Factors

I find factors, levels and labels one of the hardest things to remember and be confident that they are coded correctly. I have added my notes to the R4DS RMarkdown file on factors to hopefully help me to understand it better. Maybe it will help you too, **Anthony**.

Introduction

In R, factors are used to work with categorical variables. Categorical variables 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. For example with `ggplot2` barplots.

Historically, factors were much easier to work with than characters. As a result, many of the functions in base R automatically convert characters to factors. This means that factors often crop up in places where they're not actually helpful. Fortunately, you don't need to worry about that in the `tidyverse`, and can focus on situations where factors are genuinely useful.

Prerequisites

To work with factors, we'll use the `forcats` package, which provides tools for dealing with **cat**egorical variables (and it's an anagram of factors!). It provides a wide range of helpers for working with factors. `forcats` is not part of the core `tidyverse`, so we need to load it explicitly as so.

```
library(tidyverse)
```

```
## Warning: package 'ggplot2' was built under R version 3.5.3

## Warning: package 'tibble' was built under R version 3.5.3

## Warning: package 'tidyr' was built under R version 3.5.3

## Warning: package 'purrr' was built under R version 3.5.3
```

```
library(forcats)
```

Learning more

If you want to learn more about factors, I recommend reading Amelia McNamara and Nicholas Horton's paper, *Wrangling categorical data in R*. This paper lays out some of the history discussed in *stringsAsFactors: An unauthorized biography* and *stringsAsFactors = <sigh>*, and compares the tidy approaches to categorical data outlined in this book with base R methods. A early version of the paper help motivate and scope the forcats package; thanks Amelia & Nick!

Creating factors

Imagine that you have a variable that records month:

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

Using a string to record this variable has two problems:

1. There are only twelve possible months, and there's nothing saving you from typos:

   ```
   x2 <- c("Dec", "Apr", "Jam", "Mar")
   ```

2. It doesn't sort in a useful way:

   ```
   sort(x1)
   ```

```
## [1] "Apr" "Dec" "Jan" "Mar"
```

You can fix both of these problems with a factor. 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"
)
```

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
```

And any values not in the set will be silently converted to NA:

```
y2 <- factor(x2, levels = month_levels)
y2
```

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

If you want a warning, you can use `readr::parse_factor()`:

```
y2 <- parse_factor(x2, levels = month_levels)
```

```
## Warning: 1 parsing failure.
## row col           expected actual
##   3  -- value in level set    Jam
```

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
```

Sometimes you'd prefer that the order of the levels match the order of the first appearance in the data. *This is where I get stuck.* You can do that when creating the factor by setting levels to `unique(x)`:

```
f1 <- factor(x1, levels = unique(x1))
f1
```

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

or after the fact with `fct_inorder()`:

```
f2 <- x1 %>% factor() %>% fct_inorder()
f2
```

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

If you ever need to access the set of valid levels directly, you can do so with `levels()`:

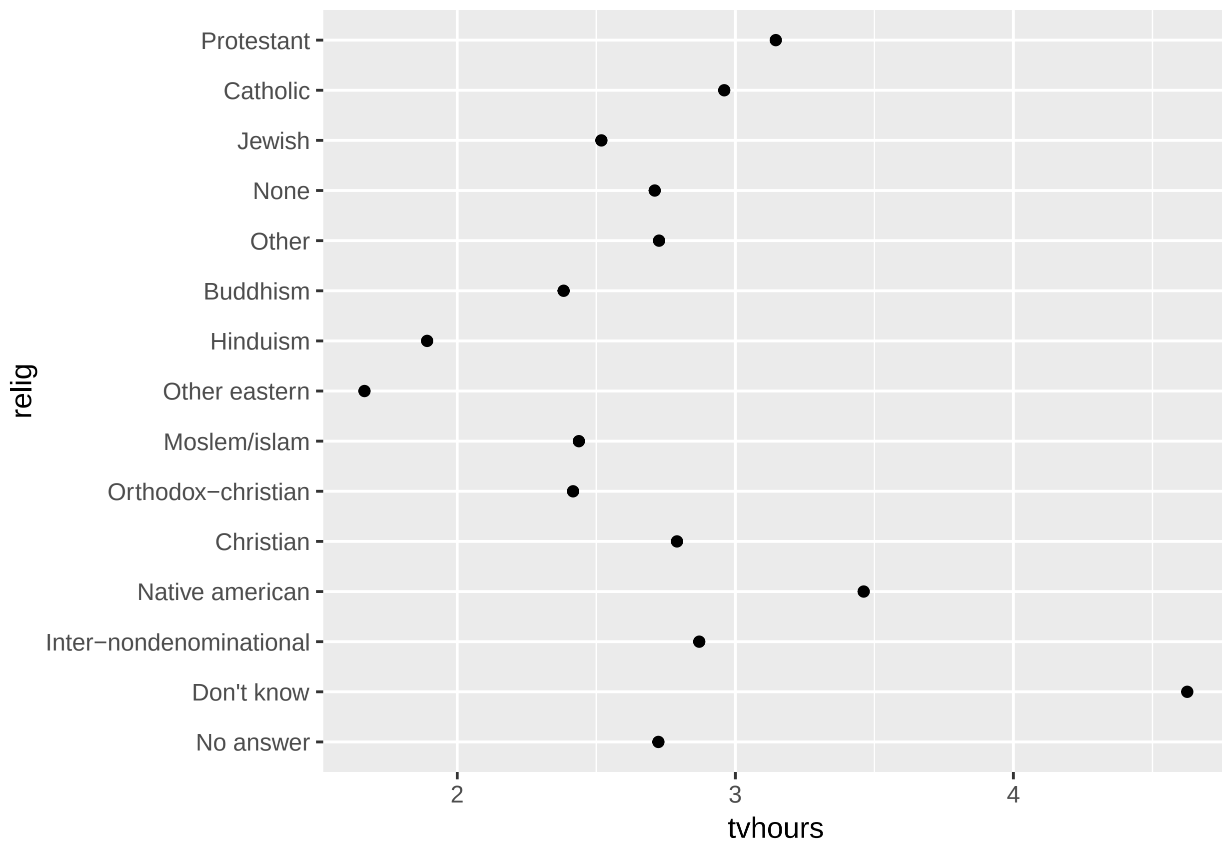
```r
levels(f2)
```

```
## [1] "Dec" "Apr" "Jan" "Mar"
```

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:

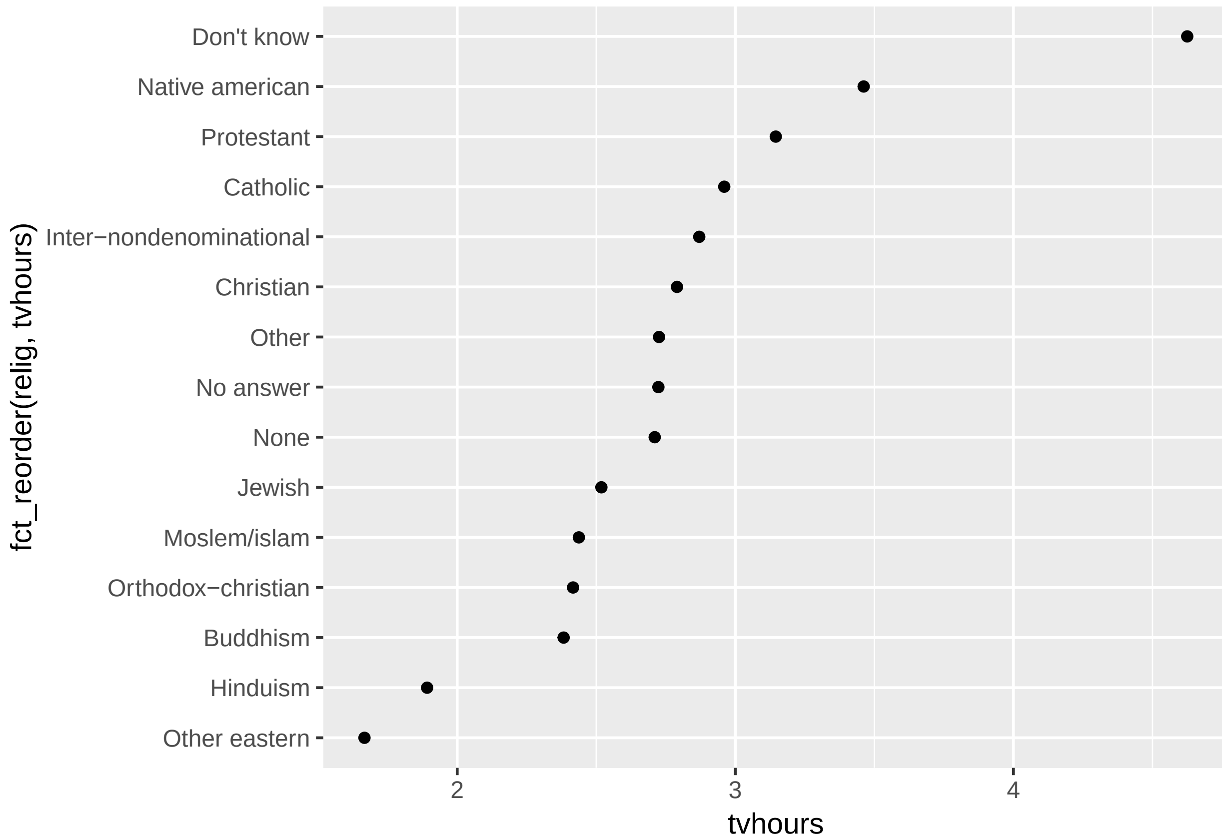
```r
relig_summary <- gss_cat %>%
  group_by(relig) %>%
  summarise(
    age = mean(age, na.rm = TRUE),
    tvhours = mean(tvhours, na.rm = TRUE),
    n = n()
  )

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



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`.

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



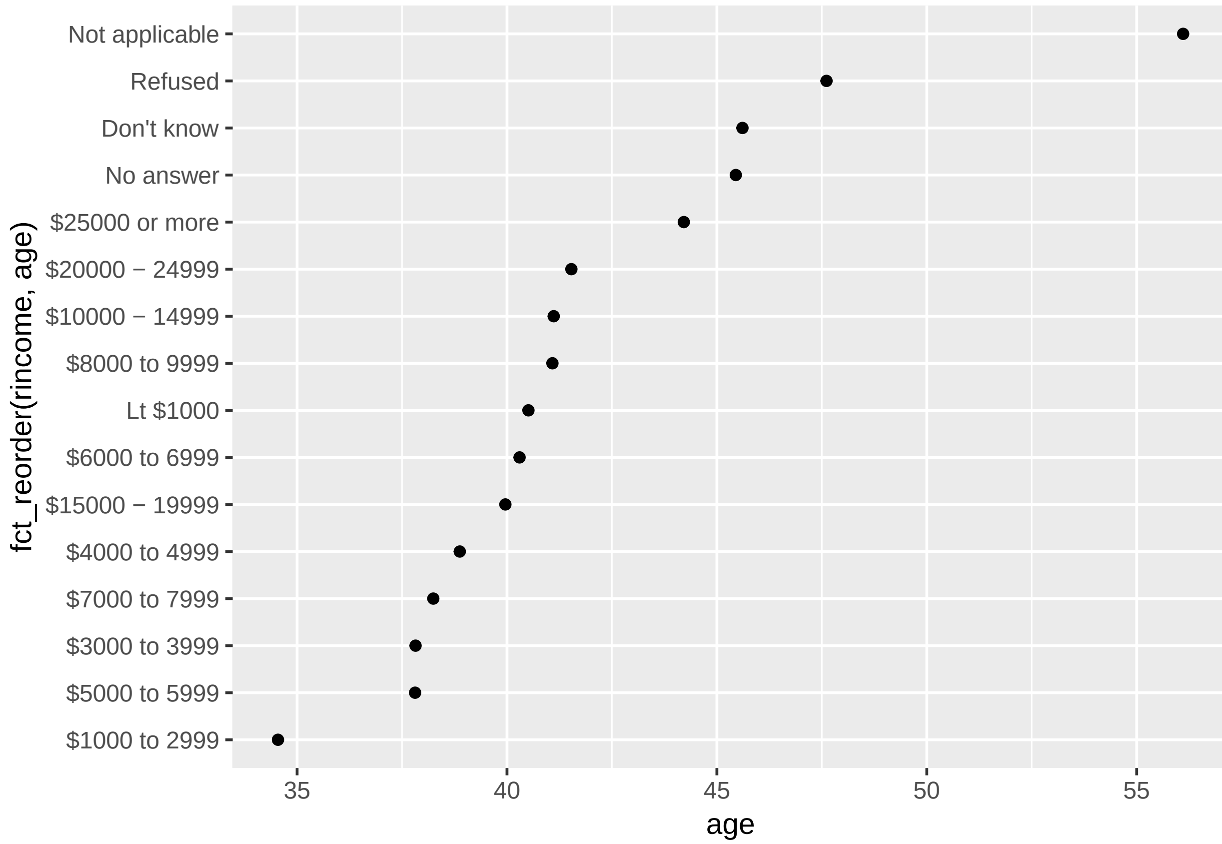
Reordering religion makes it much easier to see that people in the "Don't know" category watch much more TV, and Hinduism & Other Eastern religions watch much less.

As you start making more complicated transformations, I'd recommend moving them out of `aes()` and into a separate `mutate()` step. For example, you could rewrite the plot above as:

```r
relig_summary %>%
  mutate(relig = fct_reorder(relig, tvhours)) %>%
  ggplot(aes(tvhours, relig)) +
    geom_point()
```

What if we create a similar plot looking at how average age varies across reported income level?

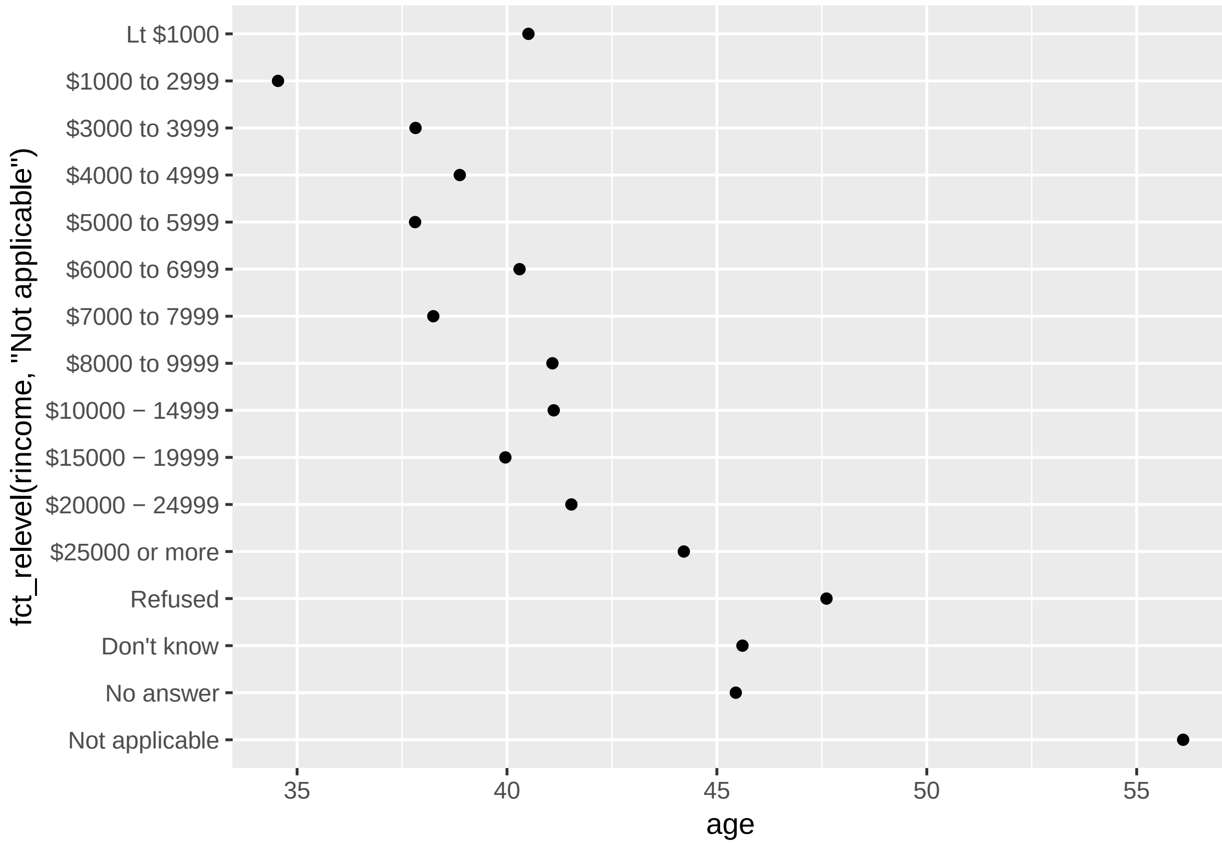
```r
rincome_summary <- gss_cat %>%
  group_by(rincome) %>%
  summarise(
    age = mean(age, na.rm = TRUE),
    tvhours = mean(tvhours, na.rm = TRUE),
    n = n()
  )

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



Here, arbitrarily reordering the levels isn't a good idea! That's because `rincome` already has a principled order that we shouldn't mess with. Reserve `fct_reorder()` for factors whose levels are arbitrarily ordered.

However, it does make sense to pull "Not applicable" to the front with the other special levels. You can use `fct_relevel()`. It takes a factor, `f`, and then any number of levels that you want to move to the front of the line.

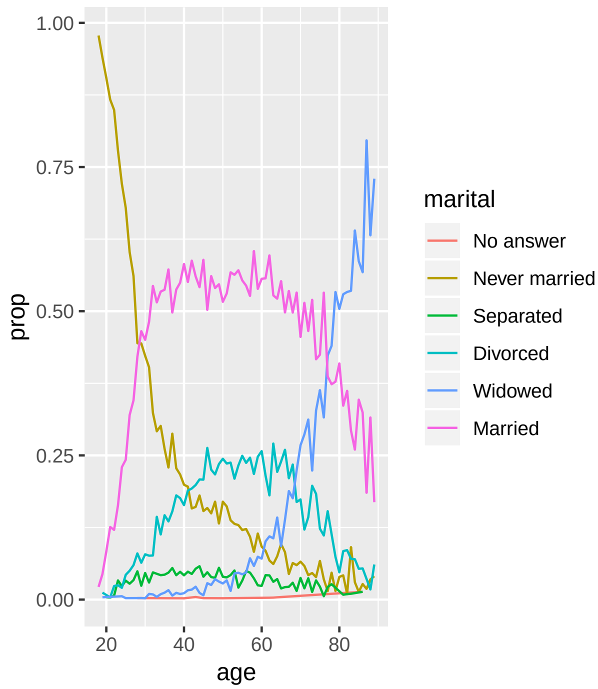
```
ggplot(rincome_summary, aes(age, fct_relevel(rincome, "Not applicable"))) +
  geom_point()
```



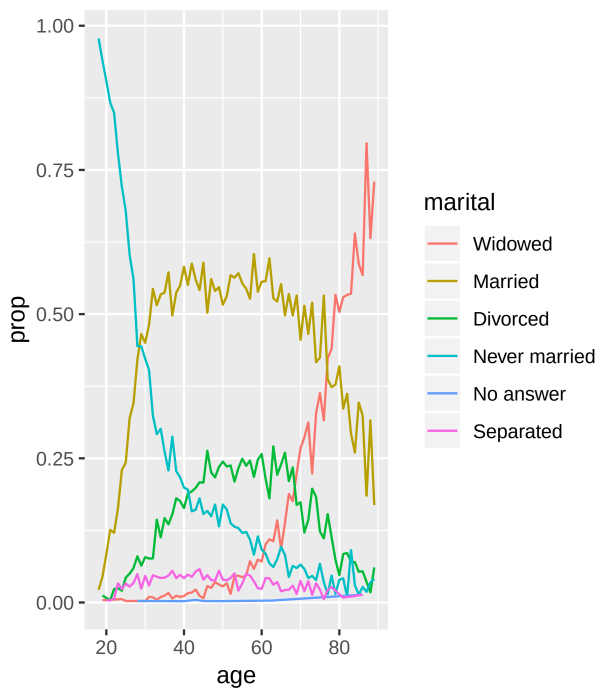
Why do you think the average age for "Not applicable" is so high?

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.

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

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



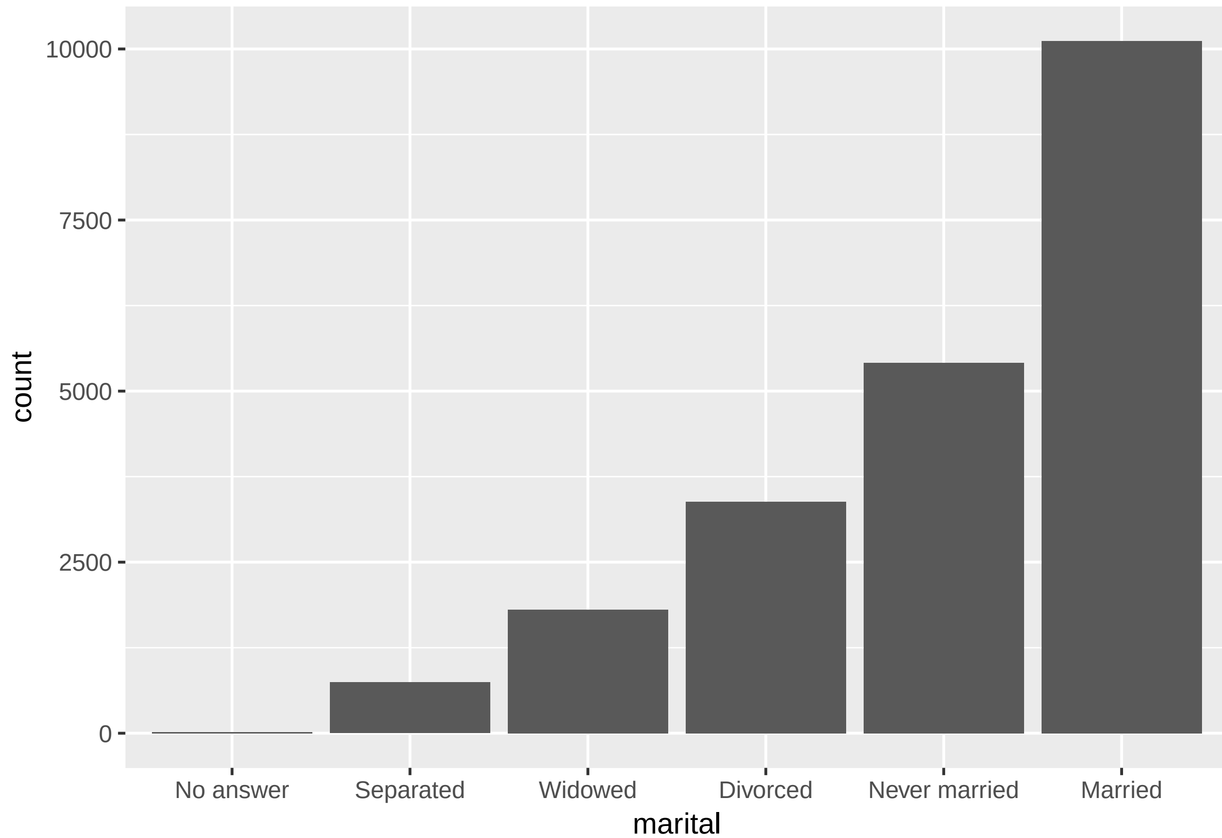

```
ggplot(by_age, aes(age, prop, colour = fct_reorder2(marital, age, prop))) +
  geom_line() +
  labs(colour = "marital")
```



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()`.

```
gss_cat %>%
  mutate(marital = marital %>% fct_infreq() %>% fct_rev()) %>%
```

```r
  ggplot(aes(marital)) +
    geom_bar()
```



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.

```r
gss_cat
```

```
## # A tibble: 21,483 x 9
##     year marital     age race  rincome   partyid    relig   denom   tvhours
##    <int> <fct>     <int> <fct> <fct>     <fct>      <fct>   <fct>     <int>
##  1  2000 Never ma~    26 White $8000 to~ Ind,near ~ Protes~ Southe~      12
##  2  2000 Divorced     48 White $8000 to~ Not str r~ Protes~ Baptis~      NA
##  3  2000 Widowed      67 White Not appl~ Independe~ Protes~ No den~       2
##  4  2000 Never ma~    39 White Not appl~ Ind,near ~ Orthod~ Not ap~       4
##  5  2000 Divorced     25 White Not appl~ Not str d~ None    Not ap~       1
##  6  2000 Married      25 White $20000 -~ Strong de~ Protes~ Southe~      NA
##  7  2000 Never ma~    36 White $25000 o~ Not str r~ Christ~ Not ap~       3
##  8  2000 Divorced     44 White $7000 to~ Ind,near ~ Protes~ Luther~      NA
##  9  2000 Married      44 White $25000 o~ Not str d~ Protes~ Other         0
## 10  2000 Married      47 White $25000 o~ Strong re~ Protes~ Southe~       3
## # ... 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`.)

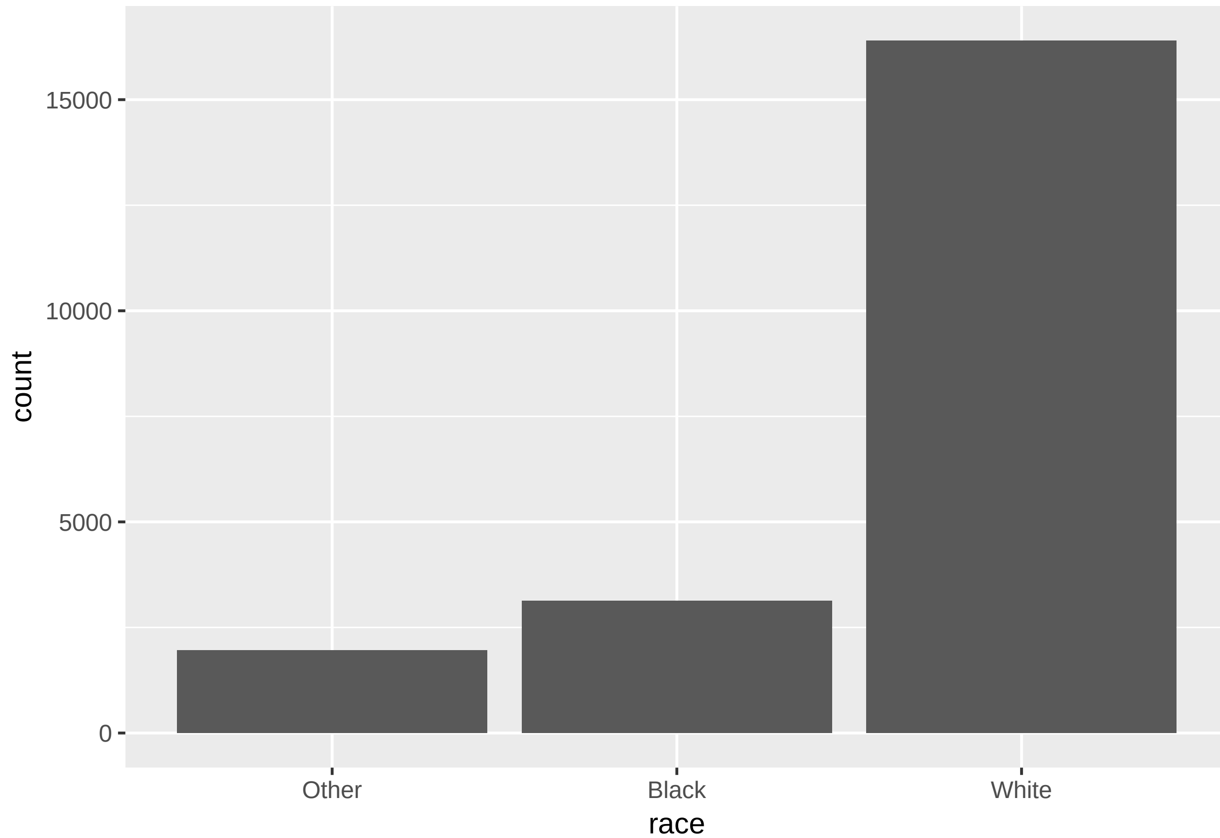
When factors are stored in a tibble, you can't see their levels so easily. One way to see them is with `count()`:

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

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

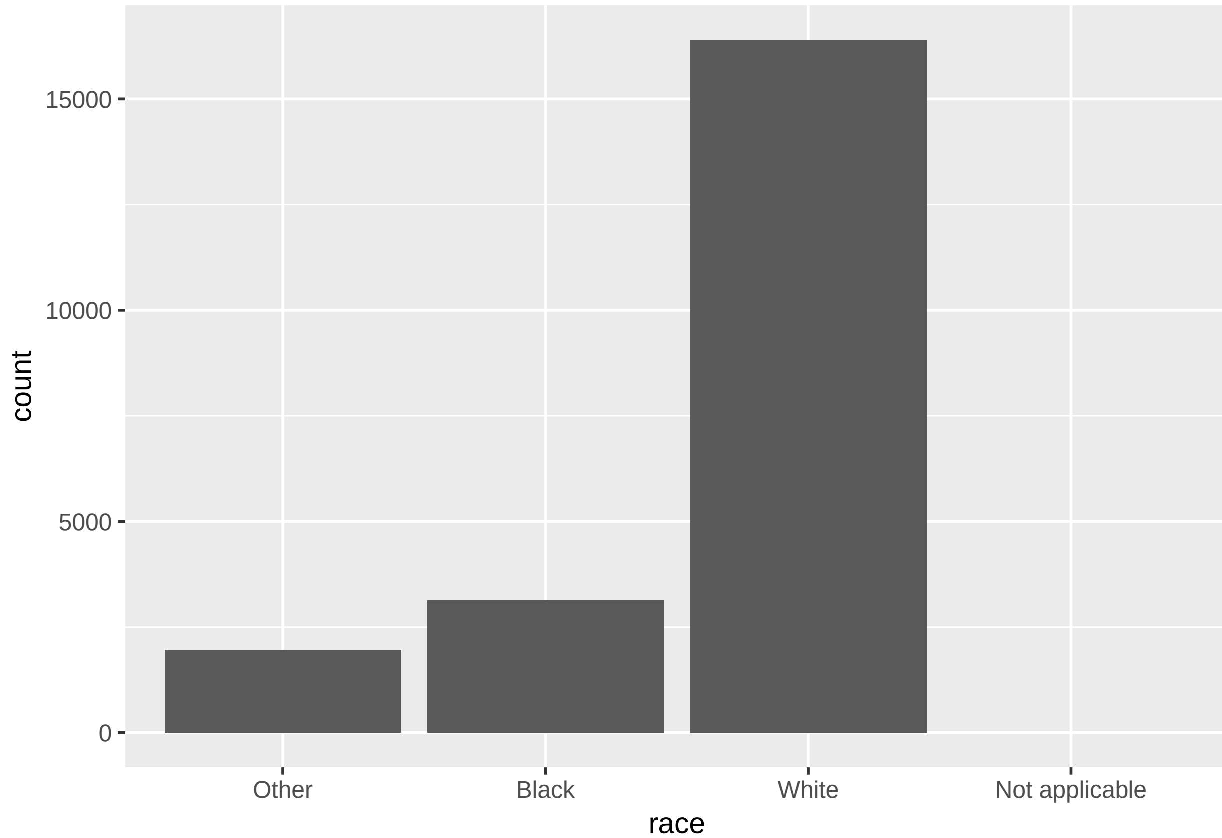
Or with a bar chart:

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



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)
```



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.

When working with factors, the two most common operations are changing the order of the levels, and changing the values of the levels. Those operations are described in the sections below.

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
```

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
```

`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.

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.

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
```

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.

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
```

Pactise exercises

Exercise 1

1. Explore the distribution of `rincome` (reported income). What makes the default bar chart hard to understand? How could you improve the plot?
2. What is the most common `relig` in this survey? What's the most common `partyid`?
3. Which `relig` does `denom` (denomination) apply to? How can you find out with a table? How can you find out with a visualisation?

Exercises 2

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?

Exercises 3

1. How have the proportions of people identifying as Democrat, Republican, and Independent changed over time?
2. How could you collapse `rincome` into a small set of categories?

Appendix

A1: Wrangling categorical data in R

Amelia McNamara and Nicholas Horton's paper, *Wrangling categorical data in R* has a good example of refactoring and releveling in "standard R" and "tidyverse".

McNamara et al. 2017

Abstract

Data wrangling is a critical foundation of data science, and wrangling of categorical data is an important component of this process. However, categorical data can introduce unique issues in data wrangling, particularly in real-world settings with collaborators and periodically-updated dynamic data. This paper discusses common problems arising from categorical variable transformations in R, demonstrates the use of factors, and suggests approaches to address data wrangling challenges. For each problem, we present at least two strategies for management, one in base R and the other from the 'tidyverse.' We consider several motivating examples, suggest defensive coding strategies, and outline principles for data wrangling to help ensure data quality and sound analysis.

Direct notes

Wrangling skills provide an intellectual and practical foundation for data science. Careless data cleaning operations can lead to errors or inconsistencies in analysis@HerMur2015, FitzPen2014. The wrangling of categorical data presents particular challenges and is highly relevant because many variables are categorical (e.g., gender, income bracket, U.S. state), and categorical data is often coded with numerical values. It is easy to break the relationship between category numbers and category labels without realizing it, thus losing the information encoded in a variable. If data sources change upstream (for example, if a domain expert is providing spreadsheet data at regular intervals), code that worked on the initial data may not generate an error message, but could silently produce incorrect results.

Statistical and data science tools need to foster good practice and provide a robust environment for data wrangling and data management. This paper focuses on how @R deals with categorical data, and showcases best practices for categorical data manipulation in @R to produce reproducible workflows. We consider a number of common idioms related to categorical data that arise frequently in data cleaning and preparation, propose some guidelines for defensive coding, and discuss settings where analysts often get tripped up when working with categorical data.

For example, data ingested into @R from spreadsheets can lead to problems with categorical data because of the different storage methods possible in both @R and the spreadsheets themselves@WilBry2016. The examples below help flag when these issues arise or avoid them altogether.

To ground our work, we compare and contrast how categorical data are treated in @base @R and the tidyverse@Wic2014, Wic2016b. Tools from the tidyverse@RosWicRob2018, are designed to make analysis purer, more predictable, and pipeable. Key components of the tidyverse we address in this paper include @dplyr, @tidyr, @forcats, and @readr. This suite of packages helps facilitate a reproducible workflow where a new version of the data could be supplied in the code with updated results produced@Bro2015, LowBes2017. While `R` code written in `base` syntax can also have this quality, a common tendency is to use row or column numbers in code, which makes the result less reproducible. Wrangling of categorical data can make this task even more complex (e.g., if a new level of a categorical variable is added in an updated dataset or inadvertently introduced by a careless error in a spreadsheet to be ingested into `r`).

Our goal is to make the case that it is better to work with categorical data using tidyverse packages than with @base @R. Tidyverse code is more human readable, which can help reduce errors from the start, and the functions we highlight have been designed to make it harder to accidentally remove relationships implicit in categorical data. Because these issues are even more salient for new users, we recommend that instructors teach tidyverse approaches from the start.