than you have to use `as.data.frame(my_tibble)`.

Tibbles are Stricter than `data.frames`



```
cars <- cars[1:5,]
```

```
cars$spe      # partial matching
```

```
## [1] 4 4 7 7 8
```

```
vehicles$spe  # no partial matching
```

```
## Warning: Unknown or uninitialised column: `spe`.
```

```
## NULL
```

```
cars$gear
```

```
## NULL
```

```
vehicles$gear
```

```
## Warning: Unknown or uninitialised column: `gear`.
```

```
## NULL
```

Loading Data

In `tidyverse` you import data using `readr` package that provides a number of useful data import functions:

- `read_delim()` a generic function for reading *-delimited files. There are a number of convenience wrappers:
 - `read_csv()` used to read comma-delimited files,
 - `read_csv2()` reads semicolon-delimited files, `read_tsv()` that reads tab-delimited files.
- `read_fwf` for reading fixed-width files with its wrappers:
 - `fwf_widths()` for width-based reading,
 - `fwf_positions()` for positions-based reading and
 - `read_table()` for reading white space-delimited fixed-width files.
- `read_log()` for reading Apache-style logs. The most commonly used `read_csv()` has some familiar arguments like:
- `skip` -- to specify the number of rows to skip (headers),
- `col_names` -- to supply a vector of column names,
- `comment` -- to specify what character designates a comment,
- `na` -- to specify how missing values are represented.

Importing Data Using `readr`



When reading and parsing a file, `readr` attempts to guess proper parser for each column by looking at the 1000 first rows.

```
tricky_dataset <- read_csv(readr_example('challenge.csv'))
```

```
## Rows: 2000 Columns: 2
## — Column specification —————
## Delimiter: ","
## dbl (1): x
## date (1): y
##
## i Use `spec()` to retrieve the full column specification for this data.
## i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

OK, so there are some parsing failures. We can examine them more closely using `problems()` as suggested in the above output.

Looking at Problematic Columns

```
(p <- problems(tricky_dataset))
```

```
## # A tibble: 0 × 5  
## #   5 variables: row <int>, col <int>, expected <chr>, actual <chr>, file <chr>
```

OK, let's see which columns cause trouble:

```
p %>% table(col)
```

```
## < table of extent 0 >
```

Looks like the problem occurs only in the  column.

Fixing Problematic Columns

So, how can we fix the problematic columns?

1. We can explicitly tell what parser to use:

```
tricky_dataset <- read_csv(readr_example('challenge.csv'),  
                           col_types = cols(x = col_double(),  
                                             y = col_character()))  
tricky_dataset %>% tail(n = 5)
```

```
## # A tibble: 5 × 2  
##       x y  
##   <dbl> <chr>  
## 1 0.164 2018-03-29  
## 2 0.472 2014-08-04  
## 3 0.718 2015-08-16  
## 4 0.270 2020-02-04  
## 5 0.608 2019-01-06
```

As you can see, we can still do better by parsing the `y` column as *date*, not as *character*.

Fixing Problematic Columns cted.



But knowing that the parser is guessed based on the first 1000 lines, we can see what sits past the 1000-th line in the data:

```
tricky_dataset %>% head(n = 1002) %>% tail(n = 4)
```

```
## # A tibble: 4 × 2
##       x y
##   <dbl> <chr>
## 1 4569   <NA>
## 2 4548   <NA>
## 3   0.238 2015-01-16
## 4   0.412 2018-05-18
```

It seems, we were very unlucky, because up till 1000-th line there are only integers in the x column and **NA**s in the y column so the parser cannot be guessed correctly. To fix this:

```
tricky_dataset <- read_csv(readr_example('challenge.csv'),
                           guess_max = 1001)
```

```
## Rows: 2000 Columns: 2
## — Column specification —————
## Delimiter: ","
## dbl (1): x
## date (1): y
##
## i Use `spec()` to retrieve the full column specification for this data.
## i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

Writing to a File

The `readr` package also provides functions useful for writing tibbled data into a file:

- `write_csv()`
- `write_tsv()`
- `write_excel_csv()`

They **always** save:

- text in UTF-8,
- dates in ISO8601

But saving in csv (or tsv) does mean you lose information about the type of data in particular columns. You can avoid this by using:

- `write_rds()` and `read_rds()` to read/write objects in R binary rds format,
- use `write_feather()` and `read_feather()` from package `feather` to read/write objects in a fast binary format that other programming languages can access.

Basic Data Transformations with **dplyr**

Let us create a tibble:

```
(bijou <- as_tibble(diamonds) %>% head(n = 10))
```

```
## # A tibble: 10 × 10
```

```
##   carat cut      color clarity depth table price      x      y      z
##   <dbl> <ord>    <ord> <ord>    <dbl> <dbl> <int> <dbl> <dbl> <dbl>
## 1  0.23 Ideal    E     SI2     61.5   55   326   3.95   3.98   2.43
## 2  0.21 Premium E     SI1     59.8   61   326   3.89   3.84   2.31
## 3  0.23 Good    E     VS1     56.9   65   327   4.05   4.07   2.31
## 4  0.29 Premium I     VS2     62.4   58   334   4.2    4.23   2.63
## 5  0.31 Good    J     SI2     63.3   58   335   4.34   4.35   2.75
## 6  0.24 Very Good J     VVS2    62.8   57   336   3.94   3.96   2.48
## 7  0.24 Very Good I     VVS1    62.3   57   336   3.95   3.98   2.47
## 8  0.26 Very Good H     SI1     61.9   55   337   4.07   4.11   2.53
## 9  0.22 Fair    E     VS2     65.1   61   337   3.87   3.78   2.49
## 10 0.23 Very Good H     VS1     59.4   61   338   4      4.05   2.39
```



Picking Observations using `filter()`

```
bijou %>% filter(cut == 'Ideal' | cut == 'Premium', carat >= 0.23) %>% head(n = 5)
```

```
## # A tibble: 2 × 10
##   carat cut      color clarity depth table price      x      y      z
##   <dbl> <ord>    <ord> <ord>    <dbl> <dbl> <int> <dbl> <dbl> <dbl>
## 1  0.23 Ideal    E      SI2      61.5   55   326  3.95  3.98  2.43
## 2  0.29 Premium I      VS2      62.4   58   334  4.2   4.23  2.63
```

Be careful with floating point comparisons! Also, rows with comparison resulting in `NA` are skipped by default!

```
bijou %>% filter(near(0.23, carat) | is.na(carat)) %>% head(n = 5)
```

```
## # A tibble: 3 × 10
##   carat cut      color clarity depth table price      x      y      z
##   <dbl> <ord>    <ord> <ord>    <dbl> <dbl> <int> <dbl> <dbl> <dbl>
## 1  0.23 Ideal    E      SI2      61.5   55   326  3.95  3.98  2.43
## 2  0.23 Good      E      VS1      56.9   65   327  4.05  4.07  2.31
## 3  0.23 Very Good H      VS1      59.4   61   338  4     4.05  2.39
```

Rearranging Observations using `arrange()`

```
bijou %>% arrange(cut, carat, desc(price))
```

```
## # A tibble: 10 × 10
##   carat cut      color clarity depth table price      x      y      z
##   <dbl> <ord>    <ord> <ord>    <dbl> <dbl> <int> <dbl> <dbl> <dbl>
## 1  0.22 Fair      E      VS2     65.1   61   337   3.87   3.78   2.49
## 2  0.23 Good      E      VS1     56.9   65   327   4.05   4.07   2.31
## 3  0.31 Good      J      SI2     63.3   58   335   4.34   4.35   2.75
## 4  0.23 Very Good H      VS1     59.4   61   338   4      4.05   2.39
## 5  0.24 Very Good J      VVS2    62.8   57   336   3.94   3.96   2.48
## 6  0.24 Very Good I      VVS1    62.3   57   336   3.95   3.98   2.47
## 7  0.26 Very Good H      SI1     61.9   55   337   4.07   4.11   2.53
## 8  0.21 Premium  E      SI1     59.8   61   326   3.89   3.84   2.31
## 9  0.29 Premium  I      VS2     62.4   58   334   4.2    4.23   2.63
## 10 0.23 Ideal     E      SI2     61.5   55   326   3.95   3.98   2.43
```

The `NA`s always end up at the end of the rearranged tibble.

Selecting Variables with `select()`

Simple `select` with a range:

```
bijou %>% select(color, clarity, x:z) %>% head(n = 4)
```

```
## # A tibble: 4 × 5
##   color clarity      x      y      z
##   <ord> <ord>    <dbl> <dbl> <dbl>
## 1 E     SI2      3.95  3.98  2.43
## 2 E     SI1      3.89  3.84  2.31
## 3 E     VS1      4.05  4.07  2.31
## 4 I     VS2      4.2   4.23  2.63
```

Exclusive `select`:

```
bijou %>% select(-(x:z)) %>% head(n = 4)
```

```
## # A tibble: 4 × 7
##   carat cut      color clarity depth table price
##   <dbl> <ord>    <ord> <ord>    <dbl> <dbl> <int>
## 1 0.23 Ideal  E     SI2      61.5    55    326
## 2 0.21 Premium E     SI1      59.8    61    326
## 3 0.23 Good   E     VS1      56.9    65    327
## 4 0.29 Premium I     VS2      62.4    58    334
```

Selecting Variables with `select()` cted.

`rename` is a variant of `select`, here used with `everything()` to move `x` to the beginning and rename it to `var_x`

```
bijou %>% rename(var_x = x) %>% head(n = 5)
```

```
## # A tibble: 5 × 10
##   carat cut      color clarity depth table price var_x      y      z
##   <dbl> <ord>   <ord> <ord>   <dbl> <dbl> <int> <dbl> <dbl> <dbl>
## 1  0.23 Ideal    E     SI2     61.5   55   326  3.95  3.98  2.43
## 2  0.21 Premium E     SI1     59.8   61   326  3.89  3.84  2.31
## 3  0.23 Good     E     VS1     56.9   65   327  4.05  4.07  2.31
## 4  0.29 Premium I     VS2     62.4   58   334  4.2   4.23  2.63
## 5  0.31 Good     J     SI2     63.3   58   335  4.34  4.35  2.75
```

use `everything()` to bring some columns to the front:

```
bijou %>% select(x:z, everything()) %>% head(n = 4)
```

```
## # A tibble: 4 × 10
##       x      y      z carat cut      color clarity depth table price
##   <dbl> <dbl> <dbl> <dbl> <ord>   <ord> <ord>   <dbl> <dbl> <int>
## 1  3.95  3.98  2.43  0.23 Ideal    E     SI2     61.5   55   326
## 2  3.89  3.84  2.31  0.21 Premium E     SI1     59.8   61   326
## 3  4.05  4.07  2.31  0.23 Good     E     VS1     56.9   65   327
## 4  4.2   4.23  2.63  0.29 Premium I     VS2     62.4   58   334
```

Create/alter new Variables with `mutate`

```
bijou %>% mutate(p = x + z, q = p + y) %>% select(-(depth:price)) %>% head(n = 5)
```

```
## # A tibble: 5 × 9
##   carat cut      color clarity      x      y      z      p      q
##   <dbl> <ord>    <ord> <ord>    <dbl> <dbl> <dbl> <dbl> <dbl>
## 1  0.23 Ideal    E      SI2      3.95  3.98  2.43  6.38  10.4
## 2  0.21 Premium E      SI1      3.89  3.84  2.31  6.2   10.0
## 3  0.23 Good     E      VS1      4.05  4.07  2.31  6.36  10.4
## 4  0.29 Premium I      VS2      4.2   4.23  2.63  6.83  11.1
## 5  0.31 Good     J      SI2      4.34  4.35  2.75  7.09  11.4
```

or with `transmute` (only the transformed variables will be retained)

```
bijou %>% transmute(carat, cut, sum = x + y + z) %>% head(n = 5)
```

```
## # A tibble: 5 × 3
##   carat cut      sum
##   <dbl> <ord>    <dbl>
## 1  0.23 Ideal    10.4
## 2  0.21 Premium 10.0
## 3  0.23 Good     10.4
## 4  0.29 Premium 11.1
## 5  0.31 Good     11.4
```

Group and Summarize

```
bijou %>% group_by(cut) %>% summarize(max_price = max(price),  
                                     mean_price = mean(price),  
                                     min_price = min(price))
```

```
## # A tibble: 5 × 4  
##   cut      max_price mean_price min_price  
##   <ord>      <int>      <dbl>      <int>  
## 1 Fair      337        337        337  
## 2 Good      335        331        327  
## 3 Very Good 338        337.        336  
## 4 Premium   334        330        326  
## 5 Ideal     326        326        326
```

```
bijou %>% group_by(cut, color) %>%  
  summarize(max_price = max(price),  
            mean_price = mean(price),  
            min_price = min(price)) %>% head(n = 4)
```

```
## # A tibble: 4 × 5  
## # Groups:   cut [3]  
##   cut      color max_price mean_price min_price  
##   <ord>      <ord>      <int>      <dbl>      <int>  
## 1 Fair      E      337        337        337  
## 2 Good      E      327        327        327  
## 3 Good      J      335        335        335  
## 4 Very Good H      338        338.        337
```

Other data manipulation tips

```
bijou %>% group_by(cut) %>% summarize(count = n())
```

```
## # A tibble: 5 × 2
##   cut      count
##   <ord>    <int>
## 1 Fair         1
## 2 Good         2
## 3 Very Good    4
## 4 Premium      2
## 5 Ideal        1
```

When you need to regroup within the same pipe, use `ungroup()`.

The Concept of Tidy Data

Data are tidy *sensu Wickham* if:

- each and every observation is represented as exactly one row,
- each and every variable is represented by exactly one column,
- thus each data table cell contains only one value.

country	year	cases	population
Afghanistan	1999	7745	19987071
Afghanistan	2000	8666	20595360
Brazil	1999	37737	172006362
Brazil	2000	80488	174004898
China	1999	214258	1272915272
China	2000	216766	1280425583

variables

country	year	cases	population
Afghanistan	1999	7745	19987071
Afghanistan	2000	8666	20595360
Brazil	1999	37737	172006362
Brazil	2000	80488	174004898
China	1999	214258	1272915272
China	2000	216766	1280425583

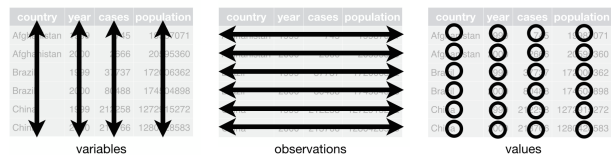
observations

country	year	cases	population
Afghanistan	99	745	19987071
Afghanistan	00	866	20595360
Brazil	99	37737	172006362
Brazil	00	80488	174004898
China	99	214258	1272915272
China	00	216766	1280425583

values

Usually data are untidy in only one way. However, if you are unlucky, they are really untidy and thus a pain to work with...

Tidy Data



Are these data tidy?

Sepal.Length	Sepal.Width	Petal.Length	Petal.Width	Species	Species	variable	value
5.1	3.5	1.4	0.2	setosa	setosa	Sepal.Length	5.1
4.9	3.0	1.4	0.2	setosa	setosa	Sepal.Length	4.9
4.7	3.2	1.3	0.2	setosa	setosa	Sepal.Length	4.7

Sepal.L.W	Petal.L.W	Species	Sepal.Length	5.1	4.9	4.7	4.6
5.1/3.5	1.4/0.2	setosa	Sepal.Width	3.5	3.0	3.2	3.1
4.9/3	1.4/0.2	setosa	Petal.Length	1.4	1.4	1.3	1.5
4.7/3.2	1.3/0.2	setosa	Petal.Width	0.2	0.2	0.2	0.2
			Species	setosa	setosa	setosa	setosa

Tidying Data with `tidyr::pivot_longer`

If some of your column names are actually values of a variable, use `pivot_longer` (replaces `gather`):

```
bijou2 %>% head(n = 5)
```

```
## # A tibble: 5 × 3
##   cut      `2008` `2009`
##   <ord>    <int> <dbl>
## 1 Ideal      326   329.
## 2 Premium    326   329.
## 3 Good       327   330.
## 4 Premium    334   337.
## 5 Good       335   338.
```

```
bijou2 %>%
  pivot_longer(c(`2008`, `2009`), names_to = 'year', values_to = 'price') %>%
  head(n = 5)
```

```
## # A tibble: 5 × 3
##   cut      year price
##   <ord>    <chr> <dbl>
## 1 Ideal   2008   326
## 2 Ideal   2009   329.
## 3 Premium 2008   326
## 4 Premium 2009   329.
## 5 Good    2008   327
```


Tidying Data with `tidyr::pivot_wider`

If some of your observations are scattered across many rows, use `pivot_wider` (replaces `gather`):

```
bijou3
```

```
## # A tibble: 9 × 5
##   cut      price clarity dimension measurement
##   <ord>    <int> <ord>    <chr>          <dbl>
## 1 Ideal      326 SI2     x             3.95
## 2 Premium    326 SI1     x             3.89
## 3 Good       327 VS1     x             4.05
## 4 Ideal      326 SI2     y             3.98
## 5 Premium    326 SI1     y             3.84
## 6 Good       327 VS1     y             4.07
## 7 Ideal      326 SI2     z             2.43
## 8 Premium    326 SI1     z             2.31
## 9 Good       327 VS1     z             2.31
```

```
bijou3 %>%
  pivot_wider(names_from=dimension, values_from=measurement) %>%
  head(n = 4)
```

```
## # A tibble: 3 × 6
##   cut      price clarity      x      y      z
##   <ord>    <int> <ord>    <dbl> <dbl> <dbl>
## 1 Ideal      326 SI2     3.95  3.98  2.43
## 2 Premium    326 SI1     3.89  3.84  2.31
## 3 Good       327 VS1     4.05  4.07  2.31
```

Tidying Data with `separate`

If some of your columns contain more than one value, use `separate`:

```
bijou4
```

```
## # A tibble: 5 × 4
##   cut      price clarity dim
##   <ord>   <int> <ord>   <chr>
## 1 Ideal     326 SI2    3.95/3.98/2.43
## 2 Premium  326 SI1    3.89/3.84/2.31
## 3 Good     327 VS1    4.05/4.07/2.31
## 4 Premium  334 VS2    4.2/4.23/2.63
## 5 Good     335 SI2    4.34/4.35/2.75
```

```
bijou4 %>%
  separate(dim, into = c("x", "y", "z"), sep = "/", convert = T)
```

```
## # A tibble: 5 × 6
##   cut      price clarity      x      y      z
##   <ord>   <int> <ord>   <dbl> <dbl> <dbl>
## 1 Ideal     326 SI2    3.95  3.98  2.43
## 2 Premium  326 SI1    3.89  3.84  2.31
## 3 Good     327 VS1    4.05  4.07  2.31
## 4 Premium  334 VS2    4.2   4.23  2.63
## 5 Good     335 SI2    4.34  4.35  2.75
```

Tidying Data with `unite`

If some of your columns contain more than one value, use `separate`:

```
bijou5
```

```
## # A tibble: 5 × 7
##   cut      price clarity_prefix clarity_suffix      x      y      z
##   <ord>    <int> <chr>          <chr>          <dbl> <dbl> <dbl>
## 1 Ideal      326 SI          2          3.95  3.98  2.43
## 2 Premium    326 SI          1          3.89  3.84  2.31
## 3 Good       327 VS          1          4.05  4.07  2.31
## 4 Premium    334 VS          2          4.2   4.23  2.63
## 5 Good       335 SI          2          4.34  4.35  2.75
```

```
bijou5 %>% unite(clarity, clarity_prefix, clarity_suffix, sep='')
```

```
## # A tibble: 5 × 6
##   cut      price clarity      x      y      z
##   <ord>    <int> <chr>    <dbl> <dbl> <dbl>
## 1 Ideal      326 SI2      3.95  3.98  2.43
## 2 Premium    326 SI1      3.89  3.84  2.31
## 3 Good       327 VS1      4.05  4.07  2.31
## 4 Premium    334 VS2      4.2   4.23  2.63
## 5 Good       335 SI2      4.34  4.35  2.75
```

Note: that `sep` is here interpreted as the position to split on. It can also be a *regular expression* or a delimiting string/character. Pretty flexible approach!

Completing Missing Values Using `complete`

```
bijou %>% head(n = 10) %>%  
  select(cut, clarity, price) %>%  
  mutate(continent = sample(c('AusOce', 'Eur'),  
                             size = 10,  
                             replace = T)) -> missing_stones
```

```
missing_stones %>% complete(cut, continent)
```

```
## # A tibble: 13 × 4  
##   cut      continent clarity price  
##   <ord>    <chr>      <ord>  <int>  
## 1 Fair     AusOce     <NA>    NA  
## 2 Fair     Eur        VS2     337  
## 3 Good     AusOce     <NA>    NA  
## 4 Good     Eur        VS1     327  
## 5 Good     Eur        SI2     335  
## 6 Very Good AusOce     VVS1    336  
## 7 Very Good AusOce     SI1     337  
## 8 Very Good Eur        VVS2    336  
## 9 Very Good Eur        VS1     338  
## 10 Premium AusOce     VS2     334  
## 11 Premium Eur        SI1     326  
## 12 Ideal   AusOce     <NA>    NA  
## 13 Ideal   Eur        SI2     326
```

Some Other Friends



- `stringr` for string manipulation and regular expressions,
- `forcats` for working with factors,
- `lubridate` for working with dates.

Thank you. Questions?

Graphics from  freepik.com

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