Introduction to the tidyverse: transformation with strings, dates, factors

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Work with strings: `stringr`

Goals

- Introduce you to how `stringr` works
- Set you up to get more out of it by learning regular expressions

```
library(tidyverse)
```

```
## Warning: package 'tibble' was built under R version 3.4.3
```

```
## Warning: package 'tidyr' was built under R version 3.4.3
```

```
## Warning: package 'stringr' was built under R version 3.4.3
```

```
library(stringr)
```

String basics

You can create strings with either single quotes or double quotes. Unlike other languages, there is no difference in behaviour. I recommend always using ", unless you want to create a string that contains multiple ".

```
string1 <- "This is a string"
string2 <- 'If I want to include a "quote" inside a string, I use single
```

String basics

If you forget to close a quote, you'll see +, the continuation character:

```
> "This is a string without a closing quote
+
+
+ HELP I'M STUCK
```

If this happen to you, press Escape and try again!

String basics

To include a literal single or double quote in a string you can use \ to “escape” it:

```
double_quote <- "\"" # or '"'
single_quote <- '\'' # or "'"
```

That means if you want to include a literal backslash, you’ll need to double it up: `"\\"`.

String basics

Beware that the printed representation of a string is not the same as string itself, because the printed representation shows the escapes. To see the raw contents of the string, use `writeLines()`:

```
x <- c("\"", "\\")
x
```

```
## [1] "\"" "\\"
```

```
writeLines(x)
```

```
## "
## \
```

String basics

There are a handful of other special characters. The most common are `"\n"`, newline, and `"\t"`, tab, but you can see the complete list by requesting help on `"`: `?'"'`, or `?"'"`. You'll also sometimes see strings like `"\u00b5"`, this is a way of writing non-English characters that works on all platforms:

```
x <- "\u00b5"
x
```

```
## [1] "µ"
```

String basics

Multiple strings are often stored in a character vector, which you can create with `c()`:

```
c("one", "two", "three")
```

```
## [1] "one"   "two"   "three"
```

String length

Base R contains many functions to work with strings but we'll avoid them because they can be inconsistent, which makes them hard to remember. Instead we'll use functions from stringr. These have more intuitive names, and all start with `str_`. For example, `str_length()` tells you the number of characters in a string:

```
str_length(c("a", "R for data science", NA))
```

```
## [1]  1 18 NA
```

Combining strings

To combine two or more strings, use `str_c()`:

```
str_c("x", "y")
```

```
## [1] "xy"
```

```
str_c("x", "y", "z")
```

```
## [1] "xyz"
```

Combining strings

Use the `sep` argument to control how they're separated:

```
str_c("x", "y", sep = ", ")
```

```
## [1] "x, y"
```

Combining strings

Like most other functions in R, missing values are contagious. If you want them to print as `"NA"`, use `str_replace_na()`:

```
x <- c("abc", NA)
str_c("|-", x, "-|")
```

```
## [1] "|-abc-|" NA
```

```
str_c("|-", str_replace_na(x), "-|")
```

```
## [1] "|-abc-|" "|-NA-|"
```

Combining strings

Objects of length 0 are silently dropped. This is particularly useful in conjunction with `if`:

```
name <- "Hadley"
time_of_day <- "morning"
birthday <- FALSE

str_c(
  "Good ", time_of_day, " ", name,
  if (birthday) " and HAPPY BIRTHDAY",
  "."
)
```

```
## [1] "Good morning Hadley."
```

Combining strings

To collapse a vector of strings into a single string, use `collapse`:

```
str_c(c("x", "y", "z"), collapse = ", ")
```

```
## [1] "x, y, z"
```

Subsetting strings

You can extract parts of a string using `str_sub()`. As well as the string, `str_sub()` takes `start` and `end` arguments which give the (inclusive) position of the substring:

```
x <- c("Apple", "Banana", "Pear")
str_sub(x, 1, 3)
```

```
## [1] "App" "Ban" "Pea"
```

```
# negative numbers count backwards from end
str_sub(x, -3, -1)
```

```
## [1] "ple" "ana" "ear"
```

Combining strings

Note that `str_sub()` won't fail if the string is too short: it will just return as much as possible:

```
str_sub("a", 1, 5)
```

```
## [1] "a"
```

You can also use the assignment form of `str_sub()` to modify strings:

```
str_sub(x, 1, 1) <- str_to_lower(str_sub(x, 1, 1))
x
```

```
## [1] "apple"  "banana" "pear"
```

Locales

If you work outside of US English a lot, check out the book's section on setting locales.

Exercise

1. Write a function that turns (e.g.) a vector `c("a", "b", "c")` into the string `a, b, and c`. Think carefully about what it should do if given a vector of length 0, 1, or 2.

Matching patterns with regular expressions

- Regexps are a very terse language that allow you to describe patterns in strings.
- Learning them will take more time than we have today
- Study up on your own; they take a little while to get your head around, but once you understand them, you'll find them extremely useful.

Detect matches

To determine if a character vector matches a pattern, use `str_detect()`. It returns a logical vector the same length as the input:

```
x <- c("apple", "banana", "pear")
str_detect(x, "e")
```

```
## [1]  TRUE FALSE  TRUE
```

Detect matches

Remember that when you use a logical vector in a numeric context, `FALSE` becomes 0 and `TRUE` becomes 1. That makes `sum()` and `mean()` useful if you want to answer questions about matches across a larger vector:

```
# How many common words start with t?
sum(str_detect(words, "^t"))
```

```
## [1] 65
```

```
# What proportion of common words end with a vowel?
mean(str_detect(words, "[aeiou]$"))
```

```
## [1] 0.2765306
```

Detect matches

When you have complex logical conditions (e.g. match a or b but not c unless d) it's often easier to combine multiple `str_detect()` calls with logical operators, rather than trying to create a single regular expression. For example, here are two ways to find all words that don't contain any vowels:

```
# Find all words containing at least one vowel, and negate
no_vowels_1 <- !str_detect(words, "[aeiou]")
# Find all words consisting only of consonants (non-vowels)
no_vowels_2 <- str_detect(words, "^[^aeiou]+$")
identical(no_vowels_1, no_vowels_2)
```

```
## [1] TRUE
```

Detect matches

A common use of `str_detect()` is to select the elements that match a pattern. You can do this with logical subsetting, or the convenient `str_subset()` wrapper:

```
words[str_detect(words, "x$")]
```

```
## [1] "box" "sex" "six" "tax"
```

```
str_subset(words, "x$")
```

```
## [1] "box" "sex" "six" "tax"
```

Detect matches

Typically, however, your strings will be one column of a data frame, and you'll want to use filter instead:

```
df <- tibble(
  word = words,
  i = seq_along(word)
)
df %>%
  filter(str_detect(words, "x$"))
```

```
## Warning: package 'bindrcpp' was built under R version 3.4.4
```

```
## # A tibble: 4 x 2
##   word      i
##   <chr> <int>
## 1 box     108
## 2 sex     747
## 3 six     772
## 4 tax     841
```

Replacing matches

`str_replace()` and `str_replace_all()` allow you to replace matches with new strings. The simplest use is to replace a pattern with a fixed string:

```
x <- c("apple", "pear", "banana")
str_replace(x, "[aeiou]", "-")
```

```
## [1] "-pple"  "p-ar"   "b-nana"
```

```
str_replace_all(x, "[aeiou]", "-")
```

```
## [1] "-ppl-"  "p--r"   "b-n-n-"
```

Replacing matches

With `str_replace_all()` you can perform multiple replacements by supplying a named vector:

```r
x <- c("1 house", "2 cars", "3 people")
str_replace_all(x, c("1" = "one", "2" = "two", "3" = "three"))
```

```
## [1] "one house"    "two cars"     "three people"
```

Replacing matches

Instead of replacing with a fixed string you can use backreferences to insert components of the match. In the following code, I flip the order of the second and third words.

```
sentences %>%
  str_replace("([^ ]+) ([^ ]+) ([^ ]+)", "\\1 \\3 \\2") %>%
  head(5)
```

```
## [1] "The canoe birch slid on the smooth planks."
## [2] "Glue sheet the to the dark blue background."
## [3] "It's to easy tell the depth of a well."
## [4] "These a days chicken leg is a rare dish."
## [5] "Rice often is served in round bowls."
```

Splitting

Use `str_split()` to split a string up into pieces. For example, we could split sentences into words:

```
sentences %>%
  head(5) %>%
  str_split(" ")
```

```
## [[1]]
## [1] "The"     "birch"   "canoe"   "slid"    "on"      "the"     "smoot
## [8] "planks."
##
## [[2]]
## [1] "Glue"        "the"         "sheet"       "to"          "the"
## [6] "dark"        "blue"        "background."
##
## [[3]]
## [1] "It's"  "easy"  "to"    "tell"  "the"   "depth" "of"    "a"     "v
##
## [[4]]
## [1] "These"   "days"    "a"       "chicken" "leg"     "is"      "a"
## [8] "rare"    "dish."
##
## [[5]]
## [1] "Rice"   "is"     "often"  "served" "in"     "round"  "bowls."
```

Splitting

Because each component might contain a different number of pieces, this returns a list. If you're working with a length-1 vector, the easiest thing is to just extract the first element of the list:

```
"a|b|c|d" %>%
  str_split("\\|") %>%
  .[[1]]
```

```
## [1] "a" "b" "c" "d"
```

Splitting

Otherwise, like the other stringr functions that return a list, you can use `simplify = TRUE` to return a matrix:

```
sentences %>%
  head(5) %>%
  str_split(" ", simplify = TRUE)
```

```
##      [,1]    [,2]    [,3]    [,4]      [,5]  [,6]    [,7]
## [1,] "The"   "birch" "canoe" "slid"    "on"  "the"   "smooth"
## [2,] "Glue"  "the"   "sheet" "to"      "the" "dark"  "blue"
## [3,] "It's"  "easy"  "to"    "tell"    "the" "depth" "of"
## [4,] "These" "days"  "a"     "chicken" "leg" "is"    "a"
## [5,] "Rice"  "is"    "often" "served"  "in"  "round" "bowls."
##      [,8]          [,9]
## [1,] "planks."     ""
## [2,] "background." ""
## [3,] "a"           "well."
## [4,] "rare"        "dish."
## [5,] ""            ""
```

Splitting

You can also request a maximum number of pieces:

```
fields <- c("Name: Hadley", "Country: NZ", "Age: 35")
fields %>% str_split(": ", n = 2, simplify = TRUE)
```

```
##      [,1]      [,2]
## [1,] "Name"    "Hadley"
## [2,] "Country" "NZ"
## [3,] "Age"     "35"
```

Splitting

Instead of splitting up strings by patterns, you can also split up by character, line, sentence and word `boundary()`s:

```
x <- "This is a sentence.  This is another sentence."
str_view_all(x, boundary("word"))
```

```
This is a sentence.  This is another
sentence.
```

```
str_split(x, " ")[[1]]
```

```
## [1] "This"      "is"        "a"         "sentence." ""          "This'
## [7] "is"        "another"   "sentence."
```

```
str_split(x, boundary("word"))[[1]]
```

```
## [1] "This"      "is"        "a"         "sentence" "This"      "is"
## [7] "another"   "sentence"
```

Exercises

1. Split up a string like `"apples, pears, and bananas"` into individual components.

Find matches

`str_locate()` and `str_locate_all()` give you the starting and ending positions of each match. These are particularly useful when none of the other functions does exactly what you want. You can use `str_locate()` to find the matching pattern, `str_sub()` to extract and/or modify them.

Other types of patterns

When you use a pattern that's a string, it's automatically wrapped into a call to `regex()`:

```
# The regular call:
str_view(fruit, "nana")
# Is shorthand for
str_view(fruit, regex("nana"))
```

Other uses of regular expressions

There are two useful function in base R that also use regular expressions:

- `apropos()` searches all objects available from the global environment. This is useful if you can't quite remember the name of the function.

```r
apropos("replace")
```

```
## [1] "%+replace%"        "replace"           "replace_na"
## [4] "setReplaceMethod" "str_replace"       "str_replace_all"
## [7] "str_replace_na"    "theme_replace"
```

Other uses of regular expressions

- `dir()` lists all the files in a directory. The `pattern` argument takes a regular expression and only returns file names that match the pattern. For example, you can find all the R Markdown files in the current directory with:

```
head(dir(pattern = "\\.Rmd$"))
```

```
## [1] "part1_intro.Rmd"                   "part2_dplyr.Rmd"
## [3] "part3_tidyr.Rmd"                   "part4_strings_dates_factors.
## [5] "part5_data_analysis.Rmd"           "part6_ggplot_intro.Rmd"
```

Dates and times

The key tidyverse tool is the **lubridate** package. Must be loaded separately. We will also need nycflights13 for practice data.

```
library(tidyverse)

library(lubridate)
library(nycflights13)
```

```
## Warning: package 'nycflights13' was built under R version 3.4.4
```

Creating date/times

There are three types of date/time data that refer to an instant in time:

- A **date**. Tibbles print this as `<date>`.
- A **time** within a day. Tibbles print this as `<time>`.
- A **date-time** is a date plus a time: it uniquely identifies an instant in time (typically to the nearest second). Tibbles print this as `<dttm>`. Elsewhere in R these are called POSIXct, but I don’t think that’s a very useful name.

Today

To get the current date or date-time you can use `today()` or `now()`:

```
today()
```

```
## [1] "2018-07-18"
```

```
now()
```

```
## [1] "2018-07-18 04:15:04 GMT"
```

Datetimes from strings

Use the helpers provided by lubridate. They automatically work out the format once you specify the order of the component. To use them, identify the order in which year, month, and day appear in your dates, then arrange “y”, “m”, and “d” in the same order.

```
ymd("2017-01-31")
```

```
## [1] "2017-01-31"
```

```
mdy("January 31st, 2017")
```

```
## [1] "2017-01-31"
```

```
dmy("31-Jan-2017")
```

```
## [1] "2017-01-31"
```

```
## [1] "2017-01-31"
```

Can also pass an unquoted number

These functions also take unquoted numbers. This is the most concise way to create a single date/time object, as you might need when filtering date/time data. `ymd()` is short and unambiguous:

```
ymd(20170131)
```

```
## [1] "2017-01-31"
```

Create date-times, not just dates

`ymd()` and friends create dates. To create a date-time, add an underscore and one or more of “h”, “m”, and “s” to the name of the parsing function:

```
ymd_hms("2017-01-31 20:11:59")
```

```
## [1] "2017-01-31 20:11:59 UTC"
```

```
mdy_hm("01/31/2017 08:01")
```

```
## [1] "2017-01-31 08:01:00 UTC"
```

From individual components

Instead of a single string, sometimes you'll have the individual components of the date-time spread across multiple columns. This is what we have in the flights data:

```
flights %>%
  select(year, month, day, hour, minute)
```

```
## # A tibble: 336,776 x 5
##     year month   day  hour minute
##    <int> <int> <int> <dbl>  <dbl>
##  1  2013     1     1    5.    15.
##  2  2013     1     1    5.    29.
##  3  2013     1     1    5.    40.
##  4  2013     1     1    5.    45.
##  5  2013     1     1    6.     0.
##  6  2013     1     1    5.    58.
##  7  2013     1     1    6.     0.
##  8  2013     1     1    6.     0.
##  9  2013     1     1    6.     0.
## 10  2013     1     1    6.     0.
## # ... with 336,766 more rows
```

From individual components

To create a date/time from this sort of input, use `make_date()` for dates, or `make_datetime()` for date-times:

```
flights %>%
  select(year, month, day, hour, minute) %>%
  mutate(departure = make_datetime(year, month, day, hour, minute))
```

```
## # A tibble: 336,776 x 6
##     year month   day  hour minute departure
##    <int> <int> <int> <dbl>  <dbl> <dttm>
##  1  2013     1     1     5.    15. 2013-01-01 05:15:00
##  2  2013     1     1     5.    29. 2013-01-01 05:29:00
##  3  2013     1     1     5.    40. 2013-01-01 05:40:00
##  4  2013     1     1     5.    45. 2013-01-01 05:45:00
##  5  2013     1     1     6.     0. 2013-01-01 06:00:00
##  6  2013     1     1     5.    58. 2013-01-01 05:58:00
##  7  2013     1     1     6.     0. 2013-01-01 06:00:00
##  8  2013     1     1     6.     0. 2013-01-01 06:00:00
##  9  2013     1     1     6.     0. 2013-01-01 06:00:00
## 10  2013     1     1     6.     0. 2013-01-01 06:00:00
## # ... with 336,766 more rows
```

From other types

You may want to switch between a date-time and a date. That's the job of `as_datetime()` and `as_date()`:

```
as_datetime(today())
```

```
## [1] "2018-07-18 UTC"
```

```
as_date(now())
```

```
## [1] "2018-07-18"
```

Getting components

You can pull out individual parts of the date with the accessor functions `year()`, `month()`, `mday()` (day of the month), `yday()` (day of the year), `wday()` (day of the week), `hour()`, `minute()`, and `second()`.

```
datetime <- ymd_hms("2016-07-08 12:34:56")

year(datetime)
```

```
## [1] 2016
```

```
month(datetime)
```

```
## [1] 7
```

```
mday(datetime)
```

```
## [1] 8
```

```r
yday(datetime)
```

```
## [1] 190
```

```r
wday(datetime)
```

```
## [1] 6
```

Getting components

For `month()` and `wday()` you can set `label = TRUE` to return the abbreviated name of the month or day of the week. Set `abbr = FALSE` to return the full name.

```
month(datetime, label = TRUE)
```

```
## [1] Jul
## 12 Levels: Jan < Feb < Mar < Apr < May < Jun < Jul < Aug < Sep < ... <
```

```
wday(datetime, label = TRUE, abbr = FALSE)
```

```
## [1] Friday
## 7 Levels: Sunday < Monday < Tuesday < Wednesday < Thursday < ... < Sat
```

Time spans

Next you'll learn about how arithmetic with dates works, including subtraction, addition, and division. Along the way, you'll learn about three important classes that represent time spans:

- **durations**, which represent an exact number of seconds.
- **periods**, which represent human units like weeks and months.
- **intervals**, which represent a starting and ending point.

Durations

In R, when you subtract two dates, you get a difftime object:

```
# How old is Hadley?
h_age <- today() - ymd(19791014)
h_age
```

```
## Time difference of 14157 days
```

Durations

A difftime class object records a time span of seconds, minutes, hours, days, or weeks. This ambiguity can make difftimes a little painful to work with, so lubridate provides an alternative which always uses seconds: the **duration**.

```
as.duration(h_age)
```

```
## [1] "1223164800s (~38.76 years)"
```

Durations

Durations come with a bunch of convenient constructors:

```
dseconds(15)
```

```
## [1] "15s"
```

```
dminutes(10)
```

```
## [1] "600s (~10 minutes)"
```

```
dhours(c(12, 24))
```

```
## [1] "43200s (~12 hours)" "86400s (~1 days)"
```

```
ddays(0:5)
```

```
## [1] "0s"                 "86400s (~1 days)"   "172800s (~2 days)"
## [4] "259200s (~3 days)"  "345600s (~4 days)"  "432000s (~5 days)"
```

```r
dweeks(3)
```

```
## [1] "1814400s (~3 weeks)"
```

```r
dyears(1)
```

```
## [1] "31536000s (~52.14 weeks)"
```

Durations

Durations always record the time span in seconds. Larger units are created by converting minutes, hours, days, weeks, and years to seconds at the standard rate (60 seconds in a minute, 60 minutes in an hour, 24 hours in day, 7 days in a week, 365 days in a year).

You can add and multiply durations:

```
2 * dyears(1)
```

```
## [1] "63072000s (~2 years)"
```

```
dyears(1) + dweeks(12) + dhours(15)
```

```
## [1] "38847600s (~1.23 years)"
```

Durations

You can add and subtract durations to and from days:

```
tomorrow <- today() + ddays(1)
last_year <- today() - dyears(1)
```

Durations

However, because durations represent an exact number of seconds, sometimes you might get an unexpected result:

```
one_pm <- ymd_hms("2016-03-12 13:00:00", tz = "America/New_York")

one_pm
```

```
## Warning in as.POSIXlt.POSIXct(x, tz): unknown timezone 'zone/tz/2018c
## zoneinfo/America/Chicago'
```

```
## [1] "2016-03-12 13:00:00 EST"
```

```
one_pm + ddays(1)
```

```
## Warning in as.POSIXlt.POSIXct(x): unknown timezone 'zone/tz/2018c.1.0/
## zoneinfo/America/Chicago'

## Warning in as.POSIXlt.POSIXct(x): unknown timezone 'zone/tz/2018c.1.0/
## zoneinfo/America/Chicago'
```

```
## [1] "2016-03-13 14:00:00 EDT"
```

Why is one day after 1pm on March 12, 2pm on March 13?! If you look carefully at the date you might also notice that the time zones have changed. Because of DST, March 12 only has 23 hours, so if add a full days worth of seconds we end up with a different time.

Periods

To solve this problem, lubridate provides **periods**. Periods are time spans but don't have a fixed length in seconds, instead they work with "human" times, like days and months. That allows them work in a more intuitive way:

```
one_pm
```

```
## Warning in as.POSIXlt.POSIXct(x, tz): unknown timezone 'zone/tz/2018c
## zoneinfo/America/Chicago'
```

```
## [1] "2016-03-12 13:00:00 EST"
```

```
one_pm + days(1)
```

```
## Warning in as.POSIXlt.POSIXct(date): unknown timezone 'zone/tz/2018c.
## zoneinfo/America/Chicago'
```

```
## Warning in as.POSIXct.POSIXlt(object): unknown timezone 'zone/tz/2018c
## zoneinfo/America/Chicago'
```

```
## Warning in as.POSIXlt.POSIXct(new): unknown timezone 'zone/tz/2018c.1
## zoneinfo/America/Chicago'
```

```
## Warning in as.POSIXct.POSIXlt(new): unknown timezone 'zone/tz/2018c.1
## zoneinfo/America/Chicago'
```

```
## Warning in as.POSIXlt.POSIXct(x, tz): unknown timezone 'zone/tz/2018c
## zoneinfo/America/Chicago'
```

```
## [1] "2016-03-13 13:00:00 EDT"
```

Periods

Like durations, periods can be created with a number of friendly constructor functions.

```
seconds(15)
```

```
## [1] "15S"
```

```
minutes(10)
```

```
## [1] "10M 0S"
```

```
hours(c(12, 24))
```

```
## [1] "12H 0M 0S" "24H 0M 0S"
```

```
days(7)
```

```
## [1] "7d 0H 0M 0S"
```

```r
months(1:6)
```

```
## [1] "1m 0d 0H 0M 0S" "2m 0d 0H 0M 0S" "3m 0d 0H 0M 0S" "4m 0d 0H 0M 0S
## [5] "5m 0d 0H 0M 0S" "6m 0d 0H 0M 0S"
```

```r
weeks(3)
```

```
## [1] "21d 0H 0M 0S"
```

```r
years(1)
```

```
## [1] "1y 0m 0d 0H 0M 0S"
```

Periods

You can add and multiply periods:

```r
10 * (months(6) + days(1))
```

```
## [1] "60m 10d 0H 0M 0S"
```

```r
days(50) + hours(25) + minutes(2)
```

```
## [1] "50d 25H 2M 0S"
```

Periods

And of course, add them to dates. Compared to durations, periods are more likely to do what you expect:

```
# A leap year
ymd("2016-01-01") + dyears(1)
```

```
## [1] "2016-12-31"
```

```
ymd("2016-01-01") + years(1)
```

```
## [1] "2017-01-01"
```

```
# Daylight Savings Time
one_pm + ddays(1)
```

```
## Warning in as.POSIXlt.POSIXct(x): unknown timezone 'zone/tz/2018c.1.0/
## zoneinfo/America/Chicago'
```

```
## Warning in as.POSIXlt.POSIXct(x, tz): unknown timezone 'zone/tz/2018c
```

```
## zoneinfo/America/Chicago'
```

```
## [1] "2016-03-13 14:00:00 EDT"
```

```r
one_pm + days(1)
```

```
## Warning in as.POSIXlt.POSIXct(date): unknown timezone 'zone/tz/2018c.1
## zoneinfo/America/Chicago'
```

```
## Warning in as.POSIXct.POSIXlt(object): unknown timezone 'zone/tz/2018c
## zoneinfo/America/Chicago'
```

```
## Warning in as.POSIXlt.POSIXct(new): unknown timezone 'zone/tz/2018c.1
## zoneinfo/America/Chicago'
```

```
## Warning in as.POSIXct.POSIXlt(new): unknown timezone 'zone/tz/2018c.1
## zoneinfo/America/Chicago'
```

```
## Warning in as.POSIXlt.POSIXct(x, tz): unknown timezone 'zone/tz/2018c
## zoneinfo/America/Chicago'
```

```
## [1] "2016-03-13 13:00:00 EDT"
```

Working with factors: `forcats`

In R, factors are used to work with categorical variables, variables that have a fixed and known set of possible values. They are also useful when you want to display character vectors in a non-alphabetical order.

Prerequisites

```
library(tidyverse)
library(forcats)
```

Creating factors

Imagine that you have a variable that records month:

```r
x1 <- c("Dec", "Apr", "Jan", "Mar")
```

Creating factors

To create a factor you must start by creating a list of the valid **levels**:

```
month_levels <- c(
  "Jan", "Feb", "Mar", "Apr", "May", "Jun",
  "Jul", "Aug", "Sep", "Oct", "Nov", "Dec"
)
```

Creating factors

Now you can create a factor:

```
y1 <- factor(x1, levels = month_levels)
y1
```

```
## [1] Dec Apr Jan Mar
## Levels: Jan Feb Mar Apr May Jun Jul Aug Sep Oct Nov Dec
```

```
sort(y1)
```

```
## [1] Jan Mar Apr Dec
## Levels: Jan Feb Mar Apr May Jun Jul Aug Sep Oct Nov Dec
```

Creating factors

If you omit the levels, they'll be taken from the data in alphabetical order:

```
factor(x1)
```

```
## [1] Dec Apr Jan Mar
## Levels: Apr Dec Jan Mar
```

Example data: General Social Survey

For the rest of this chapter, we're going to focus on `forcats::gss_cat`. It's a sample of data from the General Social Survey, which is a long-running US survey conducted by the independent research organization NORC at the University of Chicago. The survey has thousands of questions, so in `gss_cat` I've selected a handful that will illustrate some common challenges you'll encounter when working with factors.

```
gss_cat
```

```
## # A tibble: 21,483 x 9
##     year marital           age race  rincome   partyid   relig   denom   tvl
##    <int> <fct>           <int> <fct> <fct>     <fct>     <fct>   <fct>    <
##  1  2000 Never married      26 White $8000 t… Ind,nea… Prote… South…
##  2  2000 Divorced           48 White $8000 t… Not str… Prote… Bapti…
##  3  2000 Widowed            67 White Not app… Indepen… Prote… No de…
##  4  2000 Never married      39 White Not app… Ind,nea… Ortho… Not a…
```

```
##  5  2000 Divorced          25 White Not app… Not str… None    Not a…
##  6  2000 Married           25 White $20000 … Strong … Prote… South…
##  7  2000 Never married     36 White $25000 … Not str… Chris… Not a…
##  8  2000 Divorced          44 White $7000 t… Ind,nea… Prote… Luthe…
##  9  2000 Married           44 White $25000 … Not str… Prote… Other
## 10  2000 Married           47 White $25000 … Strong … Prote… South…
## # ... with 21,473 more rows
```

(Remember, since this dataset is provided by a package, you can get more information about the variables with `?gss_cat`.)

Example data: General Social Survey

When factors are stored in a tibble, you can't see their levels so easily. One way to see them is with `count()`:

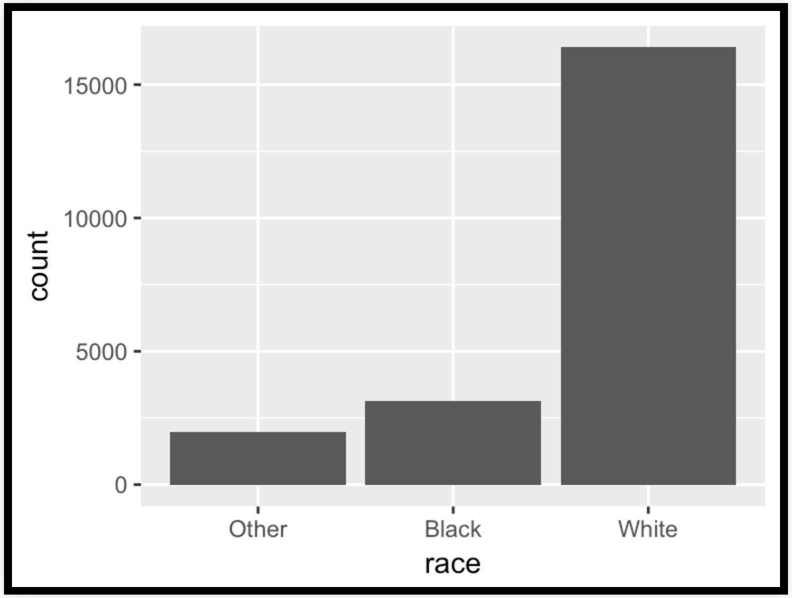
```
gss_cat %>%
  count(race)
```

```
## # A tibble: 3 x 2
##   race      n
##   <fct> <int>
## 1 Other  1959
## 2 Black  3129
## 3 White 16395
```

Example data: General Social Survey

Or with a bar chart:

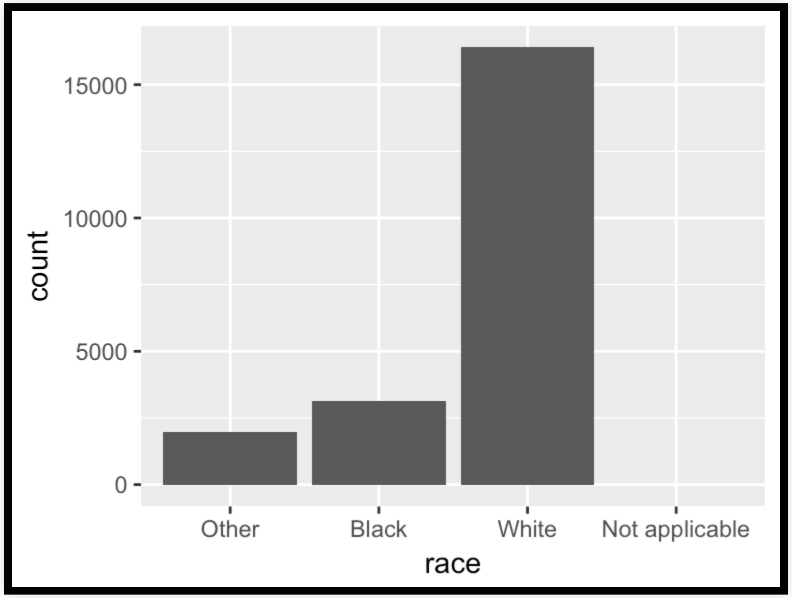
```
ggplot(gss_cat, aes(race)) +
  geom_bar()
```



Example data: General Social Survey

By default, ggplot2 will drop levels that don't have any values.
You can force them to display with:

```
ggplot(gss_cat, aes(race)) +
  geom_bar() +
  scale_x_discrete(drop = FALSE)
```



Example data: General Social Survey

These levels represent valid values that simply did not occur in this dataset. Unfortunately, dplyr doesn't yet have a `drop` option, but it will in the future.

Exercise

1. What is the most common `relig` in this survey? What's the most common `partyid`?

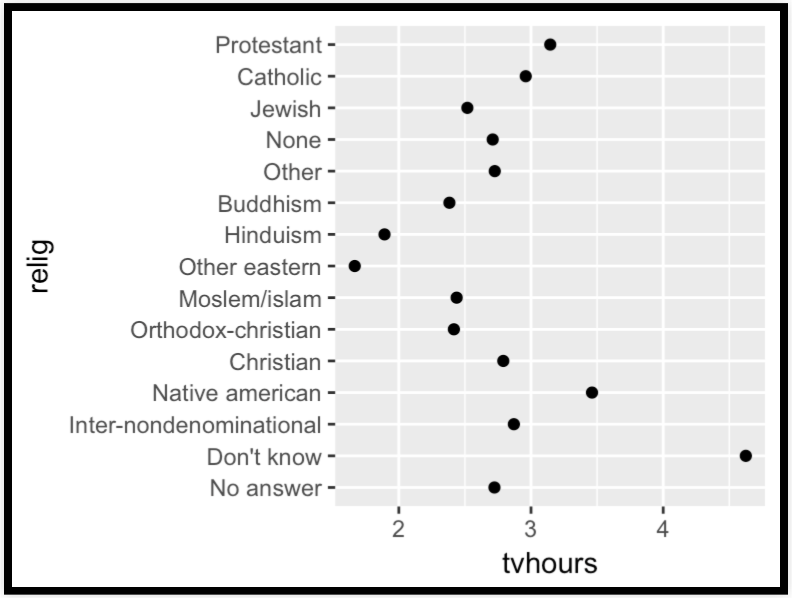
Modifying factor order

It’s often useful to change the order of the factor levels in a visualisation. For example, imagine you want to explore the average number of hours spent watching TV per day across religions:

Modifying factor order

```
relig_summary <- gss_cat %>%
  group_by(relig) %>%
  summarise(
    age = mean(age, na.rm = TRUE),
    tvhours = mean(tvhours, na.rm = TRUE),
    n = n()
  )

ggplot(relig_summary, aes(tvhours, relig)) + geom_point()
```



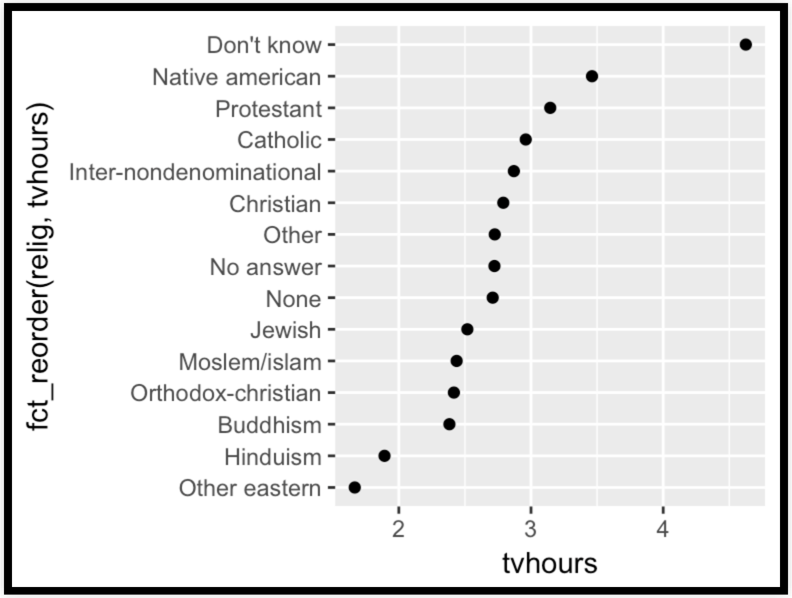
Modifying factor order

It is difficult to interpret this plot because there's no overall pattern. We can improve it by reordering the levels of `relig` using `fct_reorder()`. `fct_reorder()` takes three arguments:

- `f`, the factor whose levels you want to modify.
- `x`, a numeric vector that you want to use to reorder the levels.
- Optionally, `fun`, a function that's used if there are multiple values of `x` for each value of `f`. The default value is `median`.

Modifying factor order

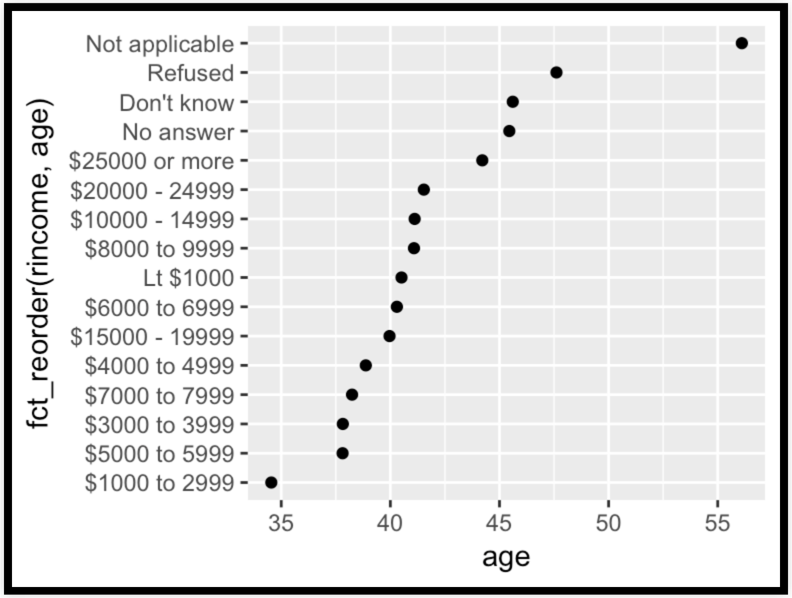
```
ggplot(relig_summary, aes(tvhours, fct_reorder(relig, tvhours))) +
  geom_point()
```



Modifying factor order

```
rincome_summary <- gss_cat %>%
  group_by(rincome) %>%
  summarise(
    age = mean(age, na.rm = TRUE),
    tvhours = mean(tvhours, na.rm = TRUE),
    n = n()
  )

ggplot(rincome_summary, aes(age, fct_reorder(rincome, age))) + geom_point
```



Modifying factor order

Another type of reordering is useful when you are colouring the lines on a plot. `fct_reorder2()` reorders the factor by the `y` values associated with the largest `x` values. This makes the plot easier to read because the line colours line up with the legend.

Modifying factor order

```
by_age <- gss_cat %>%
  filter(!is.na(age)) %>%
  group_by(age, marital) %>%
  count() %>%
  mutate(prop = n / sum(n))

ggplot(by_age, aes(age, prop, colour = marital)) +
  geom_line(na.rm = TRUE)
```

```
## geom_path: Each group consists of only one observation. Do you need to
## adjust the group aesthetic?
```


```
ggplot(by_age, aes(age, prop, colour = fct_reorder2(marital, age, prop))
  geom_line() +
  labs(colour = "marital")
```

```
## geom_path: Each group consists of only one observation. Do you need to
## adjust the group aesthetic?
```

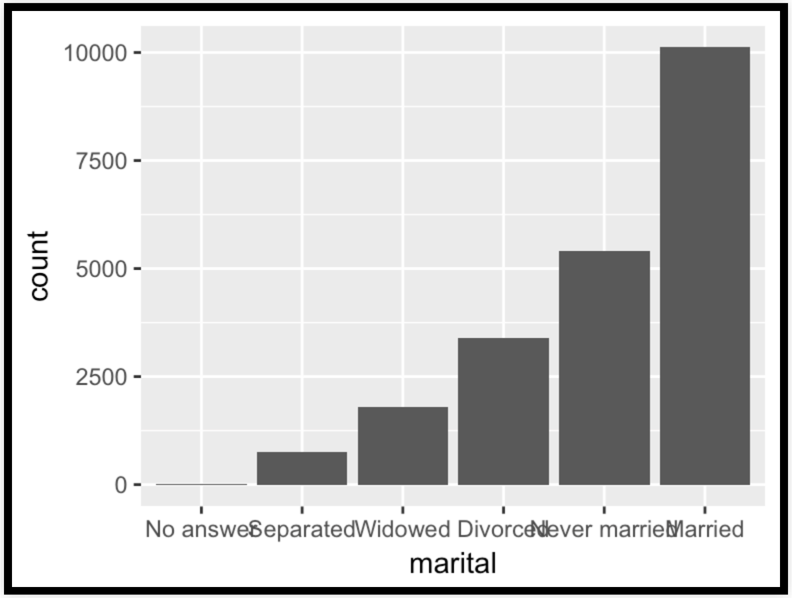
1.50
1.25
1.00
0.75
0.50
prop
20
40
60
80
age
marital
No answer
Never married
Separated
Divorced
Widowed
Married

Modifying factor order

Finally, for bar plots, you can use `fct_infreq()` to order levels in increasing frequency: this is the simplest type of reordering because it doesn't need any extra variables. You may want to combine with `fct_rev()`.

Modifying factor order

```
gss_cat %>%
  mutate(marital = marital %>% fct_infreq() %>% fct_rev()) %>%
  ggplot(aes(marital)) +
    geom_bar()
```



Exercises

1. There are some suspiciously high numbers in `tvhours`. Is the mean a good summary?
2. For each factor in `gss_cat` identify whether the order of the levels is arbitrary or principled.
3. Why did moving "Not applicable" to the front of the levels move it to the bottom of the plot?

Modifying factor levels

More powerful than changing the orders of the levels is changing their values. This allows you to clarify labels for publication, and collapse levels for high-level displays. The most general and powerful tool is `fct_recode()`. It allows you to recode, or change, the value of each level. For example, take the `gss_cat$partyid`:

```
gss_cat %>% count(partyid)
```

```
## # A tibble: 10 x 2
##    partyid                n
##    <fct>              <int>
##  1 No answer            154
##  2 Don't know             1
##  3 Other party          393
##  4 Strong republican   2314
##  5 Not str republican  3032
##  6 Ind,near rep        1791
##  7 Independent         4119
##  8 Ind,near dem        2499
```

```
##  9 Not str democrat    3690
## 10 Strong democrat     3490
```

Modifying factor order

The levels are terse and inconsistent. Let’s tweak them to be longer and use a parallel construction.

```
gss_cat %>%
  mutate(partyid = fct_recode(partyid,
    "Republican, strong"    = "Strong republican",
    "Republican, weak"      = "Not str republican",
    "Independent, near rep" = "Ind,near rep",
    "Independent, near dem" = "Ind,near dem",
    "Democrat, weak"        = "Not str democrat",
    "Democrat, strong"      = "Strong democrat"
  )) %>%
  count(partyid)
```

```
## # A tibble: 10 x 2
##    partyid                   n
##    <fct>                 <int>
##  1 No answer               154
##  2 Don't know                1
##  3 Other party             393
##  4 Republican, strong     2314
##  5 Republican, weak       3032
##  6 Independent, near rep  1791
##  7 Independent            4119
```

```
##  8 Independent, near dem  2499

##  9 Democrat, weak         3690
## 10 Democrat, strong       3490
```

Modifying factor levels

`fct_recode()` will leave levels that aren't explicitly mentioned as is, and will warn you if you accidentally refer to a level that doesn't exist.

Modifying factor order

To combine groups, you can assign multiple old levels to the same new level:

```
gss_cat %>%
  mutate(partyid = fct_recode(partyid,
    "Republican, strong"    = "Strong republican",
    "Republican, weak"      = "Not str republican",
    "Independent, near rep" = "Ind,near rep",
    "Independent, near dem" = "Ind,near dem",
    "Democrat, weak"        = "Not str democrat",
    "Democrat, strong"      = "Strong democrat",
    "Other"                 = "No answer",
    "Other"                 = "Don't know",
    "Other"                 = "Other party"
  )) %>%
  count(partyid)
```

```
## # A tibble: 8 x 2
##   partyid                   n
##   <fct>                 <int>
## 1 Other                   548
## 2 Republican, strong     2314
## 3 Republican, weak       3032
## 4 Independent, near rep  1791
```

```
## 5 Independent              4119

## 6 Independent, near dem  2499
## 7 Democrat, weak          3690
## 8 Democrat, strong        3490
```

You must use this technique with care: if you group together categories that are truly different you will end up with misleading results.

Modifying factor levels

If you want to collapse a lot of levels, `fct_collapse()` is a useful variant of `fct_recode()`. For each new variable, you can provide a vector of old levels:

```
gss_cat %>%
  mutate(partyid = fct_collapse(partyid,
    other = c("No answer", "Don't know", "Other party"),
    rep = c("Strong republican", "Not str republican"),
    ind = c("Ind,near rep", "Independent", "Ind,near dem"),
    dem = c("Not str democrat", "Strong democrat")
  )) %>%
  count(partyid)
```

```
## # A tibble: 4 x 2
##   partyid     n
##   <fct>   <int>
## 1 other     548
## 2 rep      5346
## 3 ind      8409
## 4 dem      7180
```

Modifying factor levels

Sometimes you just want to lump together all the small groups to make a plot or table simpler. That's the job of `fct_lump()`:

```
gss_cat %>%
  mutate(relig = fct_lump(relig)) %>%
  count(relig)
```

```
## # A tibble: 2 x 2
##   relig          n
##   <fct>      <int>
## 1 Protestant 10846
## 2 Other      10637
```

The default behaviour is to progressively lump together the smallest groups, ensuring that the aggregate is still the smallest group. In this case it's not very helpful: it is true that the majority of Americans in this survey are Protestant, but we've probably over collapsed.

we've probably over collapsed.

Instead, we can use the `n` parameter to specify how many groups (excluding other) we want to keep:

```
gss_cat %>%
  mutate(relig = fct_lump(relig, n = 10)) %>%
  count(relig, sort = TRUE) %>%
  print(n = Inf)
```

```
## # A tibble: 10 x 2
##    relig                       n
##    <fct>                   <int>
##  1 Protestant              10846
##  2 Catholic                 5124
##  3 None                     3523
##  4 Christian                 689
##  5 Other                     458
##  6 Jewish                    388
##  7 Buddhism                  147
##  8 Inter-nondenominational   109
##  9 Moslem/islam              104
## 10 Orthodox-christian         95
```