Data types

Data Science in a Box

datasciencebox.org

Modified by Tyler George

Why should you care about data types?

Example: Cat lovers

A survey asked respondents their name and number of cats. The instructions said to enter the number of cats as a numerical value.

```
cat_lovers <- read_csv("data/cat-lovers.csv")
```

```
## # A tibble: 60 x 3
##   name           number_of_cats handedness
##   <chr>          <chr>          <chr>
## 1 Bernice Warren 0              left
## 2 Woodrow Stone  0              left
## 3 Willie Bass    1              left
## 4 Tyrone Estrada 3              left
## 5 Alex Daniels   3              left
## 6 Jane Bates     2              left
## # ... with 54 more rows
```

Oh why won't you work?!

```
cat_lovers %>%
  summarise(mean_cats = mean(number_of_cats))
```

```
## Warning in mean.default(number_of_cats): argument is not numeric
## or logical: returning NA

## # A tibble: 1 x 1
##   mean_cats
##       <dbl>
## 1        NA
```

```
?mean
```

mean {base} R Documentation

Arithmetic Mean

Description

Generic function for the (trimmed) arithmetic mean.

Usage

```
mean(x, ...)

## Default S3 method:
mean(x, trim = 0, na.rm = FALSE, ...)
```

Arguments

`x`	An `R` object. Currently there are methods for numeric/logical vectors and date, date-time and time interval objects. Complex vectors are allowed for `trim = 0`, only.
`trim`	the fraction (0 to 0.5) of observations to be trimmed from each end of `x` before the mean is computed. Values of trim outside that range are taken as the nearest endpoint.
`na.rm`	a logical value indicating whether `NA` values should be stripped before the computation proceeds.
`...`	further arguments passed to or from other methods.

Oh why won't you still work??!!

```
cat_lovers %>%
  summarise(mean_cats = mean(number_of_cats, na.rm = TRUE))
```

```
## Warning in mean.default(number_of_cats, na.rm = TRUE): argument
## is not numeric or logical: returning NA
```

```
## # A tibble: 1 x 1
##   mean_cats
##       <dbl>
## 1        NA
```

Take a breath and look at your data

> What is the type of the `number_of_cats` variable?

```
glimpse(cat_lovers)
```

```
## Rows: 60
## Columns: 3
## $ name           <chr> "Bernice Warren", "Woodrow Stone", "Will~
## $ number_of_cats <chr> "0", "0", "1", "3", "3", "2", "1", "1", ~
## $ handedness     <chr> "left", "left", "left", "left", "left", ~
```

Let's take another look

Show 10 entries Search:

	name	number_of_cats	handedness
1	Bernice Warren	0	left
2	Woodrow Stone	0	left
3	Willie Bass	1	left
4	Tyrone Estrada	3	left
5	Alex Daniels	3	left
6	Jane Bates	2	left
7	Latoya Simpson	1	left
8	Darin Woods	1	left
9	Agnes Cobb	0	left
10	Tabitha Grant	0	left

Showing 1 to 10 of 60 entries Previous 1 2 3 4 5 6 Next

Sometimes you might need to babysit your respondents

```
cat_lovers %>%
  mutate(number_of_cats = case_when(
    name == "Ginger Clark" ~ 2,
    name == "Doug Bass"    ~ 3,
    TRUE                   ~ as.numeric(number_of_cats)
    )) %>%
  summarise(mean_cats = mean(number_of_cats))
```

```
## Warning in eval_tidy(pair$rhs, env = default_env): NAs introduced
## by coercion

## # A tibble: 1 x 1
##   mean_cats
##       <dbl>
## 1     0.833
```

Always you need to respect data types

```
cat_lovers %>%
  mutate(
    number_of_cats = case_when(
      name == "Ginger Clark" ~ "2",
      name == "Doug Bass"    ~ "3",
      TRUE                   ~ number_of_cats
      ),
    number_of_cats = as.numeric(number_of_cats)
    ) %>%
  summarise(mean_cats = mean(number_of_cats))
```

```
## # A tibble: 1 x 1
##   mean_cats
##       <dbl>
## 1     0.833
```

Now that we know what we're doing...

```
cat_lovers <- cat_lovers %>%
  mutate(
    number_of_cats = case_when(
      name == "Ginger Clark" ~ "2",
      name == "Doug Bass"    ~ "3",
      TRUE                   ~ number_of_cats
      ),
    number_of_cats = as.numeric(number_of_cats)
    )
```

Moral of the story

- If your data does not behave how you expect it to, type coercion upon reading in the data might be the reason.
- Go in and investigate your data, apply the fix, *save your data*, live happily ever after.

now that we have a good motivation for learning about data types in R

let's learn about data types in R!

Data types

Data types in R

- **logical**
- **double**
- **integer**
- **character**
- and some more, but we won't be focusing on those

Logical & character

logical - boolean values TRUE and FALSE

```
typeof(TRUE)
```

```
## [1] "logical"
```

character - character strings

```
typeof("hello")
```

```
## [1] "character"
```

Double & integer

double - floating point numerical values (default numerical type)

```
typeof(1.335)
```

```
## [1] "double"
```

```
typeof(7)
```

```
## [1] "double"
```

integer - integer numerical values (indicated with an L)

```
typeof(7L)
```

```
## [1] "integer"
```

```
typeof(1:3)
```

```
## [1] "integer"
```

Concatenation

Vectors can be constructed using the `c()` function.

```
c(1, 2, 3)
```

```
## [1] 1 2 3
```

```
c("Hello", "World!")
```

```
## [1] "Hello"  "World!"
```

```
c(c("hi", "hello"), c("bye", "jello"))
```

```
## [1] "hi"    "hello" "bye"   "jello"
```

Converting between types

with intention...

```
x <- 1:3
x
```

```
## [1] 1 2 3
```

```
typeof(x)
```

```
## [1] "integer"
```

Converting between types

with intention...

```
x <- 1:3
x
```

```
## [1] 1 2 3
```

```
typeof(x)
```

```
## [1] "integer"
```

```
y <- as.character(x)
y
```

```
## [1] "1" "2" "3"
```

```
typeof(y)
```

```
## [1] "character"
```

Converting between types

with intention...

```
x <- c(TRUE, FALSE)
x
```

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

```
typeof(x)
```

```
## [1] "logical"
```

Converting between types

with intention...

```
x <- c(TRUE, FALSE)
x
```

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

```
typeof(x)
```

```
## [1] "logical"
```

```
y <- as.numeric(x)
y
```

```
## [1] 1 0
```

```
typeof(y)
```

```
## [1] "double"
```

Converting between types

without intention...

R will happily convert between various types without complaint when different types of data are concatenated in a vector, and that's not always a great thing!

```
c(1, "Hello")
```

```
## [1] "1"     "Hello"
```

```
c(FALSE, 3L)
```

```
## [1] 0 3
```

Converting between types

without intention...

R will happily convert between various types without complaint when different types of data are concatenated in a vector, and that's not always a great thing!

```
c(1, "Hello")
```

```
## [1] "1"     "Hello"
```

```
c(1.2, 3L)
```

```
## [1] 1.2 3.0
```

```
c(FALSE, 3L)
```

```
## [1] 0 3
```

```
c(2L, "two")
```

```
## [1] "2"   "two"
```

Explicit vs. implicit coercion

Let's give formal names to what we've seen so far:

Explicit vs. implicit coercion

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- **Explicit coercion** is when you call a function like `as.logical()`, `as.numeric()`, `as.integer()`, `as.double()`, or `as.character()`

Explicit vs. implicit coercion

Let's give formal names to what we've seen so far:

- **Explicit coercion** is when you call a function like `as.logical()`, `as.numeric()`, `as.integer()`, `as.double()`, or `as.character()`
- **Implicit coercion** happens when you use a vector in a specific context that expects a certain type of vector

Your turn!

- RStudio > `AE 05 - Hotels + Data types` > open `type-coercion.Rmd` and knit.
- What is the type of the given vectors? First, guess. Then, try it out in R. If your guess was correct, great! If not, discuss why they have that type.

Your turn!

- RStudio > `AE 05 - Hotels + Data types` > open `type-coercion.Rmd` and knit.
- What is the type of the given vectors? First, guess. Then, try it out in R. If your guess was correct, great! If not, discuss why they have that type.

Example: Suppose we want to know the type of `c(1, "a")`. First, I'd look at:

```
typeof(1)
```

```
## [1] "double"
```

```
typeof("a")
```

```
## [1] "character"
```

and make a guess based on these. Then finally I'd check:

```
typeof(c(1, "a"))
```

```
## [1] "character"
```

Special values

Special values

- `NA`: Not available
- `NaN`: Not a number
- `Inf`: Positive infinity
- `-Inf`: Negative infinity

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```
pi / 0
```

```
## [1] Inf
```

```
0 / 0
```

```
## [1] NaN
```

```
1/0 - 1/0
```

```
## [1] NaN
```

```
1/0 + 1/0
```

```
## [1] Inf
```

NAs are special ❄s

```
x <- c(1, 2, 3, 4, NA)
```

```
mean(x)
```

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

```
mean(x, na.rm = TRUE)
```

```
## [1] 2.5
```

```
summary(x)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
##    1.00    1.75    2.50    2.50    3.25    4.00       1
```

NAs are logical

R uses NA to represent missing values in its data structures.

```
typeof(NA)
```

```
## [1] "logical"
```

Mental model for NAs

- Unlike NaN, NAs are genuinely unknown values
- But that doesn't mean they can't function in a logical way
- Let's think about why NAs are logical...

Mental model for NAs

- Unlike NaN, NAs are genuinely unknown values
- But that doesn't mean they can't function in a logical way
- Let's think about why NAs are logical...

> Why do the following give different answers?

```
# TRUE or NA
TRUE | NA
```

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

```
# FALSE or NA
FALSE | NA
```

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

→ See next slide for answers...

- `NA` is unknown, so it could be `TRUE` or `FALSE`

- `TRUE | NA`

```
TRUE | TRUE  # if NA was TRUE
```

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

```
TRUE | FALSE # if NA was FALSE
```

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

- `FALSE | NA`

```
FALSE | TRUE  # if NA was TRUE
```

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

```
FALSE | FALSE # if NA was FALSE
```

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

- Doesn't make sense for mathematical operations
- Makes sense in the context of missing data

Data classes

Data classes

We talked about *types* so far, next we'll introduce the concept of *classes*

- Vectors are like Lego building blocks

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Data classes

We talked about *types* so far, next we'll introduce the concept of *classes*

- Vectors are like Lego building blocks
- We stick them together to build more complicated constructs, e.g. *representations of data*
- The **class** attribute relates to the S3 class of an object which determines its behaviour
  - You don't need to worry about what S3 classes really mean, but you can read more about it here if you're curious

Data classes

We talked about *types* so far, next we'll introduce the concept of *classes*

- Vectors are like Lego building blocks
- We stick them together to build more complicated constructs, e.g. *representations of data*
- The **class** attribute relates to the S3 class of an object which determines its behaviour
  - You don't need to worry about what S3 classes really mean, but you can read more about it here if you're curious
- Examples: factors, dates, and data frames

Factors

R uses factors to handle categorical variables, variables that have a fixed and known set of possible values

```
x <- factor(c("BS", "MS", "PhD", "MS"))
x
```

```
## [1] BS  MS  PhD MS
## Levels: BS MS PhD
```

Factors

R uses factors to handle categorical variables, variables that have a fixed and known set of possible values

```
x <- factor(c("BS", "MS", "PhD", "MS"))
x
```

```
## [1] BS  MS  PhD MS
## Levels: BS MS PhD
```

```
typeof(x)
```

```
## [1] "integer"
```

```
class(x)
```

```
## [1] "factor"
```

More on factors

We can think of factors like character (level labels) and an integer (level numbers) glued together

```
glimpse(x)
```

```
##  Factor w/ 3 levels "BS","MS","PhD": 1 2 3 2
```

```
as.integer(x)
```

```
## [1] 1 2 3 2
```

Dates

```
y <- as.Date("2020-01-01")
y
```

```
## [1] "2020-01-01"
```

```
typeof(y)
```

```
## [1] "double"
```

```
class(y)
```

```
## [1] "Date"
```

More on dates

We can think of dates like an integer (the number of days since the origin, 1 Jan 1970) and an integer (the origin) glued together

```
as.integer(y)
```

```
## [1] 18262
```

```
as.integer(y) / 365 # roughly 50 yrs
```

```
## [1] 50.03288
```

Data frames

We can think of data frames like like vectors of equal length glued together

```
df <- data.frame(x = 1:2, y = 3:4)
df
```

```
##   x y
## 1 1 3
## 2 2 4
```

```
typeof(df)
```

```
## [1] "list"
```

```
class(df)
```

```
## [1] "data.frame"
```

Lists

Lists are a generic vector container vectors of any type can go in them

```
l <- list(
  x = 1:4,
  y = c("hi", "hello", "jello"),
  z = c(TRUE, FALSE)
)
l
```

```
## $x
## [1] 1 2 3 4
##
## $y
## [1] "hi"    "hello" "jello"
##
## $z
## [1]  TRUE FALSE
```

Lists and data frames

- A data frame is a special list containing vectors of equal length
- When we use the `pull()` function, we extract a vector from the data frame

```
df
```

```
##   x y
## 1 1 3
## 2 2 4
```

```
df %>%
  pull(y)
```

```
## [1] 3 4
```

Working with factors

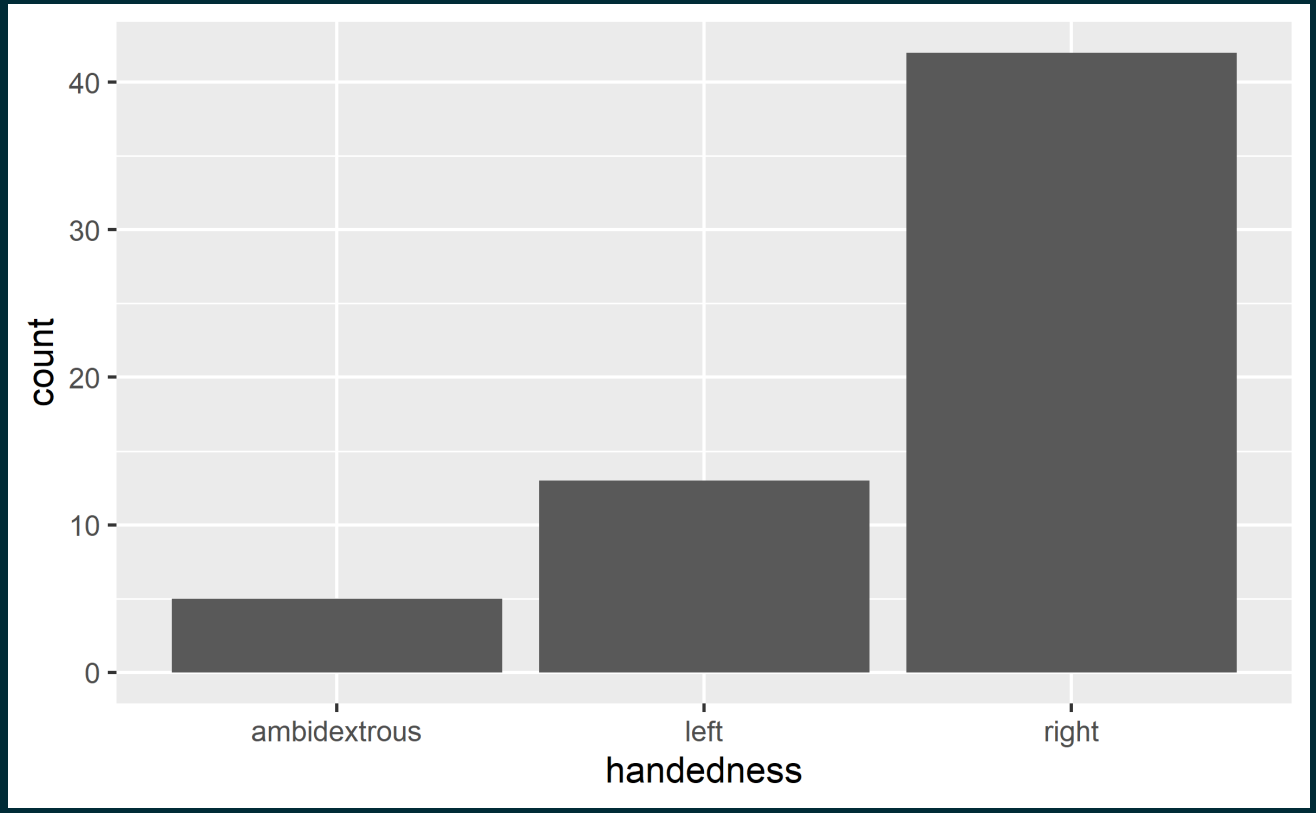
Read data in as character strings

```
glimpse(cat_lovers)
```

```
## Rows: 60
## Columns: 3
## $ name           <chr> "Bernice Warren", "Woodrow Stone", "Will~
## $ number_of_cats <chr> "0", "0", "1", "3", "3", "2", "1", "1", ~
## $ handedness     <chr> "left", "left", "left", "left", "left", ~
```

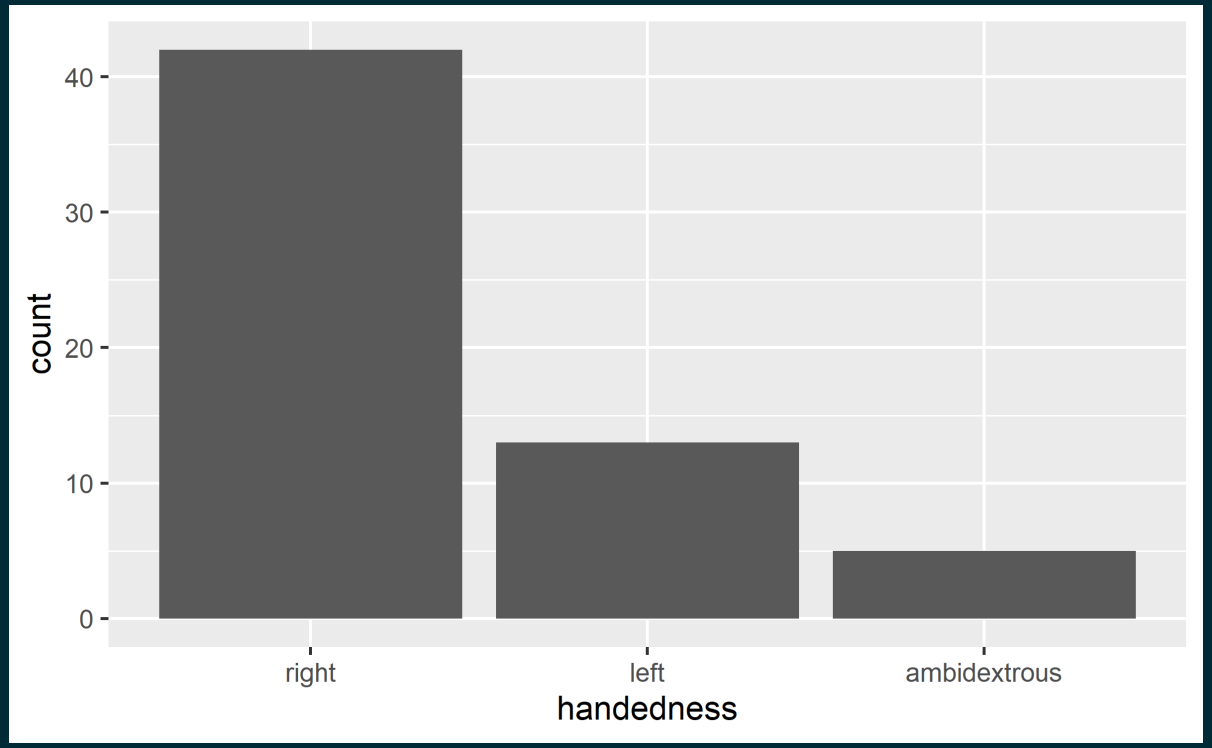
But coerce when plotting

```
ggplot(cat_lovers, mapping = aes(x = handedness)) +
  geom_bar()
```



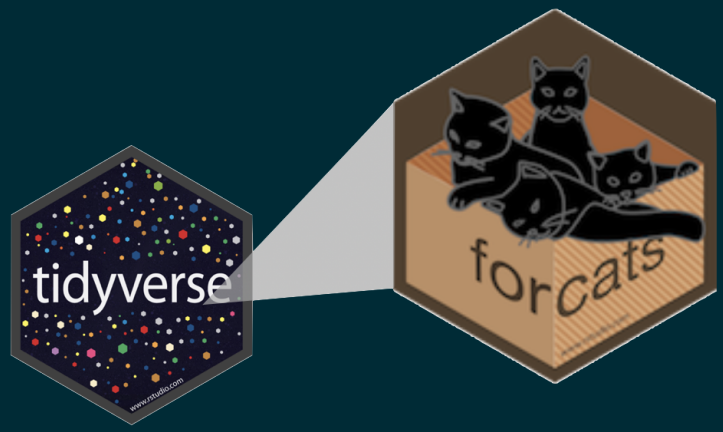
Use forcats to manipulate factors

```
cat_lovers %>%
  mutate(handedness = fct_infreq(handedness)) %>%
  ggplot(mapping = aes(x = handedness)) +
  geom_bar()
```



Come for the functionality

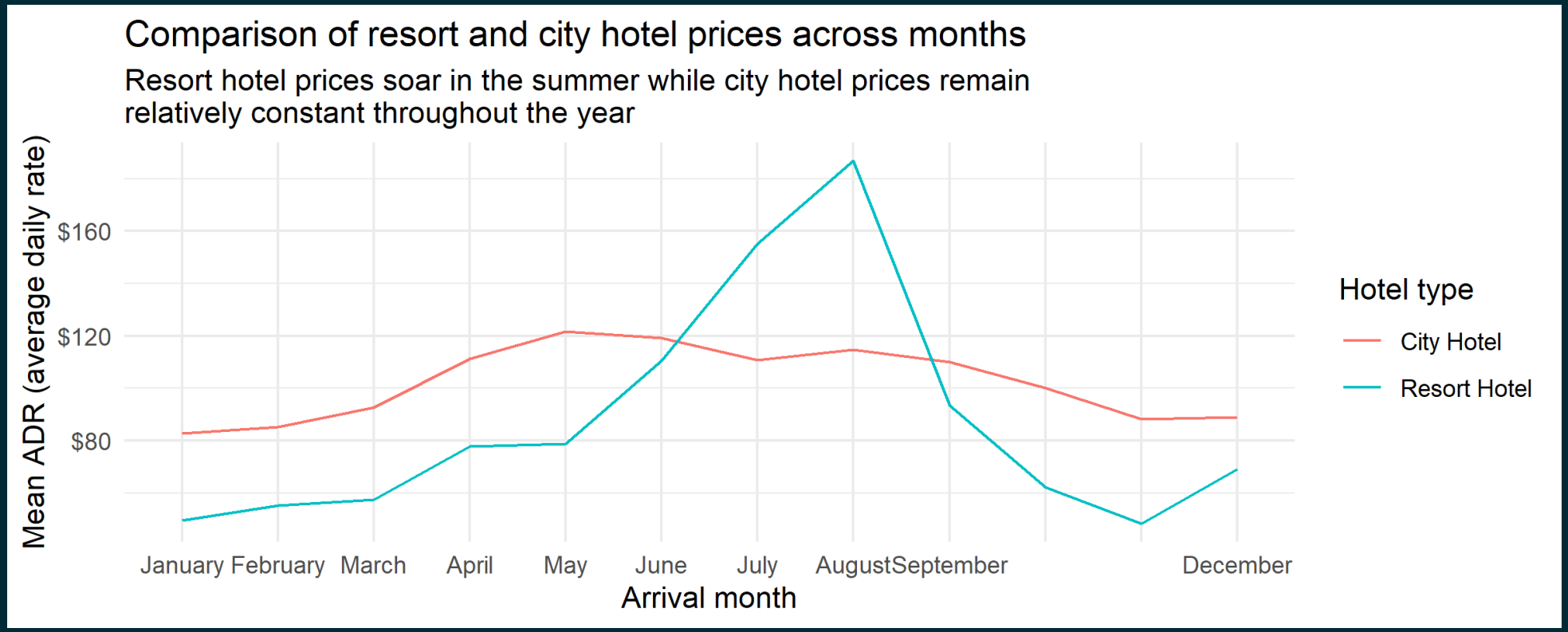
... stay for the logo



- Factors are useful when you have true categorical data and you want to override the ordering of character vectors to improve display
- They are also useful in modeling scenarios
- The **forcats** package provides a suite of useful tools that solve common problems with factors

Your turn!

- RStudio > `AE 05 - Hotels + Data types` > `hotels-forcats.Rmd` > knit
- Recreate the x-axis of the following plot.
- **Stertch goal:** Recreate the y-axis.



Working with dates

Make a date

- **lubridate** is the tidyverse-friendly package that makes dealing with dates a little easier
- It's not one of the *core* tidyverse packages, hence it's installed with `install.packages("tidyverse)` but it's not loaded with it, and needs to be explicitly loaded with `library(lubridate)`

we're just going to scratch the surface of working with dates in R here...

Calculate and visualise the number of bookings on any given arrival date.

```
hotels %>%
  select(starts_with("arrival_"))
```

```
## # A tibble: 119,390 x 4
##   arrival_date_year arrival_date_month arrival_date_week_number
##               <dbl> <chr>                                  <dbl>
## 1              2015 July                                      27
## 2              2015 July                                      27
## 3              2015 July                                      27
## 4              2015 July                                      27
## 5              2015 July                                      27
## 6              2015 July                                      27
## # ... with 119,384 more rows, and 1 more variable:
## #   arrival_date_day_of_month <dbl>
```

Step 1. Construct dates

```
library(glue)

hotels %>%
  mutate(
    arrival_date = glue("{arrival_date_year} {arrival_date_month} {arrival_date_day_of_month}")
    ) %>%
  relocate(arrival_date)
```

```
## # A tibble: 119,390 x 33
##   arrival_date hotel       is_canceled lead_time arrival_date_ye~
##   <glue>       <chr>             <dbl>     <dbl>            <dbl>
## 1 2015 July 1  Resort Hot~           0       342             2015
## 2 2015 July 1  Resort Hot~           0       737             2015
## 3 2015 July 1  Resort Hot~           0         7             2015
## 4 2015 July 1  Resort Hot~           0        13             2015
...
```

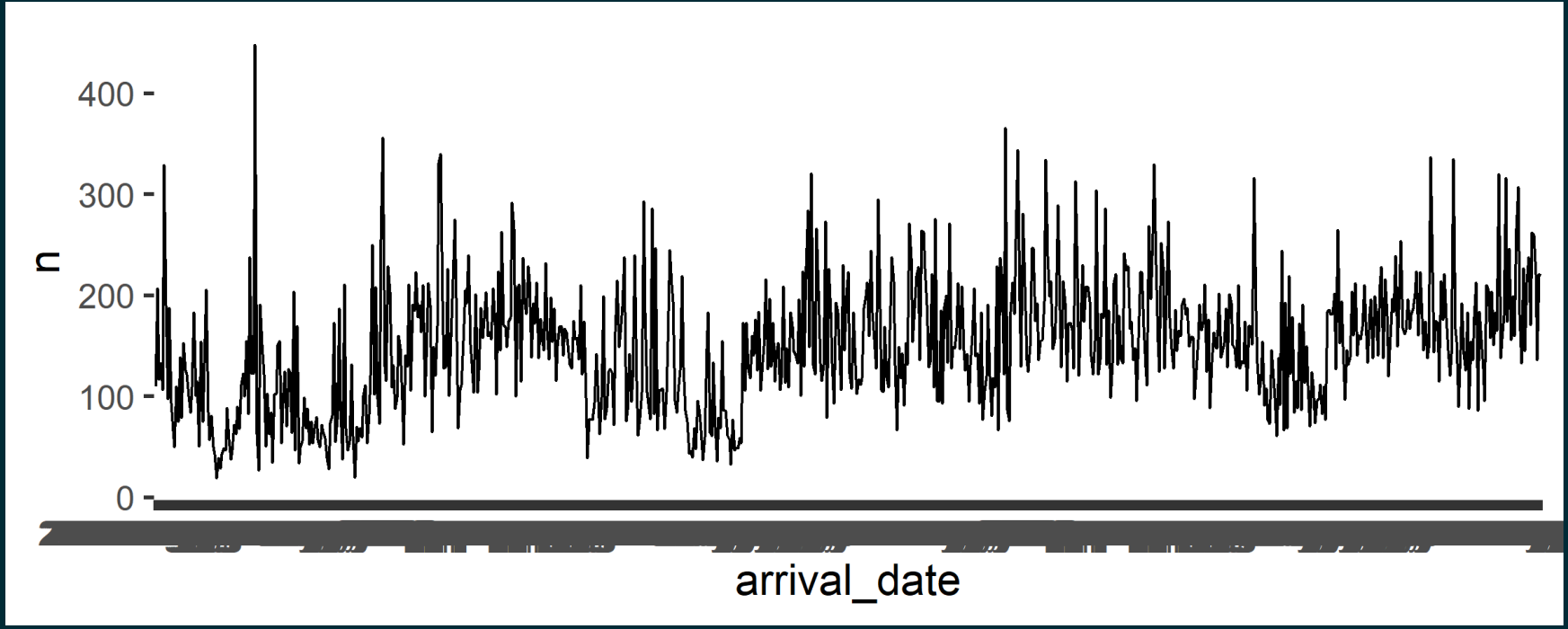
Step 2. Count bookings per date

```
hotels %>%
  mutate(arrival_date = glue("{arrival_date_year} {arrival_date_month} {arrival_date_day_of_month
  count(arrival_date)
```

```
## # A tibble: 793 x 2
##   arrival_date       n
##   <glue>         <int>
## 1 2015 August 1    110
## 2 2015 August 10   207
## 3 2015 August 11   117
## 4 2015 August 12   133
## 5 2015 August 13   107
## 6 2015 August 14   329
## # ... with 787 more rows
```

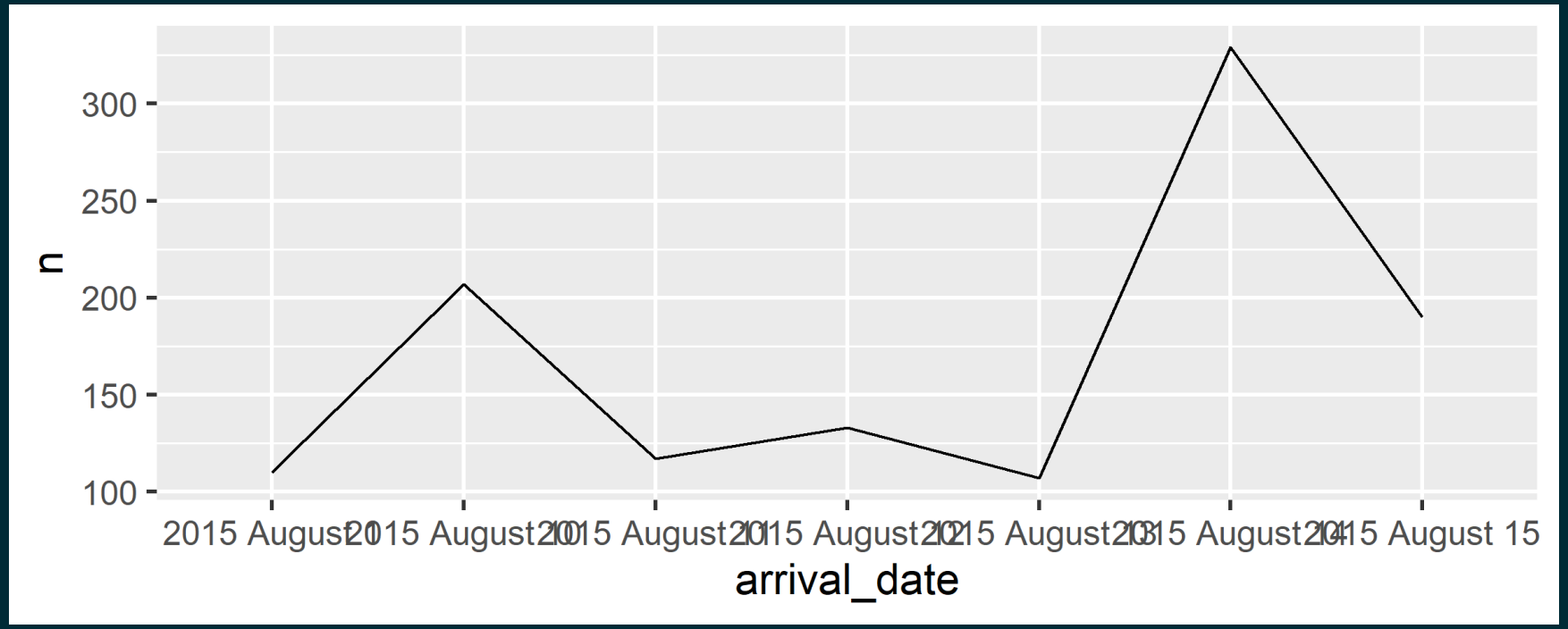
Step 3. Visualise bookings per date

```
hotels %>%
  mutate(arrival_date = glue("{arrival_date_year} {arrival_date_month} {arrival_date_day_of_month
  count(arrival_date) %>%
  ggplot(aes(x = arrival_date, y = n, group = 1)) +
  geom_line()
```



zooming in a bit...

> Why does the plot start with August when we know our data start in July? And why does 10 August come after 1 August?



Step 1. *REVISED* Construct dates "as dates"

```
library(lubridate)

hotels %>%
  mutate(
    arrival_date = ymd(glue("{arrival_date_year} {arrival_date_month} {arrival_date_day_of_month}
    ) %>%
  relocate(arrival_date)
```

```
## # A tibble: 119,390 x 33
##   arrival_date hotel       is_canceled lead_time arrival_date_ye~
##   <date>       <chr>             <dbl>     <dbl>            <dbl>
## 1 2015-07-01   Resort Hot~           0       342             2015
## 2 2015-07-01   Resort Hot~           0       737             2015
## 3 2015-07-01   Resort Hot~           0         7             2015
## 4 2015-07-01   Resort Hot~           0        13             2015
...
```

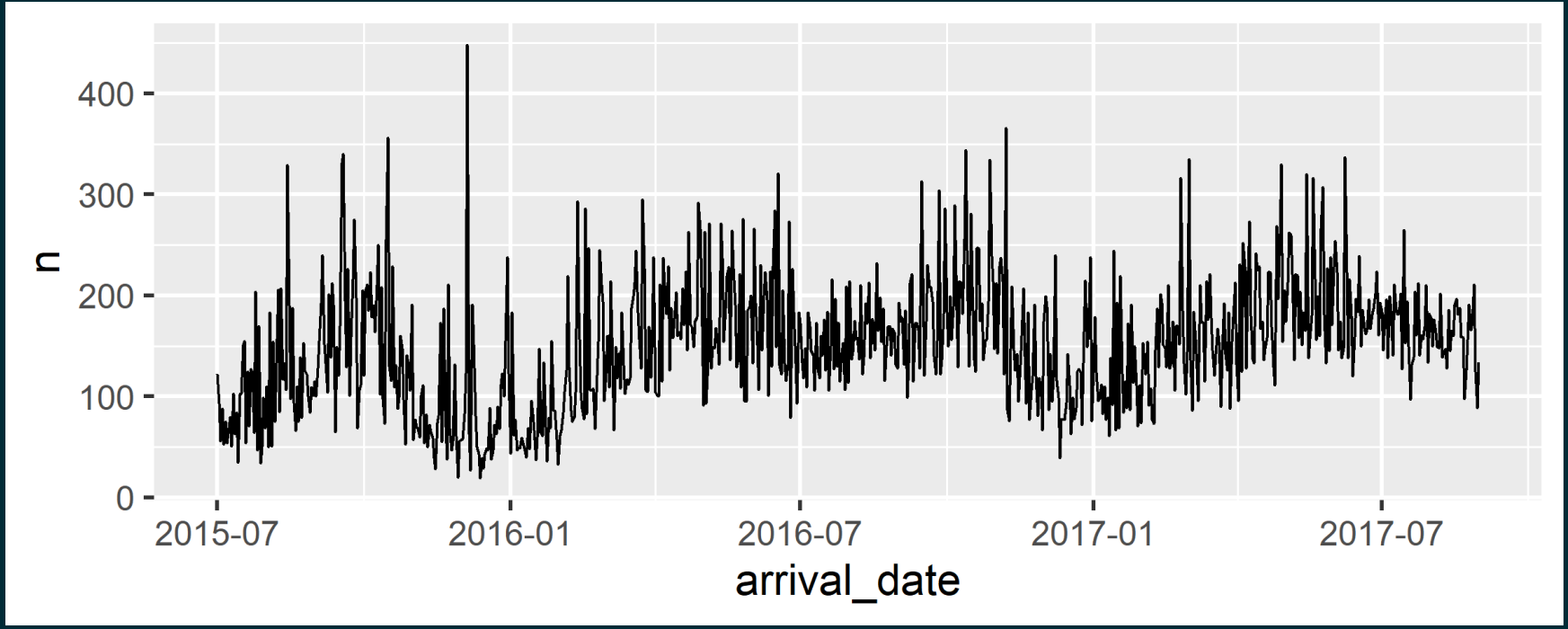
Step 2. Count bookings per date

```
hotels %>%
  mutate(arrival_date = ymd(glue("{arrival_date_year} {arrival_date_month} {arrival_date_day_of_
  count(arrival_date)
```

```
## # A tibble: 793 x 2
##   arrival_date     n
##   <date>       <int>
## 1 2015-07-01     122
## 2 2015-07-02      93
## 3 2015-07-03      56
## 4 2015-07-04      88
## 5 2015-07-05      53
## 6 2015-07-06      75
## # ... with 787 more rows
```

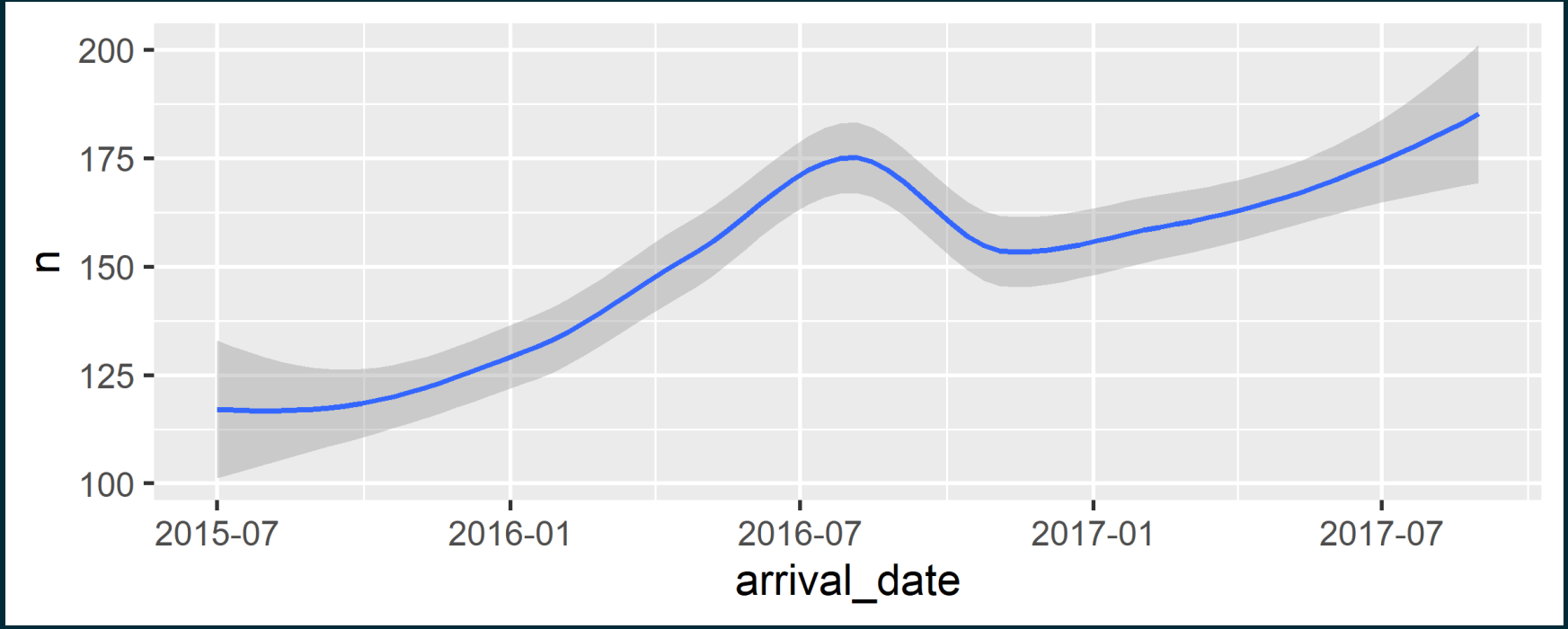
Step 3a. Visualise bookings per date

```
hotels %>%
  mutate(arrival_date = ymd(glue("{arrival_date_year} {arrival_date_month} {arrival_date_day_of_r
  count(arrival_date) %>%
  ggplot(aes(x = arrival_date, y = n, group = 1)) +
  geom_line()
```



Step 3b. Visualise using a smooth curve

```
hotels %>%
  mutate(arrival_date = ymd(glue("{arrival_date_year} {arrival_date_month} {arrival_date_day_of_r
  count(arrival_date) %>%
  ggplot(aes(x = arrival_date, y = n, group = 1)) +
  geom_smooth()
```



Reading rectangular data into R


readr
www.rstudio.com


readxl
www.rstudio.com

readr

- `read_csv()` - comma delimited files
- `read_csv2()` - semicolon separated files (common in countries where , is used as the decimal place)
- `read_tsv()` - tab delimited files
- `read_delim()` - reads in files with any delimiter
- `read_fwf()` - fixed width files
- ...

readr

- `read_csv()` - comma delimited files
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- `read_tsv()` - tab delimited files
- `read_delim()` - reads in files with any delimiter
- `read_fwf()` - fixed width files
- ...

readxl

- `read_excel()` - read xls or xlsx files
- ...

Reading data

```
nobel <- read_csv(file = "data/nobel.csv")
nobel
```

```
## # A tibble: 935 x 26
##      id firstname      surname    year category affiliation city
##   <dbl> <chr>          <chr>     <dbl> <chr>    <chr>       <chr>
## 1     1 Wilhelm Conrad Röntgen    1901 Physics  Munich Uni~ Muni~
## 2     2 Hendrik A.     Lorentz    1902 Physics  Leiden Uni~ Leid~
## 3     3 Pieter         Zeeman     1902 Physics  Amsterdam ~ Amst~
## 4     4 Henri          Becquerel  1903 Physics  École Poly~ Paris
## 5     5 Pierre         Curie      1903 Physics  École muni~ Paris
## 6     6 Marie          Curie      1903 Physics  <NA>        <NA>
## # ... with 929 more rows, and 19 more variables: country <chr>,
## #   born_date <date>, died_date <date>, gender <chr>,
## #   born_city <chr>, born_country <chr>,
## #   born_country_code <chr>, died_city <chr>,
## #   died_country <chr>, died_country_code <chr>,
## #   overall_motivation <chr>, share <dbl>, motivation <chr>,
## #   born_country_original <chr>, born_city_original <chr>, ...
```

Writing data

- Write a file

```
df <- tribble(
  ~x, ~y,
  1,  "a",
  2,  "b",
  3,  "c"
)

write_csv(df, file = "data/df.csv")
```

Writing data

- Write a file

```
df <- tribble(
  ~x, ~y,
  1,  "a",
  2,  "b",
  3,  "c"
)

write_csv(df, file = "data/df.csv")
```

- Read it back in to inspect

```
read_csv("data/df.csv")
```

```
## # A tibble: 3 x 2
##       x y
##   <dbl> <chr>
## 1     1 a
## 2     2 b
## 3     3 c
```

Your turn!

- RStudio > `AE 06 - Nobels and sales + Data import` > open `nobels-csv.Rmd` and knit.
- Read in the `nobels.csv` file from the `data-raw/` folder.
- Split into two (STEM and non-STEM):
  - Create a new data frame, `nobel_stem`, that filters for the STEM fields (Physics, Medicine, Chemistry, and Economics).
  - Create another data frame, `nobel_nonstem`, that filters for the remaining fields.
- Write out the two data frames to `nobel-stem.csv` and `nobel-nonstem.csv`, respectively, to `data/`.

Hint: Use the `%in%` operator when `filter()`ing.

Variable names

Data with bad names

```
edibnb_badnames <- read_csv("data/edibnb-badnames.csv")
names(edibnb_badnames)
```

```
##  [1] "ID"                  "Price"
##  [3] "neighbourhood"       "accommodates"
##  [5] "Number of bathrooms" "Number of Bedrooms"
##  [7] "n beds"              "Review Scores Rating"
##  [9] "Number of reviews"   "listing_url"
```

Data with bad names

```
edibnb_badnames <- read_csv("data/edibnb-badnames.csv")
names(edibnb_badnames)
```

```
##  [1] "ID"                  "Price"
##  [3] "neighbourhood"       "accommodates"
##  [5] "Number of bathrooms" "Number of Bedrooms"
##  [7] "n beds"              "Review Scores Rating"
##  [9] "Number of reviews"   "listing_url"
```

... but R doesn't allow spaces in variable names

```
ggplot(edibnb_badnames, aes(x = Number of bathrooms, y = Price)) +
  geom_point()
```

```
## Error: <text>:1:40: unexpected symbol
## 1: ggplot(edibnb_badnames, aes(x = Number of
##                                         ^
```

Option 1 - Define column names

```
edibnb_col_names <- read_csv("data/edibnb-badnames.csv",
                             col_names = c("id", "price",
                                           "neighbourhood", "accommodates",
                                           "bathroom", "bedroom",
                                           "bed", "review_scores_rating",
                                           "n_reviews", "url"))

names(edibnb_col_names)
```

```
##  [1] "id"                  "price"
##  [3] "neighbourhood"       "accommodates"
##  [5] "bathroom"            "bedroom"
##  [7] "bed"                 "review_scores_rating"
##  [9] "n_reviews"           "url"
```

Option 2 - Format text to snake_case

```
edibnb_clean_names <- read_csv("data/edibnb-badnames.csv") %>%
  janitor::clean_names()

names(edibnb_clean_names)
```

```
##  [1] "id"                  "price"
##  [3] "neighbourhood"       "accommodates"
##  [5] "number_of_bathrooms" "number_of_bedrooms"
##  [7] "n_beds"              "review_scores_rating"
##  [9] "number_of_reviews"   "listing_url"
```

Variable types

Which type is x? Why?

x	y	z
1	a	hi
NA	b	hello
3	Not applicable	9999
4	d	ola
5	e	hola
.	f	whatup
7	g	wassup
8	h	sup
9	i	

```
read_csv("data/df-na.csv")
```

```
## # A tibble: 9 x 3
##   x     y              z
##   <chr> <chr>          <chr>
## 1 1     a              hi
## 2 <NA>  b              hello
## 3 3     Not applicable 9999
## 4 4     d              ola
## 5 5     e              hola
## 6 .     f              whatup
## 7 7     g              wassup
## 8 8     h              sup
## 9 9     i              <NA>
```

Option 1. Explicit NAs

```
read_csv("data/df-na.csv",
         na = c("", "NA", ".", "9999", "Not applicable"))
```

x	y	z
1	a	hi
NA	b	hello
3	Not applicable	9999
4	d	ola
5	e	hola
.	f	whatup
7	g	wassup
8	h	sup
9	i	

```
## # A tibble: 9 x 3
##       x y     z
##   <dbl> <chr> <chr>
## 1     1 a     hi
## 2    NA b     hello
## 3     3 <NA>  <NA>
## 4     4 d     ola
## 5     5 e     hola
## 6    NA f     whatup
## 7     7 g     wassup
## 8     8 h     sup
## 9     9 i     <NA>
```

Option 2. Specify column types

```
read_csv("data/df-na.csv", col_types = list(col_double(),
                                            col_character(),
                                            col_character()))
```

```
## Warning: One or more parsing issues, see `problems()` for details
```

```
## # A tibble: 9 x 3
##       x y              z
##   <dbl> <chr>          <chr>
## 1     1 a              hi
## 2    NA b              hello
## 3     3 Not applicable 9999
## 4     4 d              ola
## 5     5 e              hola
## 6    NA f              whatup
## 7     7 g              wassup
## 8     8 h              sup
## 9     9 i              <NA>
```

Column types

type function	data type
`col_character()`	character
`col_date()`	date
`col_datetime()`	POSIXct (date-time)
`col_double()`	double (numeric)
`col_factor()`	factor
`col_guess()`	let readr guess (default)
`col_integer()`	integer
`col_logical()`	logical
`col_number()`	numbers mixed with non-number characters
`col_numeric()`	double or integer
`col_skip()`	do not read
`col_time()`	time

Wondering where you remember these from?

```
read_csv("data/df-na.csv")
```

```
##

Rows: 9 Columns: 3
##  [36mi [39m Building  [34mu2-Jumbo03-u2-10-11-12-13.rmd [39m into  [32mu2-Jumbo03-u2-10 [39m...

##

##  [36mi [39m Building  [34mu2-Jumbo03-u2-10-11-12-13.rmd [39m into  [32mu2-Jumbo03-u2-10 [39m...


-- Column specification ----------------------------------------
##  [36mi [39m Building  [34mu2-Jumbo03-u2-10-11-12-13.rmd [39m into  [32mu2-Jumbo03-u2-10 [39m...


Delimiter: ","
## chr (3): x, y, z
##
##  [36mi [39m Building  [34mu2-Jumbo03-u2-10-11-12-13.rmd [39m into  [32mu2-Jumbo03-u2-10 [39m...
```

Case study: Favourite foods

Favourite foods

Student ID	Full Name	favourite.food	mealPlan	AGE	SES
1	Sunil Huffmann	Strawberry yoghurt	Lunch only	4	High
2	Barclay Lynn	French fries	Lunch only	5	Middle
3	Jayendra Lyne	N/A	Breakfast and lunch	7	Low
4	Leon Rossini	Anchovies	Lunch only	99999	Middle
5	Chidiegwu Dunkel	Pizza	Breakfast and lunch	five	High

Favourite foods

Student ID	Full Name	favourite.food	mealPlan	AGE	SES
1	Sunil Huffmann	Strawberry yoghurt	Lunch only	4	High
2	Barclay Lynn	French fries	Lunch only	5	Middle
3	Jayendra Lyne	N/A	Breakfast and lunch	7	Low
4	Leon Rossini	Anchovies	Lunch only	99999	Middle
5	Chidiegwu Dunkel	Pizza	Breakfast and lunch	five	High

```
fav_food <- read_excel("data/favourite-food.xlsx")

fav_food
```

```
## # A tibble: 5 x 6
##   `Student ID` `Full Name`  favourite.food  mealPlan  AGE   SES
##          <dbl> <chr>        <chr>           <chr>     <chr> <chr>
## 1            1 Sunil Huffm~ Strawberry yog~ Lunch on~ 4     High
## 2            2 Barclay Lynn French fries    Lunch on~ 5     Midd~
## 3            3 Jayendra Ly~ N/A             Breakfas~ 7     Low
## 4            4 Leon Rossini Anchovies       Lunch on~ 99999 Midd~
## 5            5 Chidiegwu D~ Pizza           Breakfas~ five  High
```

Variable names

Student ID	Full Name	favourite.food	mealPlan	AGE	SES
1	Sunil Huffmann	Strawberry yoghurt	Lunch only	4	High
2	Barclay Lynn	French fries	Lunch only	5	Middle
3	Jayendra Lyne	N/A	Breakfast and lunch	7	Low
4	Leon Rossini	Anchovies	Lunch only	99999	Middle
5	Chidiegwu Dunkel	Pizza	Breakfast and lunch	five	High

Variable names

Student ID	Full Name	favourite.food	mealPlan	AGE	SES
1	Sunil Huffmann	Strawberry yoghurt	Lunch only	4	High
2	Barclay Lynn	French fries	Lunch only	5	Middle
3	Jayendra Lyne	N/A	Breakfast and lunch	7	Low
4	Leon Rossini	Anchovies	Lunch only	99999	Middle
5	Chidiegwu Dunkel	Pizza	Breakfast and lunch	five	High

```
fav_food <- read_excel("data/favourite-food.xlsx") %>%
  janitor::clean_names()

fav_food
```

```
## # A tibble: 5 x 6
##   student_id full_name   favourite_food   meal_plan   age   ses
##        <dbl> <chr>       <chr>            <chr>       <chr> <chr>
## 1          1 Sunil Huff~ Strawberry yogh~ Lunch only  4     High
## 2          2 Barclay Ly~ French fries     Lunch only  5     Midd~
## 3          3 Jayendra L~ N/A              Breakfast ~ 7     Low
## 4          4 Leon Rossi~ Anchovies        Lunch only  99999 Midd~
## 5          5 Chidiegwu ~ Pizza            Breakfast ~ five  High
```

Handling NAs

Student ID	Full Name	favourite.food	mealPlan	AGE	SES
1	Sunil Huffmann	Strawberry yoghurt	Lunch only	4	High
2	Barclay Lynn	French fries	Lunch only	5	Middle
3	Jayendra Lyne	N/A	Breakfast and lunch	7	Low
4	Leon Rossini	Anchovies	Lunch only	99999	Middle
5	Chidiegwu Dunkel	Pizza	Breakfast and lunch	five	High

Handling NAs

Student ID	Full Name	favourite.food	mealPlan	AGE	SES
1	Sunil Huffmann	Strawberry yoghurt	Lunch only	4	High
2	Barclay Lynn	French fries	Lunch only	5	Middle
3	Jayendra Lyne	N/A	Breakfast and lunch	7	Low
4	Leon Rossini	Anchovies	Lunch only	99999	Middle
5	Chidiegwu Dunkel	Pizza	Breakfast and lunch	five	High

```
fav_food <- read_excel("data/favourite-food.xlsx",
                       na = c("N/A", "99999")) %>%
  janitor::clean_names()

fav_food
```

```
## # A tibble: 5 x 6
##   student_id full_name   favourite_food   meal_plan   age   ses
##        <dbl> <chr>       <chr>            <chr>       <chr> <chr>
## 1          1 Sunil Huff~ Strawberry yogh~ Lunch only  4     High
## 2          2 Barclay Ly~ French fries     Lunch only  5     Midd~
## 3          3 Jayendra L~ <NA>             Breakfast ~ 7     Low
## 4          4 Leon Rossi~ Anchovies        Lunch only  <NA>  Midd~
## 5          5 Chidiegwu ~ Pizza            Breakfast ~ five  High
```

Make age numeric

```
fav_food <- fav_food %>%
  mutate(
    age = if_else(age == "five", "5", age),
    age = as.numeric(age)
    )

glimpse(fav_food)
```

	AGE	SES
	4	High
	5	Middle
ch	7	Low
	99999	Middle
ch	five	High

```
## Rows: 5
## Columns: 6
## $ student_id     <dbl> 1, 2, 3, 4, 5
## $ full_name      <chr> "Sunil Huffmann", "Barclay Lynn", "Jayen~
## $ favourite_food <chr> "Strawberry yoghurt", "French fries", NA~
## $ meal_plan      <chr> "Lunch only", "Lunch only", "Breakfast a~
## $ age            <dbl> 4, 5, 7, NA, 5
## $ ses            <chr> "High", "Middle", "Low", "Middle", "High"
```

Socio-economic status

What order are the levels of `ses` listed in?

```
fav_food %>%
  count(ses)
```

```
## # A tibble: 3 x 2
##   ses        n
##   <chr>  <int>
## 1 High       2
## 2 Low        1
## 3 Middle     2
```

Make `ses` factor

```
fav_food <- fav_food %>%
  mutate(ses = fct_relevel(ses, "Low", "Middle", "High"))

fav_food %>%
  count(ses)
```

```
## # A tibble: 3 x 2
##   ses        n
##   <fct>  <int>
## 1 Low        1
## 2 Middle     2
## 3 High       2
```

Putting it altogether

```
fav_food <- read_excel("data/favourite-food.xlsx", na = c("N/A", "99999")) %>%
  janitor::clean_names() %>%
  mutate(
    age = if_else(age == "five", "5", age),
    age = as.numeric(age),
    ses = fct_relevel(ses, "Low", "Middle", "High")
  )

fav_food
```

```
## # A tibble: 5 x 6
##   student_id full_name   favourite_food   meal_plan     age ses
##        <dbl> <chr>       <chr>            <chr>       <dbl> <fct>
## 1          1 Sunil Huff~ Strawberry yogh~ Lunch only      4 High
## 2          2 Barclay Ly~ French fries     Lunch only      5 Midd~
## 3          3 Jayendra L~ <NA>             Breakfast ~     7 Low
## 4          4 Leon Rossi~ Anchovies        Lunch only     NA Midd~
## 5          5 Chidiegwu ~ Pizza            Breakfast ~     5 High
```

Out and back in

```
write_csv(fav_food, file = "data/fav-food-clean.csv")

fav_food_clean <- read_csv("data/fav-food-clean.csv")
```

What happened to `ses` again?

```
fav_food_clean %>%
  count(ses)
```

```
## # A tibble: 3 x 2
##   ses        n
##   <chr>  <int>
## 1 High       2
## 2 Low        1
## 3 Middle     2
```

`read_rds()` and `write_rds()`

- CSVs can be unreliable for saving interim results if there is specific variable type information you want to hold on to.
- An alternative is RDS files, you can read and write them with `read_rds()` and `write_rds()`, respectively.

```
read_rds(path)
write_rds(x, path)
```

Out and back in, take 2

```
write_rds(fav_food, file = "data/fav-food-clean.rds")

fav_food_clean <- read_rds("data/fav-food-clean.rds")

fav_food_clean %>%
  count(ses)
```

```
## # A tibble: 3 x 2
##   ses        n
##   <fct>  <int>
## 1 Low        1
## 2 Middle     2
## 3 High       2
```

Other types of data

Other types of data

- **googlesheets4:** Google Sheets
- **haven**: SPSS, Stata, and SAS files
- **DBI**, along with a database specific backend (e.g. RMySQL, RSQLite, RPostgreSQL etc): allows you to run SQL queries against a database and return a data frame
- **jsonline**: JSON
- **xml2**: xml
- **rvest**: web scraping
- **httr**: web APIs
- **sparklyr**: data loaded into spark

Your turn!

- RStudio > `AE 06 - Nobels and sales + Data import` > `sales-excel.Rmd`.
- Load the `sales.xlsx` file from the `data-raw/` folder, using appropriate arguments for the `read_excel()` function such that it looks like the output on the left.
- **Stretch goal:** Manipulate the sales data such that it looks like the output on the right.

```
## # A tibble: 9 x 2
##   id      n
##   <chr>   <chr>
## 1 Brand 1 n
## 2 1234    8
## 3 8721    2
## 4 1822    3
## 5 Brand 2 n
## 6 3333    1
## # ... with 3 more rows
```

```
## # A tibble: 7 x 3
##   brand      id     n
##   <chr>   <dbl> <dbl>
## 1 Brand 1  1234     8
## 2 Brand 1  8721     2
## 3 Brand 1  1822     3
## 4 Brand 2  3333     1
## 5 Brand 2  2156     3
## 6 Brand 2  3987     6
## # ... with 1 more row
```

Case study: Religion and income

Income distribution by religious group

% of adults who have a household income of...

Chart | Table | Share | Save Image

Religious tradition	Less than $30,000	$30,000-$49,999	$50,000-$99,999	$100,000 or more	Sample Size
Buddhist	36%	18%	32%	13%	233
Catholic	36%	19%	26%	19%	6,137
Evangelical Protestant	35%	22%	28%	14%	7,462
Hindu	17%	13%	34%	36%	172
Historically Black Protestant	53%	22%	17%	8%	1,704
Jehovah's Witness	48%	25%	22%	4%	208
Jewish	16%	15%	24%	44%	708
Mainline Protestant	29%	20%	28%	23%	5,208
Mormon	27%	20%	33%	20%	594
Muslim	34%	17%	29%	20%	205
Orthodox Christian	18%	17%	36%	29%	155
Unaffiliated (religious "nones")	33%	20%	26%	21%	6,790

Sample sizes and margins of error vary from subgroup to subgroup, from year to year and from state to state. You can see the sample size for the estimates in this chart on rollover or in the last column of the table. And visit this table to see approximate margins of error for a group of a given size. Readers should always bear in mind the approximate margin of error for the group they are examining when making comparisons with other groups or assessing the significance of trends over time. For full question wording, see the survey questionnaire.

Source: pewforum.org/religious-landscape-study/income-distribution, Retrieved 14 April, 2020

Read data

```
library(readxl)
rel_inc <- read_excel("data/relig-income.xlsx")
```

```
## # A tibble: 12 x 6
##   `Religious tradition`         `Less than $30,~ `$30,000-$49,99~
##   <chr>                                    <dbl>            <dbl>
## 1 Buddhist                                  0.36             0.18
## 2 Catholic                                  0.36             0.19
## 3 Evangelical Protestant                    0.35             0.22
## 4 Hindu                                     0.17             0.13
## 5 Historically Black Protestant             0.53             0.22
## 6 Jehovah's Witness                         0.48             0.25
## # ... with 6 more rows, and 3 more variables:
## #   $50,000-$99,999 <dbl>, $100,000 or more <dbl>,
## #   Sample Size <dbl>
```

Rename columns

```
rel_inc %>%
  rename(
    religion = `Religious tradition`,
    n = `Sample Size`
  )
```

```
## # A tibble: 12 x 6
##   religion     `Less than $30,~ `$30,000-$49,99~ `$50,000-$99,99~
##   <chr>                   <dbl>            <dbl>            <dbl>
## 1 Buddhist                 0.36             0.18             0.32
## 2 Catholic                 0.36             0.19             0.26
## 3 Evangelical~             0.35             0.22             0.28
## 4 Hindu                    0.17             0.13             0.34
## 5 Historicall~             0.53             0.22             0.17
## 6 Jehovah's W~             0.48             0.25             0.22
## # ... with 6 more rows, and 2 more variables:
## #   $100,000 or more <dbl>, n <dbl>
```

If we want a new variable called `income` with levels such as "Less than $30,000", "$30,000-$49,999", ... etc. which function should we use?

```
## # A tibble: 48 x 4
##    religion                    n income           proportion
##    <chr>                   <dbl> <chr>                 <dbl>
##  1 Buddhist                  233 Less than $30,000      0.36
##  2 Buddhist                  233 $30,000-$49,999        0.18
##  3 Buddhist                  233 $50,000-$99,999        0.32
##  4 Buddhist                  233 $100,000 or more       0.13
##  5 Catholic                 6137 Less than $30,000      0.36
##  6 Catholic                 6137 $30,000-$49,999        0.19
##  7 Catholic                 6137 $50,000-$99,999        0.26
##  8 Catholic                 6137 $100,000 or more       0.19
##  9 Evangelical Protestant   7462 Less than $30,000      0.35
## 10 Evangelical Protestant   7462 $30,000-$49,999        0.22
## 11 Evangelical Protestant   7462 $50,000-$99,999        0.28
## 12 Evangelical Protestant   7462 $100,000 or more       0.14
## 13 Hindu                     172 Less than $30,000      0.17
## 14 Hindu                     172 $30,000-$49,999        0.13
## 15 Hindu                     172 $50,000-$99,999        0.34
## # ... with 33 more rows
```

Pivot longer

```
rel_inc %>%
  rename(
    religion = `Religious tradition`,
    n = `Sample Size`
  ) %>%
  pivot_longer(
    cols = -c(religion, n),   # all but religion and n
    names_to = "income",
    values_to = "proportion"
  )
```

```
## # A tibble: 48 x 4
##   religion     n income            proportion
##   <chr>    <dbl> <chr>                  <dbl>
## 1 Buddhist   233 Less than $30,000       0.36
## 2 Buddhist   233 $30,000-$49,999         0.18
## 3 Buddhist   233 $50,000-$99,999         0.32
## 4 Buddhist   233 $100,000 or more        0.13
## 5 Catholic  6137 Less than $30,000       0.36
## 6 Catholic  6137 $30,000-$49,999         0.19
## # ... with 42 more rows
```

Calculate frequencies

```
rel_inc %>%
  rename(
    religion = `Religious tradition`,
    n = `Sample Size`
  ) %>%
  pivot_longer(
    cols = -c(religion, n),
    names_to = "income",
    values_to = "proportion"
  ) %>%
  mutate(frequency = round(proportion * n))
```

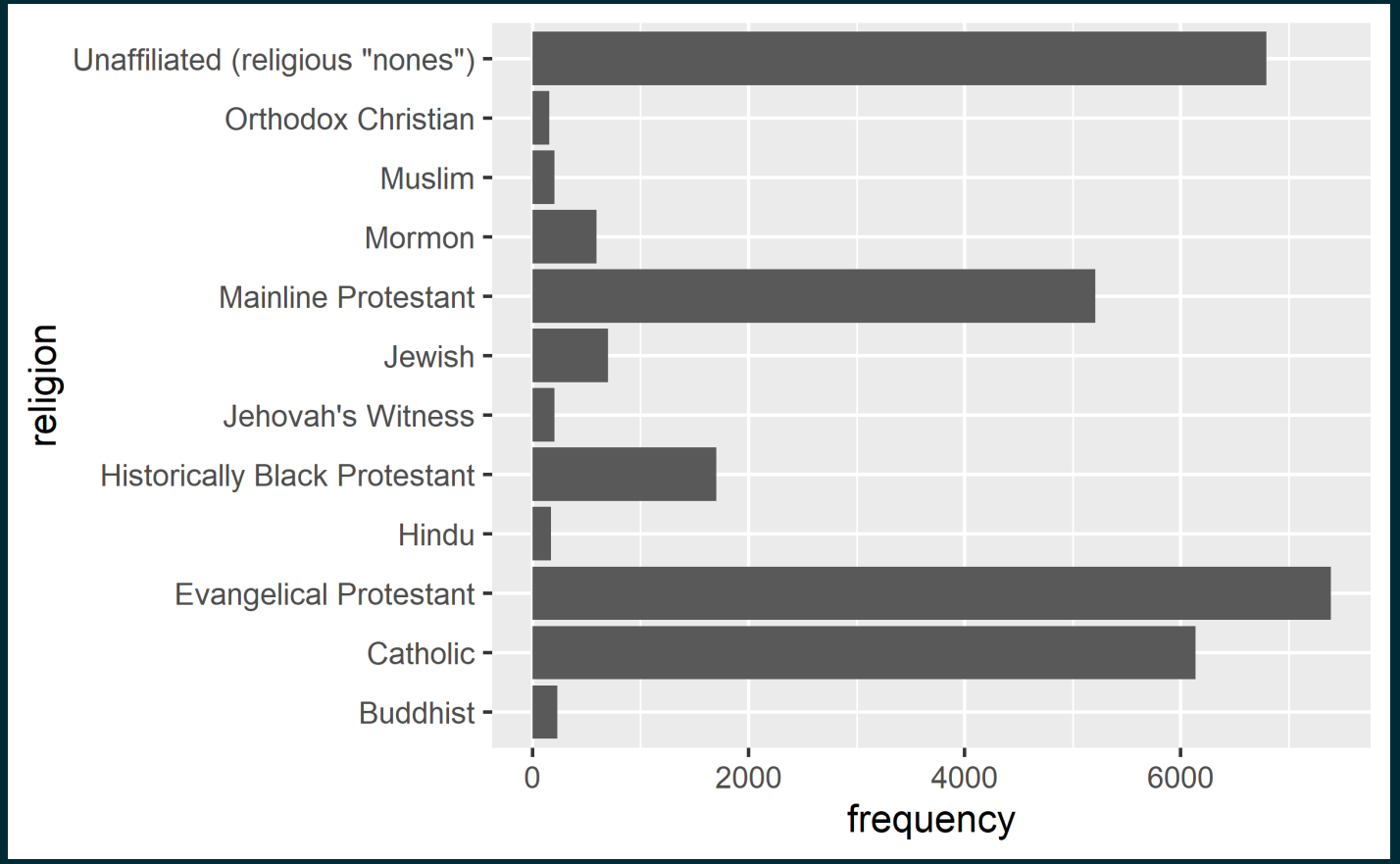
```
## # A tibble: 48 x 5
##   religion     n income            proportion frequency
##   <chr>    <dbl> <chr>                  <dbl>     <dbl>
## 1 Buddhist   233 Less than $30,000       0.36        84
## 2 Buddhist   233 $30,000-$49,999         0.18        42
## 3 Buddhist   233 $50,000-$99,999         0.32        75
## 4 Buddhist   233 $100,000 or more        0.13        30
## 5 Catholic  6137 Less than $30,000       0.36      2209
## 6 Catholic  6137 $30,000-$49,999         0.19      1166
## # ... with 42 more rows
```

Save data

```
rel_inc_long <- rel_inc %>%
  rename(
    religion = `Religious tradition`,
    n = `Sample Size`
  ) %>%
  pivot_longer(
    cols = -c(religion, n),
    names_to = "income",
    values_to = "proportion"
  ) %>%
  mutate(frequency = round(proportion * n))
```

Barplot

```
ggplot(rel_inc_long, aes(y = religion, x = frequency)) +
  geom_col()
```



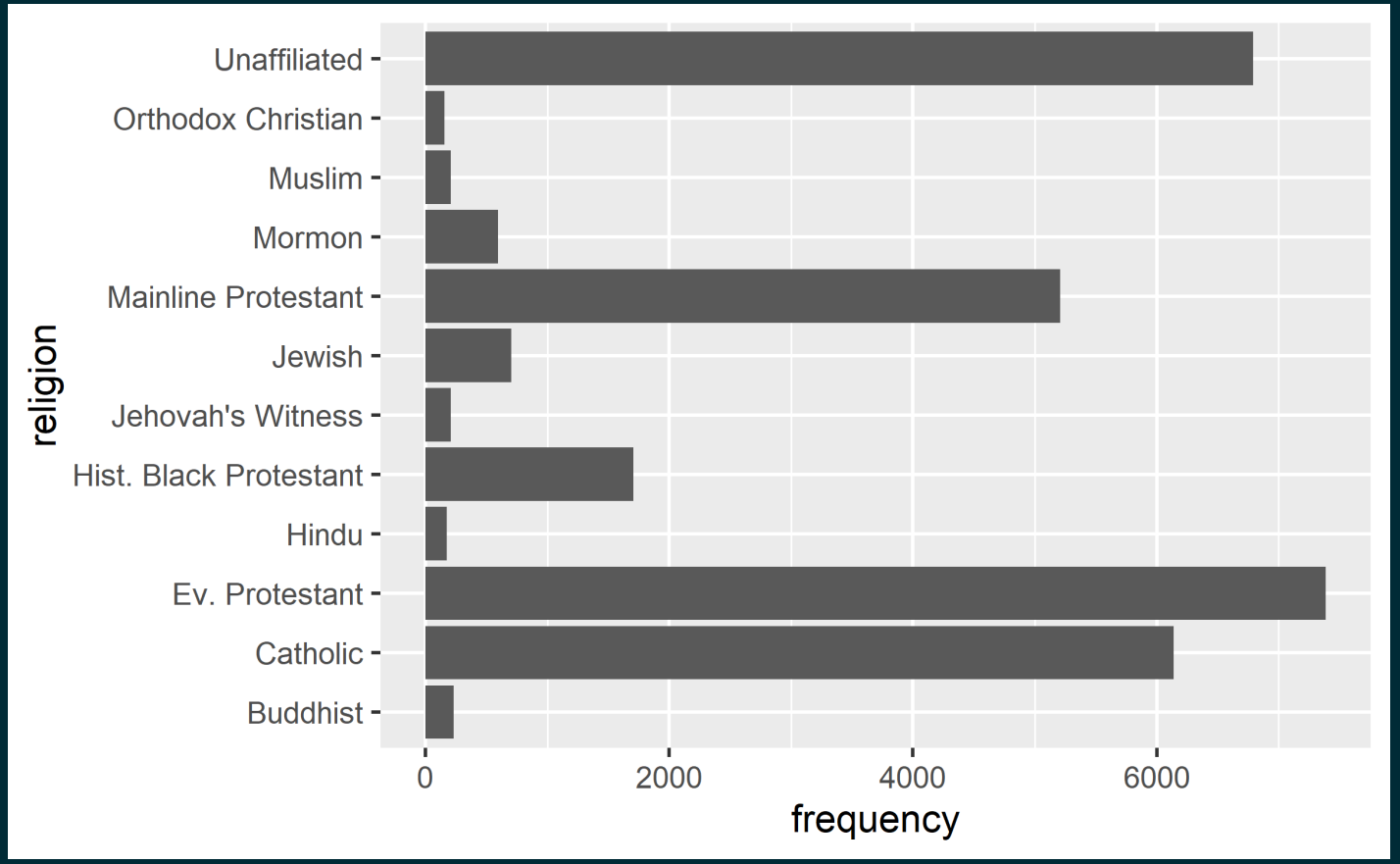
Recode religion

Recode | Plot

```
rel_inc_long <- rel_inc_long %>%
  mutate(religion = case_when(
    religion == "Evangelical Protestant"           ~ "Ev. Protestant",
    religion == "Historically Black Protestant"    ~ "Hist. Black Protestant",
    religion == 'Unaffiliated (religious "nones")' ~ "Unaffiliated",
    TRUE                                           ~ religion
  ))
```

Recode religion

Recode | Plot



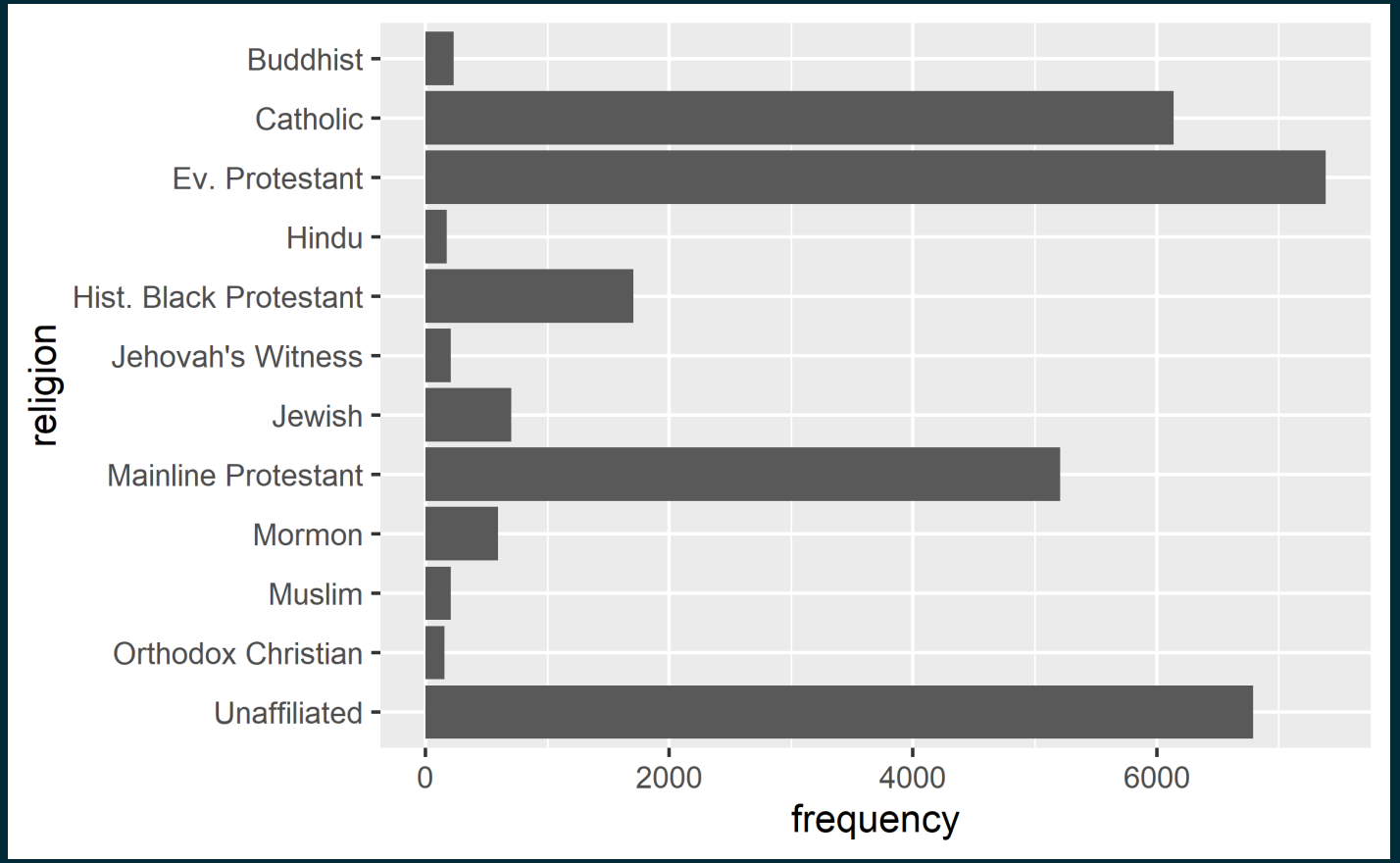
Reverse religion order

Recode | Plot

```
rel_inc_long <- rel_inc_long %>%
  mutate(religion = fct_rev(religion))
```

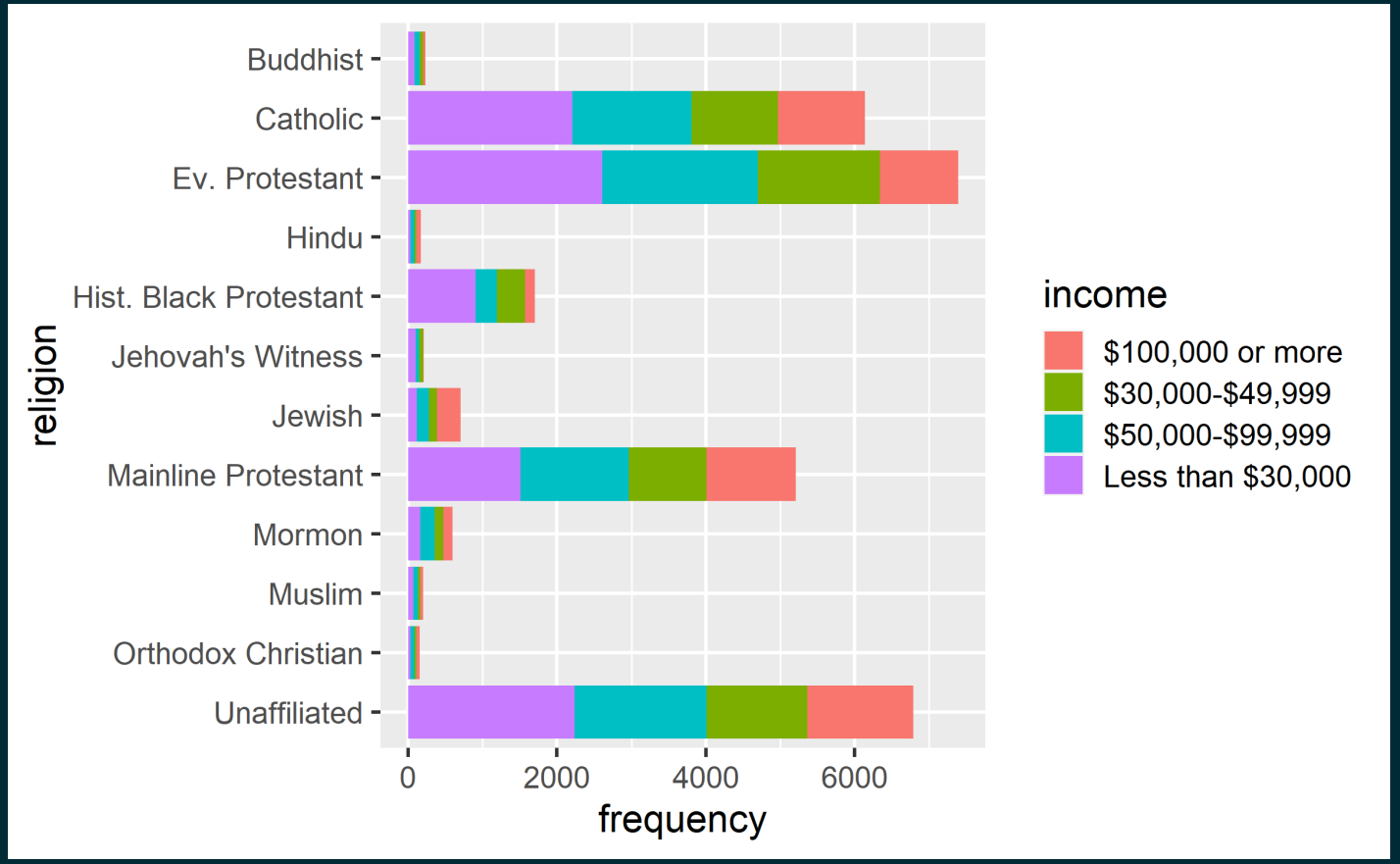
Reverse religion order

Recode | Plot



Add income

Plot Code



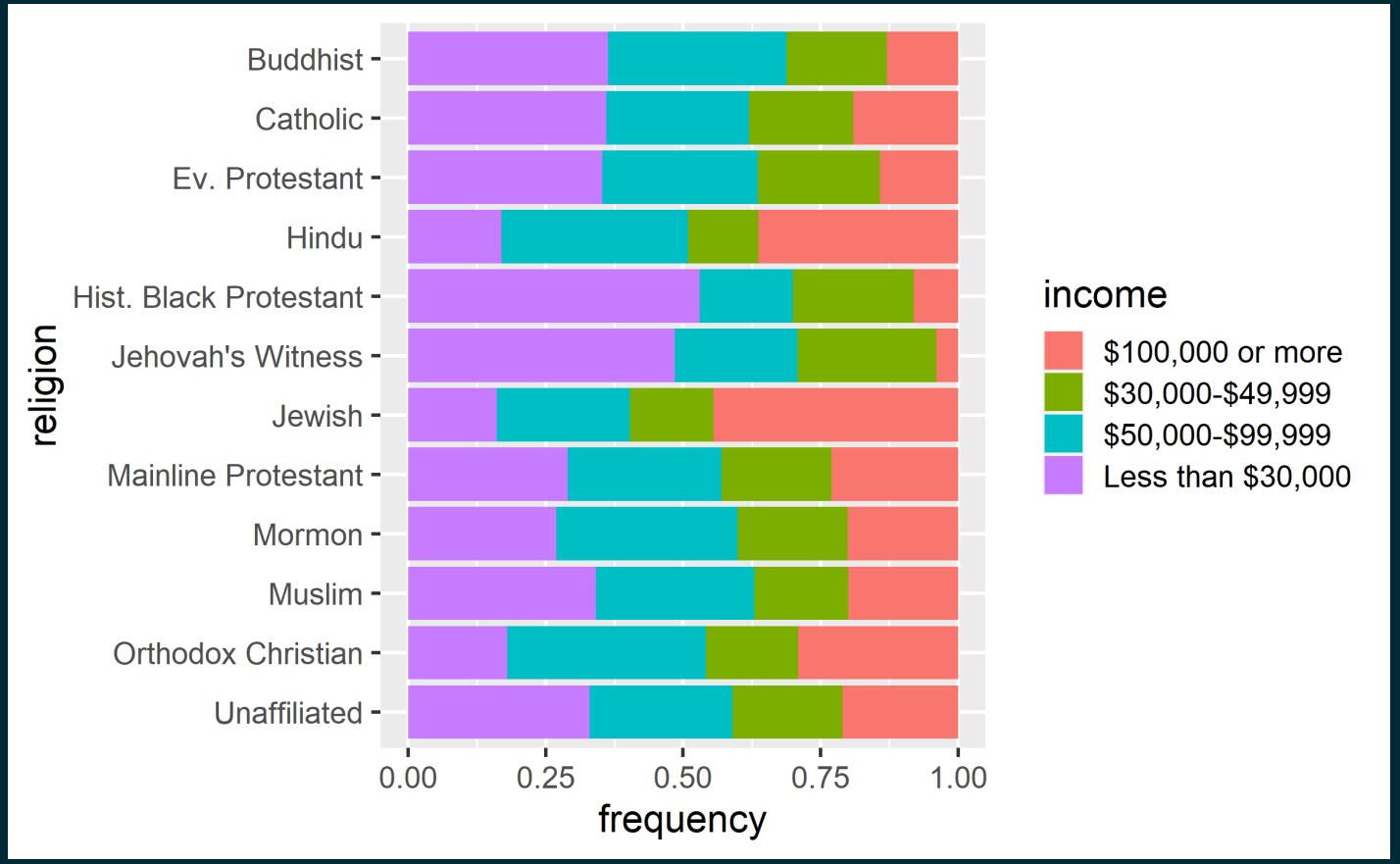
Add income

Plot | Code

```
ggplot(rel_inc_long, aes(y = religion, x = frequency, fill = income)) +
  geom_col()
```

Fill bars

Plot Code



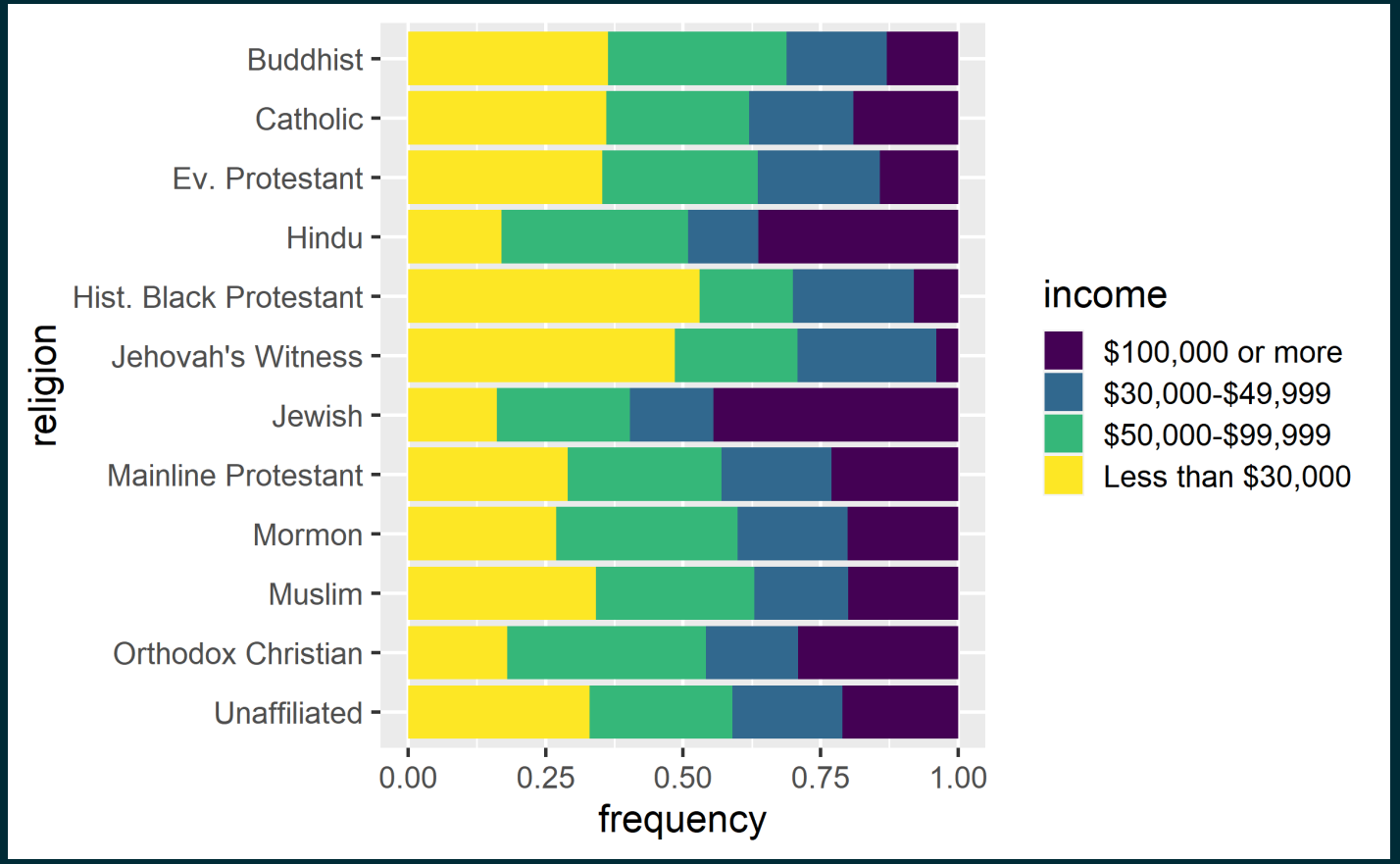
Fill bars

Plot | Code

```
ggplot(rel_inc_long, aes(y = religion, x = frequency, fill = income)) +
  geom_col(position = "fill")
```

Change colors

Plot Code



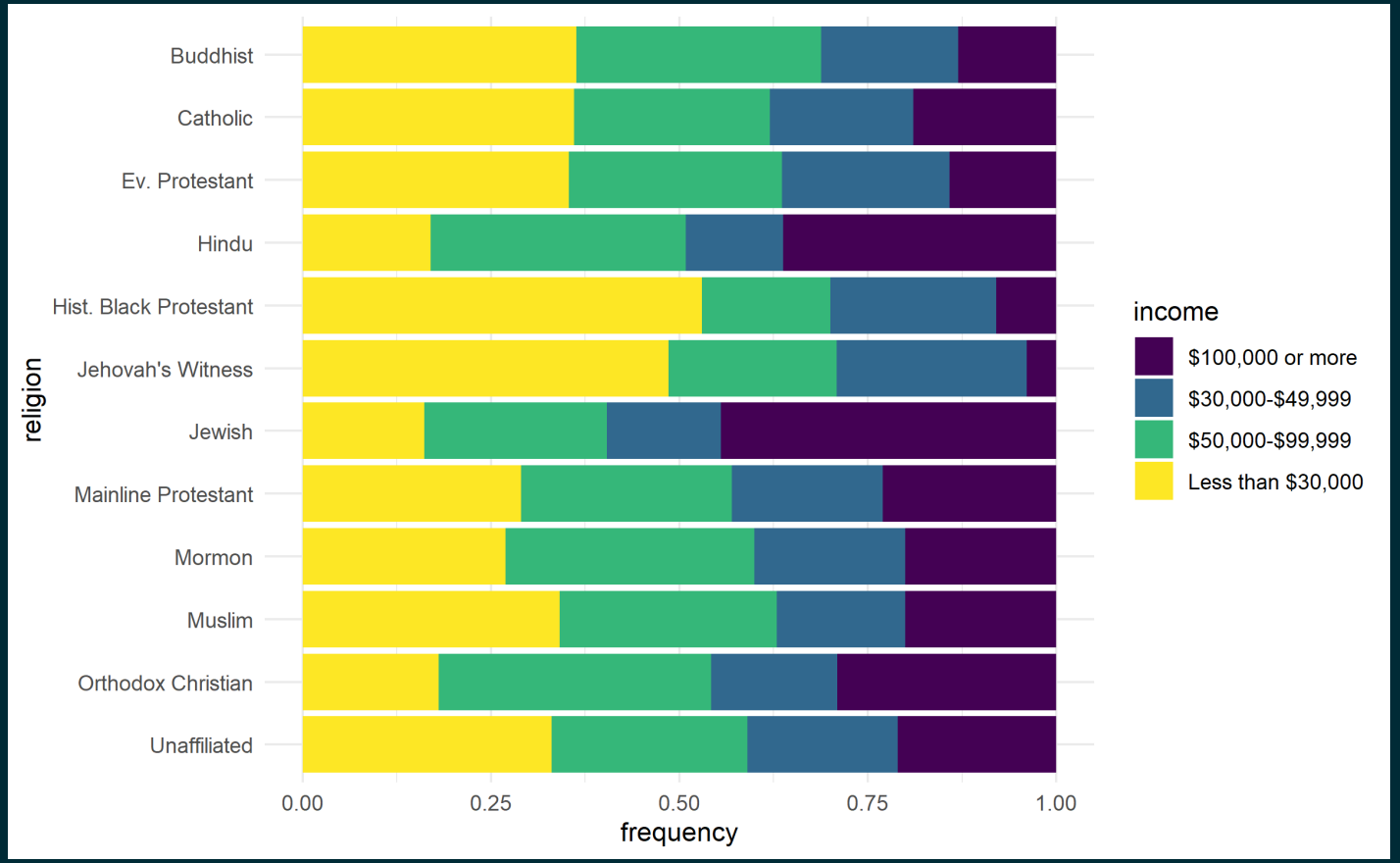
Change colors

Plot | Code

```
ggplot(rel_inc_long, aes(y = religion, x = frequency, fill = income)) +
  geom_col(position = "fill") +
  scale_fill_viridis_d()
```

Change theme

Plot Code



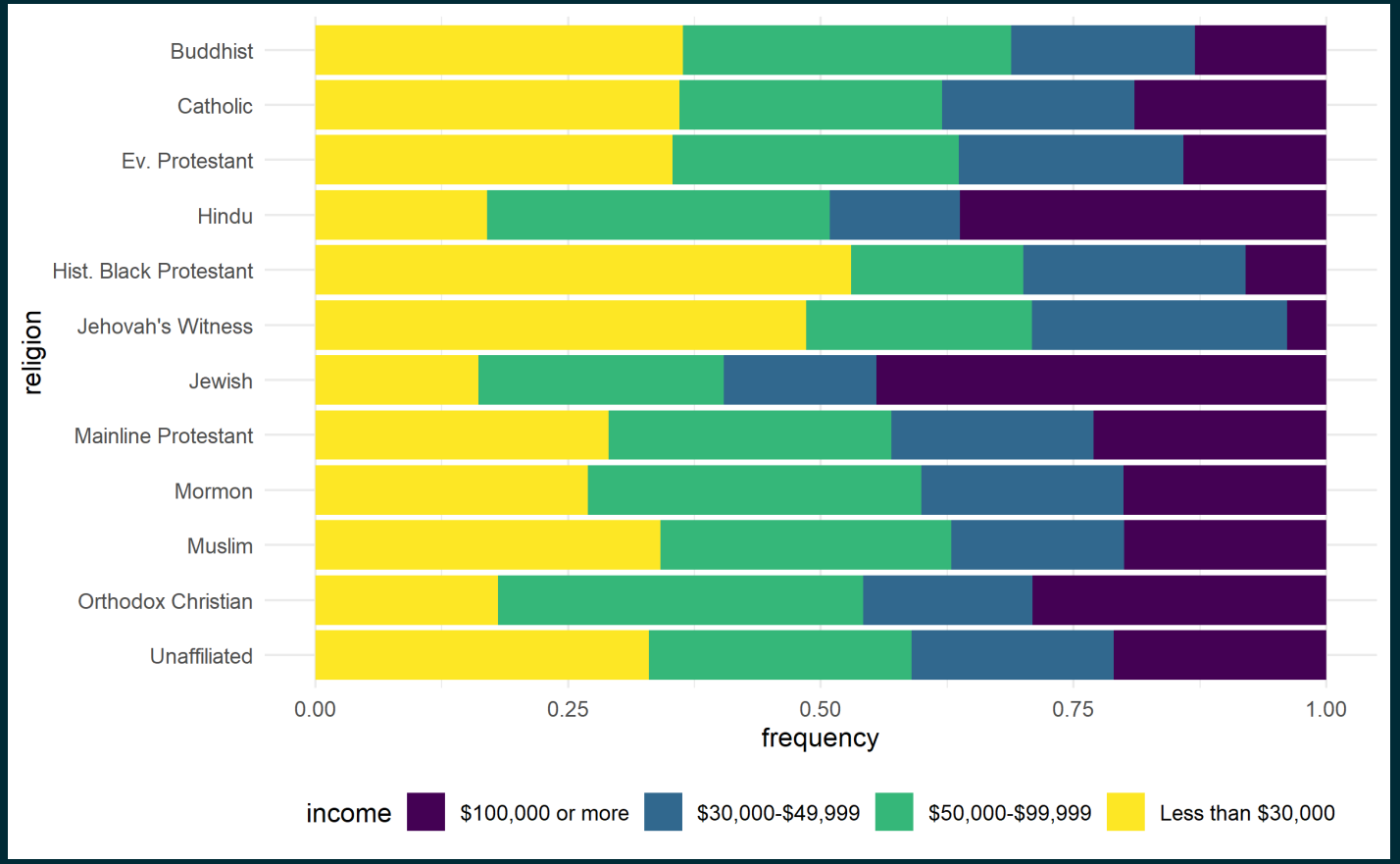
Change theme

Plot | Code

```
ggplot(rel_inc_long, aes(y = religion, x = frequency, fill = income)) +
  geom_col(position = "fill") +
  scale_fill_viridis_d() +
  theme_minimal()
```

Move legend to the bottom

Plot Code



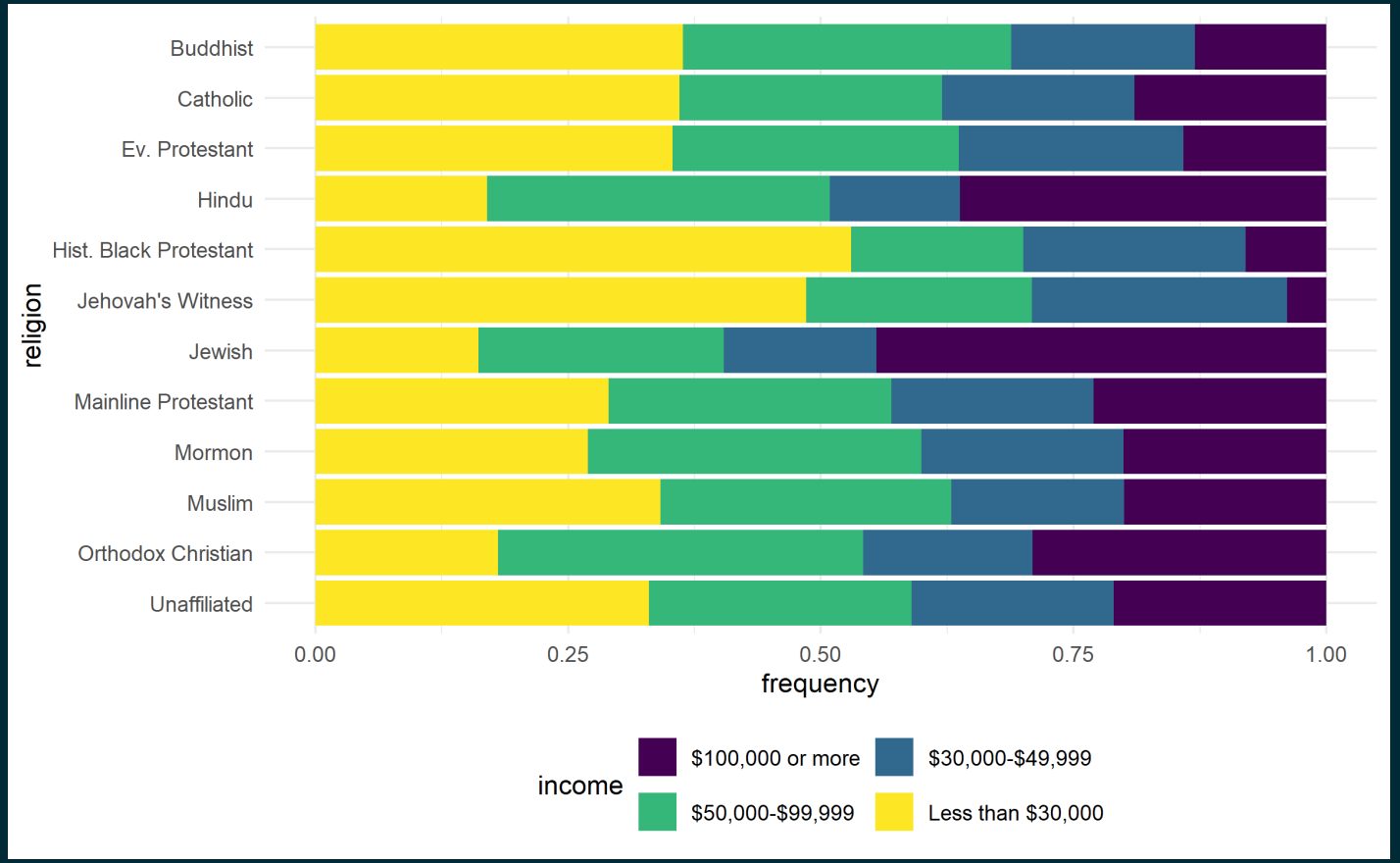
Move legend to the bottom

Plot | Code

```
ggplot(rel_inc_long, aes(y = religion, x = frequency, fill = income)) +
  geom_col(position = "fill") +
  scale_fill_viridis_d() +
  theme_minimal() +
  theme(legend.position = "bottom")
```

Legend adjustments

Plot Code



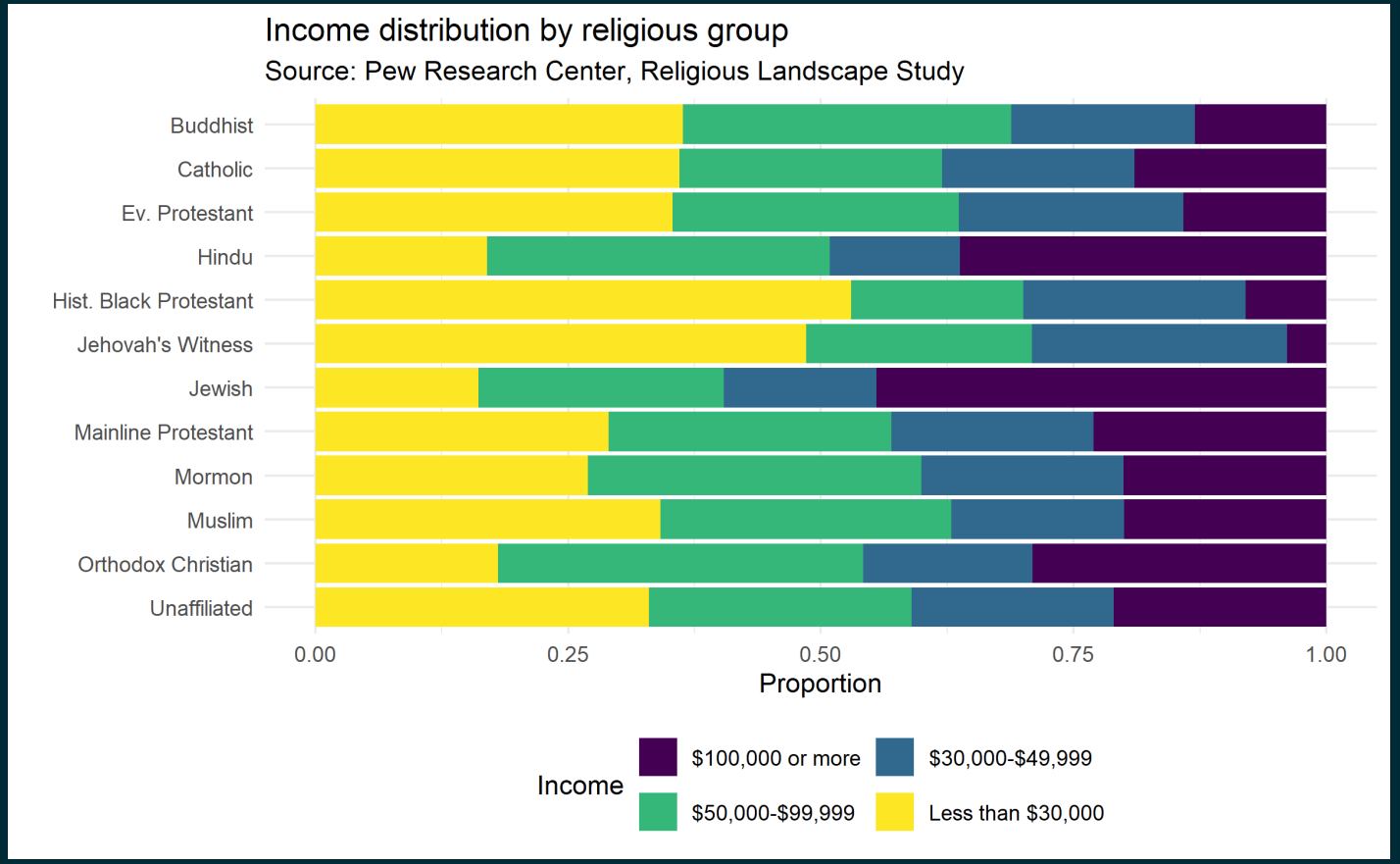
Legend adjustments

Plot | Code

```
ggplot(rel_inc_long, aes(y = religion, x = frequency, fill = income)) +
  geom_col(position = "fill") +
  scale_fill_viridis_d() +
  theme_minimal() +
  theme(legend.position = "bottom") +
  guides(fill = guide_legend(nrow = 2, byrow = TRUE))
```

Fix labels

Plot Code



Fix labels

Plot | Code

```
ggplot(rel_inc_long, aes(y = religion, x = frequency, fill = income)) +
  geom_col(position = "fill") +
  scale_fill_viridis_d() +
  theme_minimal() +
  theme(legend.position = "bottom") +
  guides(fill = guide_legend(nrow = 2, byrow = TRUE)) +
  labs(
    x = "Proportion", y = "",
    title = "Income distribution by religious group",
    subtitle = "Source: Pew Research Center, Religious Landscape Study",
    fill = "Income"
    )
```