Slow ggplot2

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Contents

Chapter 1

Introduction

The ggplot2 package in R, written by Hadley Wickham and a number of collaborators, implements the "grammer of graphics" proposal of Leland Wilkinson. This data visualization system idea is at once powerful, novel, and intuitive. Wickham conceives of and has built a system where data visualization as dividable seven parameters: data to visualize, aesthetics that represent variables in the data, geometric objects, the coordinate system, specific scales, and statistical transformation.

While intuitive, using ggplotting effectively and efficiently requires practice. The "slow ggplotting" method and examples are designed to facilitate rapid incorporation of the ggplot logic and syntax. The method relys on action-reaction thinking, one of the most powerful tools in our "how-to" teaching tool kit — "slow ggplotting" makes modifications to plots as incrementally as possible so that it is clear to users what code triggers each change.

- pulling out aes() from the ggplot() function
- using fewer functions; example - using labs() to add a title instead of ggtitle()
- using functions multiple times; example aes(x = var1) + aes(y = var2) rather than aes(x = var1, y = var2)
- using base R functions and tidyverse functions. For other packages, the :: style to call them
- write out arguments (no shortcuts) aes(x = gdppercap) not aes(gdppercap)
- order ggplot commands so that reactivity is obvious; scale adjustments to aesthetics might also be near the aesthetic declaration.

The particular collection of visualizations here was produced for the Tableau associated initiative #MakeoverMonday.

Chapter 2

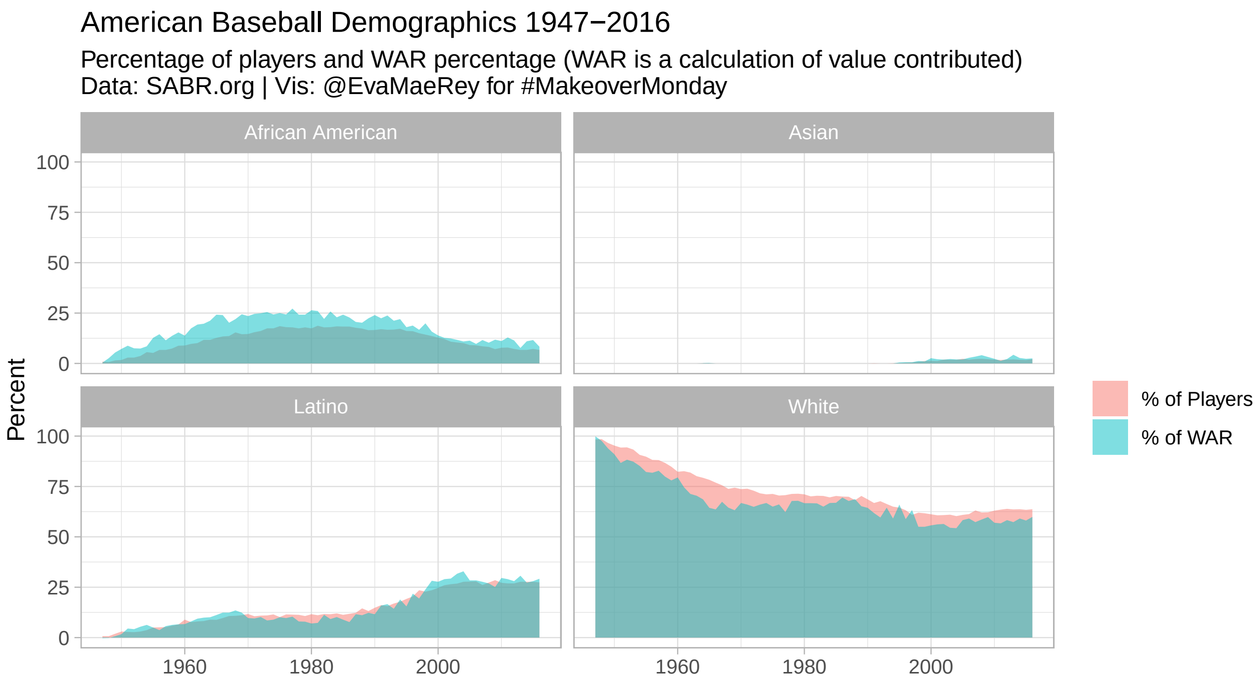
Baseball, WAR, and Ethnicity

This data visualization uses the WAR measure in baseball, a calculation based on the contributions of players. The visualizations show that new ethnicities and races started to be included in Major League baseball, the minority players that joined tended to contribute more than the expected value for players overall. For example, from 1947, when Jackie Robinson joined Major League baseball, and onward, the percent of African American players was outpaced by the percent calculated contributions (WAR) of African American players.

A random sample from the data set:

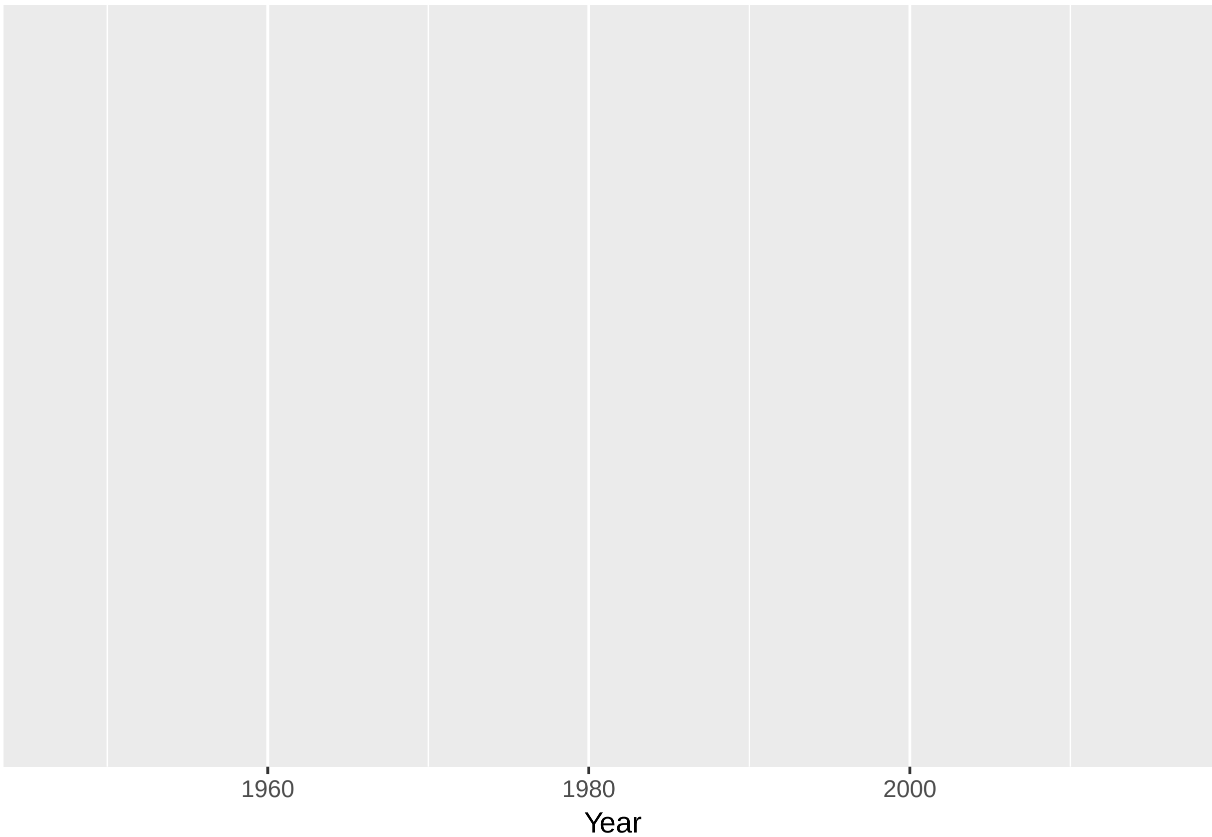
Year	Ethnicity	type	Percent
2008	African American	% of Players	8.2
1963	White	% of WAR	70.4
1973	Latino	% of Players	11.0
2012	Asian	% of WAR	2.2
1989	African American	% of WAR	22.4

```
ggplot(df_gather) +
  aes(x = Year) +
  aes(y = Percent) +
  aes(fill = type) +
  facet_wrap(~ Ethnicity) +
  geom_area(alpha = .5, position = "dodge") +
  labs(fill = "") +
  labs(x = "") +
  labs(title = "American Baseball Demographics 1947-2016") +
  labs(subtitle = "Percentage of players and WAR percentage (WAR is a calculation of value contributed)"
  theme_light()
```

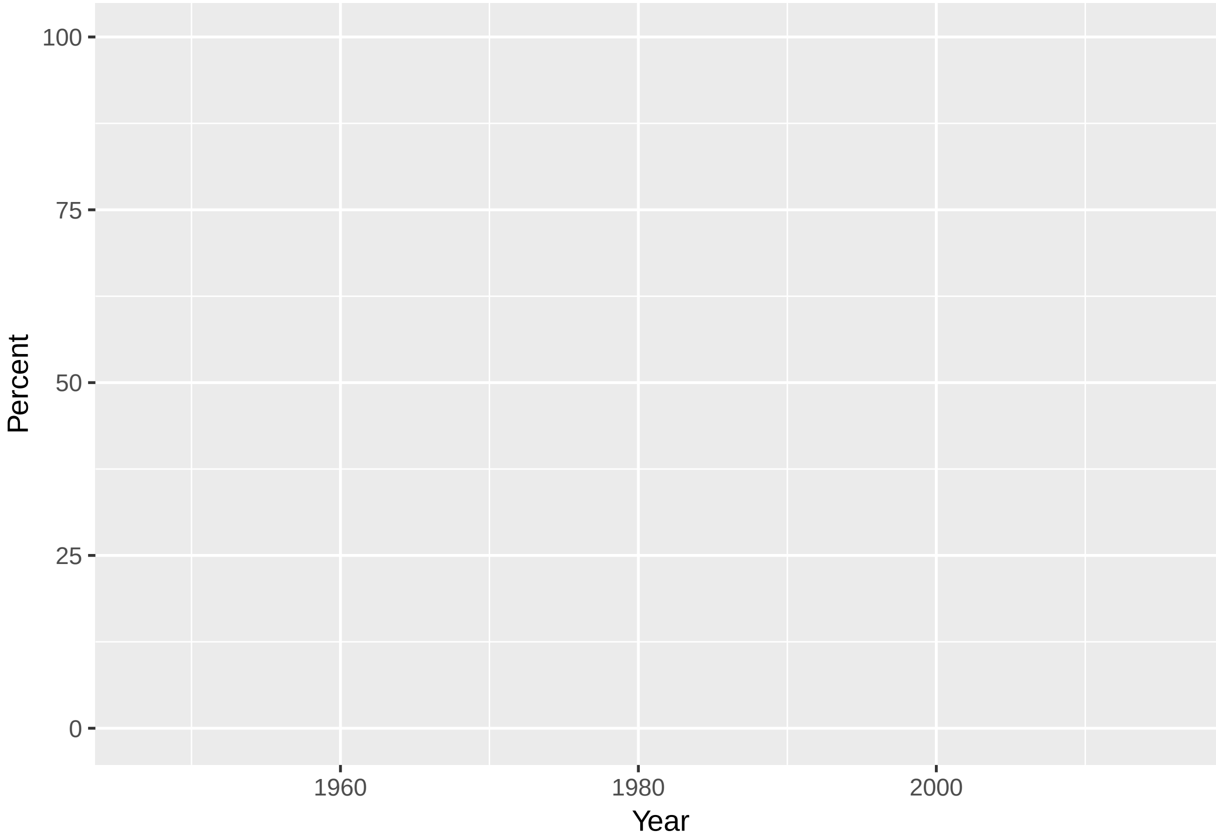

American Baseball Demographics 1947−2016
Percentage of players and WAR percentage (WAR is a calculation of value contributed)
Data: SABR.org | Vis: @EvaMaeRey for #MakeoverMonday
African American
Asian
Latino
White
Percent
100
75
50
25
0
1960
1980
2000
% of Players
% of WAR

```
ggplot(df_gather)
```

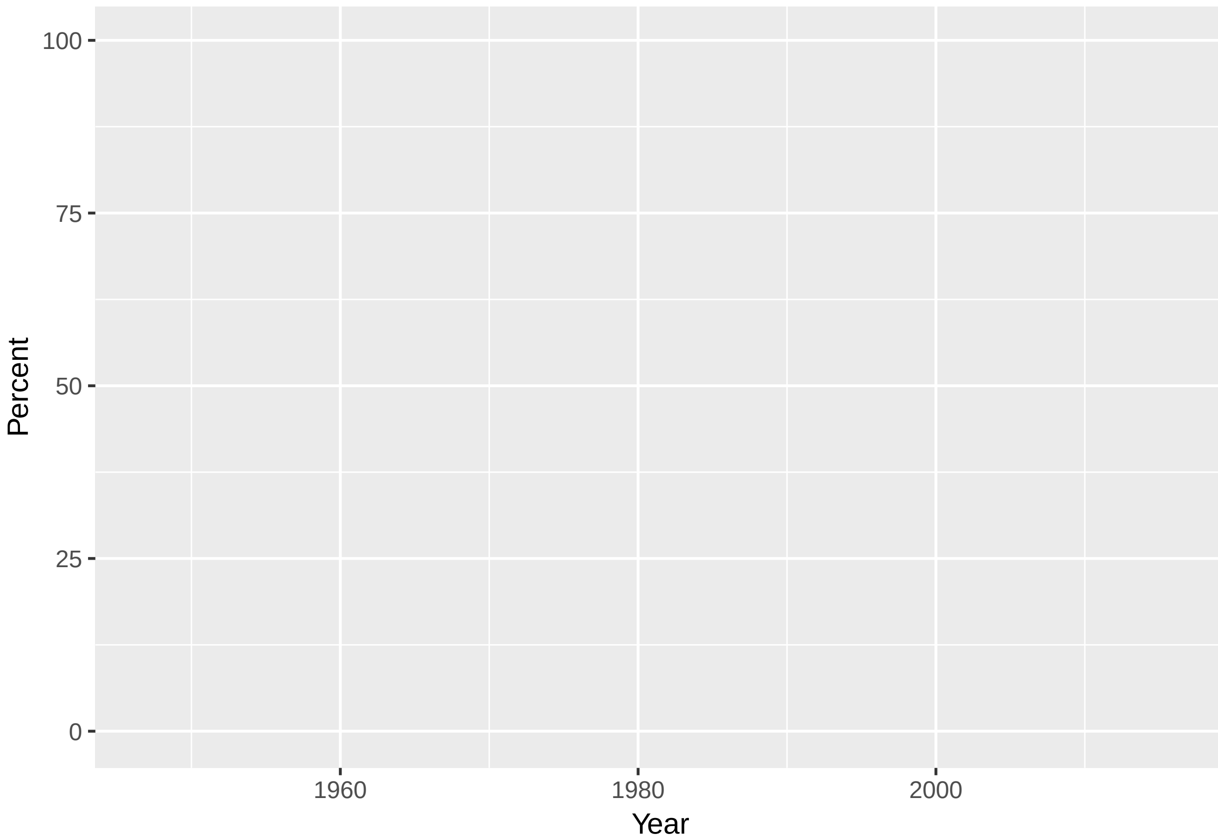
```r
ggplot(df_gather) +
  aes(x = Year)
```



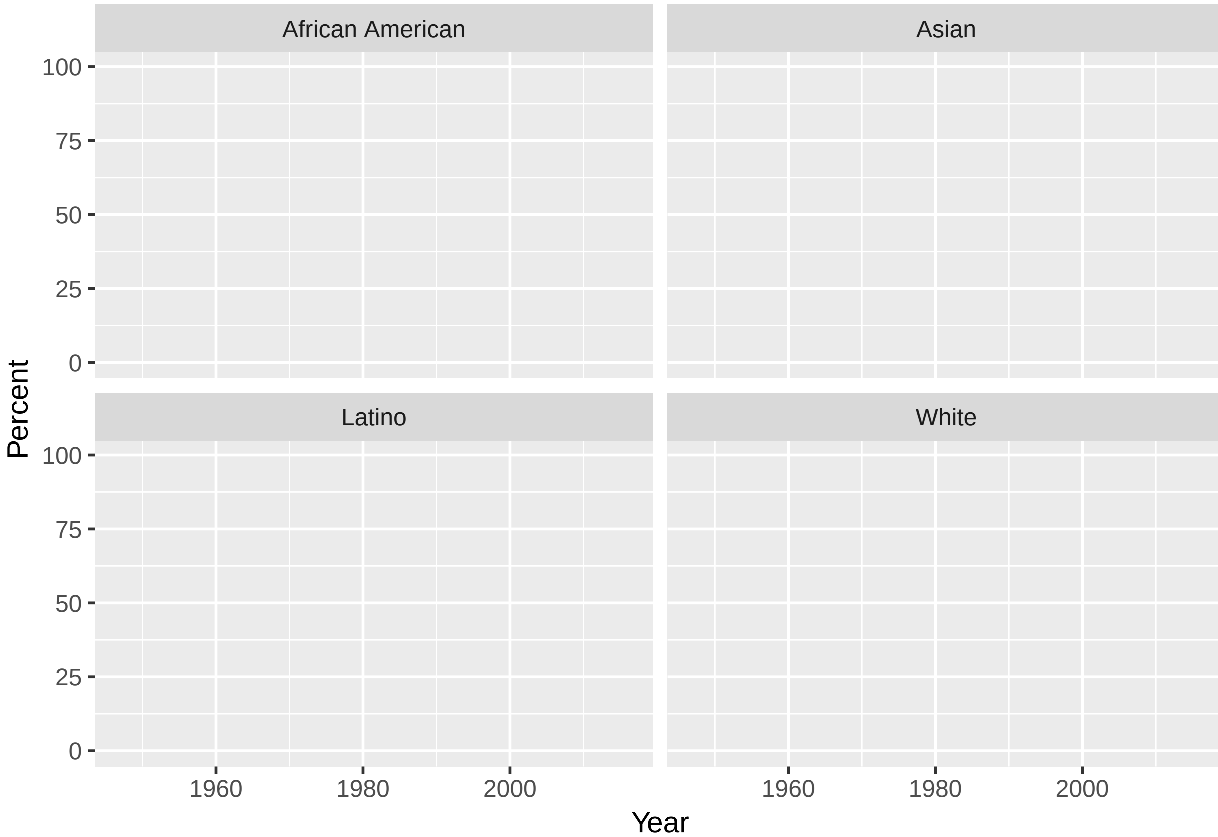
```
ggplot(df_gather) +
  aes(x = Year) +
  aes(y = Percent)
```



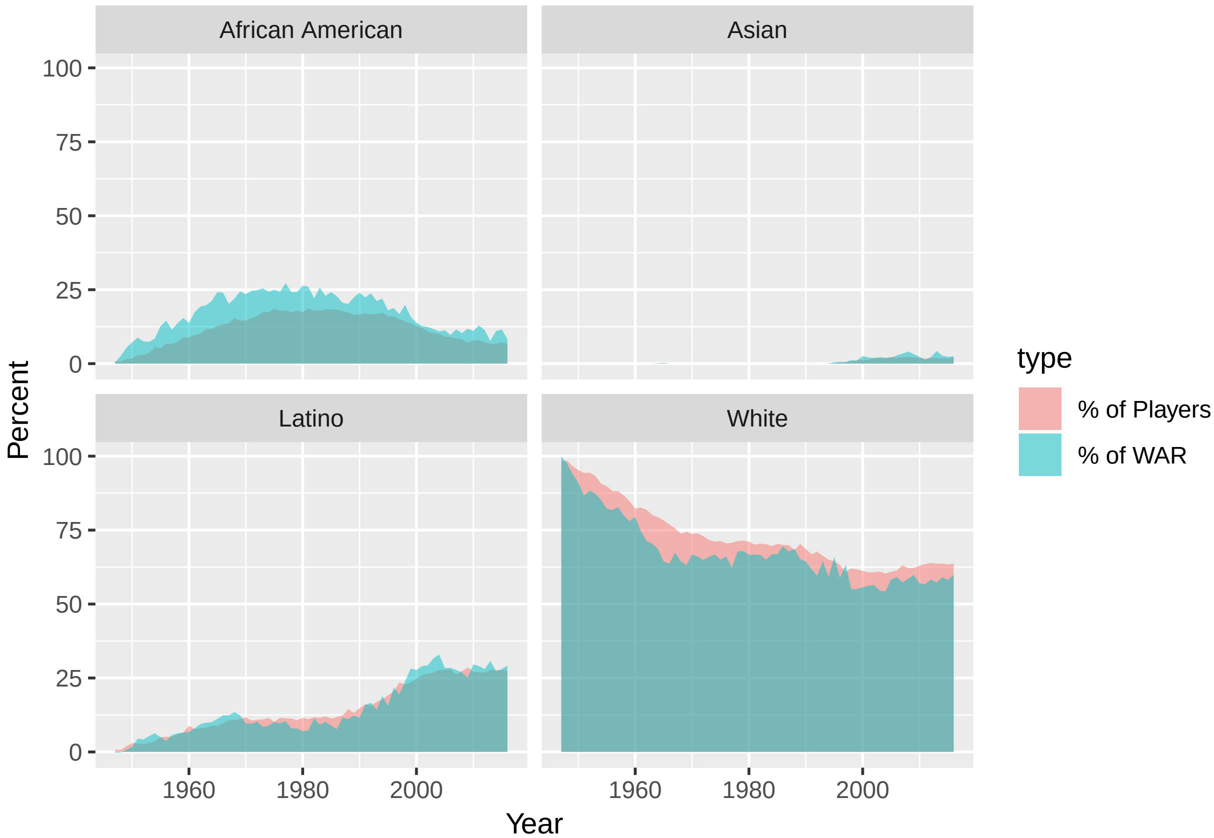
```
ggplot(df_gather) +
  aes(x = Year) +
  aes(y = Percent) +
  aes(fill = type)
```



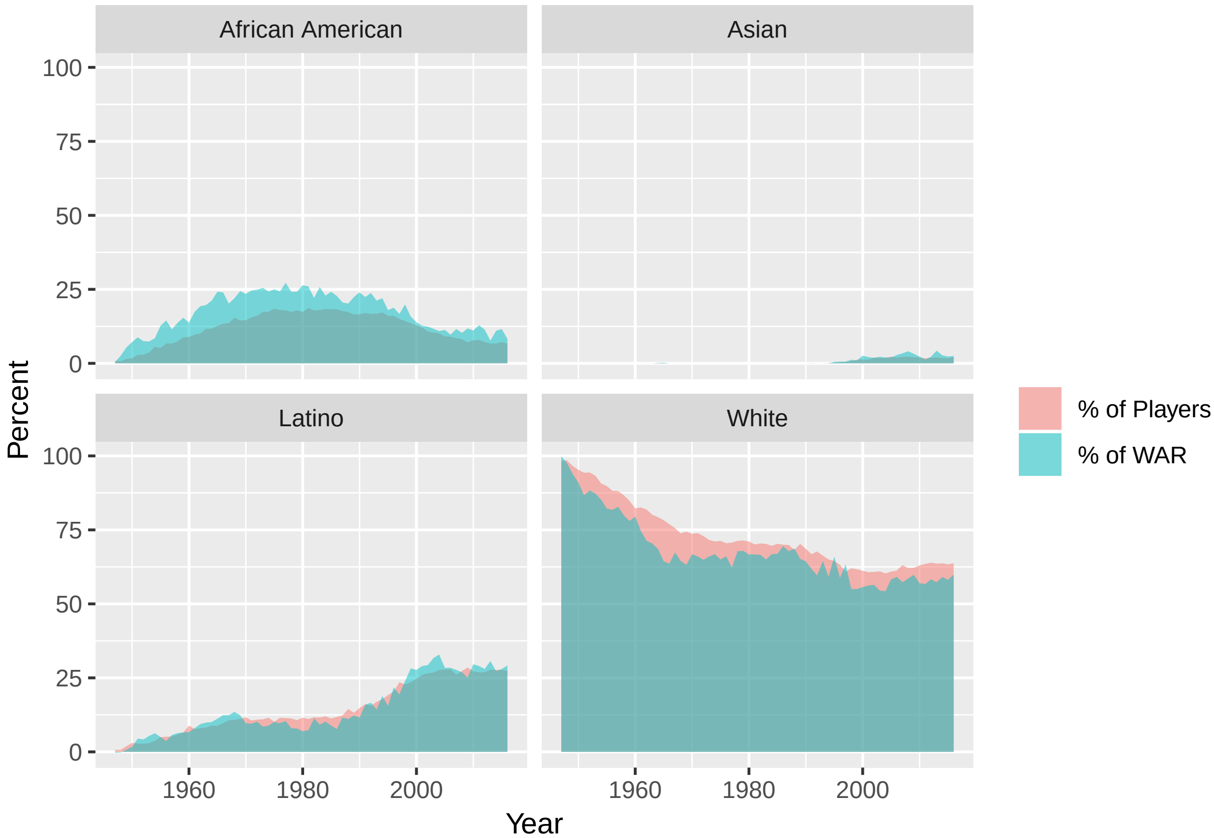
```r
ggplot(df_gather) +
  aes(x = Year) +
  aes(y = Percent) +
  aes(fill = type) +
  facet_wrap(~ Ethnicity)
```



```
ggplot(df_gather) +
  aes(x = Year) +
  aes(y = Percent) +
  aes(fill = type) +
  facet_wrap(~ Ethnicity) +
  geom_area(alpha = .5, position = "dodge")
```

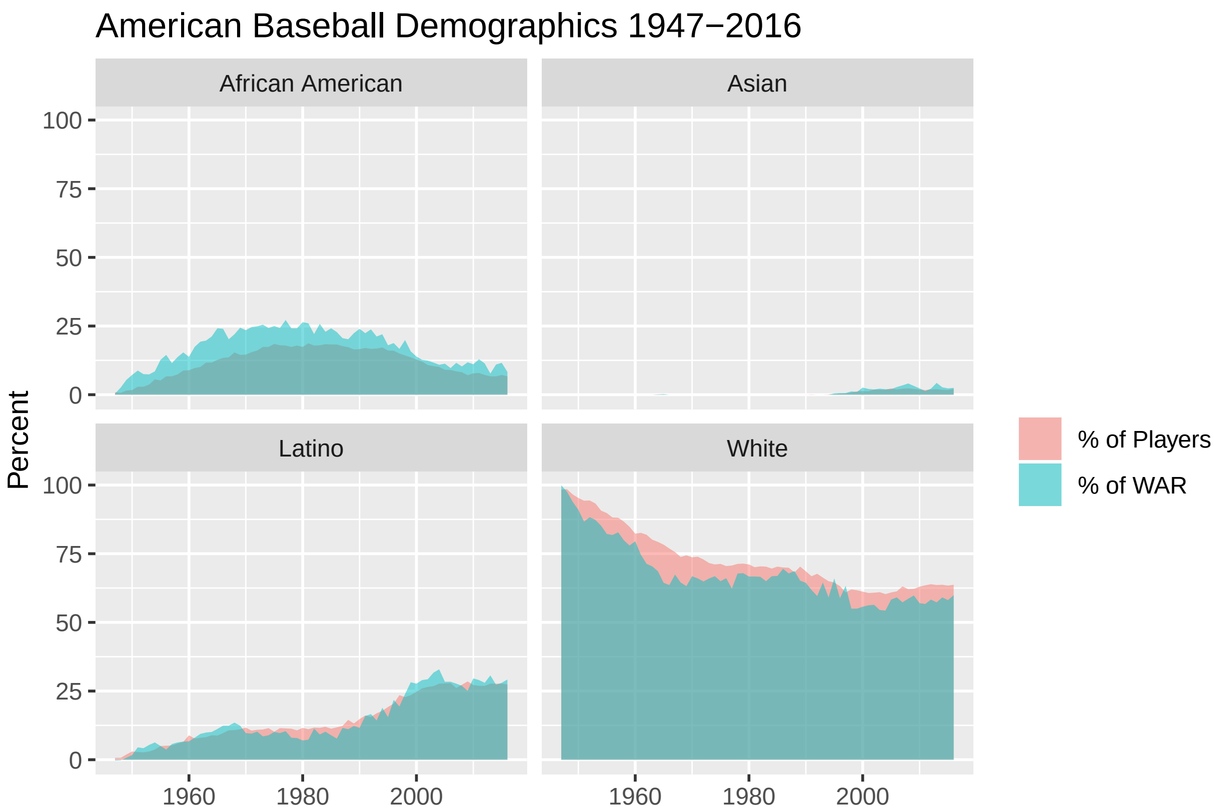


```
ggplot(df_gather) +
  aes(x = Year) +
  aes(y = Percent) +
  aes(fill = type) +
  facet_wrap(~ Ethnicity) +
  geom_area(alpha = .5, position = "dodge") +
  labs(fill = "")
```

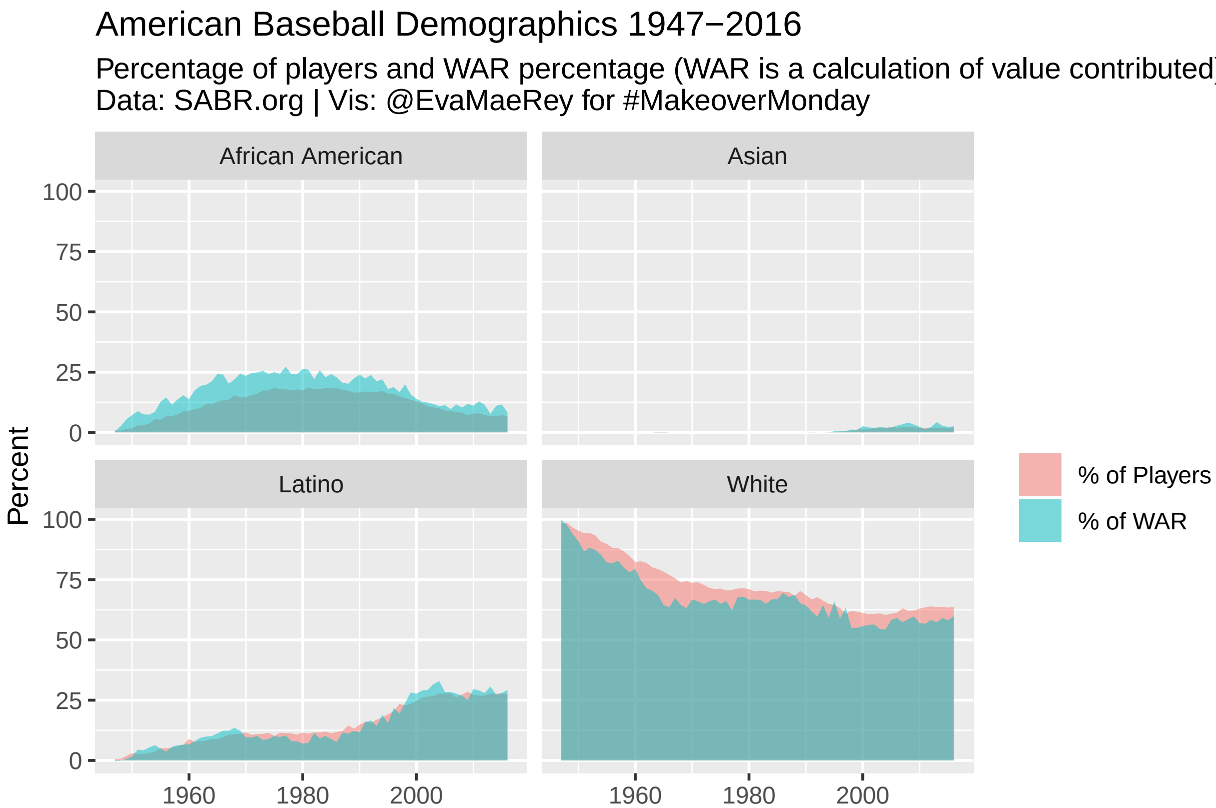


```
ggplot(df_gather) +
  aes(x = Year) +
  aes(y = Percent) +
  aes(fill = type) +
  facet_wrap(~ Ethnicity) +
  geom_area(alpha = .5, position = "dodge") +
  labs(fill = "") +
  labs(x = "")
```

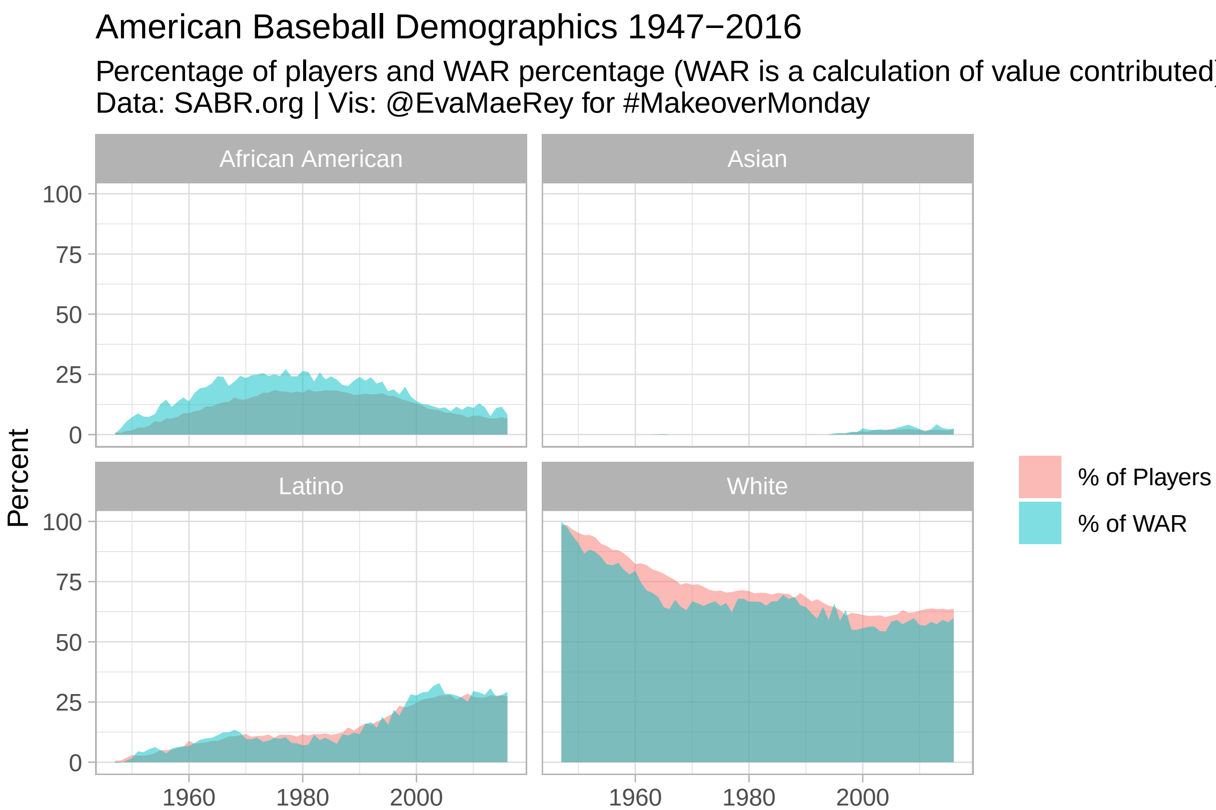
```
ggplot(df_gather) +
  aes(x = Year) +
  aes(y = Percent) +
  aes(fill = type) +
  facet_wrap(~ Ethnicity) +
  geom_area(alpha = .5, position = "dodge") +
  labs(fill = "") +
  labs(x = "") +
  labs(title = "American Baseball Demographics 1947-2016")
```



```
ggplot(df_gather) +
  aes(x = Year) +
  aes(y = Percent) +
  aes(fill = type) +
  facet_wrap(~ Ethnicity) +
  geom_area(alpha = .5, position = "dodge") +
  labs(fill = "") +
  labs(x = "") +
  labs(title = "American Baseball Demographics 1947-2016") +
  labs(subtitle = "Percentage of players and WAR percentage (WAR is a calculation of value contributed)"
```



```
ggplot(df_gather) +
  aes(x = Year) +
  aes(y = Percent) +
  aes(fill = type) +
  facet_wrap(~ Ethnicity) +
  geom_area(alpha = .5, position = "dodge") +
  labs(fill = "") +
  labs(x = "") +
  labs(title = "American Baseball Demographics 1947-2016") +
  labs(subtitle = "Percentage of players and WAR percentage (WAR is a calculation of value contributed)
  theme_light()
```



Chapter 3

Christmas Trees

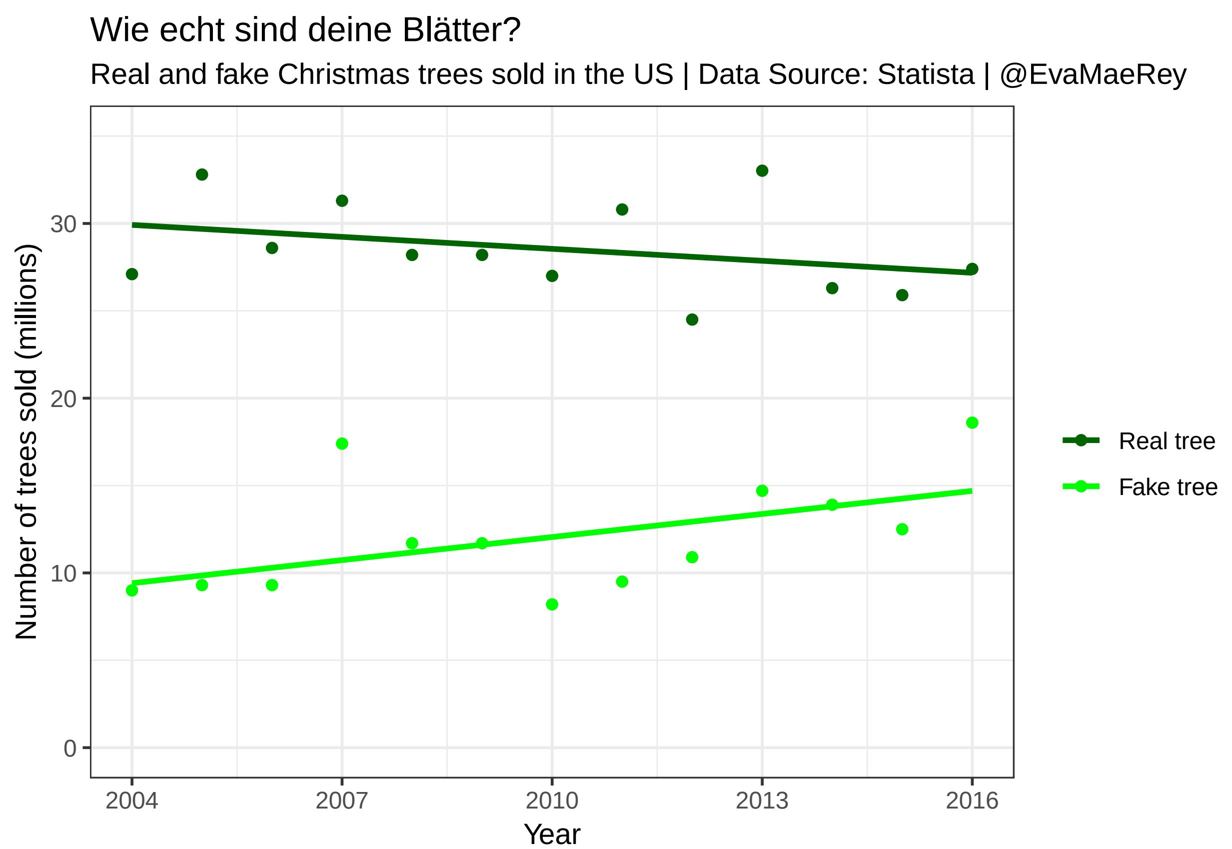
Here is a simple plot of Christmas Tree Sales in the U.S. The plot shows that artificial tree sales are on the rise, contrasting with declines in real trees. The title plays on the German Christmas Carol "O Tannenbaum", "Oh Christmas Tree" in English. "Wie echt sind deine Blätter?" means "how real are your leaves"; the original text from the carol is "Wie treu sind deine Blätter!" which means "How true your leaves are!"

I also plot the cumulative number of trees purchased of each type, artificial and real, from 2004 to 2014, comparing that to the 2016 U.S. population. Almost one real tree per person was bought over the course of 10 years!

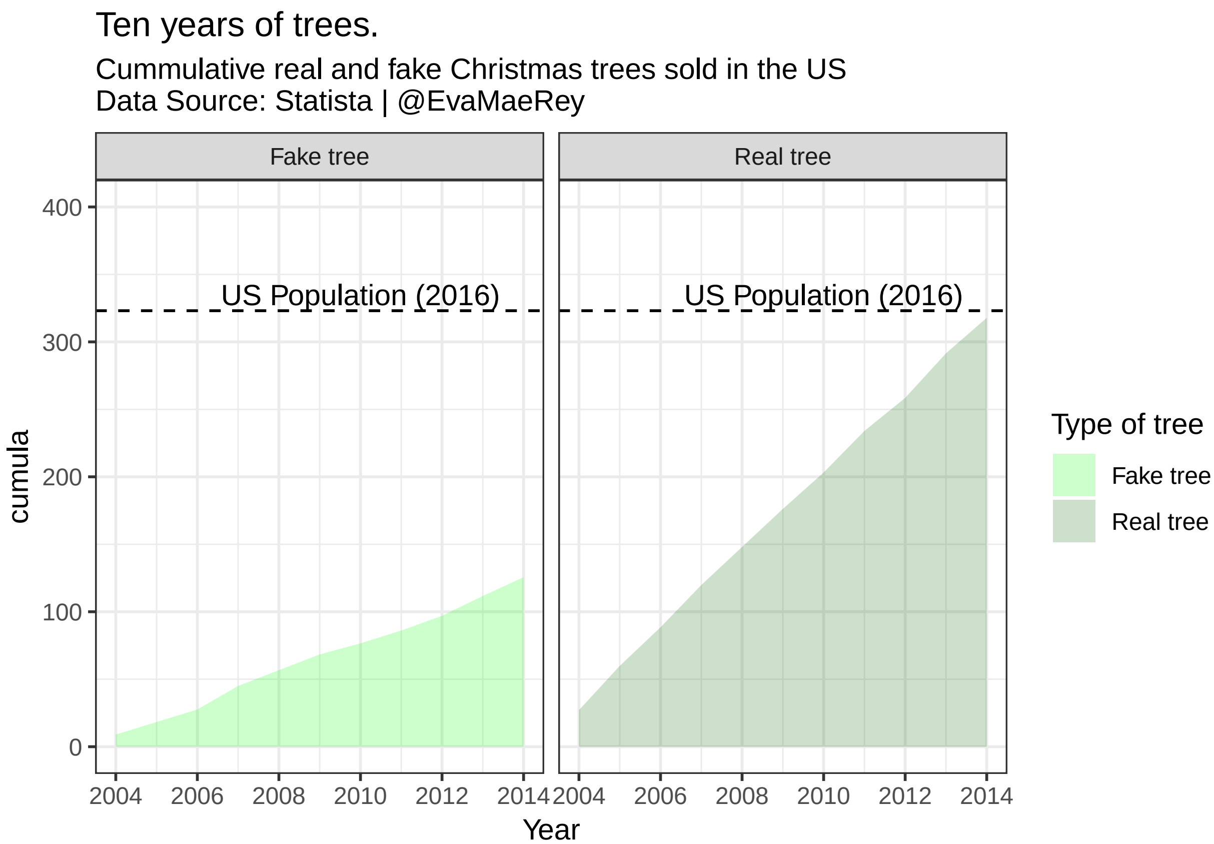
A random sample from the data set:

Year	Number of trees sold	Type of tree	Number of trees sold (millions)
2015	25900000	Real tree	25.90
2013	33020000	Real tree	33.02
2016	18600000	Fake tree	18.60
2007	31300000	Real tree	31.30
2014	13900000	Fake tree	13.90

```
ggplot(data = dta) +
  aes(Year) +
  aes(y = `Number of trees sold (millions)`) +
  geom_point() +
  aes(col = fct_rev(`Type of tree`)) +
  geom_smooth(method = "lm", se = F) +
  scale_color_manual(values = c("darkgreen", "green")) +
  ylim(c(0, 35)) +
  labs(col = "") +
  labs(title = "Wie echt sind deine Blätter?") +
  labs(subtitle = "Real and fake Christmas trees sold in the US | Data Source: Statista | @EvaMaeRey ")
  theme_bw()
```




```
dta <- dta %>%
  group_by(`Type of tree`) %>%
  mutate(cumula = cumsum(`Number of trees sold (millions)`))

ggplot(dta %>% filter(Year <= 2014)) +
  aes(Year) +
  aes(y = cumula) +
  aes(fill = `Type of tree`) +
  geom_hline(yintercept = 323.1, lty = 2) +
  geom_area(alpha = .2) + facet_wrap(~ `Type of tree`) +
  annotate(geom = "text", x = 2010, y = 335, label = "US Population (2016)") +
  labs(title = "Ten years of trees.") +
  labs(subtitle = "Cummulative real and fake Christmas trees sold in the US\nData Source: Statista | @E
  scale_fill_manual(values = c("green", "darkgreen")) +
  theme_bw() +
  ylim(c(0, 400))
```


Ten years of trees.
Cummulative real and fake Christmas trees sold in the US
Data Source: Statista | @EvaMaeRey
Fake tree
Real tree
US Population (2016)
US Population (2016)
cumula
0
100
200
300
400
2004
2006
2008
2010
2012
2014
Year
Type of tree
Fake tree
Real tree

Chapter 4

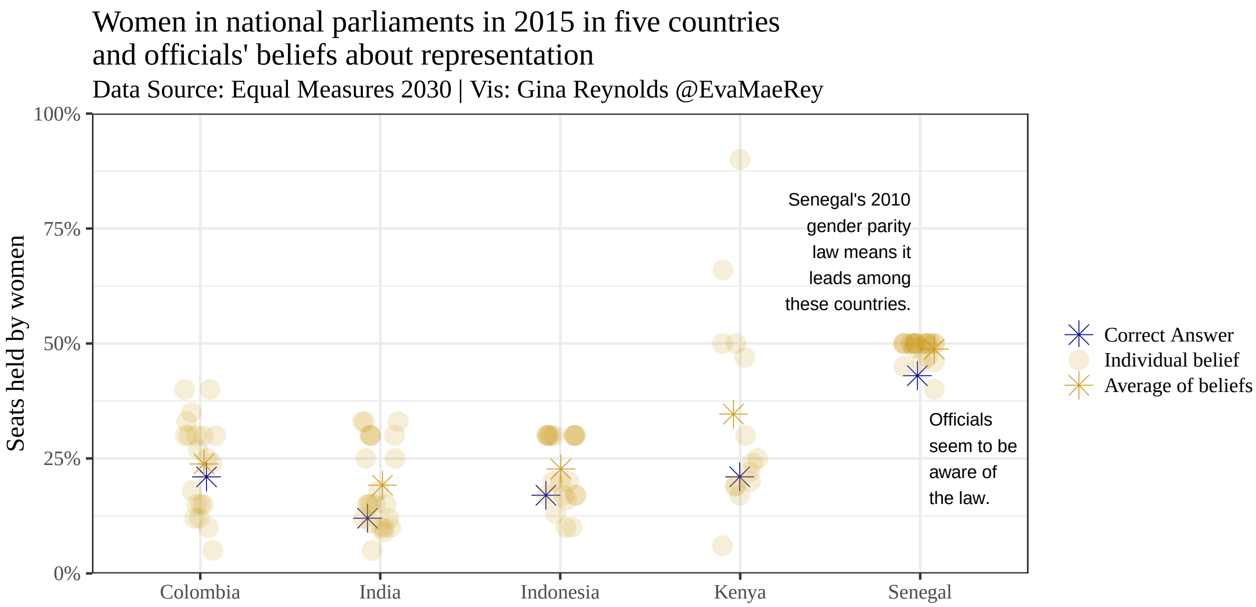
Officials' beliefs about women's representation

The data provided is based on a small survey of elite officials in five less developed countries. The question that arrises from the data is: How well do elites know the conditions in their countries. In general, the elites overestimate women's representation. But this is not the case in Senegal, where there are gender quotas in the Parliament. Most elites therefore estimate that the representation is about equal with men. I jitter the responses of the elites horizontally to avoid overplotting.

A random sample from the data set:

Country	Topic	value	value_type	alpha
Indonesia	Share of seats held by women	0.20	Individual belief	0.3
Colombia	Share of seats held by women	0.15	Individual belief	0.3
Indonesia	Share of seats held by women	0.10	Individual belief	0.3
Kenya	Share of seats held by women	0.19	Individual belief	0.3
Indonesia	Share of seats held by women	0.30	Individual belief	0.3

```
ggplot(data = df_all) +
  aes(x = Country) +
  aes(y = value) +
  aes(col = fct_inorder(value_type)) +
  aes(alpha = fct_inorder(value_type)) +
  aes(shape = fct_inorder(value_type)) +
  geom_jitter(width = .1, height = 0, size = 7) +
  geom_hline(yintercept = c(0, 100), col = "grey") +
  geom_hline(yintercept = c(50), lty = 2, col = "grey") +
  theme_bw(base_size = 20, base_family = "Times") +
  scale_y_continuous(limits = c(0, 1), expand = c(0, 0), labels = scales::percent) +
  scale_colour_manual(name = "", values = c("darkblue", "goldenrod3", "goldenrod3")) +
  scale_alpha_manual(name = "", values = c(1, .17, 1)) +
  scale_shape_manual(name = "", values = c(8, 19, 8)) +
  annotate(geom = "text", x = 4.95, y = .70, label = str_wrap("Senegal's 2010 gender parity law means i
  annotate(geom = "text", x = 5.05, y = .250, label = str_wrap("Officials seem to be aware of the law."
  labs(x = "") +
  labs(y = "Seats held by women") +
  labs(title = "Women in national parliaments in 2015 in five countries \nand officials' beliefs about 
  labs(subtitle = "Data Source: Equal Measures 2030 | Vis: Gina Reynolds @EvaMaeRey")
```


Women in national parliaments in 2015 in five countries
and officials' beliefs about representation
Data Source: Equal Measures 2030 | Vis: Gina Reynolds @EvaMaeRey
Seats held by women
100%
75%
50%
25%
0%
Colombia
India
Indonesia
Kenya
Senegal
Senegal's 2010 gender parity law means it leads among these countries.
Officials seem to be aware of the law.
Correct Answer
Individual belief
Average of beliefs

Chapter 5

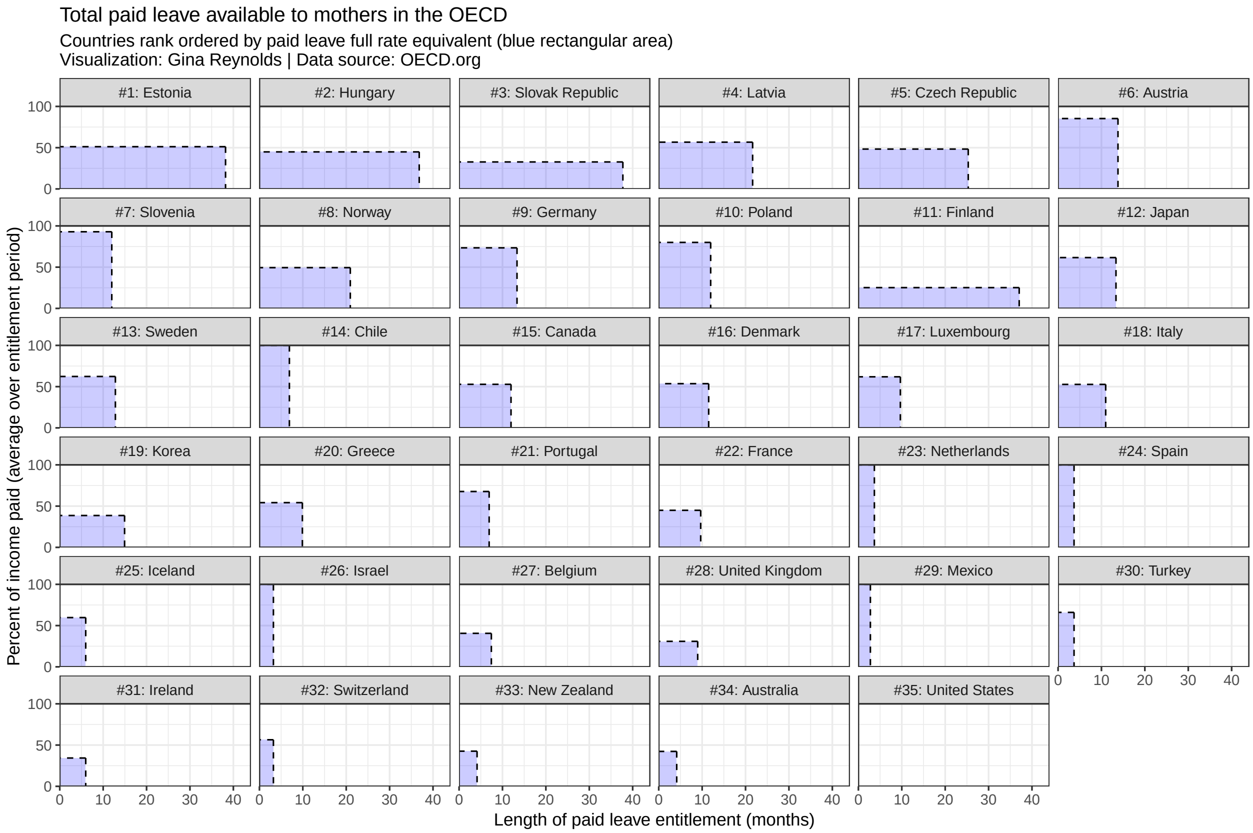
Maternal Leave

The OECD provides a comparative report on how much paid leave women are entitled to after childbirth. But leave takes different forms. In some places, the allowed leave is longer, but sometimes that means that the pay out compared to the regular salary is lower. To emphasize the different forms that law around paid leave take, I plotted the total payout available to mothers as areas of rectangles, where one side is the length of leave allowed, and the other side is the proportion of salary paid to the new mom.

A random sample from the data set:

Country	Paid maternity leave avg payment rate (%)	Paid maternity leave full rate equivalent in weeks	Paid ma
Portugal	100.0	6.0	
Italy	80.0	17.4	
New Zealand	42.6	7.7	
Latvia	80.0	12.8	
Israel	100.0	14.0	

```
ggplot(df) +
  aes(x = paid_leave_months) +
  aes(y = `Total paid leave avg payment rate (%)`) +
  aes(xmin = 0) +
  aes(xmax = paid_leave_months) +
  aes(ymin = 0) +
  aes(ymax = `Total paid leave avg payment rate (%)`) +
  facet_wrap(fct_inorder(rank_name) ~ .) +
  geom_rect(fill = "blue", alpha = .2) +
  aes(yend = 0) +
  aes(xend = 0) +
  geom_segment(aes(yend = `Total paid leave avg payment rate (%)`), lty = "dashed") +
  geom_segment(aes(xend = paid_leave_months), lty = "dashed") +
  scale_y_continuous(limits = c(0, 100), expand = c(0, 0), breaks = c(0, 50, 100)) +
  scale_x_continuous(limits = c(0, 44), expand = c(0, 0)) +
  labs(x = "Length of paid leave entitlement (months)") +
  labs(y = "Percent of income paid (average over entitlement period)") +
  labs(title = "Total paid leave available to mothers in the OECD") +
  labs(subtitle = "Countries rank ordered by paid leave full rate equivalent (blue rectangular area)\nVi
  theme_bw(base_size = 12)
```


Total paid leave available to mothers in the OECD
Countries rank ordered by paid leave full rate equivalent (blue rectangular area)
Visualization: Gina Reynolds | Data source: OECD.org
#1: Estonia
#2: Hungary
#3: Slovak Republic
#4: Latvia
#5: Czech Republic
#6: Austria
#7: Slovenia
#8: Norway
#9: Germany
#10: Poland
#11: Finland
#12: Japan
#13: Sweden
#14: Chile
#15: Canada
#16: Denmark
#17: Luxembourg
#18: Italy
#19: Korea
#20: Greece
#21: Portugal
#22: France
#23: Netherlands
#24: Spain
#25: Iceland
#26: Israel
#27: Belgium
#28: United Kingdom
#29: Mexico
#30: Turkey
#31: Ireland
#32: Switzerland
#33: New Zealand
#34: Australia
#35: United States
Percent of income paid (average over entitlement period)
Length of paid leave entitlement (months)
0
50
100
0
10
20
30
40

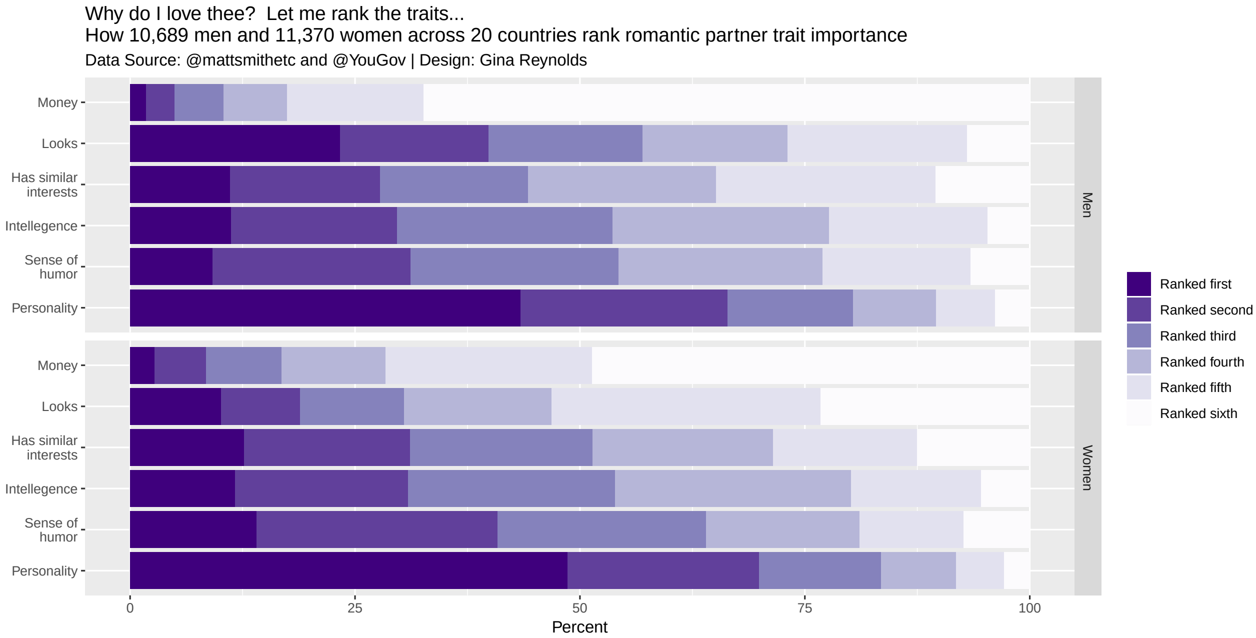
Chapter 6

Traits

A random sample from the data set:

Gender	Question_short	Rank (text)	Rank (number)	n	Percent
Men	Money	Ranked third	3	578.79	5.423678
Men	Looks	Ranked third	3	1828.66	17.107868
Men	Money	Ranked fourth	4	754.62	7.071332
Women	Personality	Ranked sixth	6	328.93	2.884144
Men	Personality	Ranked second	2	2460.32	23.013131

```
ggplot(data = world) +
  aes(x = Question_short_wrap) +
  aes(y = Percent) +
  aes(fill = `Rank (text)`) +
  facet_grid(Gender ~ .) +
  geom_col() +
  coord_flip() +
  scale_fill_manual(
    values = colorRampPalette(RColorBrewer::brewer.pal(9, "Purples"))(6)[1:6],
    guide = guide_legend(reverse = TRUE)
  ) +
  labs(fill = "") +
  xlab("") +
  labs(title = "Why do I love thee?  Let me rank the traits... \nHow 10,689 men and 11,370 women across
  labs(subtitle = "Data Source: @mattsmithetc and @YouGov | Design: Gina Reynolds")
```


Why do I love thee? Let me rank the traits...
How 10,689 men and 11,370 women across 20 countries rank romantic partner trait importance
Data Source: @mattsmithetc and @YouGov | Design: Gina Reynolds
Money
Looks
Has similar interests
Intellegence
Sense of humor
Personality
Men
Women
0
25
50
75
100
Percent
Ranked first
Ranked second
Ranked third
Ranked fourth
Ranked fifth
Ranked sixth

Chapter 7

Salarys of Trump and Obama White House Employees

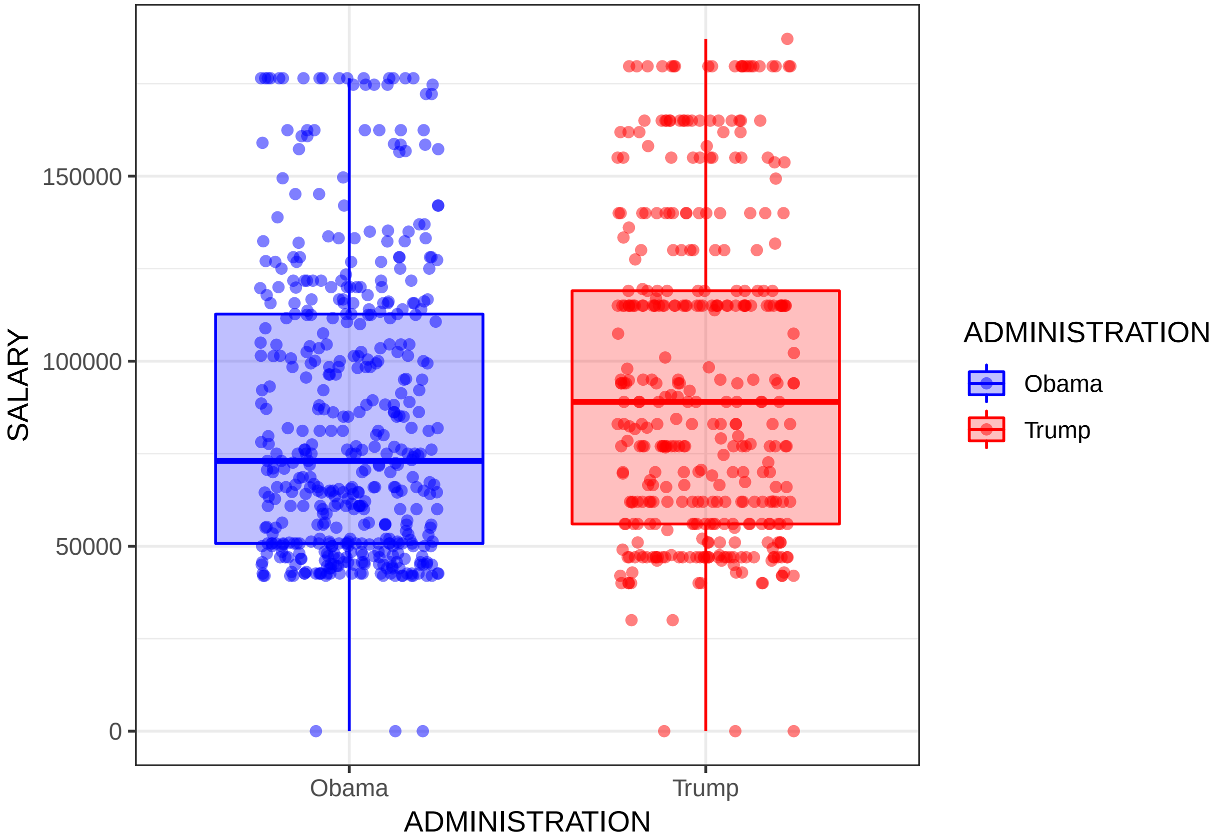
The data set, originally reported on in an NPR article, shows the difference in the distribution of salaries for the Obama and early Trump White House.

First I plot a histogram of each administration. Then I also contrast boxplots for each administration; the data points are overlayed, jittered to the widths of the boxplots. Plotly is used to make the graph interactive; mousing over will allow you to see who the point represents, their job description and exactly how much they are paid.

A random sample from the data set:

ADMINISTRATION	NAME	STATUS	SALARY	PAY BASIS	POSITION TITLE
Obama	Marketos, Cassandra G.	Employee	64500	Per Annum	DEPUTY DIRECTOR FOR DI
Obama	Kelly, Lauren M.	Employee	65949	Per Annum	DEPUTY DIRECTOR AND DE
Trump	Williams, Sherman A.	Employee	90350	Per Annum	ASSISTANT TO THE EXECUT
Obama	Aniskoff, Paulette L.	Employee	157299	Per Annum	DEPUTY ASSISTANT TO THE
Obama	Sanchez, Raul D.	Employee	42613	Per Annum	ANALYST

```
ggplot(both_data) +
  aes(x = ADMINISTRATION) +
  aes(y = SALARY) +
  geom_jitter(alpha = .5, height = 0, width = .25) +
  aes(col = ADMINISTRATION) +
  geom_boxplot(alpha = .25) +
  aes(fill = ADMINISTRATION) +
  scale_colour_manual(values = c("blue", "red")) +
  scale_fill_manual(values = c("blue", "red")) +
  theme_bw()
```


SALARY
150000
100000
50000
0
Obama
Trump
ADMINISTRATION
ADMINISTRATION
Obama
Trump

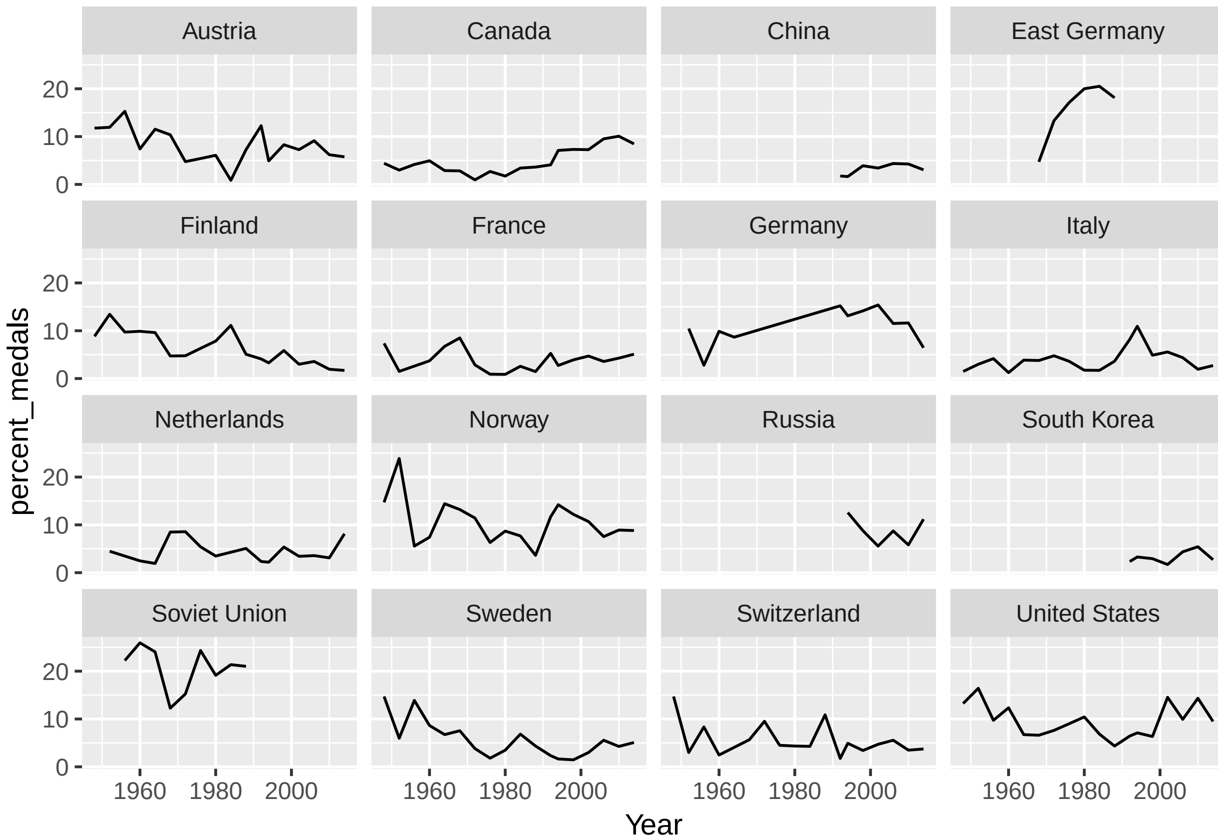
Chapter 8

Winter Games

A random sample from the data set:

Year	Sport	Event	Country	Gender	Medal Rank	Medal	Name o
1960	Ski Jumping	Men's Normal Hill, Individual	Germany	Men	1	gold	Helmut
1988	Cross-Country Skiing	Women's 20 Kilometers	Soviet Union	Women	3	bronze	Raisa S
1964	Speedskating	Women's 500 Meters	Soviet Union	Women	2	silver	Irina Yo
1948	Bobsled	Men's Four	United States	Men	1	gold	United
1994	Cross-Country Skiing	Women's 15 Kilometers	Russia	Women	3	bronze	Nina G

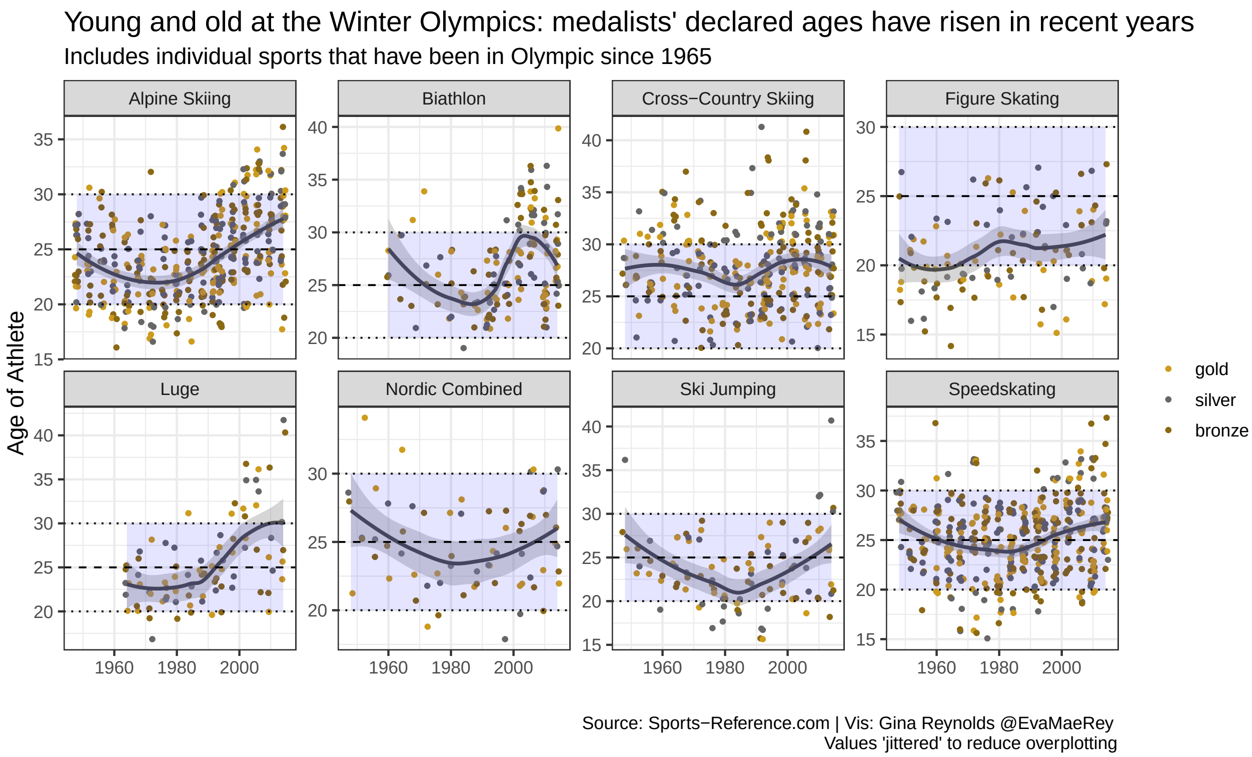
```
ggplot(data = dta) +
  aes(x = Year) +
  aes(y = percent_medals) +
  geom_line() +
  facet_wrap(~ Country)
```



A random sample from the data set:

Year	Sport	Event	Country	Gender	Medal Rank	Medal	Name of Athlete or
2006	Ski Jumping	Men's Large Hill, Team	Austria	Men	1	gold	Austria
2006	Alpine Skiing	Men's Slalom	Austria	Men	2	silver	Reinfried Herbst
1968	Cross-Country Skiing	Men's 30 Kilometers	Norway	Men	2	silver	Odd Martinsen
1998	Cross-Country Skiing	Men's 50 Kilometers	Austria	Men	3	bronze	Christian Hoffmann
1980	Cross-Country Skiing	Men's 15 Kilometers	Finland	Men	2	silver	Juha Mieto

```
ggplot(dta) +
  aes(x = Year) +
  aes(y = `Age of Athlete`) +
  facet_wrap(~ Sport, scales = "free_y", nrow = 2) +
  geom_jitter(size = 1, mapping = aes(col = fct_inorder(Medal))) +
  geom_smooth(col = "grey30") +
  geom_ribbon(ymin = 20, ymax = 30, alpha = .1, fill = "blue") +
  geom_hline(yintercept = c(20, 30), lty = "dotted") +
  geom_hline(yintercept = c(25), lty = "dashed") +
  scale_color_manual(values = c("goldenrod3", "grey40", "goldenrod4"), name = "") +
  labs(x = "") +
  labs(title = "Young and old at the Winter Olympics: medalists' declared ages have risen in recent yea
  labs(subtitle = "Includes individual sports that have been in Olympic since 1965") +
  labs(caption = "Source: Sports-Reference.com | Vis: Gina Reynolds @EvaMaeRey \nValues 'jittered' to r
  theme_bw(base_size = 13)
```



Young and old at the Winter Olympics: medalists' declared ages have risen in recent years
Includes individual sports that have been in Olympic since 1965
Alpine Skiing
Biathlon
Cross−Country Skiing
Figure Skating
Luge
Nordic Combined
Ski Jumping
Speedskating
Age of Athlete
1960
1980
2000
gold
silver
bronze
Source: Sports−Reference.com | Vis: Gina Reynolds @EvaMaeRey
Values 'jittered' to reduce overplotting

Chapter 9

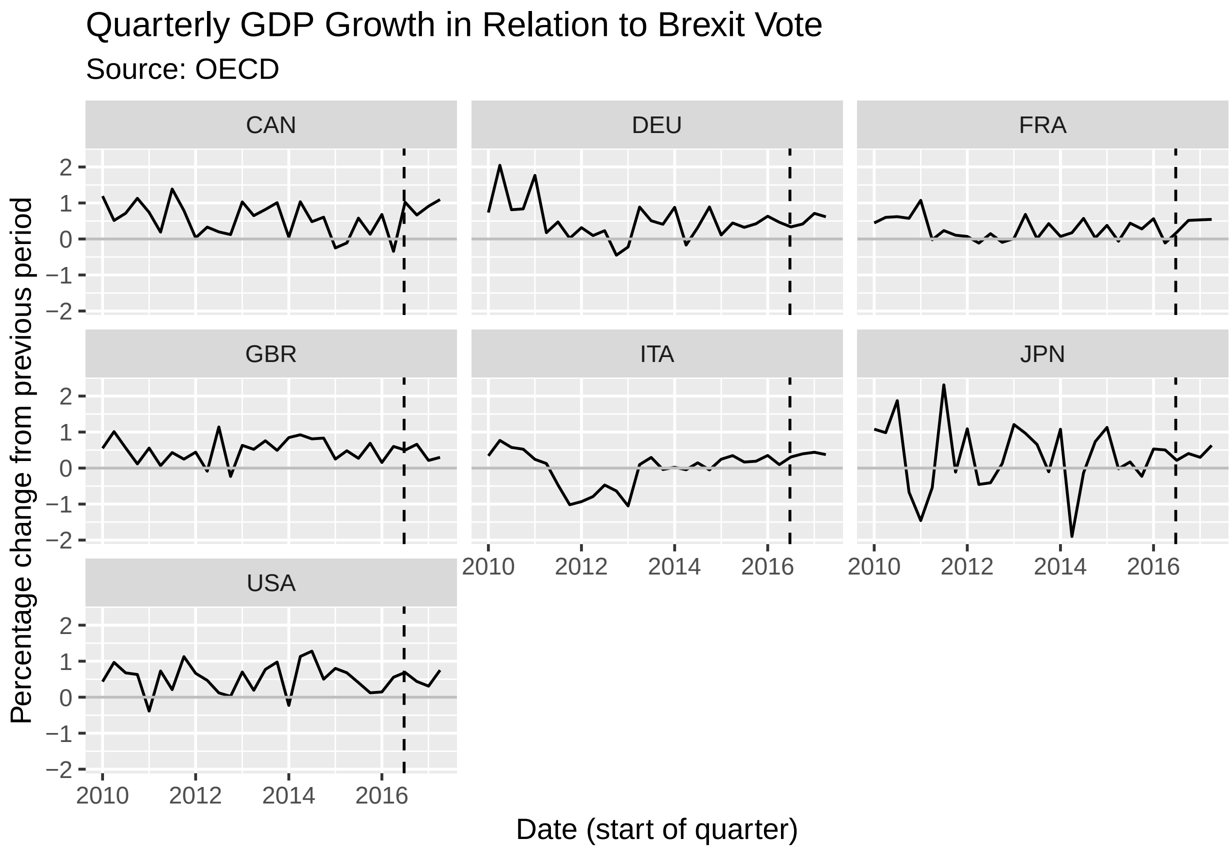
Brexit

This visualization challenge was a proposed makeover for a Financial Times visualization focusing on relative economic growth in G7 countries, with an emphasis on growth in the UK, focusing especially since Brexit. The visualization I present here is not what I created at the time of the challenge; instead it is inspired by Alan Smith a data journalist at the Financial Times, who created a really compelling visualization a couple of months after MakeoverMonday's treatment. I try to recreate his plot - which uses a ribbon to contain all G7 countries, and plot the UK's stats thereover. This declutters the graph, and makes you focus on where the UK falls among other countries, without being needlessly specific about those countries; the data story isn't about them anyway, might be Smith's thinking. My graph actually lightly traces economic growth in other countries, but deemphasizes their importance, like Smith.

A random sample from the data set:

Country	Year	Quarter	Date (start of quarter)	Percentage change from previous period	Date (start o quarter)
CAN	2013	4	2013-10-01	1.007924	2013-10-01
DEU	2012	2	2012-04-01	0.096022	2012-04-01
DEU	2014	4	2014-10-01	0.889928	2014-10-01
USA	2012	2	2012-04-01	0.466941	2012-04-01
FRA	2015	2	2015-04-01	-0.062148	2015-04-01

```
ggplot(data = data) +
  aes(x = `Date (start of quarter)`) +
  aes(y = `Percentage change from previous period`) +
  facet_wrap(~ Country) +
  geom_line() +
  geom_hline(yintercept = 0, col = "grey") +
  geom_vline(xintercept = as.numeric(as.POSIXct("2016-06-23")), lty = "dashed") +
  labs(title = "Quarterly GDP Growth in Relation to Brexit Vote") +
  labs(subtitle = "Source: OECD")
```

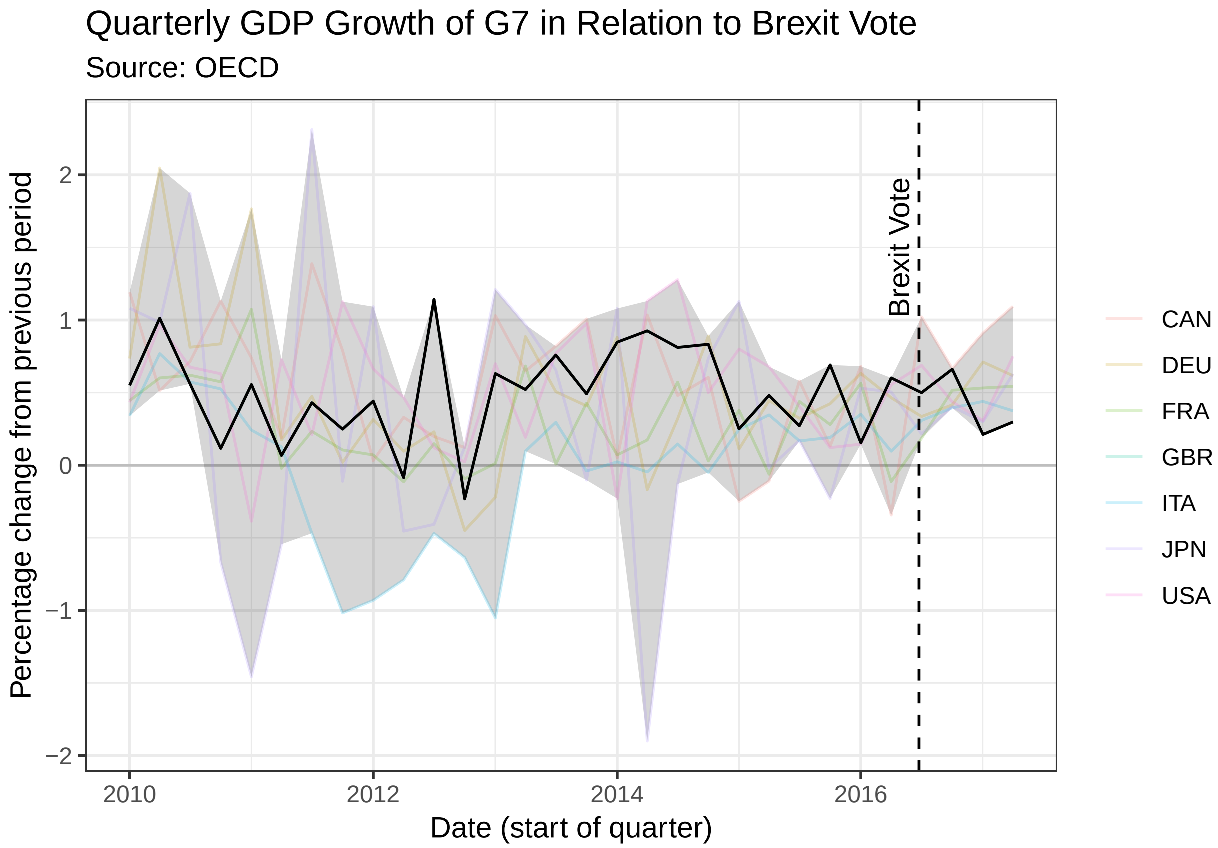


A random sample from the data set:

Country	Year	Quarter	Date (start of quarter)	Percentage change from previous period	Date (start o quarter)	
ITA	2011	2	2011-04-01	0.126761	2011-04-01	-
CAN	2016	4	2016-10-01	0.666167	2016-10-01	
CAN	2013	1	2013-01-01	1.030501	2013-01-01	-
ITA	2017	2	2017-04-01	0.374353	2017-04-01	
CAN	2010	2	2010-04-01	0.514190	2010-04-01	

```
ggplot(data = data) +
  aes(x = `Date (start of quarter)`) +
  aes(y = `Percentage change from previous period`) +
  aes(ymin = min_) +
  aes(ymax = max_) +
  geom_hline(yintercept = 0, col = "grey") +
  geom_ribbon(alpha = .2) +
  geom_line(aes(col = Country), alpha = .2) +
  geom_line(data = data %>% filter(Country == "GBR"), col = "black") +
  geom_vline(xintercept = as.numeric(as.POSIXct("2016-06-23")), lty = 2) +
  annotate(
    geom = "text", x = as.POSIXct("2016-04-23"), y = 1.5,
    label = "Brexit Vote", angle = 90
  ) +
  labs(
    title = "Quarterly GDP Growth of G7 in Relation to Brexit Vote",
    subtitle = "Source: OECD",
    col = ""
  ) +
```

```
theme_bw()
```


Quarterly GDP Growth of G7 in Relation to Brexit Vote
Source: OECD
Percentage change from previous period
2
1
0
−1
−2
2010
2012
2014
2016
Date (start of quarter)
Brexit Vote
CAN
DEU
FRA
GBR
ITA
JPN
USA

Chapter 10

Curry in London

This visualization task seemed to get at the question: Does where you eat matter. The data was the cost of identical menu items at different locations of the same restaurant, the Wetherspoon, around the UK.

First, I mapped the cost of a single menu item, the Empire Burger, across the UK. Then, I calculated the distance from Wetherspoon restaurants from the Big Ben, and plotted prices as a function of this distance – plotting only the restaurants in a 10 kilometer radius.

A random sample from the data set:

Name	Location	Latitude	Longitude	Empire State Burger	Chicken Tikka	Gammon afternoo
The Wheatsheaf	Ellesmere Port	53.28290	-2.923064	9.35	5.90	
The York Palace	Llanelli	51.68107	-4.163065	8.75	7.19	
The Observatory	Ilkeston	52.97154	-1.308131	8.75	6.99	
The Red Lion	Ripley	53.05078	-1.407486	8.75	7.19	
The Society Rooms	Macclesfield	53.25640	-2.124377	8.75	7.40	

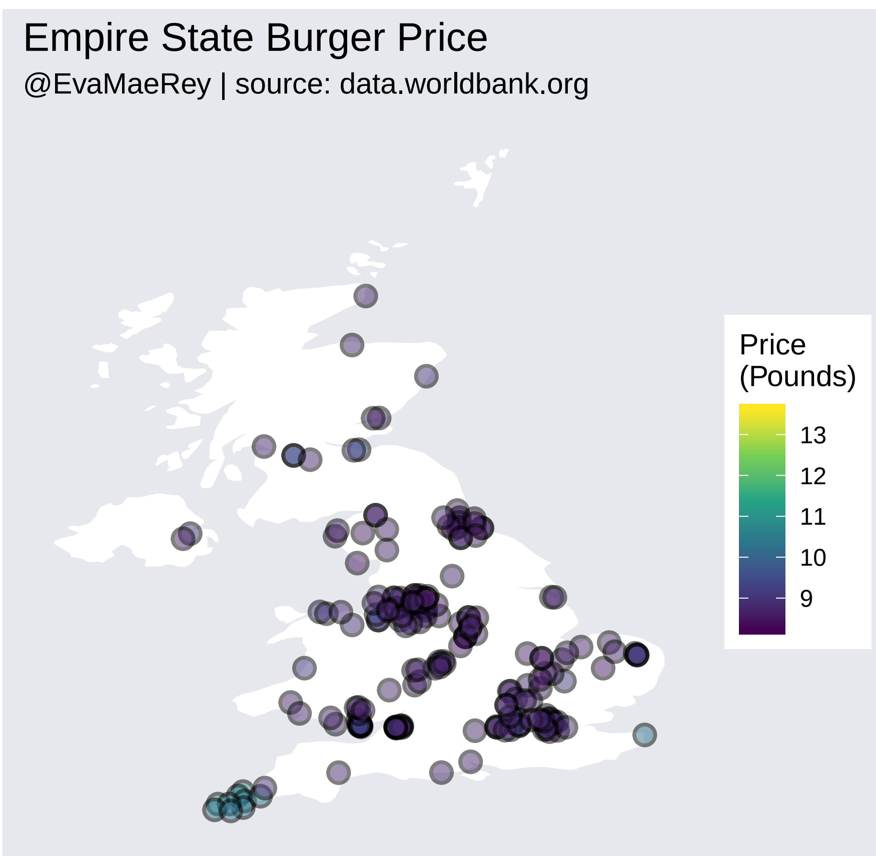
```
# Mapping data
world_map_df <- map_data("world")
```

A random sample from the data set:

	long	lat	group	order	region	subregion
88312	100.6295	6.447998	1413	88312	Thailand	NA
18728	-133.1968	68.739845	345	18728	Canada	NA
8316	137.4836	-34.252148	177	8316	Australia	NA
81664	174.7150	61.947903	1309	81664	Russia	NA
93724	-115.1252	32.683304	1501	93724	USA	NA

```
# create a blank ggplot theme
theme_opts <- theme(
  panel.grid.minor = element_blank(),
  panel.grid.major = element_blank(),
  panel.background = element_blank(),
  plot.background = element_rect(fill = "#e6e8ed"),
  panel.border = element_blank(),
  axis.line = element_blank(),
  axis.text.x = element_blank(),
  axis.text.y = element_blank(),
  axis.ticks = element_blank(),
  axis.title.x = element_blank(),
  axis.title.y = element_blank(),
```

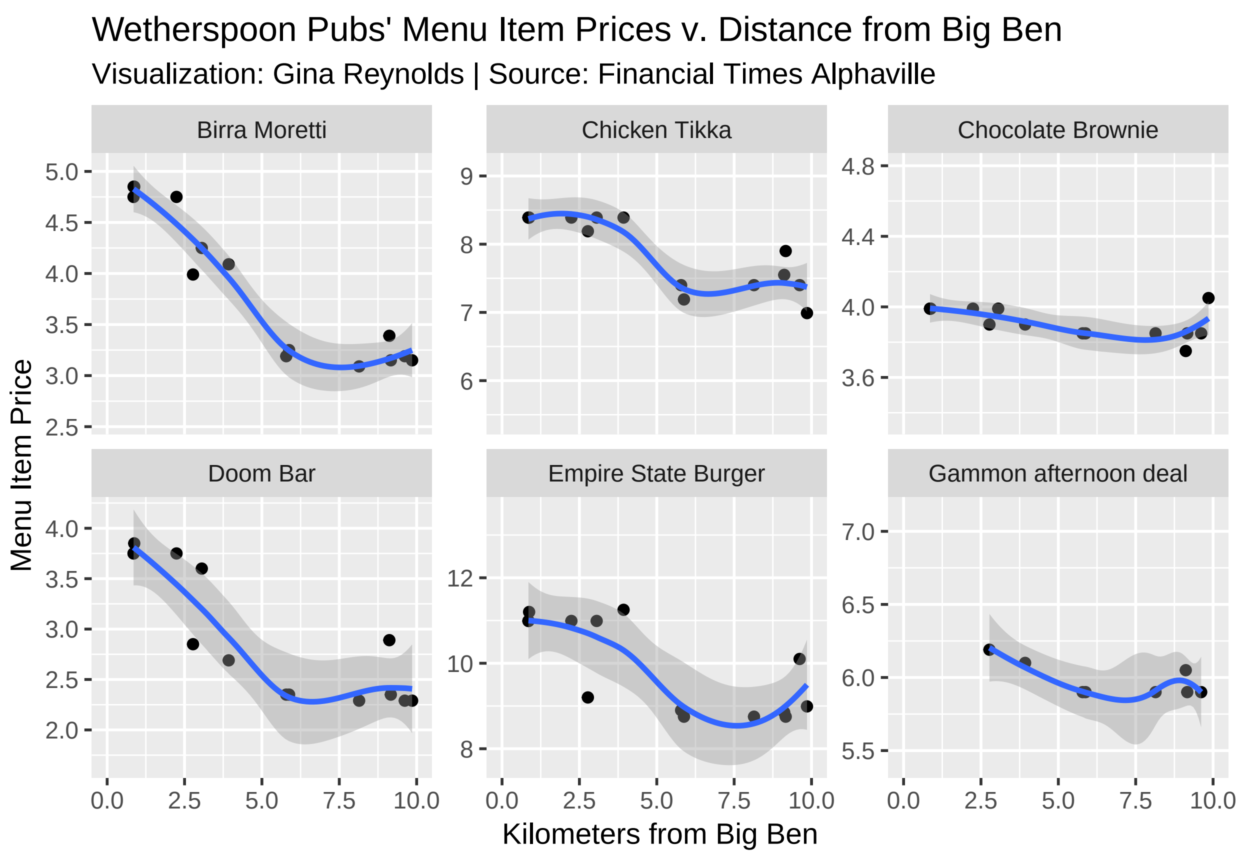
```
  plot.title = element_text(size = 15)
)


ggplot(data = world_map_df %>% filter(region == "UK")) +
  aes(x = long) +
  aes(y = lat) +
  aes(group = group) +
  geom_polygon(fill = "white") +
  coord_equal() +
  scale_fill_viridis_c(option = "viridis") +
  geom_point(data = data0,
             mapping = aes(x = Longitude, y = Latitude,
                           group = NULL, fill = `Empire State Burger`),
    colour = "black", shape = 21, stroke = 1, alpha = .5, size = 3
  ) +
  labs(fill = "Price\n(Pounds)") +
  labs(title = "Empire State Burger Price") +
  labs(subtitle = "@EvaMaeRey | source: data.worldbank.org") +
  theme_opts
```



A random sample from the data set:

Name	Location	Latitude	Longitude	Notes	Moretti as a % of a tikka	Moretti as % of bu
The Whiffler	Norwich	52.65430	1.268524	NA	0.4113924	0.359
The Kingfisher	Poynton	53.34644	-2.124271	NA	0.3920386	0.371
Bull and Stirrup Hotel	Chester	53.19436	-2.893331	NA	0.4172015	0.357
The Great Central	Wilmslow Road	53.44093	-2.219457	NA	0.4256757	0.360
The Hornet	Birmingham	52.49268	-1.819488	NA	0.4741379	0.314

```
ggplot(data = dataLong) +
  aes(x = `Kilometers from Big Ben`) +
  aes(y = `Menu Item Price`) +
  facet_wrap(~ Item, scales = "free_y") +
  geom_point() +
  geom_smooth() +
  xlim(c(0, 10)) +
  labs(title = "Wetherspoon Pubs' Menu Item Prices v. Distance from Big Ben") +
  labs(subtitle = "Visualization: Gina Reynolds | Source: Financial Times Alphaville")
```



Chapter 11

Life Expectancy Increases

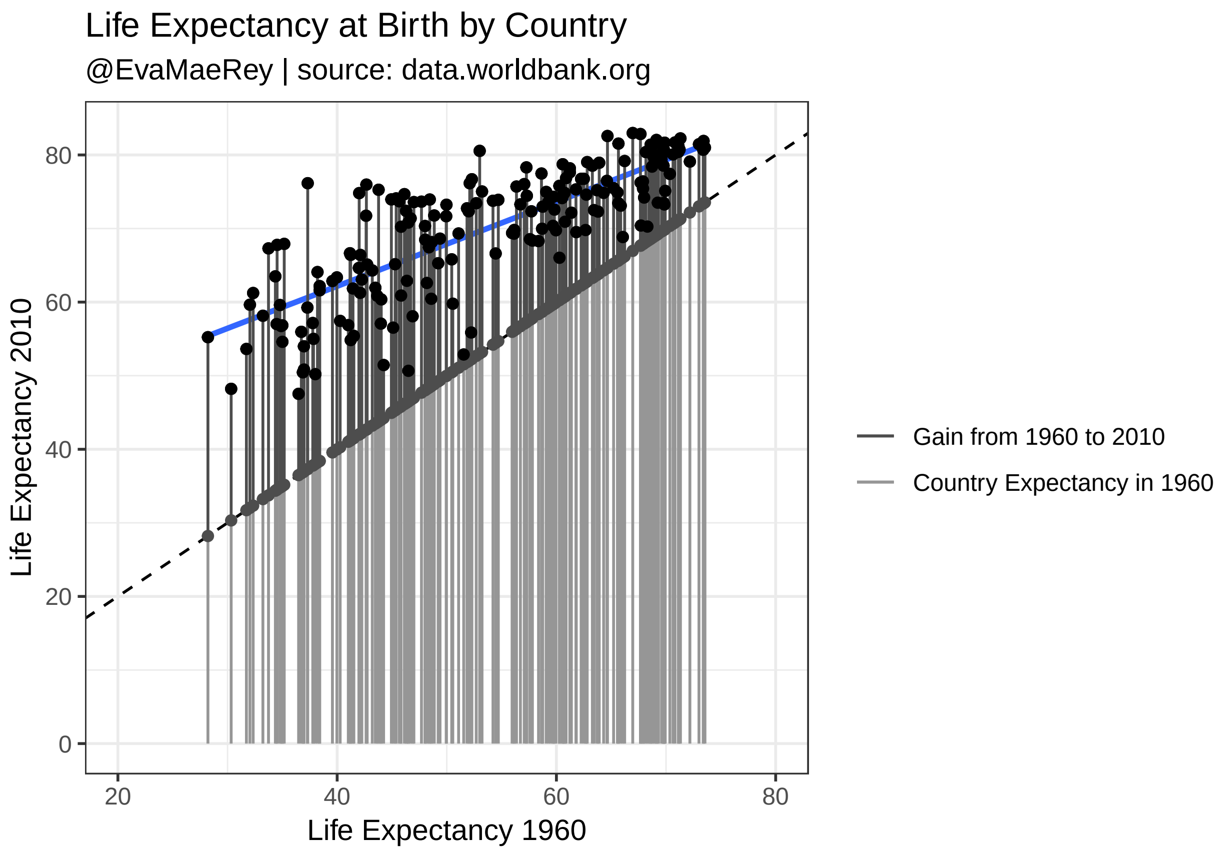
To dramatically show the increases in life expectancy by country from 1960 to 2010, I plot the variable in 1960 versus itself in 2010. The line of equivilance (a 45% angle) is used as a reference and shows the result that you would see if there where no growth. The vertical distance from this line is the increase in life expectancy. I also superimpose a linear model on top of the scatter plot. You can see that the gains are greater for countries that started off with lower life expectancies.

A random sample from the data set:

Life Expectancy 1960	Country Code	Country Name	Region	Income Group	Year
69.10927	ESP	Spain	Europe & Central Asia	High income	2010
65.56937	ABW	Aruba	Latin America & Caribbean	High income	2010
41.98105	PNG	Papua New Guinea	East Asia & Pacific	Lower middle income	2010
60.78085	AZE	Azerbaijan	Europe & Central Asia	Upper middle income	2010
68.29954	UKR	Ukraine	Europe & Central Asia	Lower middle income	2010

```r
ggplot(compare) +
  aes(x = `Life Expectancy 1960`) +
  aes(y = `Life Expectancy 2010`) +
  geom_point() +
  geom_smooth(se = F, method = "lm") +
  geom_abline(slope = 1, intercept = 0, lty = 2) +
  # coord_fixed() +
  aes(xend = `Life Expectancy 1960`) +
  aes(yend = `Life Expectancy 1960`) +
  geom_segment(mapping = aes(col = "Gain from 1960 to 2010")) +
  geom_segment(mapping = aes(y = 0, col = "Country Expectancy in 1960")) +
  scale_color_manual(
    breaks = c(
      "Gain from 1960 to 2010",
      "Country Expectancy in 1960"
    ),
    values = c("grey59", "grey30", "grey30")
  ) +
  geom_point(aes(y = `Life Expectancy 1960`), col = "grey30") +
  geom_point() +
  labs(subtitle = "@EvaMaeRey | source: data.worldbank.org", size = .7) +
  labs(title = "Life Expectancy at Birth by Country") +
  labs(col = "") +
  theme(legend.title = element_blank()) +
```

```
theme_bw() +
xlim(c(20, 80))
```



Chapter 12

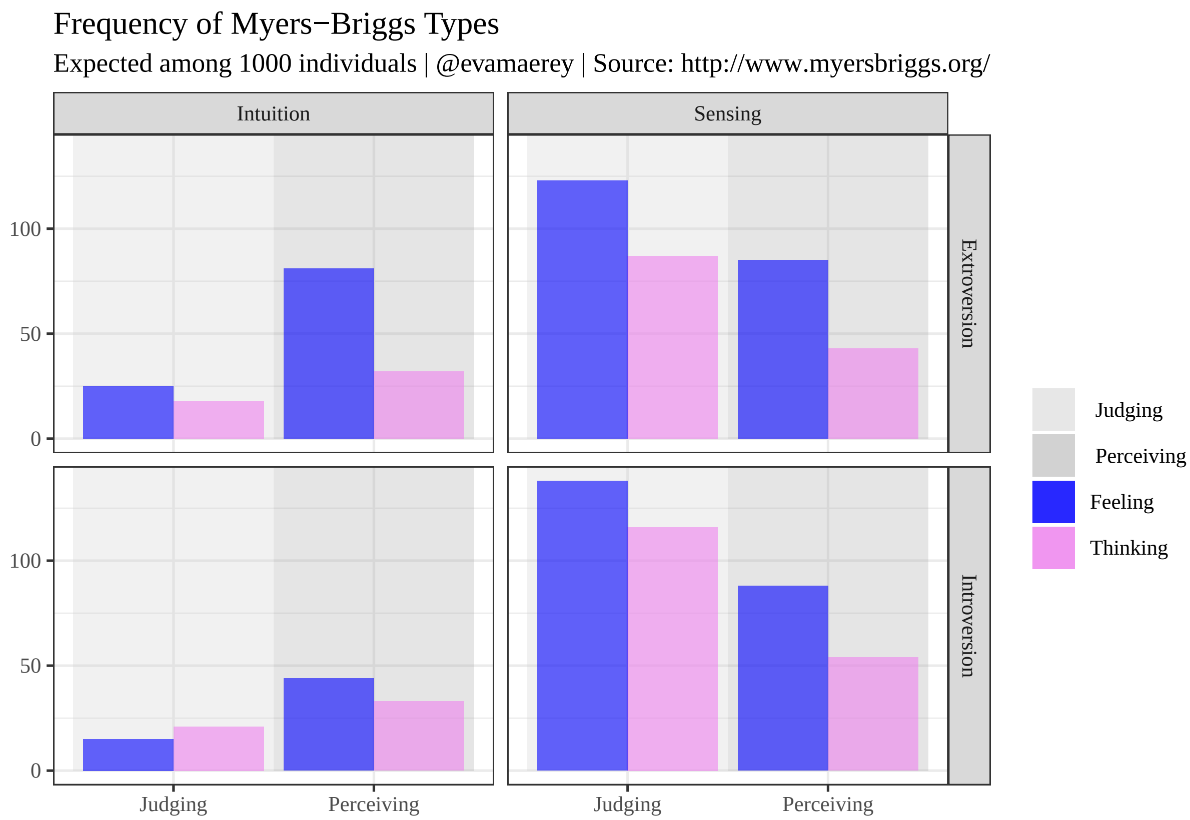
Myers Briggs

This data looks at the relationship betweeen four binary variables. The challenge is how to display that in one visualization. My first idea was to use a mosaic plot. However, I came across advice from "The Perceptual Edge", that generally advised against the use of the mosaic plot, instead favoring a kind of nested bar plot. I tried to implement that. While I do think that it is pretty, I think that it still requires a lot of the reader to interpret the graph. Perhaps more annotation could alleviate this burden.

A random sample from the data set:

(S)ensing/I(N)tuition	(T)hinking/(F)eeling	(J)udging/(P)erceiving	(E)xtroversion/(I)ntroversion	count
Intuition	Thinking	Perceiving	Introversion	1
Intuition	Feeling	Judging	Introversion	1
Intuition	Thinking	Judging	Extroversion	1
Intuition	Feeling	Perceiving	Introversion	1
Sensing	Thinking	Perceiving	Extroversion	1

```
ggplot(d) +
  aes(x = `(J)udging/(P)erceiving`) +
  aes(fill = `(T)hinking/(F)eeling`) +
  facet_grid(`(E)xtroversion/(I)ntroversion` ~
             `(S)ensing/I(N)tuition`) +
  geom_rect(aes(x = NULL, y = NULL,
              xmin = mins, xmax = max,
              fill = `judging perceiving`),
              ymin = 0, ymax = 700, data = background
  ) +
  geom_bar(position = "dodge") +
  scale_fill_manual(values = alpha(c("lightgrey", "darkgrey", "blue", "violet"), c(.3, .3, .6, .6))) +
  labs(x = "") +
  labs(y = "") +
  labs(fill = "") +
  labs(title = "Frequency of Myers-Briggs Types") +
  labs(subtitle = "Expected among 1000 individuals | @evamaerey | Source: http://www.myersbriggs.org/")
  theme_bw(base_size = 10, base_family = "Times")
```


Frequency of Myers−Briggs Types
Expected among 1000 individuals | @evamaerey | Source: http://www.myersbriggs.org/
Intuition
Sensing
Extroversion
Introversion
100
50
0
100
50
0
Judging
Perceiving
Judging
Perceiving
Judging
Perceiving
Feeling
Thinking

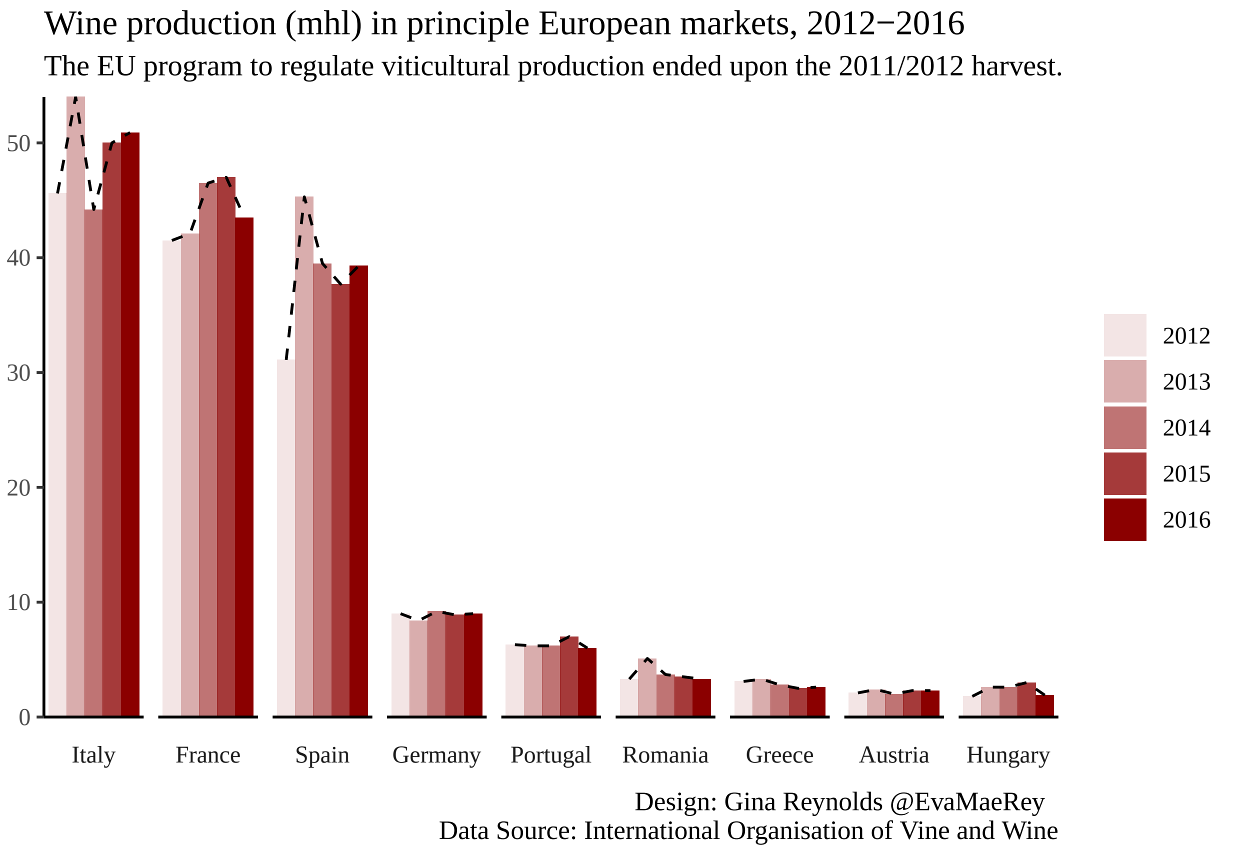
Chapter 13

Wine

Wine production in Europe may have been volitile during the years plotted because of production control policies implemented by the EU. The big three, Italy, France and Spain, particularly saw a lot of volitility early in this period.

```
df <- readxl::read_xlsx("raw_data/Wine_Production_by_country.xlsx") %>%
  filter(Country != "World total")

Europe <- c(
  "Italy", "France", "Spain",
  "Germany", "Portugal", "Romania",
  "Austria", "Greece", "Hungary"
)
```

```
  ggplot(df %>% filter(Country %in% Europe)) +
  aes(x = Year) +
  aes(y = `Wine production in mhl`) +
  facet_wrap(~ fct_inorder(Country), strip.position = "bottom", nrow = 1) +
  geom_col(aes(alpha = Year), position = "dodge", fill = "darkred", width = 1) +
  geom_line(col = "black", lty = 2) +
  scale_y_continuous(expand = c(0, 0)) +
  labs(fill = "") +
  labs(alpha = "")+
  labs(title = "Wine production (mhl) in principle European markets, 2012-2016") +
  labs(subtitle = "The EU program to regulate viticultural production ended upon the 2011/2012 harvest.
    labs(caption = "Design: Gina Reynolds @EvaMaeRey  \nData Source: International Organisation of Vine
  theme_classic(base_family = "Times") +
  theme(
    axis.title = element_blank(),
    strip.placement = "outside",
    axis.text.x = element_blank(),
    axis.ticks.x = element_blank(),
    strip.background = element_blank(),
    plot.caption = element_text(size = 10)
  )
```


Wine production (mhl) in principle European markets, 2012−2016
The EU program to regulate viticultural production ended upon the 2011/2012 harvest.
0
10
20
30
40
50
Italy
France
Spain
Germany
Portugal
Romania
Greece
Austria
Hungary
2012
2013
2014
2015
2016
Design: Gina Reynolds @EvaMaeRey
Data Source: International Organisation of Vine and Wine

Chapter 14

Arctic Ice

This visualization shows the trend in Arctic Ice Sea Extent, data from the National Snow and Ice Data Center. If I recall correctly, the definition for coverage is the case where at least 15 percent of the sea is ice.

The visualization shows melting and freezing cycles, in accordance with the seasons — and the disconcerting trend of a general decrease in ice extent over the years.

One problem that arises is due to inconsistant number of days in each year. There is a measurement for every day, but leap years contain a extra day. Which means that plotting years over years leads to imperfect alignment. My solution was just to pretend that all the data come from a single year, 2000, and plot each of the years on that scale. The earliest year cycle and last year cycle are highlighted in white.

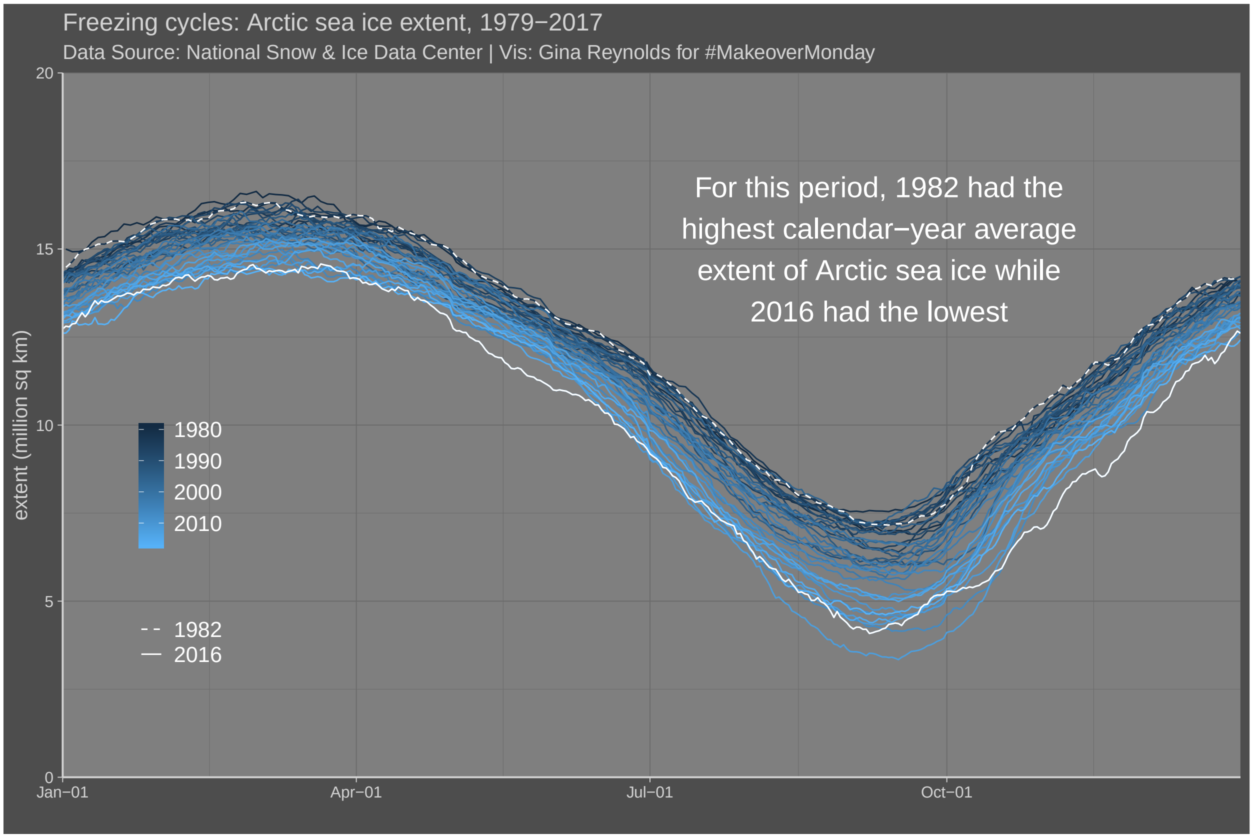
A random sample from the data set:

Date	Extent (million sq km)	year	month_day	month_day_plus	proportion_ocean_covered_in_ice	mea
2008-02-27	15.354	2008	02-27	2000-02-27	0.0426500	
1992-11-15	11.138	1992	11-15	2000-11-15	0.0309389	
1994-05-01	14.126	1994	05-01	2000-05-01	0.0392389	
2014-04-07	14.479	2014	04-07	2000-04-07	0.0402194	
2001-06-09	12.073	2001	06-09	2000-06-09	0.0335361	

year	average_coverage	num_days	average_day
1982	12.43945	182	1982-07-02 00:00:00
2016	10.15069	366	2016-07-01 12:00:00

```
# breaks for x axis.
br <- as.numeric(lubridate::ymd(c(
  "2000-01-01", "2000-04-01",
  "2000-07-01", "2000-10-01", "2001-01-01"
)))

ggplot(df) +
  aes(x = as.numeric(month_day_plus)) +
  aes(y = `Extent (million sq km)`) +
  aes(group = year) +
  geom_line() +
  aes(col = year) +
  scale_x_continuous(
    breaks = br,
    labels = c("Jan-01", "Apr-01", "Jul-01", "Oct-01", "Jan-01"),
    expand = c(0, 0)
  ) +
```

```
scale_y_continuous(expand = c(0, 0), limits = c(0, 20)) +
scale_color_continuous(
  guide = guide_colourbar(reverse = TRUE),
  breaks = seq(2010, 1980, -10)
) +
geom_line(aes(lty = factor(year)),
  data = df %>% filter(year == 2016 | year == 1982),
  col = "white"
) +
scale_linetype_manual(
  name = "",
  values = c("dashed", "solid")
) +
annotate(
  geom = "text", x = 11210, y = 15,
  label = str_wrap("For this period, 1982 had the highest calendar-year average extent of Arctic sea i
  col = "white",
  size = 7
) +
labs(x = "") +
labs(y = "extent (million sq km)") +
labs(col = "") +
labs(lty = "") +
labs(title = "Freezing cycles: Arctic sea ice extent, 1979-2017") +
labs(subtitle = "Data Source: National Snow & Ice Data Center | Vis: Gina Reynolds for #MakeoverMonday
theme_dark(base_size = 14) +
theme(
  legend.background = element_blank(),
  legend.position = c(0.1, .35),
  legend.text = element_text(colour = "white", size = 15),
  plot.background = element_rect(fill = "grey30"),
  plot.title = element_text(colour = "lightgrey"),
  plot.subtitle = element_text(colour = "lightgrey"),
  axis.title = element_text(colour = "lightgrey"),
  axis.line = element_line(colour = "lightgrey"),
  axis.text = element_text(colour = "lightgrey"),
  axis.ticks = element_line(colour = "lightgrey")
)
```


Freezing cycles: Arctic sea ice extent, 1979−2017
Data Source: National Snow & Ice Data Center | Vis: Gina Reynolds for #MakeoverMonday
For this period, 1982 had the highest calendar−year average extent of Arctic sea ice while 2016 had the lowest
extent (million sq km)
20
15
10
5
0
Jan−01
Apr−01
Jul−01
Oct−01
1980
1990
2000
2010
1982
2016