Slow ggplot2

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Contents

Chapter 1

Introduction

The ggplot2 package in R implements the "grammer of graphics" — a proposal of Leland Wilkinson and the product of the PhD and ongoing work of Hadley Wickham. 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 into 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 new layer or modification. The aim is less to be concise, but to be explicit about modifications, and facilitating more interactions with ggplot functions for newcomer internalization of the code.

Working incrementally is facilitatied by using the following (non conventional) conventions:

- 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.

Here, I contrast the usual plotting method to slow ggplotting:

Usual approach:

```
ggplot(my_data, aes(var1, y = var2, col = var3)) +
  geom_point() +
  ggtitle("My Title") +
  labs(x = "the x label", y = "the y label", col = "legend title")
```

Using new slow ggplotting conventions:

```
ggplot(data = my_data) +
  aes(x = var1) +
  labs(x = "the x label") +
  aes(y = var2) +
  labs(y = "the y label") +
```

```
  geom_point() +
  aes(col = var3) +
  labs(col = "legend title") +
  labs(title = "My title")
```

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

Chapter 2

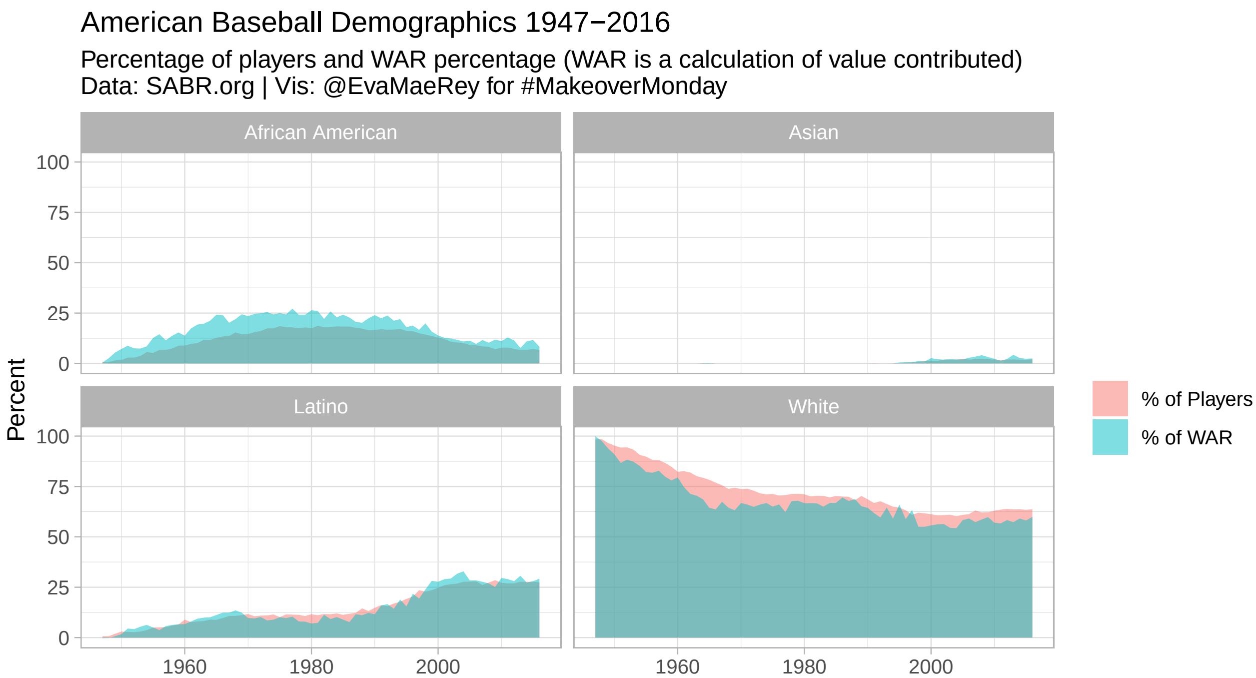
Baseball, WAR, and Ethnicity

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:

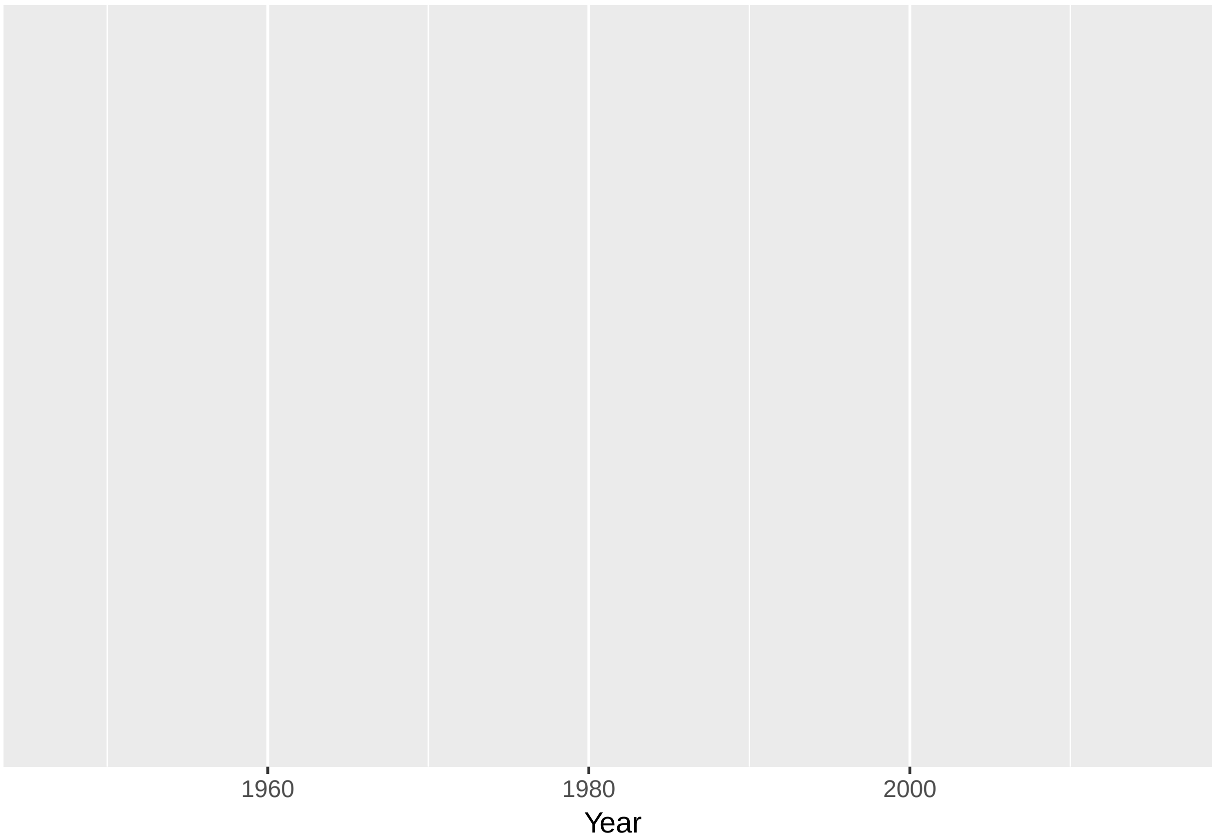
Year	Ethnicity	type	Percent
1975	Asian	% of Players	0.0
2005	Latino	% of WAR	28.4
1967	White	% of WAR	67.4
1972	Asian	% of Players	0.0
1961	Latino	% of WAR	8.0

```
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()
```

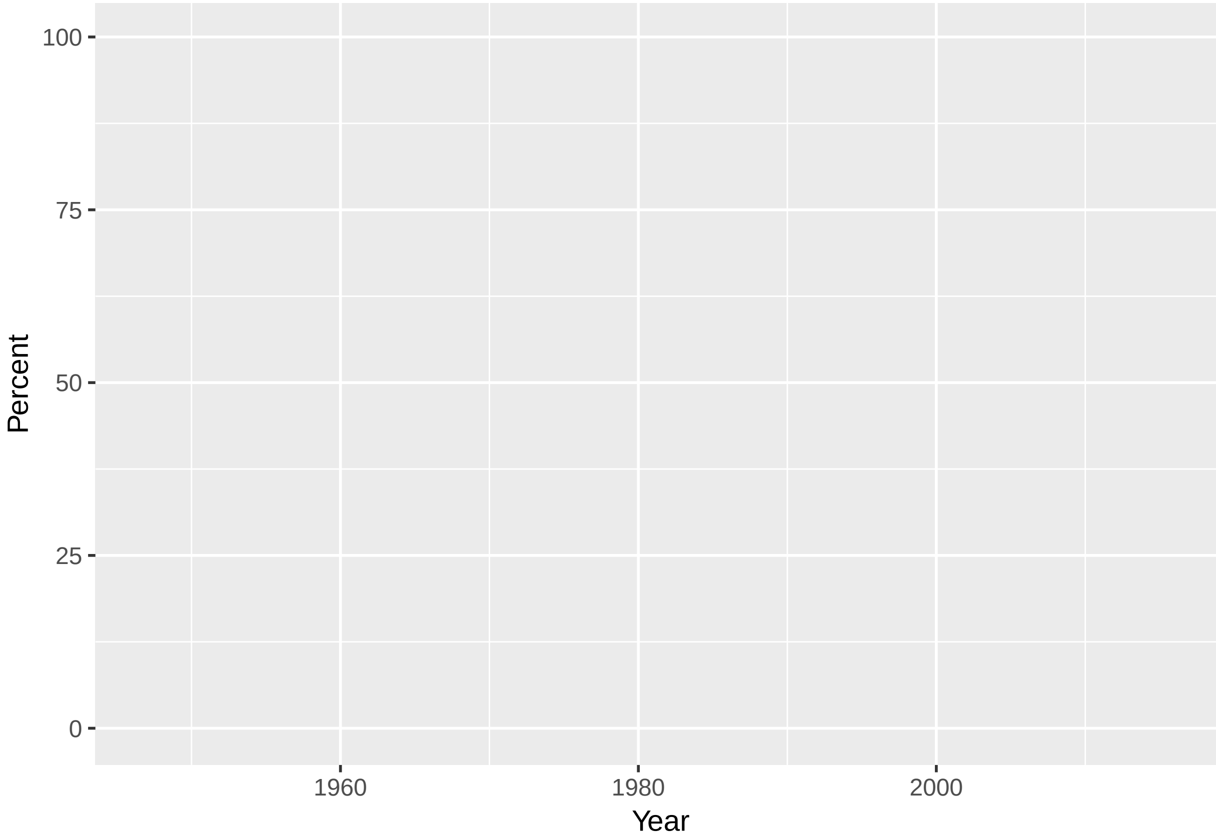

American Baseball Demographics 1947−2016
Percentage of players and WAR percentage (WAR is a calculation of value contributed)
Data: SABR.org | Vis: @EvaMaeRey for #MakeoverMonday
African American
Asian
Latino
White
Percent
100
75
50
25
0
1960
1980
2000
% of Players
% of WAR

```r
ggplot(df_gather)
```

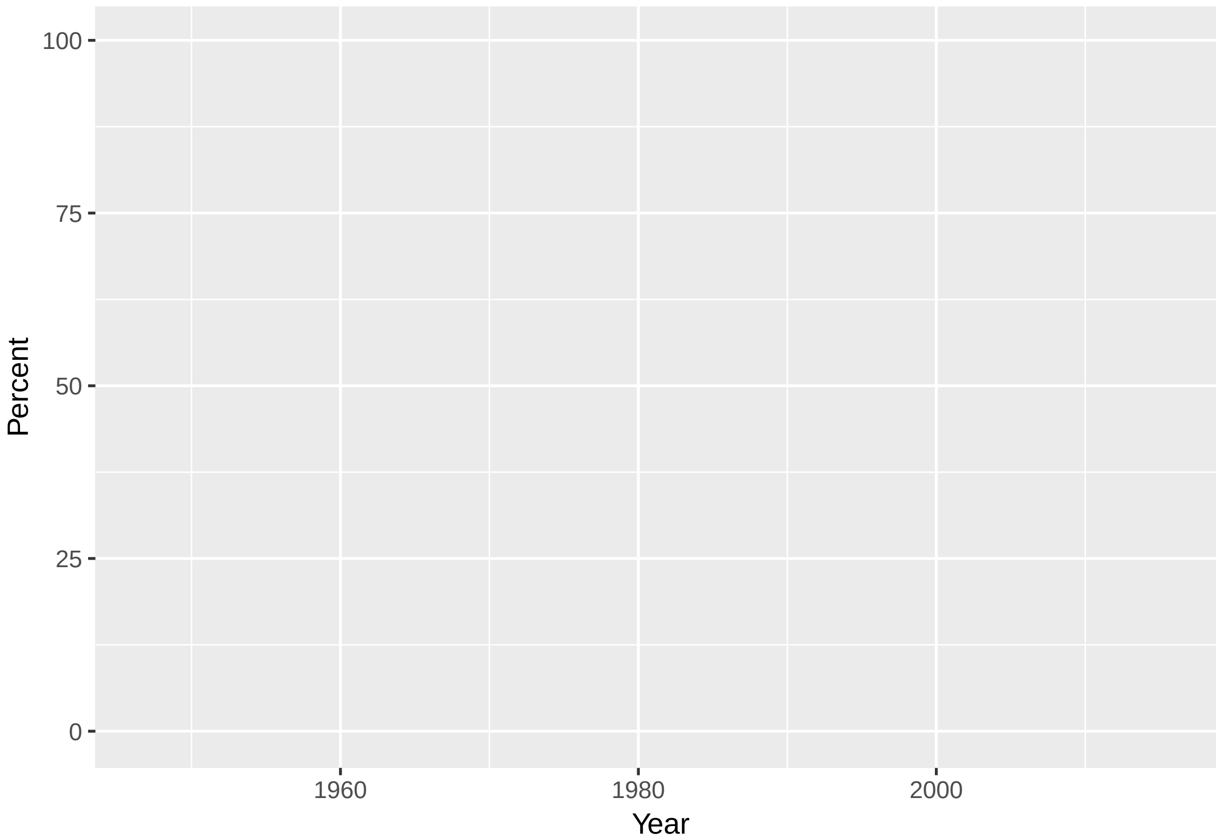
```
ggplot(df_gather) +
  aes(x = Year)
```



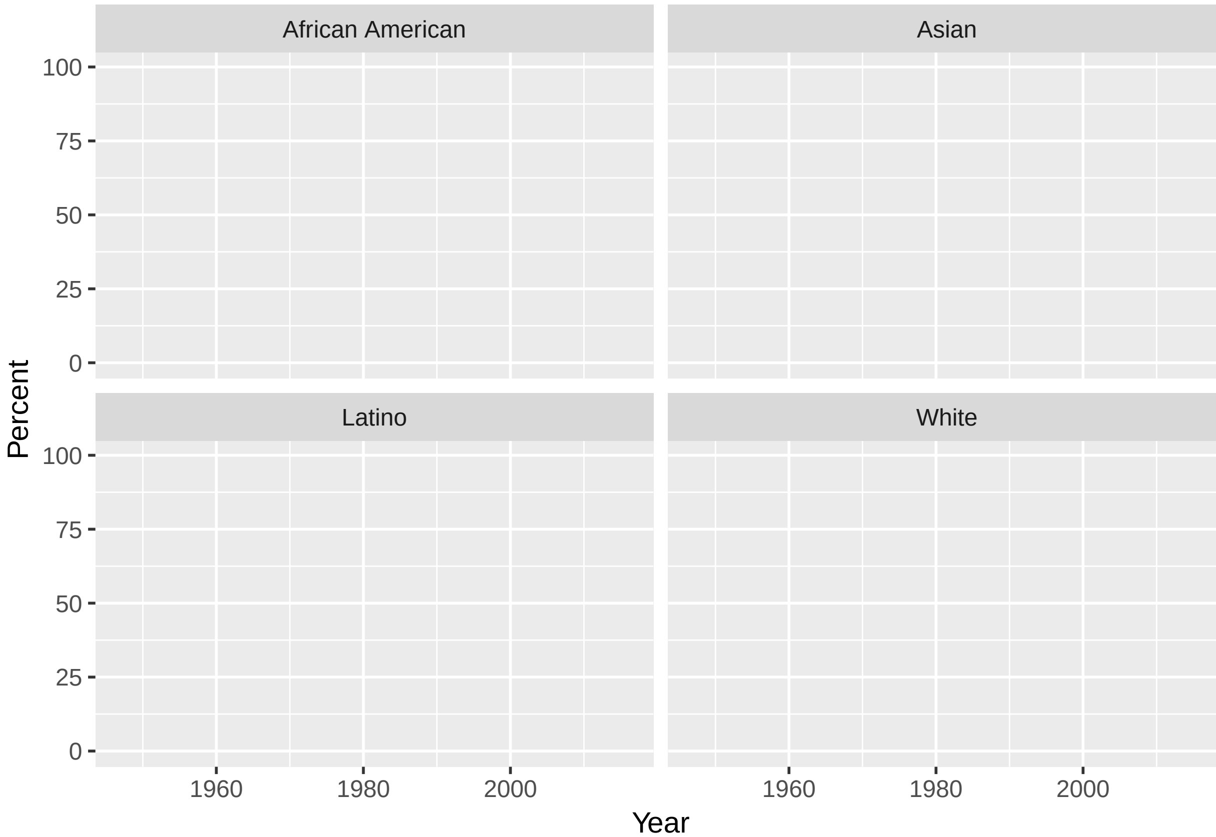
```
ggplot(df_gather) +
  aes(x = Year) +
  aes(y = Percent)
```



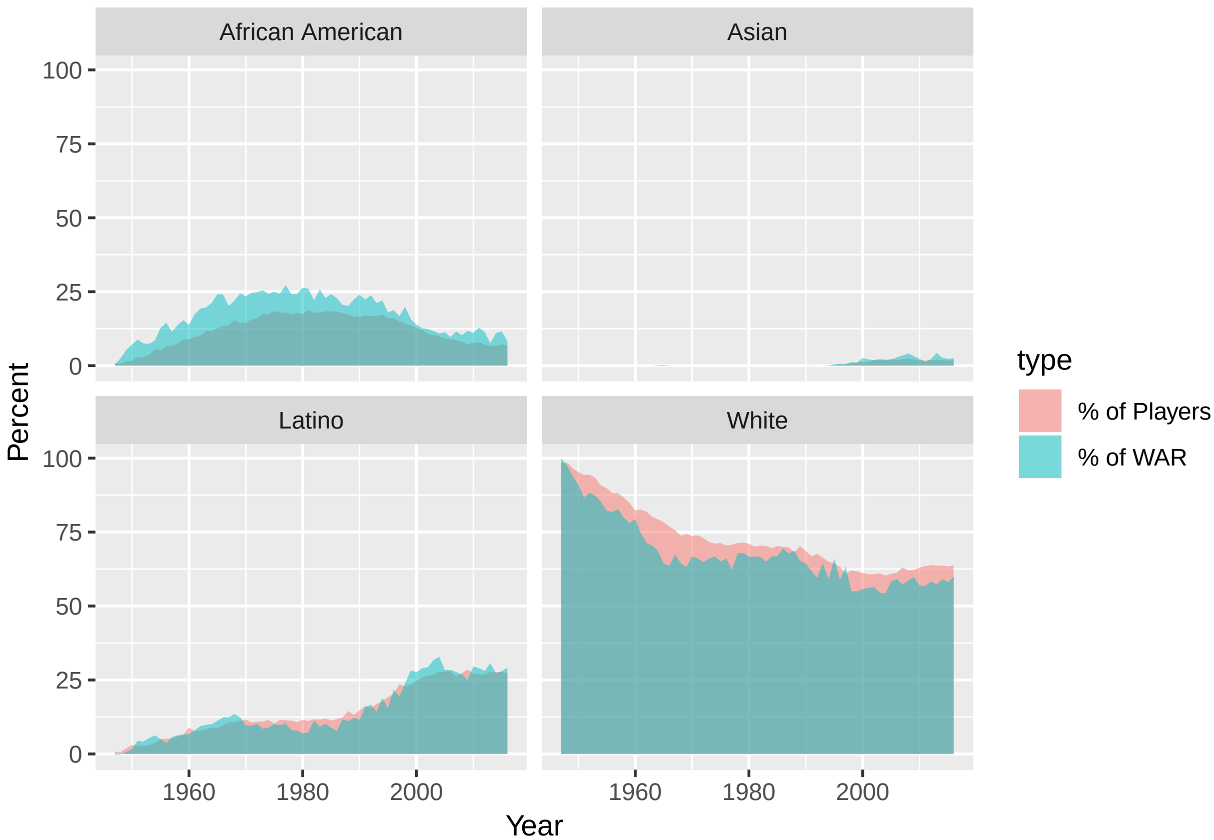
```
ggplot(df_gather) +
  aes(x = Year) +
  aes(y = Percent) +
  aes(fill = type)
```



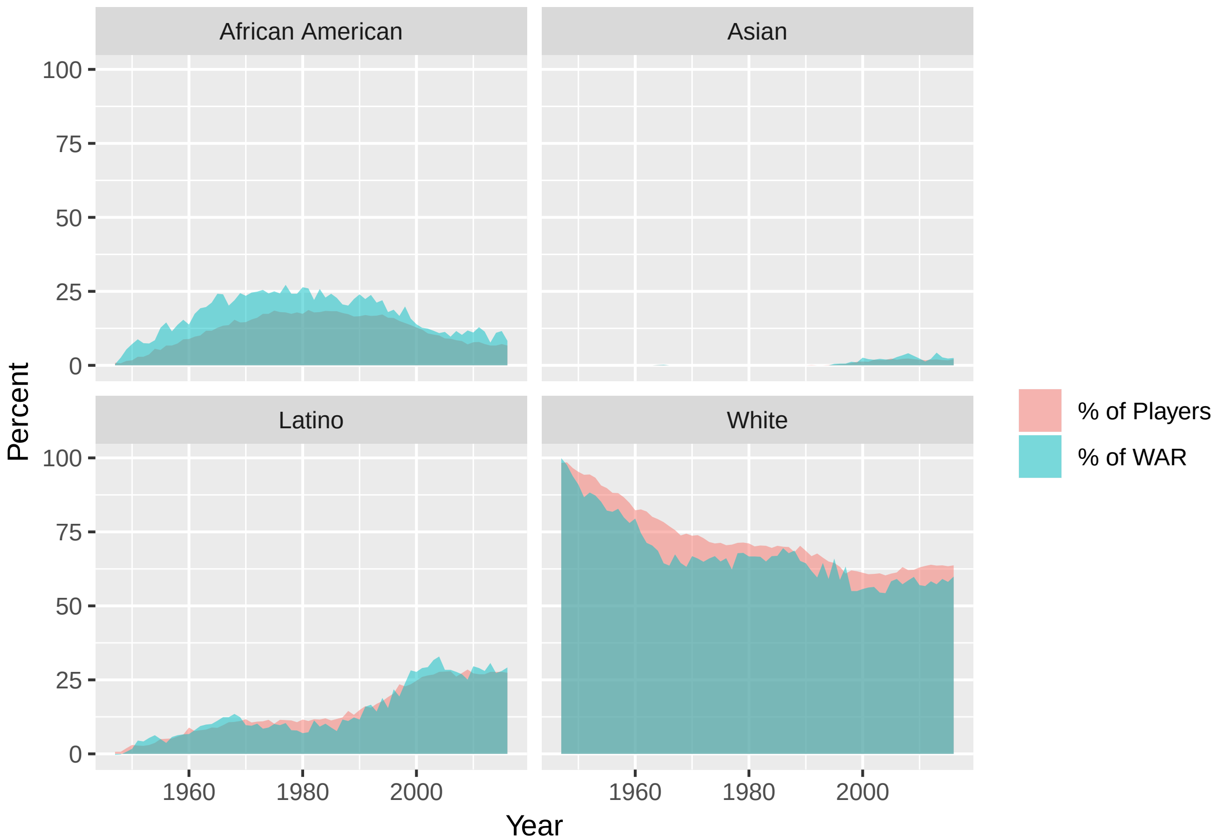
```
ggplot(df_gather) +
  aes(x = Year) +
  aes(y = Percent) +
  aes(fill = type) +
  facet_wrap(~ Ethnicity)
```



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

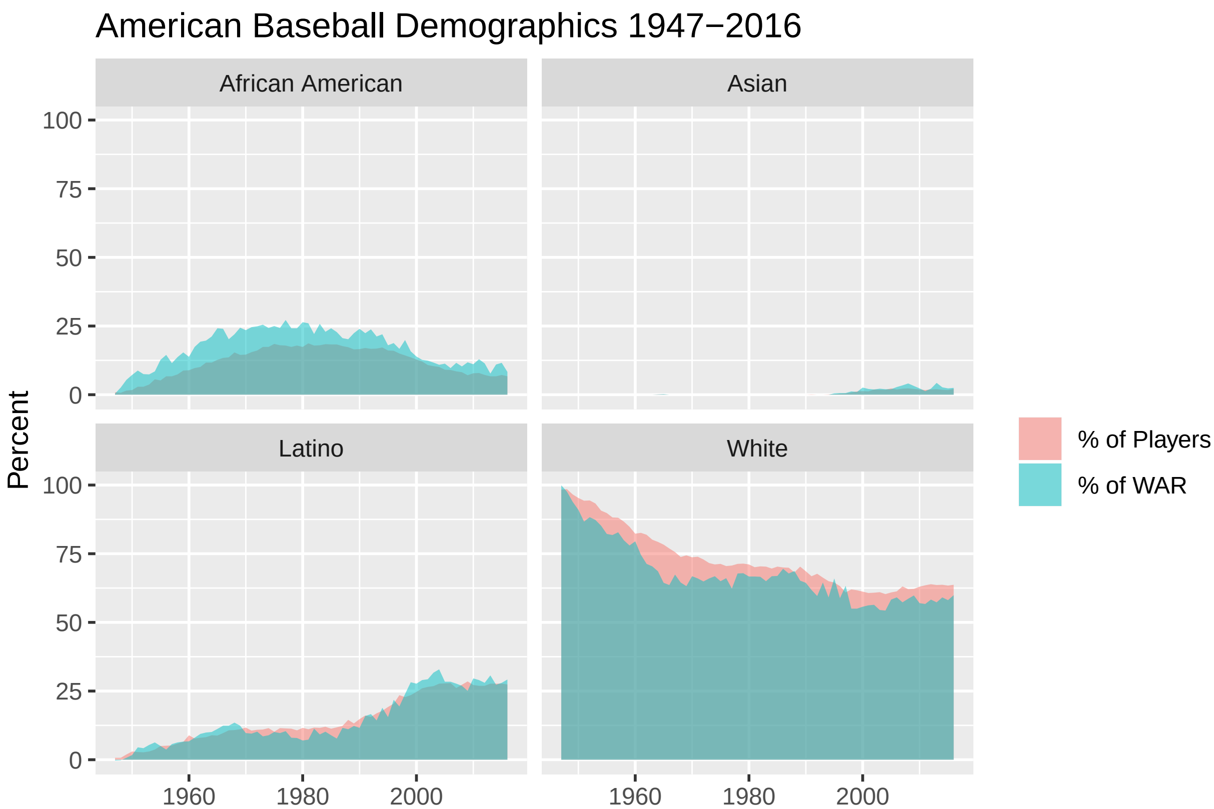


```r
ggplot(df_gather) +
  aes(x = Year) +
  aes(y = Percent) +
  aes(fill = type) +
  facet_wrap(~ Ethnicity) +
  geom_area(alpha = .5, position = "dodge") +
  labs(fill = "")
```

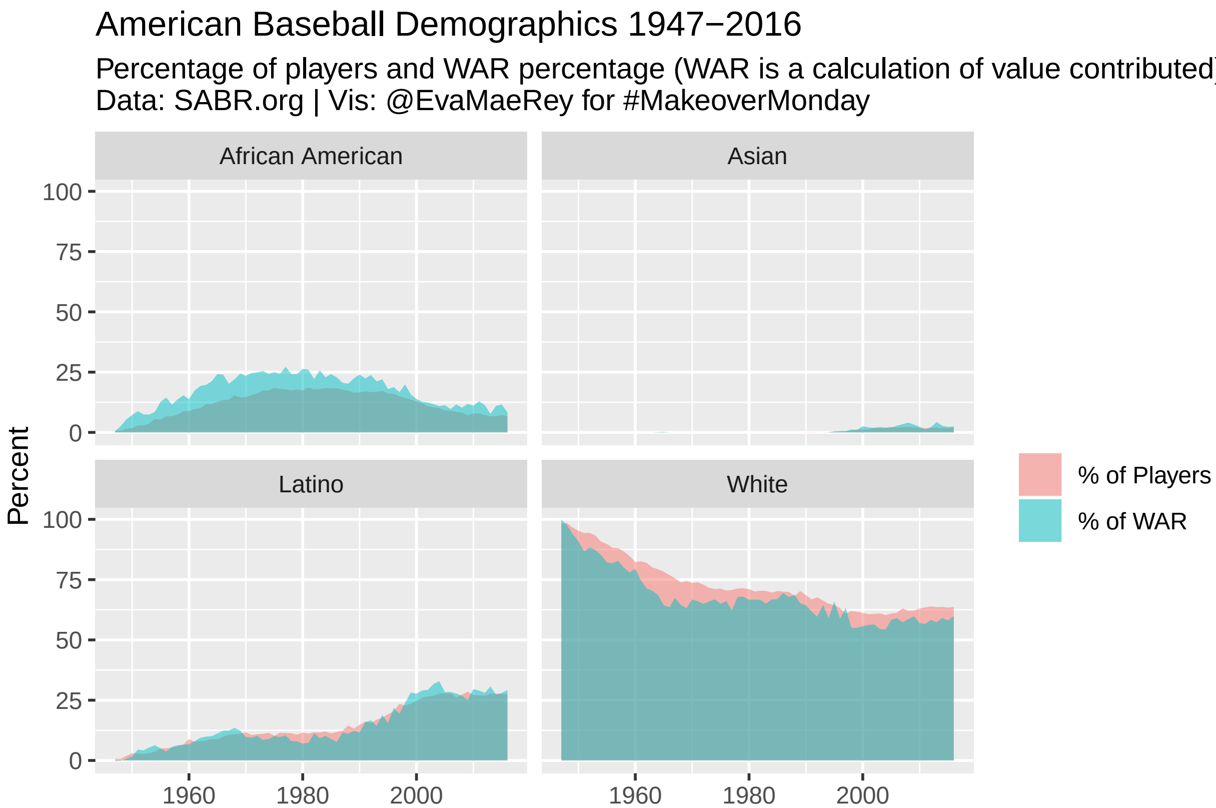


```
ggplot(df_gather) +
  aes(x = Year) +
  aes(y = Percent) +
  aes(fill = type) +
  facet_wrap(~ Ethnicity) +
  geom_area(alpha = .5, position = "dodge") +
  labs(fill = "") +
  labs(x = "")
```

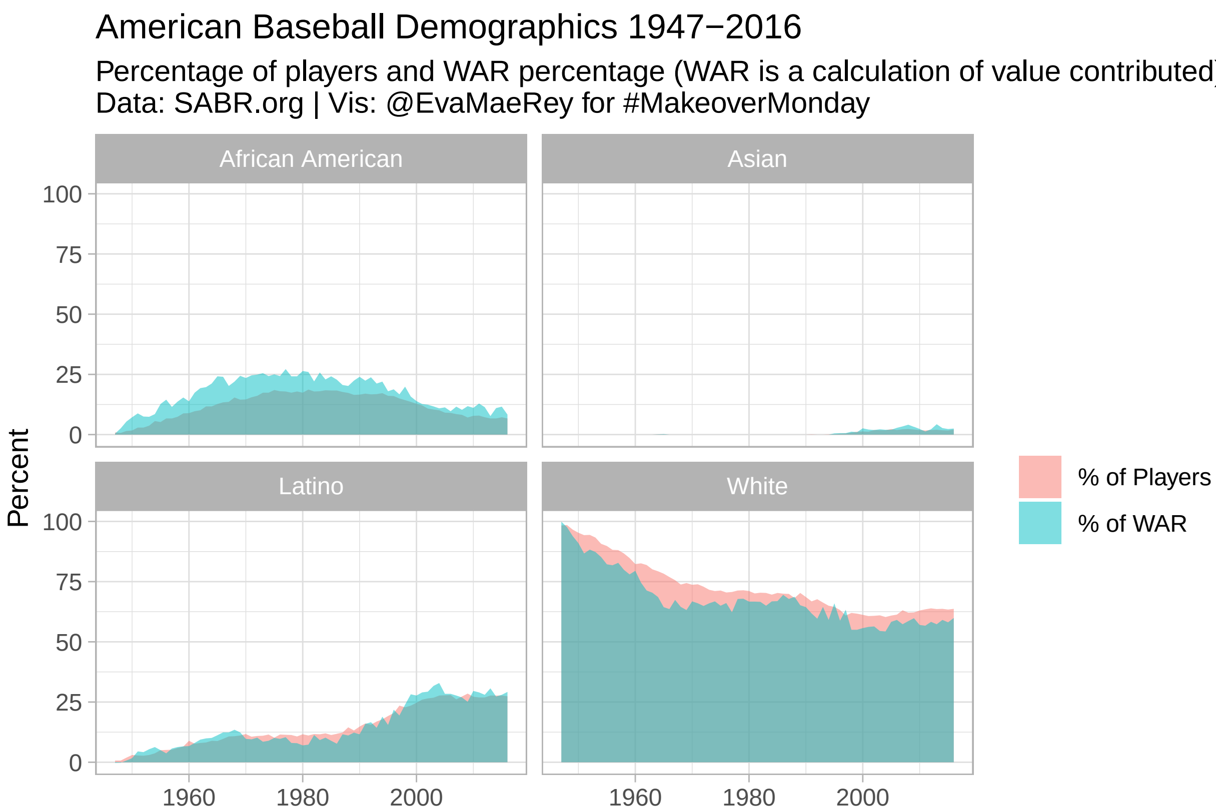
```r
ggplot(df_gather) +
  aes(x = Year) +
  aes(y = Percent) +
  aes(fill = type) +
  facet_wrap(~ Ethnicity) +
  geom_area(alpha = .5, position = "dodge") +
  labs(fill = "") +
  labs(x = "") +
  labs(title = "American Baseball Demographics 1947-2016")
```



```
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

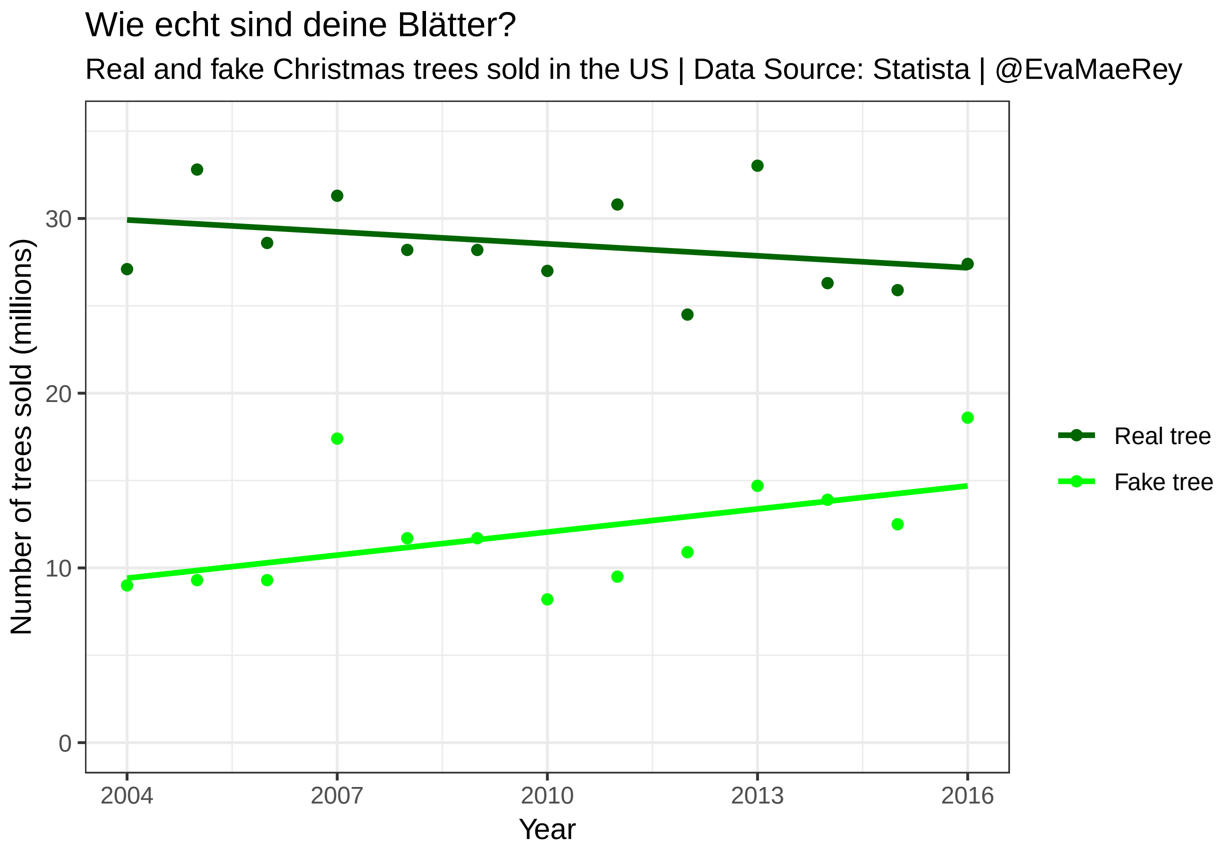
Here is a simple plot of Christmas Tree Sales in the U.S. The plot shows that artificial tree sales are on the rise, contrasting with declines in real trees. The title plays on the German Christmas Carol "O Tannenbaum", "Oh Christmas Tree" in English. "Wie echt sind deine Blätter?" means "how real are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

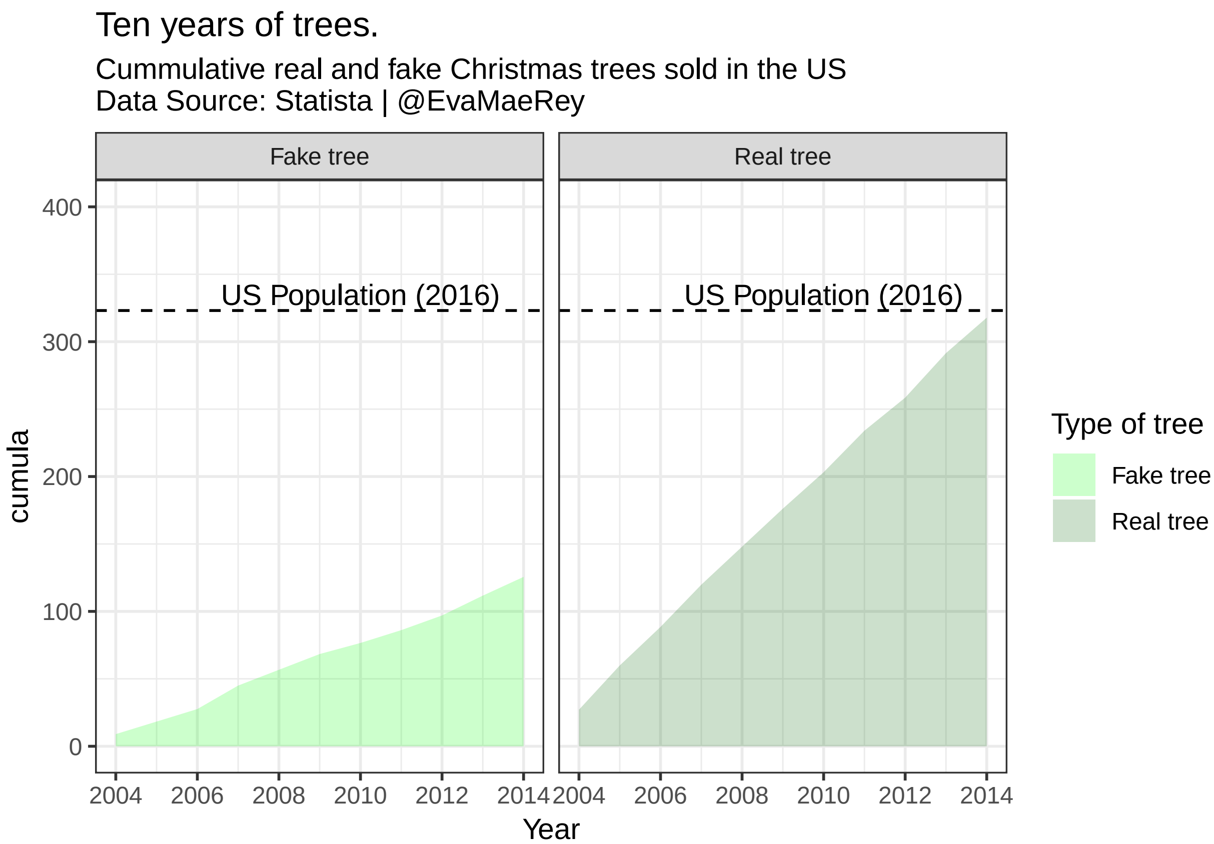
A random sample from the data set:

Year	Number of trees sold	Type of tree	Number of trees sold (millions)
2009	28200000	Real tree	28.2
2007	17400000	Fake tree	17.4
2008	28200000	Real tree	28.2
2004	9000000	Fake tree	9.0
2006	9300000	Fake tree	9.3

```
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
400
300
200
100
0
2004
2006
2008
2010
2012
2014
Year
Type of tree
Fake tree
Real tree

Chapter 4

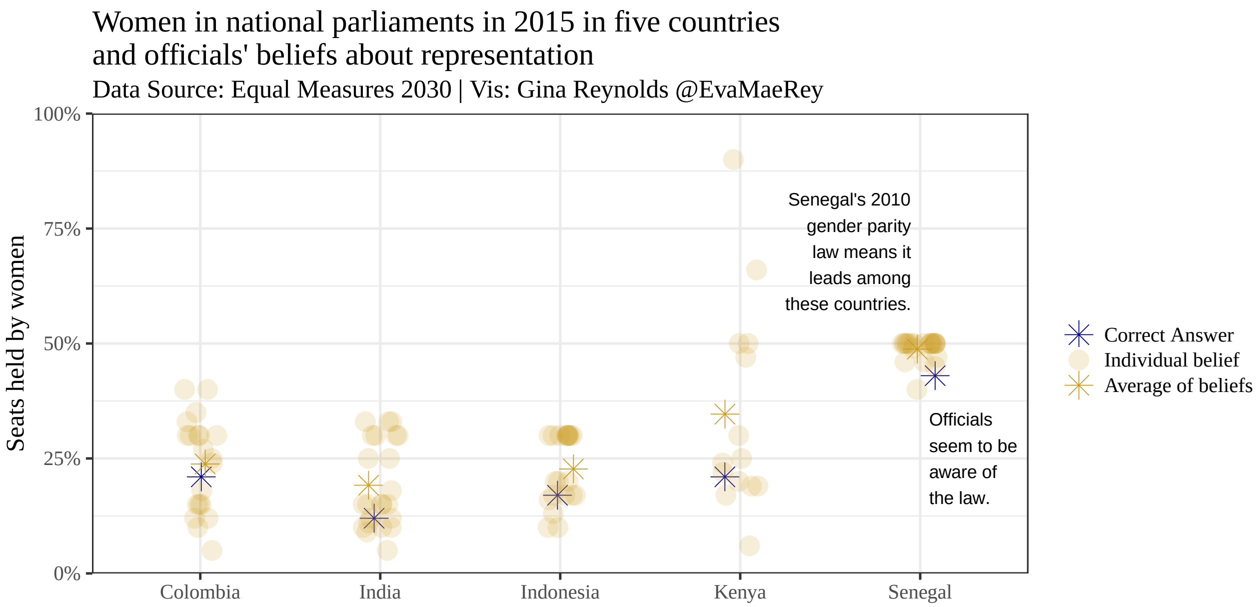
Officials' beliefs about women's representation

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
Colombia	Share of seats held by women	0.15	Individual belief	0.3
Kenya	Share of seats held by women	0.47	Individual belief	0.3
Senegal	Share of seats held by women	0.50	Individual belief	0.3
India	Share of seats held by women	0.30	Individual belief	0.3
Kenya	Share of seats held by women	0.19	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

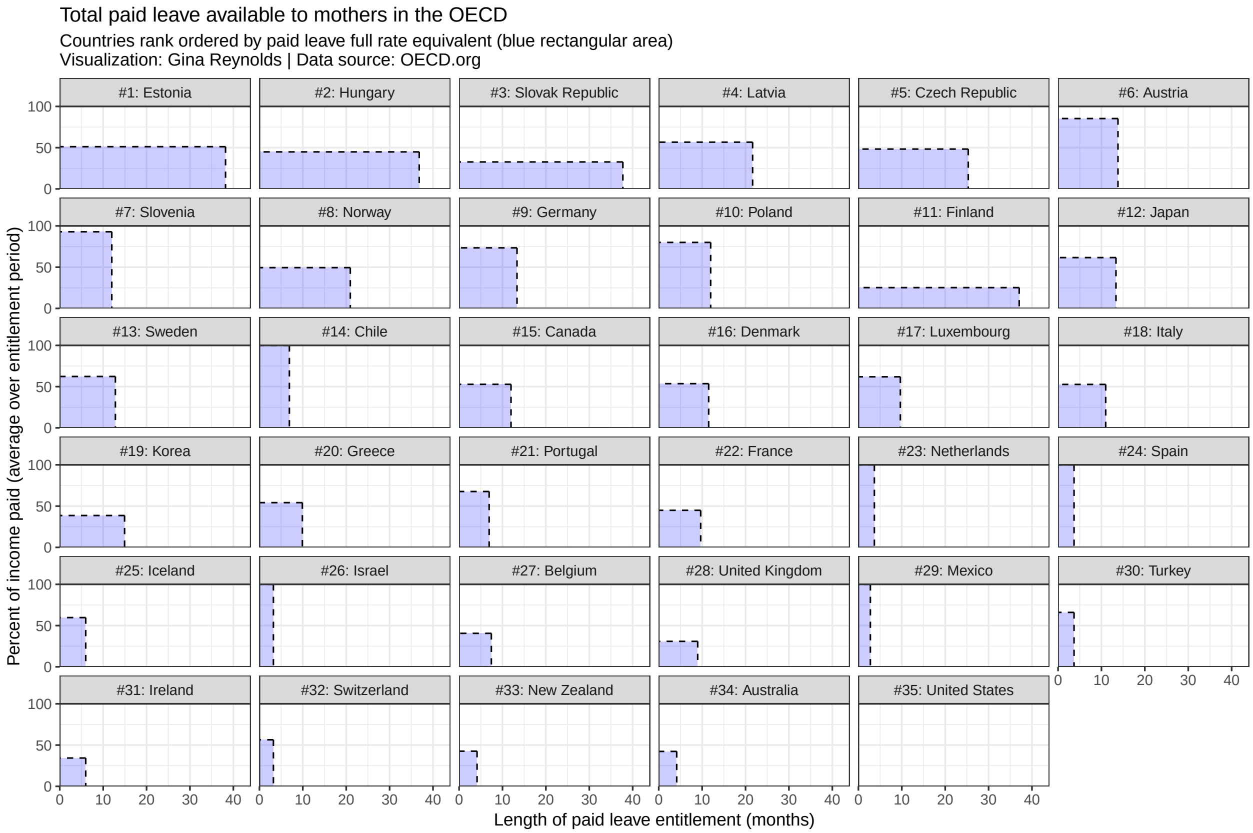
Maternal Leave

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 r
Finland	74.4	13.0	
Czech Republic	62.6	17.5	
Turkey	66.0	10.6	
Greece	54.2	23.3	
Poland	100.0	20.0	

```
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
Percent of income paid (average over entitlement period)
Length of paid leave entitlement (months)
#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

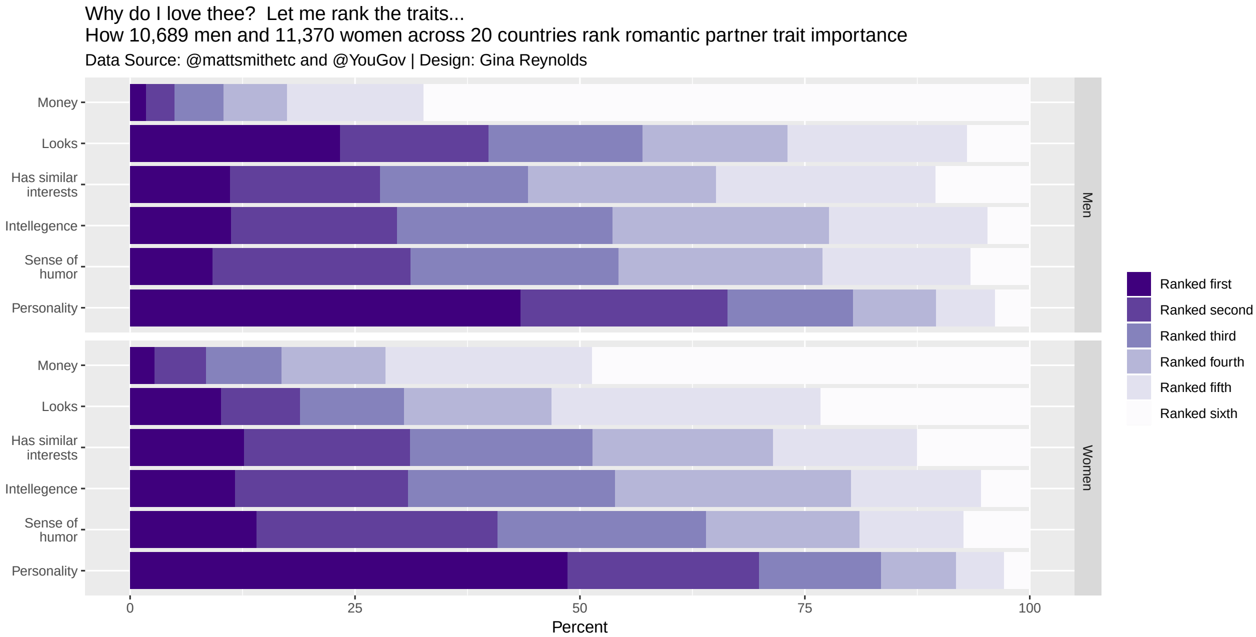
Chapter 6

Traits

A random sample from the data set:

Gender	Question_short	Rank (text)	Rank (number)	n	Percent
Men	Sense of humor	Ranked second	2	2349.83	22.011057
Women	Looks	Ranked sixth	6	2650.67	23.284416
Women	Personality	Ranked first	1	5546.56	48.633686
Men	Intellegence	Ranked sixth	6	501.65	4.699372
Men	Sense of humor	Ranked third	3	2466.30	23.102041

```
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

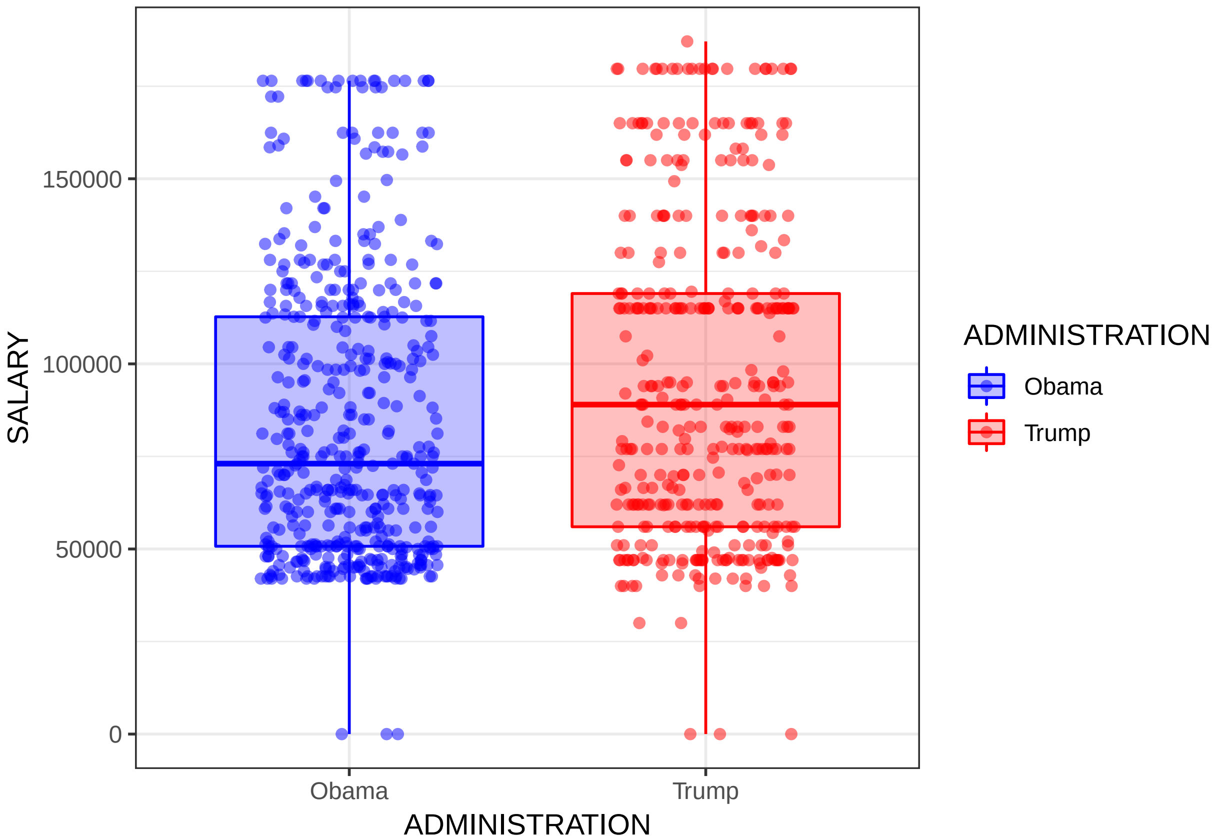
The data set, originally reported on in an NPR article, shows the difference in the distribution of salaries for the Obama and early Trump White House.

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
Trump	Biddle, Emily K.	Employee	70000	Per Annum	DEPUTY SOCIAL SECRETARY
Trump	Salvi, Mary E.	Employee	47000	Per Annum	EXECUTIVE ASSISTANT
Trump	Meyer, Joyce Y.	Employee	155000	Per Annum	DEPUTY ASSISTANT TO THE PRE
Obama	Dyer, Deesha A.	Employee	119723	Per Annum	SPECIAL ASSISTANT TO THE PRE
Trump	Eason, William J.	Employee	77000	Per Annum	LEAD PRESS REPRESENTATIVE

```
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

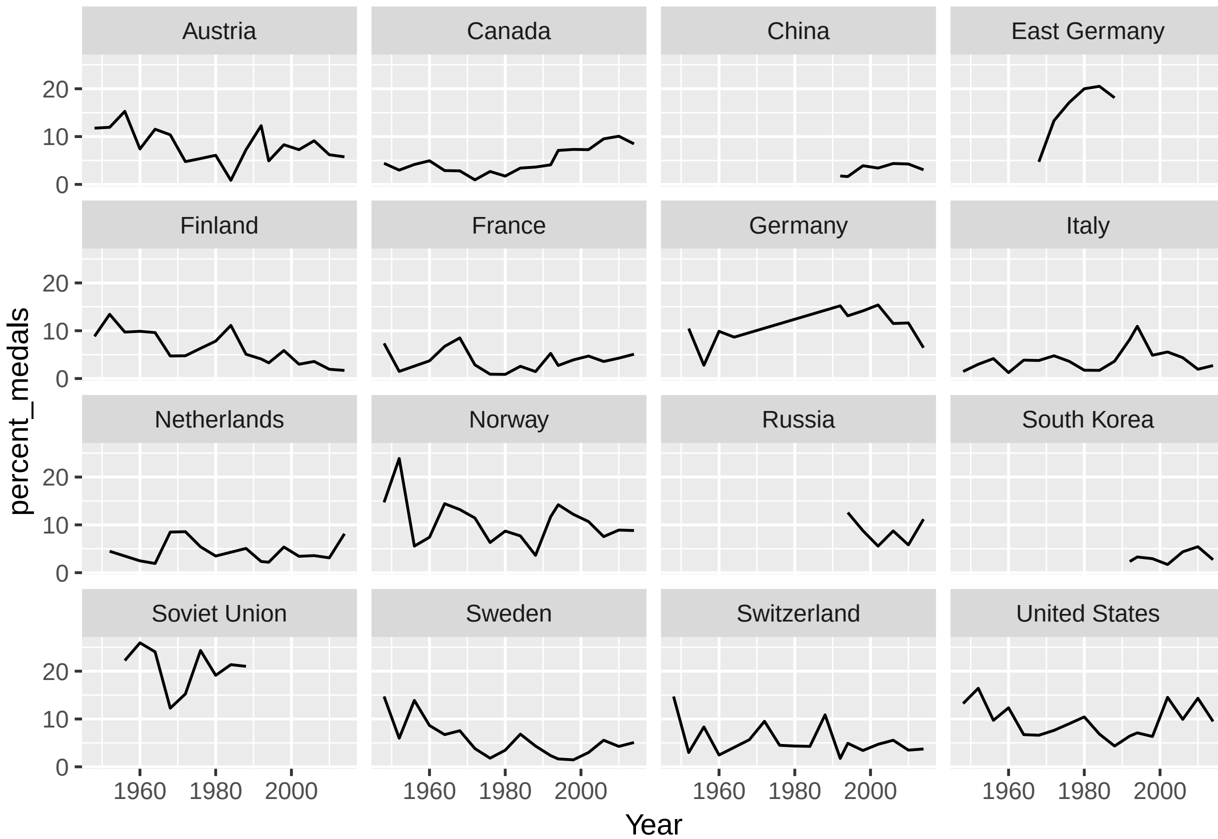
Chapter 8

Winter Games

A random sample from the data set:

Year	Sport	Event	Country	Gender	Medal Rank	Medal	Name of Athlete o
1948	Figure Skating	Men's Singles	Austria	Men	3	bronze	Edi Rada
1960	Cross-Country Skiing	Men's 50 Kilometers	Finland	Men	2	silver	Veikko Hakulinen
2014	Alpine Skiing	Women's Super G	Austria	Women	3	bronze	Nicole Hosp
1998	Speedskating	Men's 1,500 Meters	Netherlands	Men	3	bronze	Rintje Ritsma
1972	Cross-Country Skiing	Men's 50 Kilometers	Soviet Union	Men	3	bronze	Vyacheslav Veden

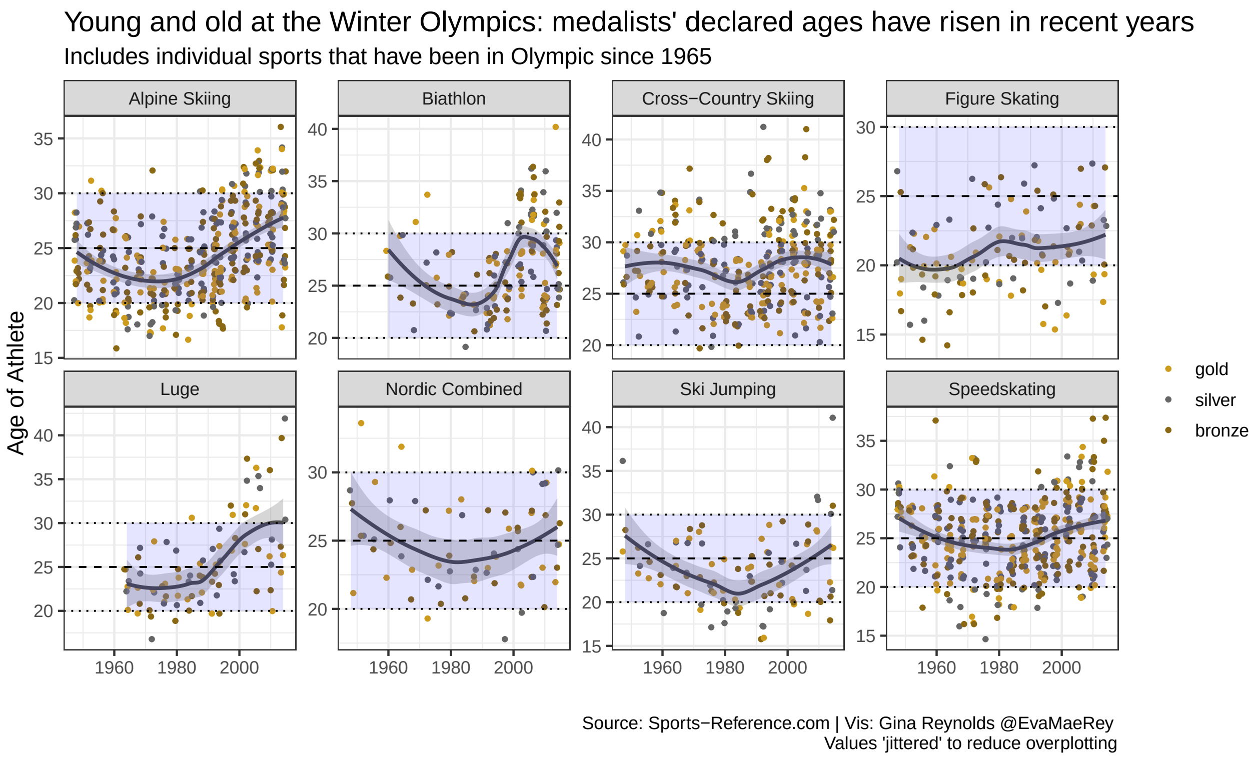
```
ggplot(data = dta) +
  aes(x = Year) +
  aes(y = percent_medals) +
  geom_line() +
  facet_wrap(~ Country)
```



A random sample from the data set:

Year	Sport	Event	Country	Gender	Medal Rank	Medal	Name of Athlete
1976	Cross-Country Skiing	Men's 30 Kilometers	United States	Men	2	silver	Bill Koch
1960	Alpine Skiing	Men's Giant Slalom	Austria	Men	3	bronze	Ernst Hinterseer
1984	Speedskating	Men's 5,000 Meters	East Germany	Men	3	bronze	RenÃ© SchÃ¶fi
1998	Speedskating	Men's 10,000 Meters	Netherlands	Men	1	gold	Gianni Romme
1984	Alpine Skiing	Women's Slalom	Liechtenstein	Women	3	bronze	Ursula Konzett

```
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
gold
silver
bronze
1960
1980
2000
Source: Sports−Reference.com | Vis: Gina Reynolds @EvaMaeRey
Values 'jittered' to reduce overplotting

Chapter 9

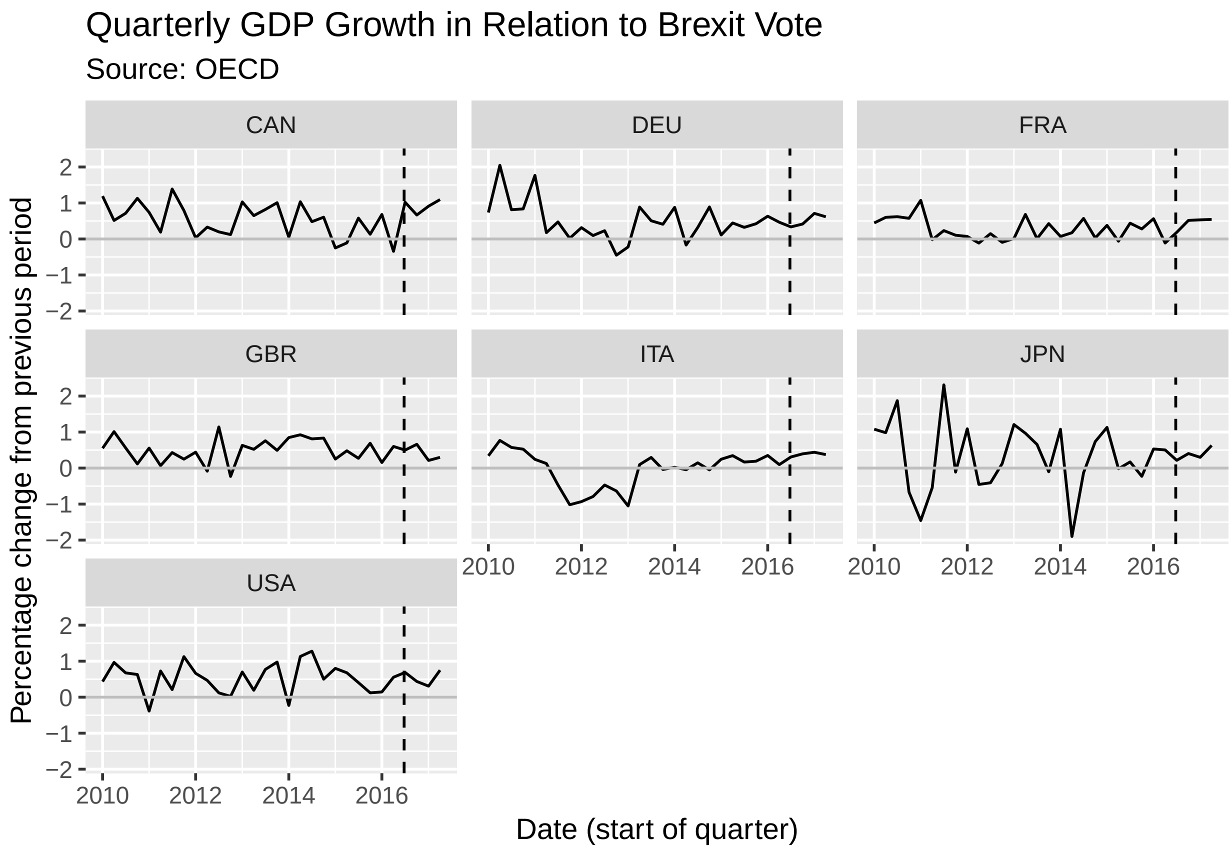
Brexit

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)
FRA	2015	3	2015-07-01	0.439134	2015-07-01
JPN	2010	3	2010-07-01	1.873702	2010-07-01
GBR	2016	2	2016-04-01	0.601298	2016-04-01
USA	2017	1	2017-01-01	0.307393	2017-01-01
ITA	2014	2	2014-04-01	-0.046314	2014-04-01

```r
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")
```

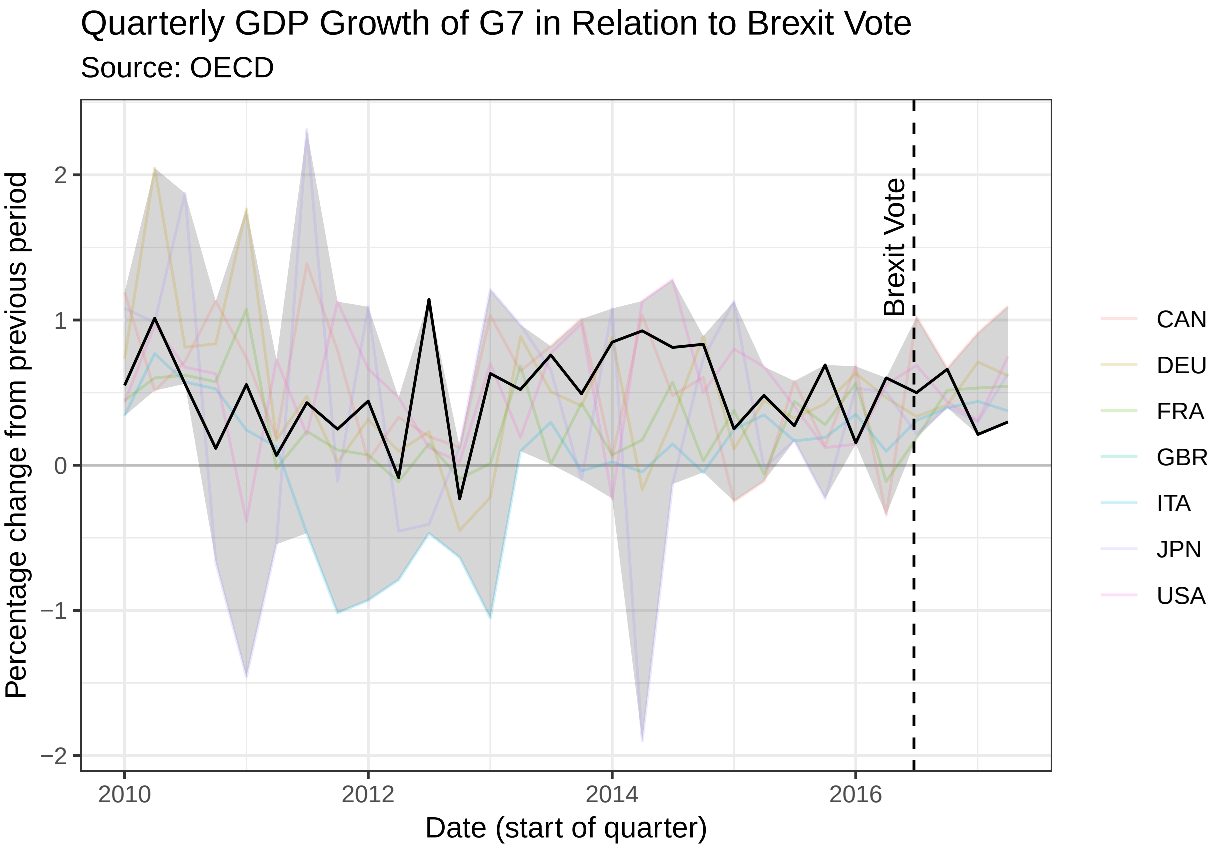


A random sample from the data set:

Country	Year	Quarter	Date (start of quarter)	Percentage change from previous period	Date (start o quarter)	
JPN	2016	3	2016-07-01	0.214856	2016-07-01	
GBR	2013	4	2013-10-01	0.491800	2013-10-01	-
FRA	2017	1	2017-01-01	0.531857	2017-01-01	
USA	2011	1	2011-01-01	-0.386237	2011-01-01	-
FRA	2014	3	2014-07-01	0.572167	2014-07-01	-

```
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 after
The Eccles Cross	Eccles	53.48334	-2.3346944	8.75	7.19	
The Baron Cadogan	Caversham	51.46808	-0.9725126	8.75	7.90	
JJ Moon's	Tooting, London	51.42787	-0.1684140	8.99	6.99	
Wetherspoons	Milton Keynes	52.03763	-0.7676750	8.75	7.49	
The Charlie Hall	Birmingham	52.52430	-1.8400000	8.45	7.40	

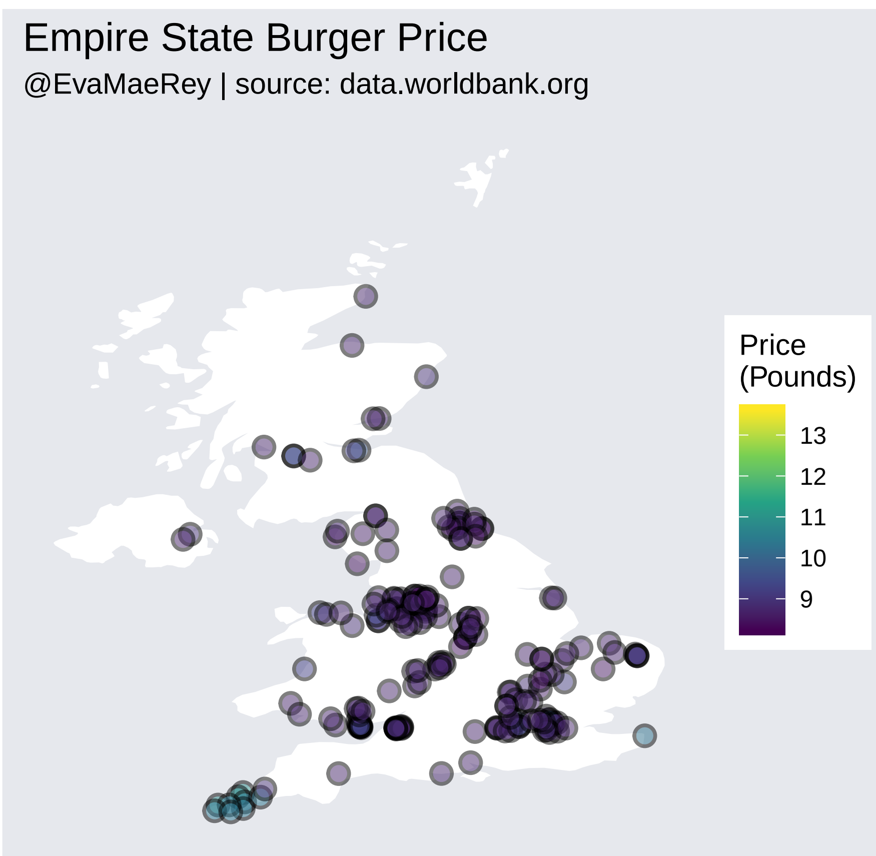
```r
# Mapping data
world_map_df <- map_data("world")
```

A random sample from the data set:

	long	lat	group	order	region	subregion
28726	109.68105	18.24712	418	28726	China	1
83396	-14.12109	22.96055	1341	83396	Western Sahara	NA
63064	95.05977	26.47397	1013	63064	Myanmar	NA
23244	-96.94648	71.79189	351	23244	Canada	Prince of Wales Island
51314	92.43047	22.82183	839	51314	India	NA

```r
# 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(),
```

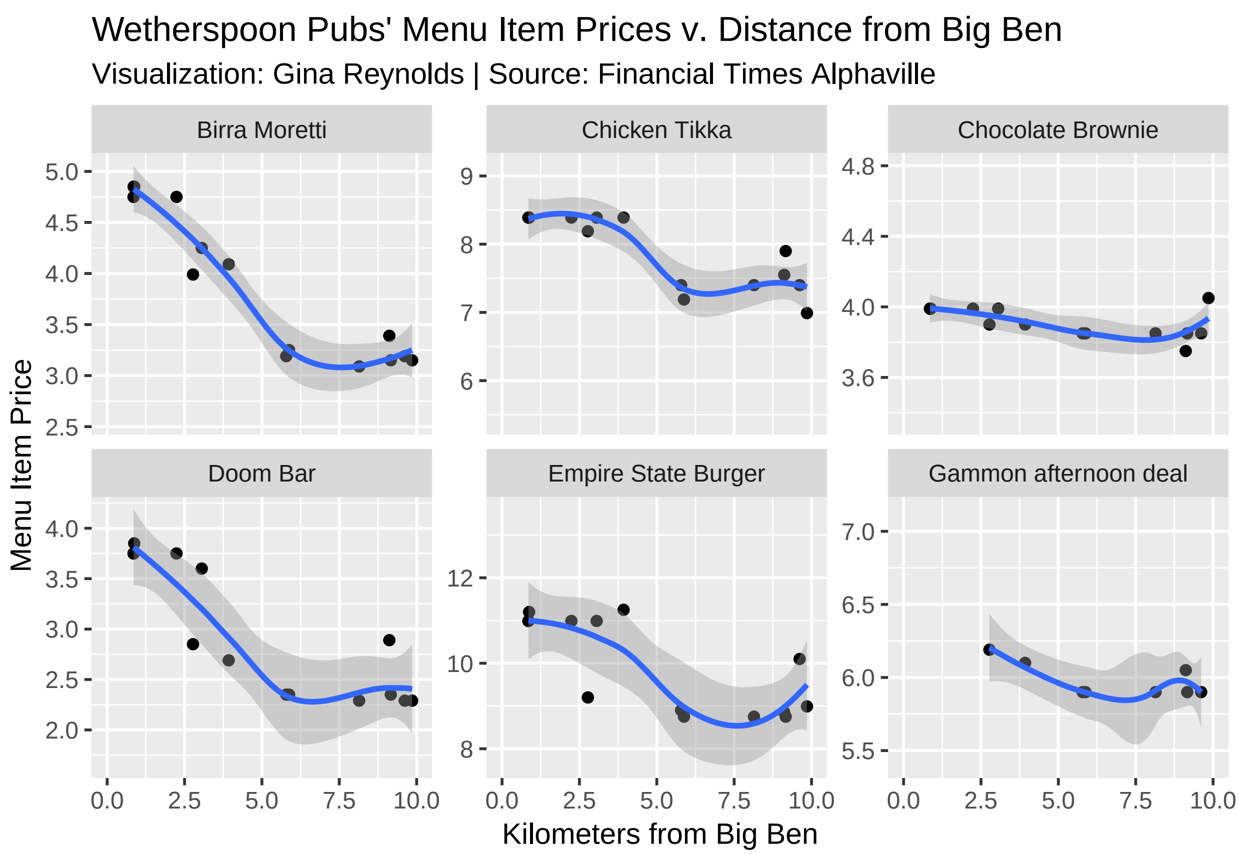
```
  plot.title = element_text(size = 15)
)


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 Queen's Arms	Winsford	53.19135	-2.5303022	NA	0.4828125	0.363
The Jolly Sailor	Bristol	51.44928	-2.5172637	NA	0.4175676	0.353
Goldengrove	Stratford, London	51.54377	0.0039464	NA	0.3987342	0.360
The Society Rooms	Macclesfield	53.25640	-2.1243769	NA	0.4175676	0.353
The Ivor Davies	Cardiff	51.48131	-3.2003483	NA	0.4200000	0.340

```r
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

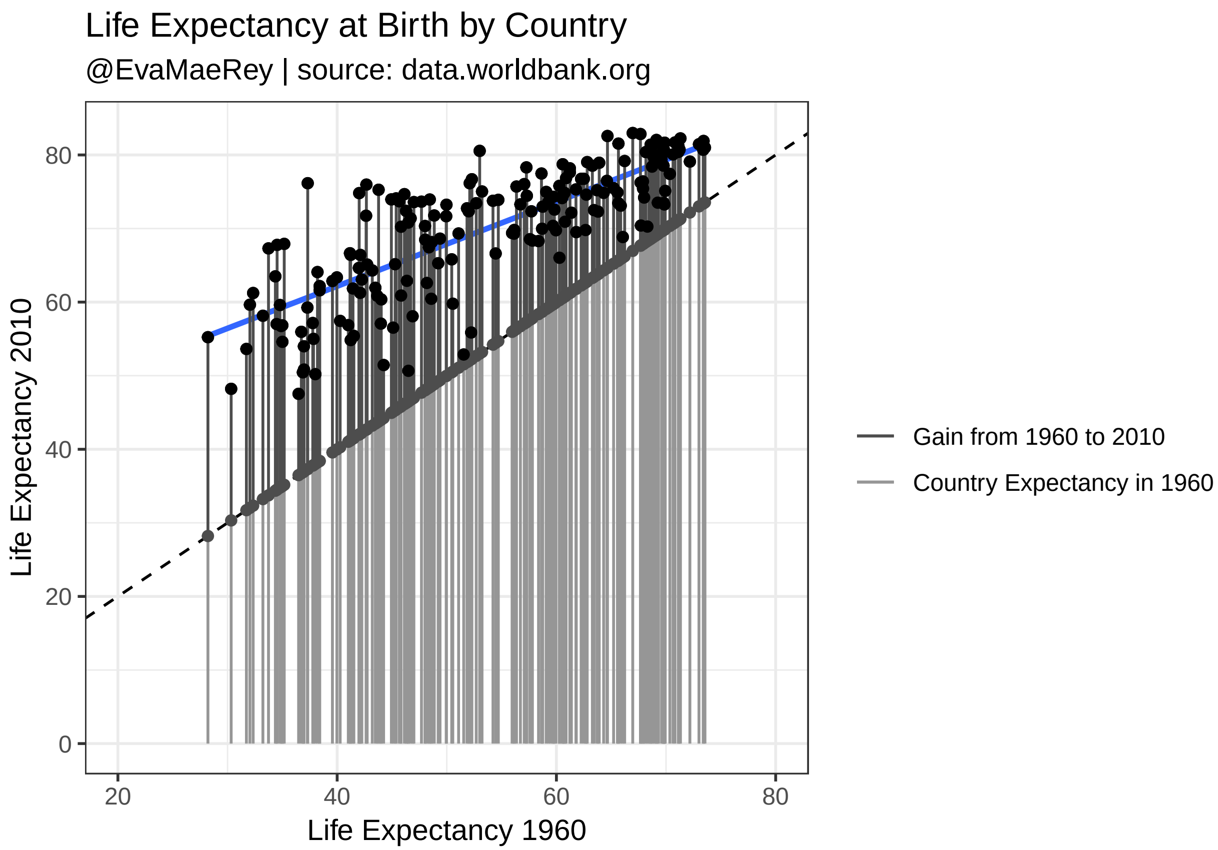
To dramatically show the increases in life expectancy by country from 1960 to 2010, I plot the variable in 1960 versus itself in 2010. The line of equivilance (a 45% angle) is used as a reference and shows the result that you would see if there where no growth. The vertical distance from this line is 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	L
54.21302	BRA	Brazil	Latin America & Caribbean	Upper middle income	2010	
48.58112	COG	Congo, Rep.	Sub-Saharan Africa	Lower middle income	2010	
NA	CUW	Curacao	Latin America & Caribbean	High income	2010	
73.39268	NLD	Netherlands	Europe & Central Asia	High income	2010	
68.71961	PRI	Puerto Rico	Latin America & Caribbean	High 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()) +
```

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



Chapter 12

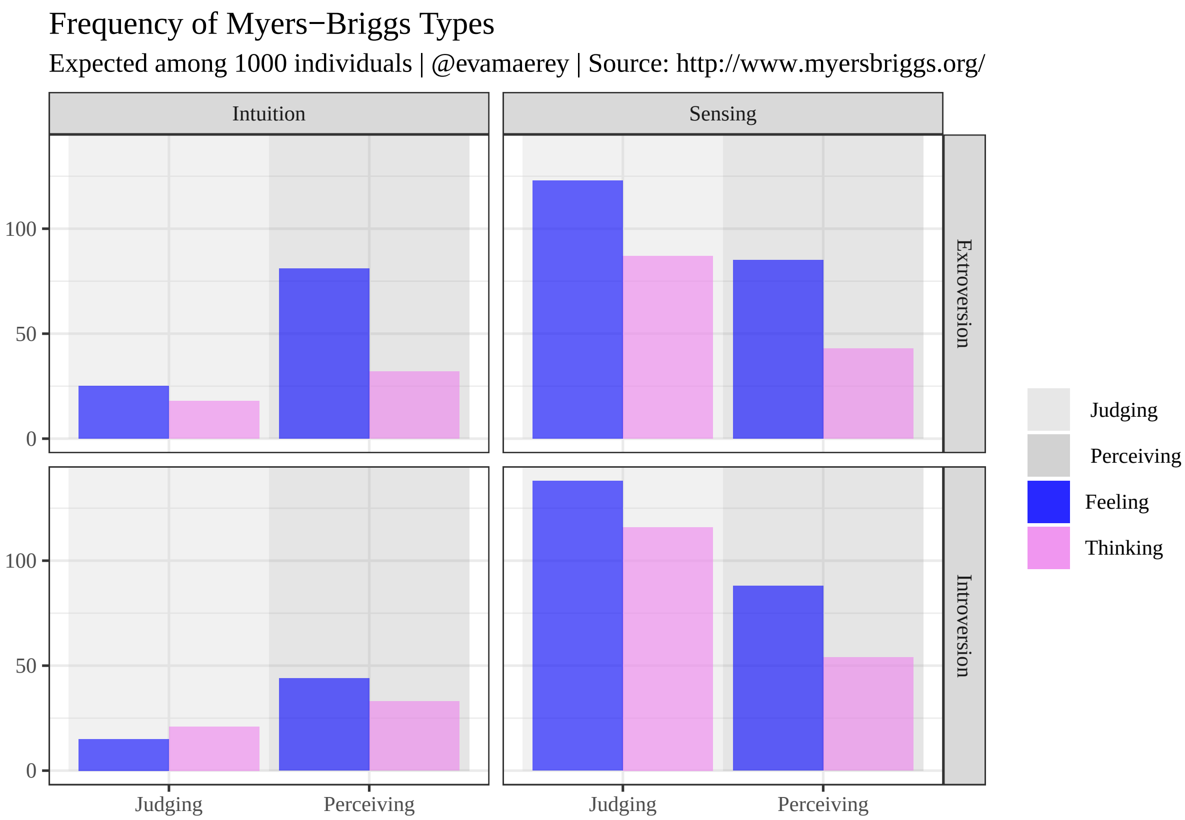
Myers Briggs

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	Feeling	Perceiving	Introversion	1
Sensing	Feeling	Judging	Introversion	1
Sensing	Thinking	Judging	Extroversion	1
Sensing	Feeling	Judging	Introversion	1
Sensing	Feeling	Judging	Introversion	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
0
50
100
0
50
100
Judging
Perceiving
Judging
Perceiving
Judging
Perceiving
Feeling
Thinking

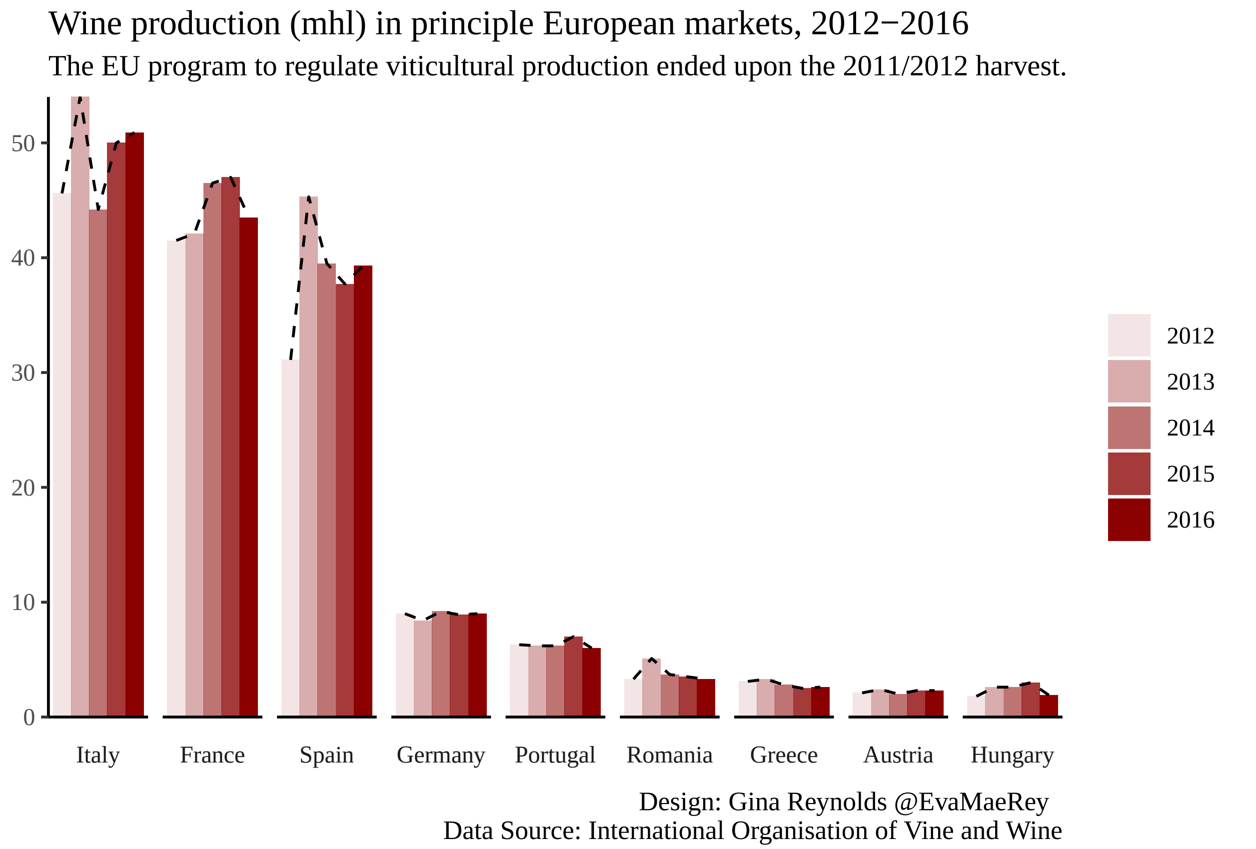
Chapter 13

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.
50
40
30
20
10
0
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.

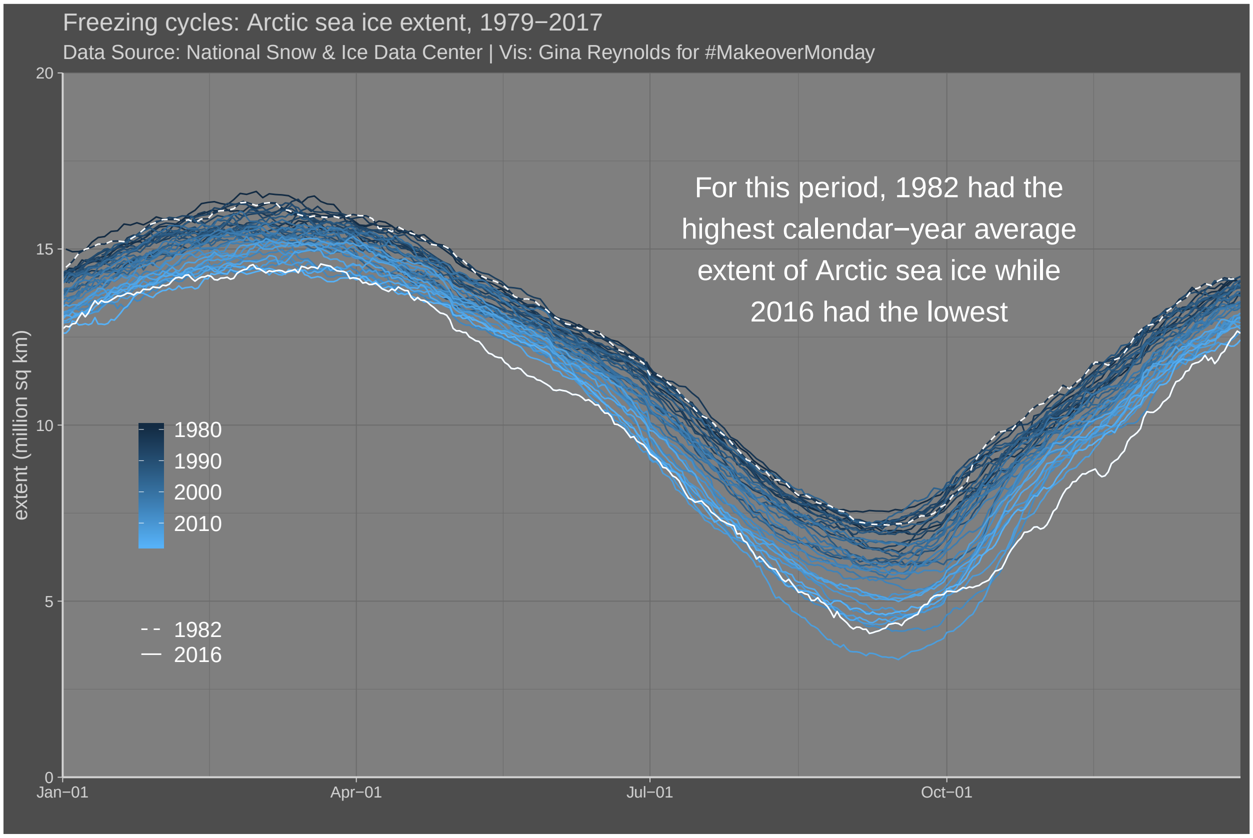
A random sample from the data set:

Date	Extent (million sq km)	year	month_day	month_day_plus	proportion_ocean_covered_in_ice	mea
2003-05-31	12.483	2003	05-31	2000-05-31	0.0346750	
1987-05-30	13.234	1987	05-30	2000-05-30	0.0367611	
1989-03-22	15.397	1989	03-22	2000-03-22	0.0427694	
1999-09-27	6.761	1999	09-27	2000-09-27	0.0187806	
2008-11-09	10.089	2008	11-09	2000-11-09	0.0280250	

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

```r
# 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
1980
1990
2000
2010
1982
2016
Jan−01
Apr−01
Jul−01
Oct−01