2019-10-22 Horror films

Data: https://github.com/rfordatascience/tidytuesday/tree/master/data/2019/2019-10-22

My code: https://github.com/mrtnj/rstuff/blob/master/tidytuesday/horror_movies.R

In time for Halloween, we got a dataset with horror film data from IMDB. (Yes, I will be mixing the terms ”film” and ”movie” wildly.)

The first week, I started with making a pretty boring plot, the way I’d normally plot things (white background, small multiples, you know the drill). I wanted to look at distribution over the year, so I plotted what month films are released and the distribution of review scores and budgets each month. After thinking about it for a while, I thought a logarithmic scale would make sense for budgets, that span a huge range. Also, after realising that the budget column actually didn’t contain dollars, but a mix of currencies, I decided not to try to convert, but use only the US dollar budgets.

I don’t often run into dates, to using the date functions from *readr* and *lubridate* was new to me, as was the built-in vector *month.abb*:

```
library(dplyr)
library(egg)
library(ggplot2)
library(ggimage)
library(lubridate)
library(readr)
library(stringr)

movies <- read_csv("horror_movies.csv")

## Parse dates

movies$release_parsed  <- parse_date(movies$release_date,
                                     format = "%d-%b-%y",
                                     locale = locale("en"))

movies$release_year <- ifelse(is.na(movies$release_parsed),
                              movies$release_date,
                              year(movies$release_parsed))

movies$release_month  <- month.abb[month(movies$release_parsed)]
```

Here, we parse the release data, and extract the release year, treating films that only have a release year separately.

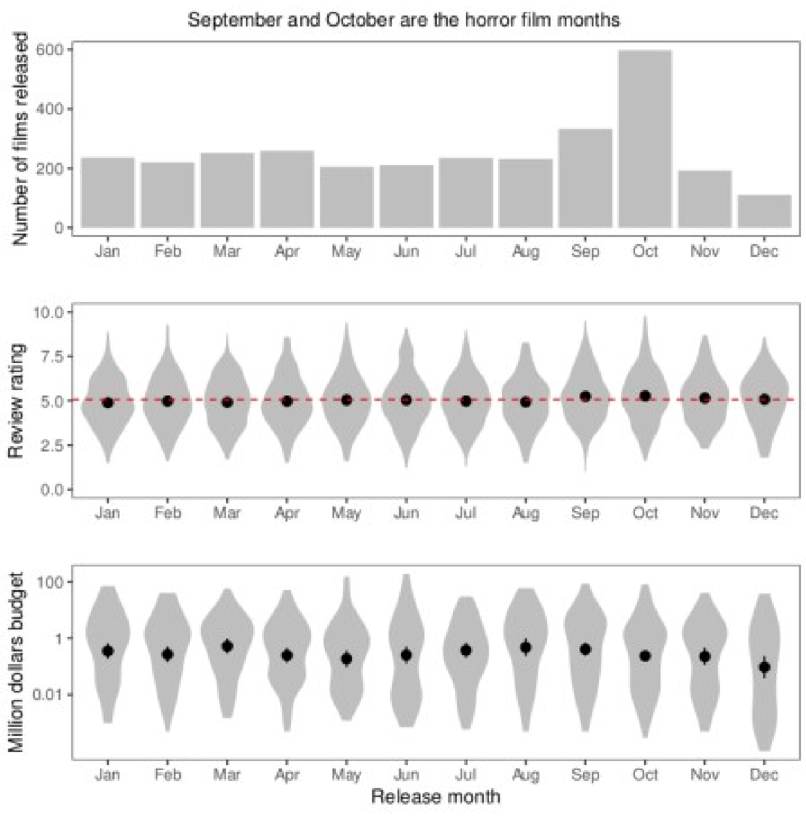
I also put in means with confidence intervals, like so, and a line for the mean review rating:

```
model  <- lm(review_rating ~ release_month, movies)

fit  <- data.frame(release_month = month.abb,
                   predict(model,
                           newdata = data.frame(release_month = month.abb),
                                                interval = "confidence"),
                   stringsAsFactors = FALSE)

grand_mean_rating  <- mean(movies$review_rating,
                           na.rm = TRUE)
```

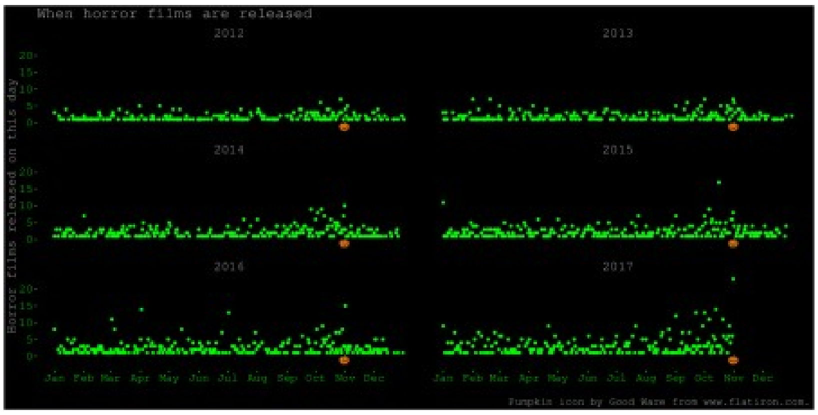
As an example of the plotting code, here is the middle panel for ratings. As usual with *ggplot2*, we layer geometries on top of each other (here: violin plots, points with range bars, and a horizontal line, followed by a lot of formatting.

```
plot_rating <- ggplot() +
    geom_violin(aes(x = release_month,
                    y = review_rating),
                fill = "grey",
                colour = NA,
                data = movies) +
    scale_x_discrete(limits = month.abb) +
    geom_pointrange(aes(x = release_month,
                        y = fit,
                        ymax = upr,
                        ymin = lwr),
                    data = fit) +
    geom_hline(yintercept = grand_mean_rating,
               linetype = 2,
               colour = "red") +
    ylim(0, 10) +
    theme_bw(base_size = 12) +
    theme(panel.grid = element_blank()) +
    xlab("") +
    ylab("Review rating")
```

There is similar code for the other two panels. Finally, I used *ggarrange* from the *egg* package to put everything together. In summary, most horror films are released in October, probably around Halloween. The review ratings of films released in this horror season are also a tiny bit higher than during the rest of the year, but there is not much of a difference in the budgets.



After that, and after seeing some of the fun horror-themed graphs other people made, I decided to make something more colourful. Here is a plot on the same theme, showing each day and year separately, an appropriately horrendous colour scheme, and a pumpkin icon to indicate the date of Halloween. I like this plot better because it shows more of the data. It shows the increase at Halloween. We also see some spikes at other dates, like 1 January of some years. It also shows how the dataset ends at Halloween 2017.



The code for this plot is mostly a lot of theme formatting. The *ggplot2 theme* function takes a lot of arguments I've never used before.

```
movies$yday  <- yday(movies$release_parsed)

daycount <- summarise(group_by(movies, yday, release_year), n = n())
```

First, we turn dates into days of the year, and count the number of film releases.

```
halloween  <-  yday("2019-10-31")

pumpkin_data  <- data.frame(x = halloween,
                            y = -1,
                            image = "pumpkin.png",
                            stringsAsFactors = FALSE)
```

Then, we set up the date of Halloween and a data frame for the pumpkin icon. We're going to use *geom_image* from the *ggimage* package to add this icon to each subplot.

```
breaks  <- yday(paste("2019-", 1:12, "-01", sep = ""))

plot_year <- ggplot() +
    geom_point(aes(x = yday,
                   y = n),
               colour = "green",
               data = na.exclude(dc)) +
    geom_image(aes(x = x,
                   y = y,
                   image = image),
               data = pumpkin_data) +
    facet_wrap(~ release_year,
               ncol = 2) +
    scale_x_continuous(breaks = breaks,
                       labels = month.abb) +
    ylim(-3, NA) +
    labs(caption = "Pumpkin icon by Good Ware from www.flatiron.com.") +
    theme(panel.grid = element_blank(),
          strip.background = element_blank(),
          text = element_text(family = "mono",
                              colour = "grey",
                              size = 16),
          axis.text = element_text(family = "mono",
                                   colour = "green",
                                   size = 14),
          axis.ticks = element_line(colour = "green"),
          strip.text = element_text(family = "mono",
                                     colour = "grey",
                                     size = 16),
          plot.background = element_rect(fill = "black"),
          panel.background = element_rect(fill = "black")) +
    xlab("") +
    ylab("Horror films released on this day") +
    ggtitle("When horror films are released")
```

A lot of other people made graphs that highlight the increase in horror film releases around Halloween in different ways. Here are some that I like:

> It's #October – that means pumpkins, falling leaves, and #horror movies! This #TidyTuesday: horror movie releases per country/month. It's been a while… Happy to be back!#rstats #dataviz #R4DS #ggplot #tidyverse
>
> Code: https://t.co/g71Fc8cn62
> Source: https://t.co/YYRtdYoUmE pic.twitter.com/lfsyyCFNog
>
> — Veerle van Son (@veerlevanson) October 25, 2019

> #TidyTuesday this week inspired by a 'calendar plot' I saw from @BBCWorld (https://t.co/v0DIBDw74C). Made my own using geom_tile. Horror movie releases are clearly targeted at Halloween. #tidyverse #rstats
>
> Code👨‍💻: https://t.co/cxJhXcfQCm
> Plot📈: https://t.co/lhL594QJTp pic.twitter.com/sH8ppgbyx6
>
> — Liam Bailey (@ldbailey255) October 23, 2019

> My first #tidytuesday contribution! Inspired by the @github contribution graph. 🙃 Horror movies are most frequently released on Fridays, esp leading up to Halloween. (Data from 2017.) Code: https://t.co/hKd2ML3RI2 pic.twitter.com/QV49nzrhoQ
>
> — Alyson La (@alysonlaaa) October 30, 2019

And, looking deeper, there is a pattern within months too:

> They love 13.
> It is the most preferred day in the month for #Horror movie releases (excl. the 1st).
> Be careful #TidyTuesday is addictive. #r4ds #rstats #tidyverse #animate
> code: https://t.co/fYEZUw7aT9 pic.twitter.com/InmTpk1NWk
>
> — Serdar Korur (@Dataatomic) October 25, 2019

Finally, I also like this plot, that makes a case for a U-shaped relationship between budget and rating:

> Horror film ratings by budget. Obsessed with annotations lately….
> Code: https://t.co/JAMMvGdUMT#TidyTuesday #dataviz #rstats pic.twitter.com/CEYgmqQfyL
>
> — Jenna DeVries (@jennaldevries) October 28, 2019

And for contrast, another that makes a different case with the same data:

> #tidytuesday Apparently big budgets don't help with horror movie ratings https://t.co/NswrlRpR8q pic.twitter.com/Qom1OtFpn7
>
> — Larry D'Agostino (@larrydag) October 24, 2019

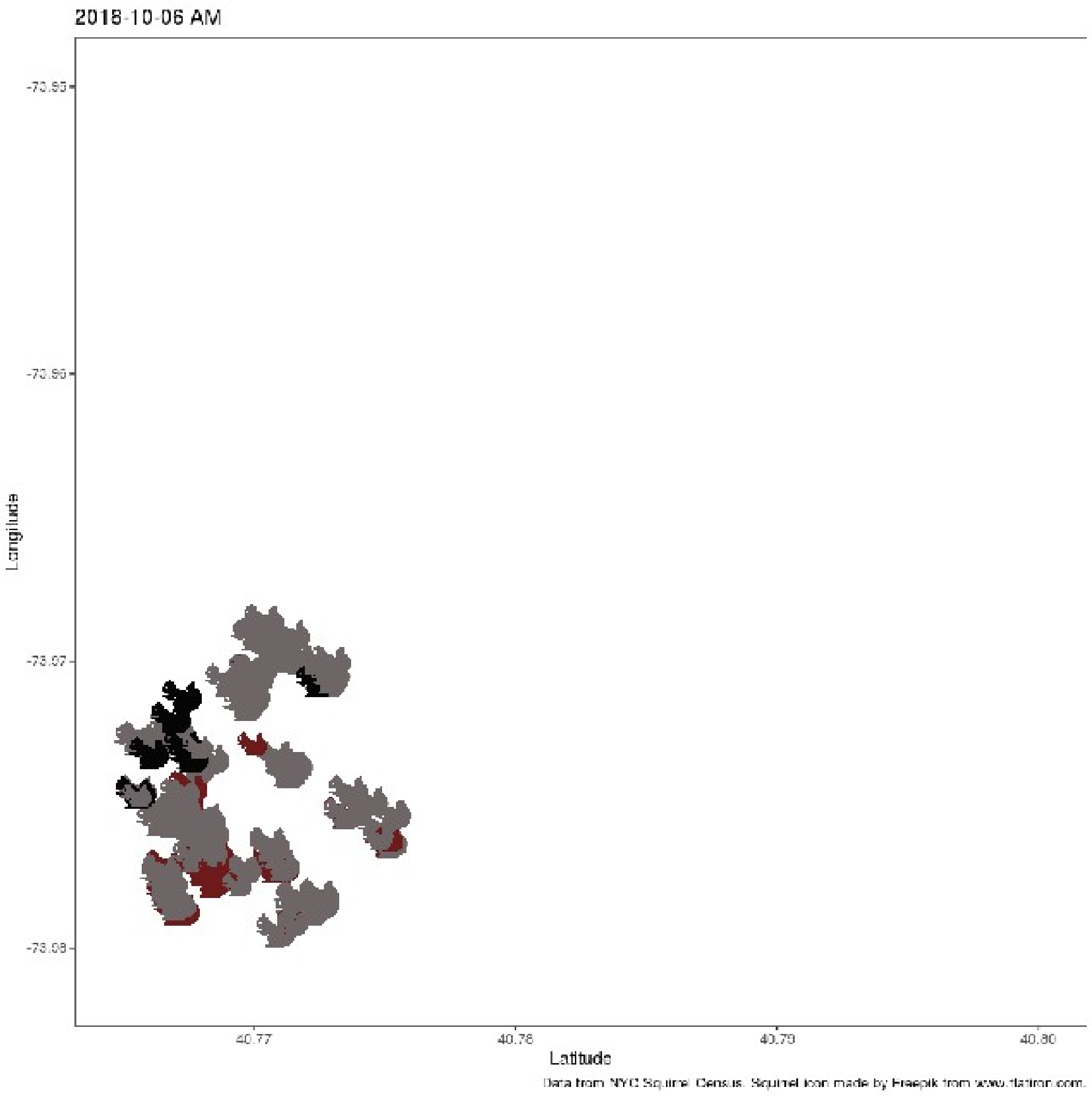
This seems to be a recurrent theme when it comes to interpretation and quantitative analysis in the Tidy Tuesday datasets. People make different modeling choices, or visualisation choices (which are modeling choices) about what to lump together, what to separate into bins, how to transform the data, and how to show uncertainty. In some cases, as with the pattern of film releases around Halloween, they all find similar results. In some other cases, they don't.

2019-10-28 NYC Squirrel Census

Data: https://github.com/rfordatascience/tidytuesday/tree/master/data/2019/2019-10-29

My code: https://github.com/mrtnj/rstuff/blob/master/tidytuesday/nyc_squirrels.R

This week, the data was about the location and activities of squirrels in New York central park on certain times. I had this vision of an animated map of squirrel locations. I ended up with an animation, but no map. The colour of the squirrel icon shows the main fur colour of the squirrels (grey, black, cinnamon), and the size shows adults and juveniles.



I had never used *gganimate* before (only *animation*, as in this post about the Game of Life), but I had seen Thomas Lin Pedersen tweet about it, and I wanted to try.

```
library(dplyr)
library(gganimate)
library(ggimage)
library(ggplot2)
library(readr)

squirrels <- read_csv("nyc_squirrels.csv")

## Parse the date
squirrels$date_parsed  <- parse_date(as.character(squirrels$date), format =
"%m%d%Y")
```

```
## Give each observation a unique ID (to use as group in the
## animation, so as to not have points turn into one another but fade
## instead.
squirrels$key  <- 1:nrow(squirrels)

## Associate the different squirrel colours with the filenames of
## icons in different colours (manually filled with GIMP).
squirrels$image  <- "squirrel.png"
squirrels$image[squirrels$primary_fur_color == "Cinnamon"]  <-
"squirrel_cinnamon.png"
squirrels$image[squirrels$primary_fur_color == "Gray"]  <- "squirrel_grey.png"
squirrels$image[is.na(squirrels$primary_fur_colour)]  <- NA
```

Again, we need to parse the date. We already have latitude and longitude. We need a unique identifier for each observation, to tell *gganimate* that we want each squirrel to be in its own group. Then, we associate squirrel colours with three different files with a squirrel icon in different colours.

First, we make two image scatterplot layers, setting the sizes of adults and juveniles manually. The colour is deal with by mapping the image column containing the file names to the *image* aesthetic. We add some formatting, and then, the *transition_states* layer, which is where the graph turns from still and boring to magical moving pictures. This will animate a series of discrete "states", which here consist of the date pasted together with the shift (AM or PM squirrel observation shift). The special "{closest_state}" variable in the title string puts this state name as plot title.

```
plot_colour <- ggplot() +
    geom_image(aes(y = long, x = lat, image = image, group = key),
               size = 0.04,
               data = filter(squirrels, age == "Adult")) +
    geom_image(aes(y = long, x = lat, image = image, group = key),
               size = 0.03,
               data = filter(squirrels, age == "Juvenile")) +
    theme_bw(base_size = 16) +
    theme(panel.grid = element_blank()) +
    xlab("Latitude") +
    ylab("Longitude") +
    labs(title = "{closest_state}",
         caption = "Data from NYC Squirrel Census. Squirrel icon made by Freepik
from www.flatiron.com.") +
    transition_states(paste(date_parsed, shift),
                      state_length = 2,
                      transition_length = 1)

## Render it and write to file
animate(plot_colour,
        fps = 10,
        nframes = 400,
        end_pause = 20,
        rewind = FALSE,
        width = 1000,
        height = 1000)
```

I was faffing around with different map packages to try to find something of Central Park. It seems *ggmaps* is the way to go. Other participants made nice maps, though:

> This is my first #tidytuesday contribution and my first attempt working with maps🙃 Code: https://t.co/xLVWkXJZWG pic.twitter.com/XthNrnxhDc
>
> — Anna L (@The_Anna_L) November 4, 2019

> Used the squirrel #TidyTuesday dataset (2019-10-29) to make some simple hexmaps of activities (eating, moving or making noise). Also trying #brickr for the first time to make some fun plots.
> Code at: https://t.co/diXAzzmkEm#rstats pic.twitter.com/0WNhPtvHZA
>
> — Jesus M. Castagnetto (@jmcastagnetto) November 4, 2019
>
> Couldn't come up with something better for this week's #TidyTuesday, so here is a little tribute to the two squirrels that were found dead during the 2018 Central Park @SquirrelCensus. I'm a little sad…
>
> Code (🙏 @CedScherer): https://t.co/91Kciy2NSN#ggplot #ThisIsNotDataViz pic.twitter.com/bbaYcruXx4
>
> — Georgios Karamanis (@geokaramanis) November 1, 2019

However, I think this was my favourite:

> Possibly the worst #tidytuesday submission ever! Recreating this classic XKCD, but with squirrels. https://t.co/ZaG5qGU6Le #rstats #r4ds pic.twitter.com/WrKhDBQG1A
>
> — Ryan Timpe 🧱📊 (@ryantimpe) October 31, 2019

https://github.com/ryantimpe/TidyTuesday/blob/master/2019w44/2019w44.R

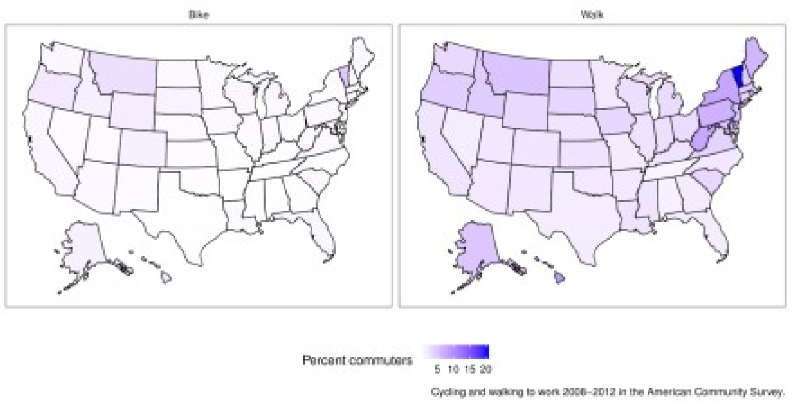
The original Squirrel Census Report seems to be amazing object, too, with a beautiful map.

2019-11-05 Biking and walking to work in the US (and Sweden)

Data: https://github.com/rfordatascience/tidytuesday/tree/master/data/2019/2019-11-05

My code: https://github.com/mrtnj/rstuff/blob/master/tidytuesday/commute.R

This week I felt I had to make a map. The end result doesn't look like much, but it took a while. Here are the average percentages of commuters who walk and bike to work in different US states 2008-2012 with data from the American Community Survey:


Bike
Walk
Percent commuters
5 10 15 20
Cycling and walking to work 2008–2012 in the American Community Survey.

```
library(dplyr)
library(ggplot2)
library(readr)
library(usmap)

commute <- read_csv("commute.csv")

## Map data from the usmap package
state_map  <- us_map(regions = "state")

## There are some incompletely labelled states; fix them
```

```
missing  <- setdiff(commute$state, state_map$full)

commute$state_modified <- commute$state
commute$state_modified[commute$state == "Ca"] <- "California"
commute$state_modified[commute$state == "Massachusett"]  <- "Massachusetts"
```

We get map coordinates for the US states from the *usmap* package (because the one in *maps* doesn't have Alaska and Hawaii).

Then we fix some mislabelling in the data.

```
## Get the average per state
state_average  <- summarise(group_by(commute, state_modified, mode),
                            average = sum(percent * n)/sum(n))

## Combine averages and coordinates
combined  <- inner_join(state_average,
                        state_map,
                        by = c("state_modified" = "full"))
```

We take a weighted average of the percentages per state and join the state averages with the state map coordinates. The map I posted on Twitter didn't weight the average, but I think that is a bit better. There is still the issue that states have different populations and different distributions of large and small cities, but that's the nature of things. In summary, there is not much biking going on, but some more walking to work.

```
plot_map  <- ggplot() +
    geom_polygon(aes(x = x, y = y, fill = average, group = group),
                 colour = "black",
                 data = combined) +
    facet_wrap(~ mode) +
    scale_fill_continuous(low = "white",
                          high = "blue",
                          name = "Percent commuters") +
    theme_bw(base_size = 16) +
    theme(panel.grid = element_blank(),
          strip.background = element_blank(),
          axis.text = element_blank(),
          axis.ticks = element_blank(),
          legend.position = "bottom") +
    xlab("") +
    ylab("") +
    labs(caption = "Cycling and walking to work 2008-2012 in the American
Community Survey.")
```

The US seems to live up to its reputation as a motorised country.…