Data Challenge: Exploratory Data Analysis

Based on material developed by Sam Clifford

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Introduction

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Tidyverse

Suite of R packages to make working with data as easy as possible (Wickham 2020), including

- ggplot2: for plotting data
- dplyr: for manipulating data frames
- tidyr: for making data tidy
- forcats: for manipulating factor variables
- magrittr: for easy chaining of commands

(Wickham and Grolemund 2017; Wickham et al. 2019)

Summarising Data

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Summarising Data

- Summary statistics one of most common data analysis tasks

- Consider the `Gestation` data from `mosaicData`

- Birth weight, date, and gestational period collected as part of the Child Health and Development Studies in 1961 and 1962. Information about the baby's parents — age, education, height, weight, and whether the mother smoked is also *recorded (Nolan and Speed 2001)*.

- We will use some functions from dplyr to choose, group and summarise data
- `verb(.data, ...)` applies a dplyr `verb` to a data frame

Summarising Data

- `count` how many babies in data set

```
library(mosaicData)
library(tidyverse)
data(Gestation)

count(Gestation) # just like nrow()
## # A tibble: 1 × 1
##         n
##     <int>
## 1   1236
```

Summarising Data

- Can also `count` for a given grouping variable

```
count(Gestation, race) # nrow can't do this
## # A tibble: 6 × 2
##   race      n
##   <chr> <int>
## 1 asian    44
## 2 black   244
## 3 mex      40
## 4 mixed    25
## 5 white   870
## 6 <NA>     13
```

Summarising Data

- The `summarise` function allows us to calculate summary statistics of a variable
- Can (and should) give names to summary columns
- Calculate the mean birth weight in the data set

```
summarise(Gestation, wt_mean = mean(wt))
## # A tibble: 1 × 1
##   wt_mean
##     <dbl>
## 1    120.
```

Summarising Data

- We can calculate multiple summaries at once

```
summarise(Gestation,
          Mean = mean(wt),
          SD   = sd(wt),
          Low  = quantile(wt, 0.025),
          High = quantile(wt, 0.975))
## # A tibble: 1 × 4
##    Mean    SD   Low  High
##   <dbl> <dbl> <dbl> <dbl>
## 1  120.  18.2    81   155
```

- summarise() applies **summary functions** to columns to create a new table.
- Summary functions **take** vectors as input and **return single values** as output.

Summarising grouped data

- We can group the rows in our data and calculate summaries for each group
- `group_by` lets us pass variable names to set the structure
- Row order is maintained

```
Gestation_grouped_by_race <- group_by(Gestation, race)

Gestation_grouped_by_race
## # A tibble: 1,236 × 23
## # Groups:   race [6]
##        id plurality  outcome  date       gestation sex      wt parity race    age
##     <dbl> <chr>      <chr>    <date>         <dbl> <chr> <dbl>  <dbl> <chr> <dbl>
##  1     15 single fe… live bi… 1964-11-11       284 male    120      1 asian    27
##  2     20 single fe… live bi… 1965-02-07       282 male    113      2 white    33
##  3     58 single fe… live bi… 1965-04-25       279 male    128      1 white    28
##  4     61 single fe… live bi… 1965-02-12        NA male    123      2 white    36
##  5     72 single fe… live bi… 1964-11-25       282 male    108      1 white    23
##  6    100 single fe… live bi… 1965-07-31       286 male    136      4 white    25
##  7    102 single fe… live bi… 1964-12-19       244 male    138      4 black    33
##  8    129 single fe… live bi… 1965-04-11       245 male    132      2 black    23
##  9    142 single fe… live bi… 1964-11-08       289 male    120      3 white    25
## 10    148 single fe… live bi… 1965-04-17       299 male    143      3 white    30
## # … with 1,226 more rows, and 13 more variables: ed <chr>, ht <dbl>,
## #   wt.1 <dbl>, drace <chr>, dage <dbl>, ded <chr>, dht <dbl>, dwt <dbl>,
## #   marital <chr>, inc <chr>, smoke <chr>, time <chr>, number <chr>
```

Summarising grouped data

- `summarise()` respects the grouping structure

```
summarise(Gestation_grouped_by_race,
          Mean = mean(wt),
          SD   = sd(wt),
          Low  = quantile(wt, 0.025),
          High = quantile(wt, 0.975))
## # A tibble: 6 × 5
##   race   Mean    SD   Low  High
##   <chr> <dbl> <dbl> <dbl> <dbl>
## 1 asian  110.  16.0  78.4  139.
## 2 black  113.  19.1  71    150
## 3 mex    124.  14.1  99.0  146.
## 4 mixed  120.  20.1  78.8  150.
## 5 white  122.  17.7  85    158
## 6 <NA>   117.  16.7  86.8  143.
```

Rows and columns

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Operating on columns

- create/modify/delete columns with dplyr's `mutate()`
- e.g. relabelling `race` so words start with a capital,

```
Gestation <- mutate(Gestation, race = str_to_title(race))

count(Gestation, race)
## # A tibble: 6 × 2
##   race       n
##   <chr> <int>
## 1 Asian     44
## 2 Black    244
## 3 Mex       40
## 4 Mixed     25
## 5 White    870
## 6 <NA>      13
```

- mutate() applies **vectorized functions** to columns to create new columns.

- Vectorized functions **take** vectors as input and return vectors of the **same length** as output.

Choosing columns

- For one reason or another we may want to `select` only certain columns of our data frame

```
head(Gestation, 1)
## # A tibble: 1 × 23
##       id plurality     outcome date         gestation sex       wt parity race    age
##    <dbl> <chr>         <chr>   <date>           <dbl> <chr> <dbl>  <dbl> <chr> <dbl>
## 1     15 single fetus live b… 1964-11-11        284 male    120      1 Asian    27
## # … with 13 more variables: ed <chr>, ht <dbl>, wt.1 <dbl>, drace <chr>,
## #   dage <dbl>, ded <chr>, dht <dbl>, dwt <dbl>, marital <chr>, inc <chr>,
## #   smoke <chr>, time <chr>, number <chr>

head(select(Gestation, race, wt, number), 1)
## # A tibble: 1 × 3
##   race      wt number
##   <chr> <dbl> <chr>
## 1 Asian   120 never
```

Choosing and renaming columns

- We can also rename columns on the fly as we select them

```
select(Gestation,
       Race                  = race,
       `Birthweight (oz)`    = wt,
       `Cigs. smoked`        = number)
## # A tibble: 1,236 × 3
##    Race   `Birthweight (oz)` `Cigs. smoked`
##    <chr>                <dbl> <chr>
##  1 Asian                  120 never
##  2 White                  113 never
##  3 White                  128 1-4 per day
##  4 White                  123 20-29 per day
##  5 White                  108 20-29 per day
##  6 White                  136 5-9 per day
##  7 Black                  138 never
##  8 Black                  132 never
##  9 White                  120 never
## 10 White                  143 15-19 per day
## # … with 1,226 more rows
```

Choosing and renaming columns

- Alternatively we can `rename` columns without worrying about failing to select columns we haven't renamed

```
names(Gestation)
##  [1] "id"         "pluralty"   "outcome"    "date"       "gestation"  "sex"
##  [7] "wt"         "parity"     "race"       "age"        "ed"         "ht"
## [13] "wt.1"       "drace"      "dage"       "ded"        "dht"        "dwt"
## [19] "marital"    "inc"        "smoke"      "time"       "number"

Gestation <- rename(Gestation, `Cigs. smoked` = number)

names(Gestation)
##  [1] "id"           "pluralty"     "outcome"      "date"         "gestation"
##  [6] "sex"          "wt"           "parity"       "race"         "age"
## [11] "ed"           "ht"           "wt.1"         "drace"        "dage"
## [16] "ded"          "dht"          "dwt"          "marital"      "inc"
## [21] "smoke"        "time"         "Cigs. smoked"
```

Choosing rows

- The dplyr equivalent of `subset` is `filter`
- Takes a logical statement and does non-standard evaluation of variable names • `filter(data, A & B)` the same as `filter(data, A, B)`

```
Gestation2 <- select(Gestation,
                     Race                 = race,
                     `Birthweight (oz)`   = wt,
                     `Cigs. smoked`)

filter(Gestation2, Race == "White", `Cigs. smoked` == "never")
## # A tibble: 352 × 3
##    Race  `Birthweight (oz)` `Cigs. smoked`
##    <chr>              <dbl> <chr>
##  1 White                113 never
##  2 White                120 never
##  3 White                144 never
##  4 White                125 never
##  5 White                122 never
##  6 White                113 never
##  7 White                134 never
##  8 White                128 never
##  9 White                129 never
## 10 White                110 never
## # … with 342 more rows
```

Choosing rows

- `slice*()` functions allow you to select rows based on their properties, e.g. which babies have lowest birth weight overall and in each race group?

```
slice_min(Gestation2, `Birthweight (oz)`)
## # A tibble: 1 × 3
##   Race  `Birthweight (oz)` `Cigs. smoked`
##   <chr>               <dbl> <chr>
## 1 Black                  55 never

slice_min(group_by(Gestation2, Race), `Birthweight (oz)`)
## # A tibble: 6 × 3
## # Groups:   Race [6]
##   Race  `Birthweight (oz)` `Cigs. smoked`
##   <chr>               <dbl> <chr>
## 1 Asian                  71 5-9 per day
## 2 Black                  55 never
## 3 Mex                    97 never
## 4 Mixed                  77 20-29 per day
## 5 White                  63 never
## 6 <NA>                   82 20-29 per day
```

Reshaping data frames

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"**TIDY DATA** is a standard way of mapping the meaning of a dataset to its structure."

—HADLEY WICKHAM

In tidy data:

- each variable forms a column
- each observation forms a row
- each cell is a single measurement

each column a variable

id	name	color
1	floof	gray
2	max	black
3	cat	orange
4	donut	gray
5	merlin	black
6	panda	calico

each row an observation

Wickham, H. (2014). Tidy Data. Journal of Statistical Software *59* (10). DOI: 10.18637/jss.v059.i10

Long and wide tidy data

To make this pivot, we specify

- which `cols` are to be converted from being columns of length *k* to one column of length *n x k*
- the `names_to` column name, which contains the names of the pivoted columns
- the `values_to` name of the column containing the `value` of each variable for each `id`

wide

id	x	y	z
1	a	c	e
2	b	d	f

Long and wide tidy data

```
Gestation_igwa <- select(Gestation, id, gestation, wt, age)

Gestation_long <- pivot_longer(
  data              = Gestation_igwa,
  cols              = c(gestation, wt, age),
  names_to          = 'name',
  values_to         = 'value')

head(Gestation_long, 6)
## # A tibble: 6 × 3
##       id name       value
##    <dbl> <chr>      <dbl>
## 1     15 gestation    284
## 2     15 wt           120
## 3     15 age           27
## 4     20 gestation    282
## 5     20 wt           113
## 6     20 age           33
```

NB: we need to use `'` quotes for `names_to` and `values_to` arguments because they are strings defining new columns

Long and wide tidy data

Or specify which columns *not* to pivot, e.g. `-id` selects all variables except `id`

```
Gestation_long <- pivot_longer(Gestation_igwa, -id)

head(Gestation_long, 6)
## # A tibble: 6 × 3
##      id name      value
##   <dbl> <chr>     <dbl>
## 1    15 gestation   284
## 2    15 wt          120
## 3    15 age          27
## 4    20 gestation   282
## 5    20 wt          113
## 6    20 age          33
```

Long and wide tidy data

- To convert to a wider format, we use `pivot_wider`
- For example, we specify:
- The *data* source
  - where we get the new column *names from*
  - where we get the new column *values from*

```
Gestation_wide <- pivot_wider(data        = Gestation_long,
                              names_from  = name,
                              values_from = value)

head(Gestation_wide, 3) # recovered original data frame
## # A tibble: 3 × 4
##      id gestation    wt   age
##   <dbl>     <dbl> <dbl> <dbl>
## 1    15       284   120    27
## 2    20       282   113    33
## 3    58       279   128    28
```

Pipe

Pipe

- dplyr imports the `%>%` pipe from magrittr
- `f(g(x))` is equivalent to `x %>% g %>% f`
- Makes it easier to chain operations together without storing temporary objects
- Output on left of `%>%` becomes first argument of function on right

  - by convention, all tidyverse functions take a data frame as their first argument

```
x %>% f_1 %>% f_2 %>% f_3

# rather than
f_3(f_2(f_1(x)))

# or even worse...
x_1 <- f_1(x)
x_2 <- f_2(x_1)
x_3 <- f_3(x_2)
```

Pipe

- An example

```
Gestation %>% group_by(race, smoke) %>%
  summarise(wt = mean(wt)) %>%  pivot_wider(names_from  = race,
                                            values_from = wt)
## # A tibble: 5 × 7
##   smoke                   Asian Black   Mex Mixed White  `NA`
##   <chr>                   <dbl> <dbl> <dbl> <dbl> <dbl> <dbl>
## 1 never                   114.   117.  123.  125.  125.  119.
## 2 now                      98.8  108.  127.  108.  116.  114.
## 3 once did, not now       111    117.   NA   134    126.   NA
## 4 until current pregnancy 117    113.  129.  111    127.   NA
## 5 <NA>                    126    119   115     NA   131.   NA
```

- NB the `smoke` variable is character and sorted alphabetically.
- We don’t *expect* you to use pipes, but they’re useful

Summary

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Summary

- Summarising data
  - `group_by` to set a group structure
  - `summarise` to calculate summary stats across group structure
  - `count` to see how many rows in each group

- Reshaping data frames
  - `pivot_longer` from variables side by side to key-value
  - `pivot_wider` from key-value to named column variables

Summary

- Dealing with rows and columns
  - `mutate` to create/modify/delete columns
  - `select` to choose columns
  - `filter` to choose rows based on logical condition
  - `slice*` to choose rows based on position or property
- Pipe
  - `%>%` to chain operations
- Wickham (2014) on what tidy data is
- Wickham et al. (2019) for more explanation of tidyverse

Visualisation with ggplot

Why do we visualise?

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Since the aim of exploratory data analysis is to learn what seems to be, it should be no surprise that pictures play a vital role in doing it well. There is nothing better than a picture for making you think of questions you had forgotten to ask (even mentally).

Tukey and Tukey (1985)

Principles

Tufte (1983) and Pantoliano (2012)

- Show the data
- Provide clarity
- Allow comparison where appropriate

  - use aesthetics to draw attention to important details
  - make clear that data has multiple levels of structure

Principles

- Produce graphs with high data density
    - make every drop of ink count
    - careful use of whitespace

- Avoid excessive and unnecessary use of graphical effects

- Reader should be able to understand what the graph means and not be
    - misled into thinking something that is untrue
    - distracted from the main point

Building plots

`ggplot2` uses a grammar of graphics (Wickham 2010)

- map variables in data frame to aesthetic options in the plot
- choose a geometry for how to display these variables
- adjustments to axis scales
- adjustments to colors, themes, etc.
- adding extra commands in a ‘do this, then do this’ manner
- python users have plotnine (Kibirige 2020) which is based on the same ideas

Building plots

How do we structure a call to `ggplot` to make a plot?

```
# library(ggplot2) # already loaded with tidyverse
ggplot(data = my.data.frame,
       aes(x = my.x.variable,
           y = my.y.variable)) +
  geom_point()
```

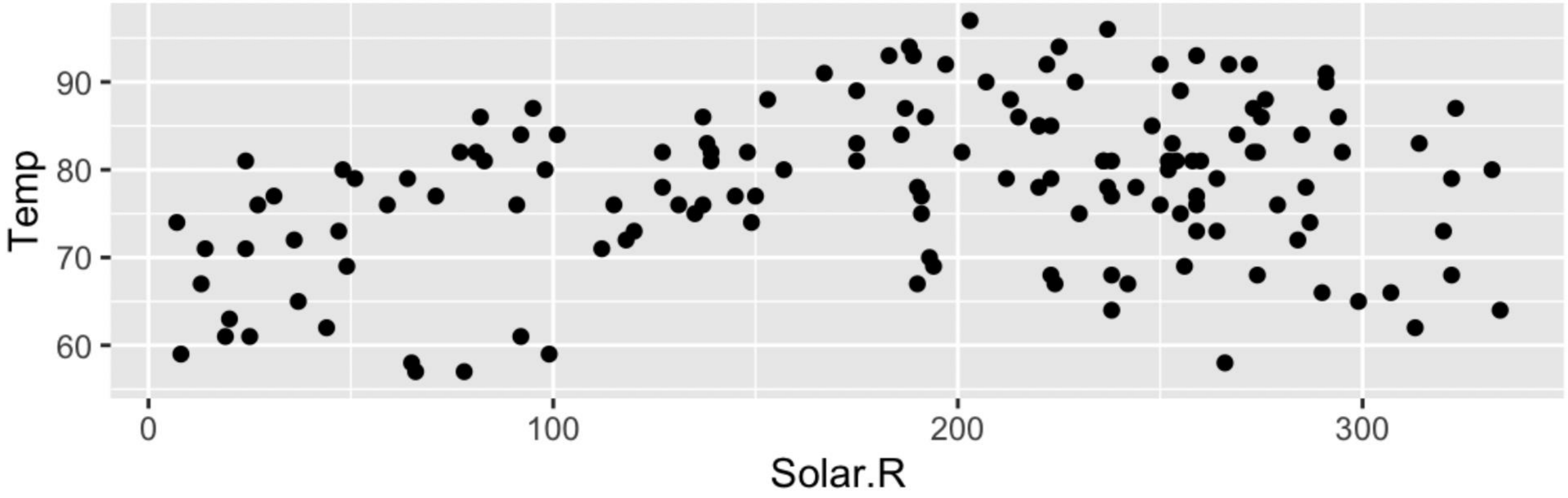
- Load ggplot2 package
- Specify we want a `ggplot` object and which data frame we're going to use,
- Set **aesthetic options** to map to the and axes of the plot
- State geometry we're using to show variables

Building plots

- For example, consider daily maximum temperature varying with solar radiation in New York City 1973
- Each row is a pair of values (x, y), shown as a point

```
data(airquality)
solar_temp_plot <- ggplot(data = airquality,
       aes(x = Solar.R, y = Temp)) + geom_point()

solar_temp_plot
```

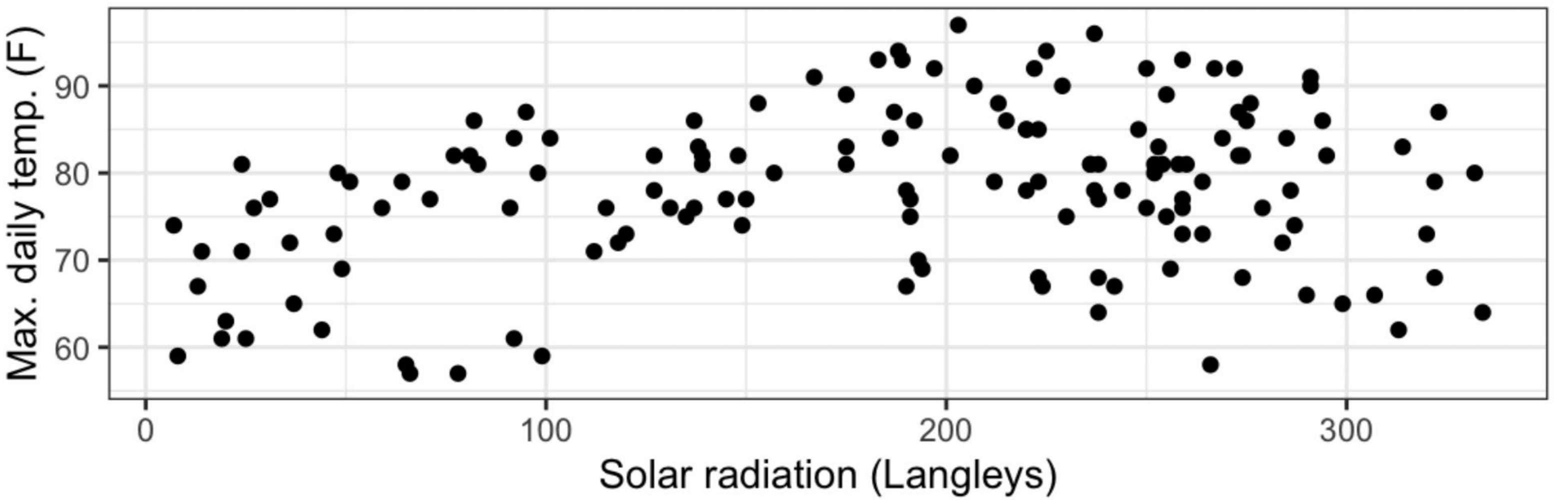


Scatter plot

We can add some human-friendly labels and change the theme

```
solar_temp_plot <- solar_temp_plot + theme_bw() +
  labs(x = 'Solar radiation (Langleys)', y = 'Max. daily temp. (F)')

solar_temp_plot
```



Some more geometries

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Line plot

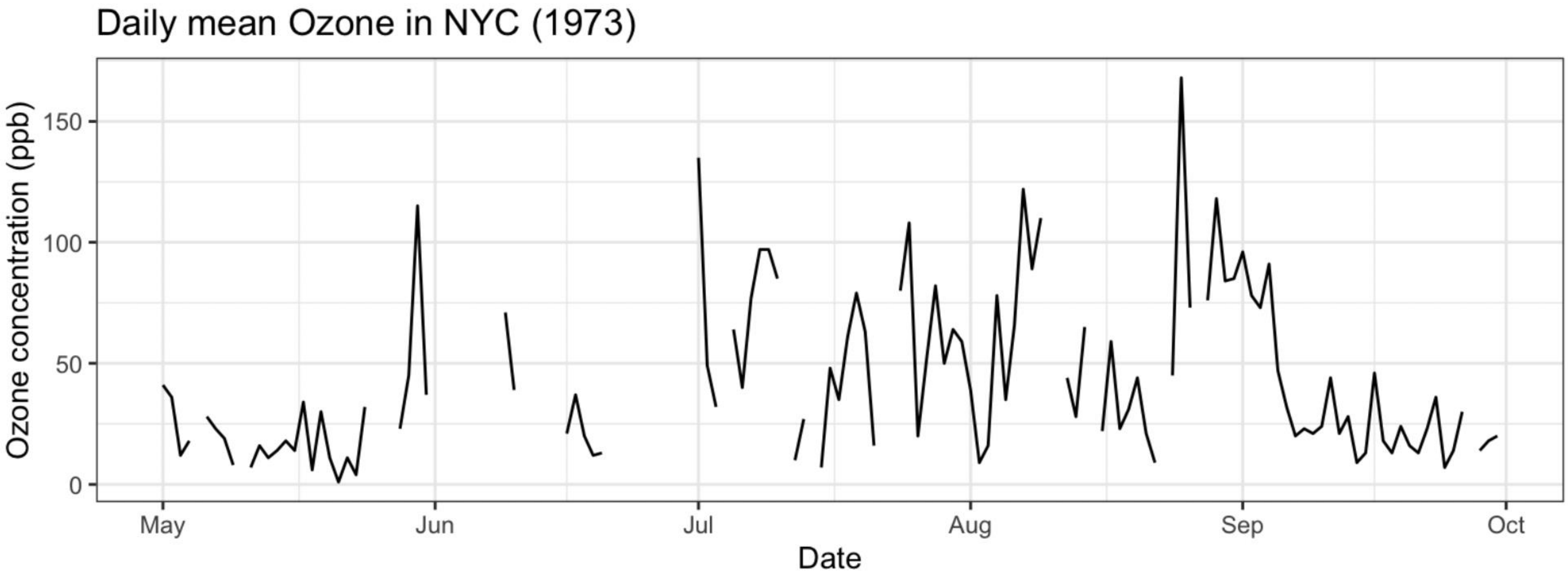
- Similar to scatter plot, but joins pairs of values
- Useful when showing how something changes over time
- If (x, y) pairs ordered by
  - x, use `geom_line()` (e.g. x is time)
  - row order, use `geom_path()`
  - nothing, don't use a line

```
airquality <- mutate(airquality, Date = as.Date(paste('1973', Month, Day, sep = '-')))

airquality_plot <- ggplot(data = airquality, aes(x=Date, y=Ozone)) +
  geom_line() + theme_bw() + labs(y     = 'Ozone concentration (ppb)',
                                  title = 'Daily mean Ozone in NYC (1973)')
```

Line plot

```
airquality_plot
```

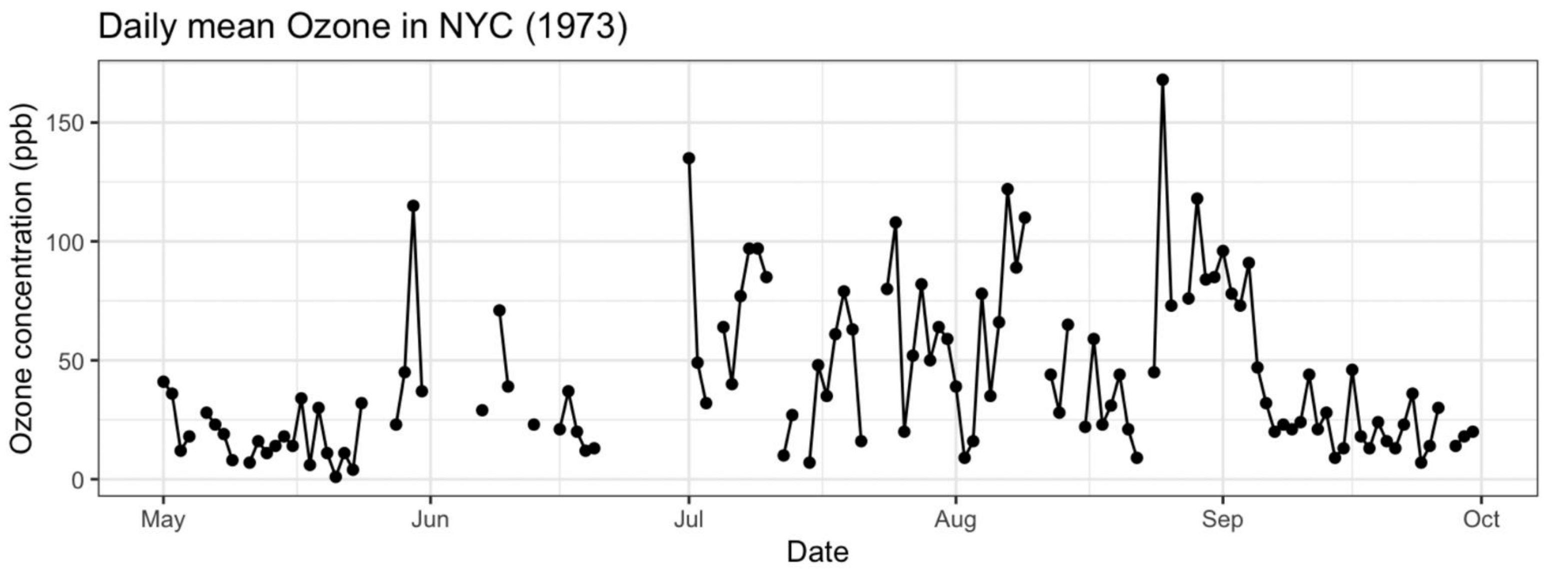


- You may see this referred to as a time series plot

Line plot

- Observations whose neighbours are `NA` values can't be plotted with a line
- Can layer multiple geometries for same aesthetic mapping

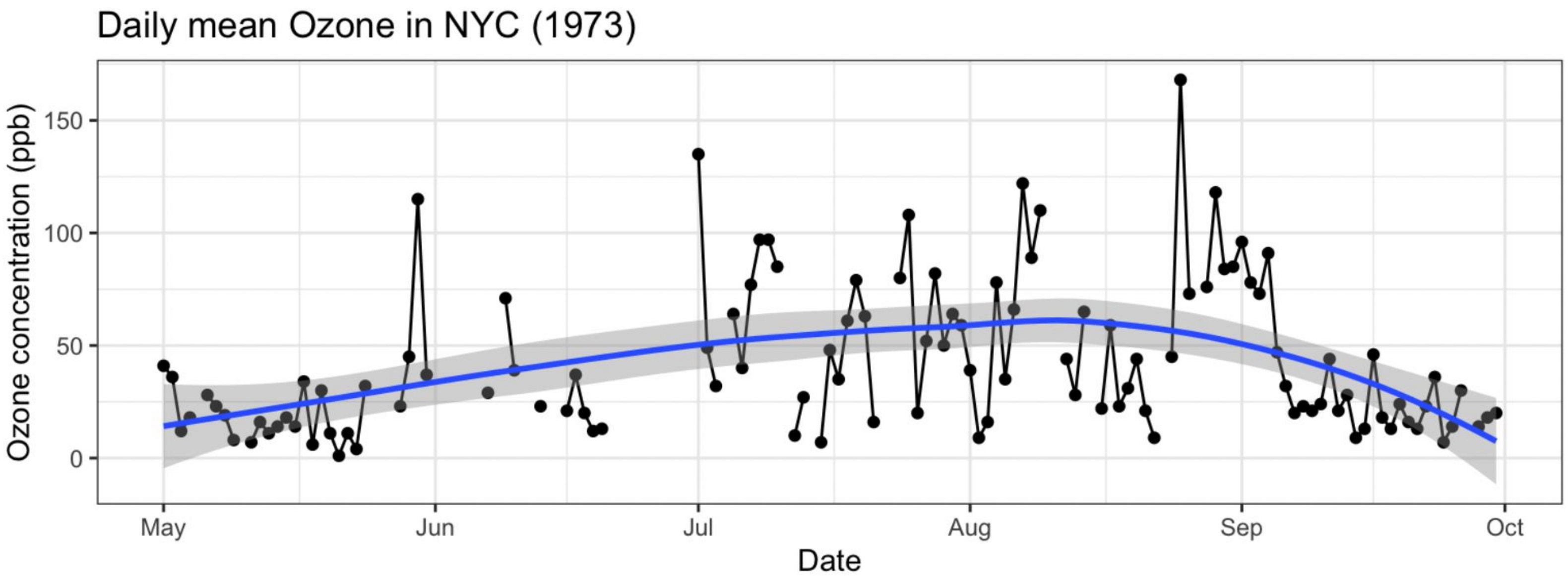
```
airquality_plot + geom_point()
```



Scatterplot smoother

- Often too much data in a scatter plot to see pattern
- Maybe we want to highlight the trend in the data

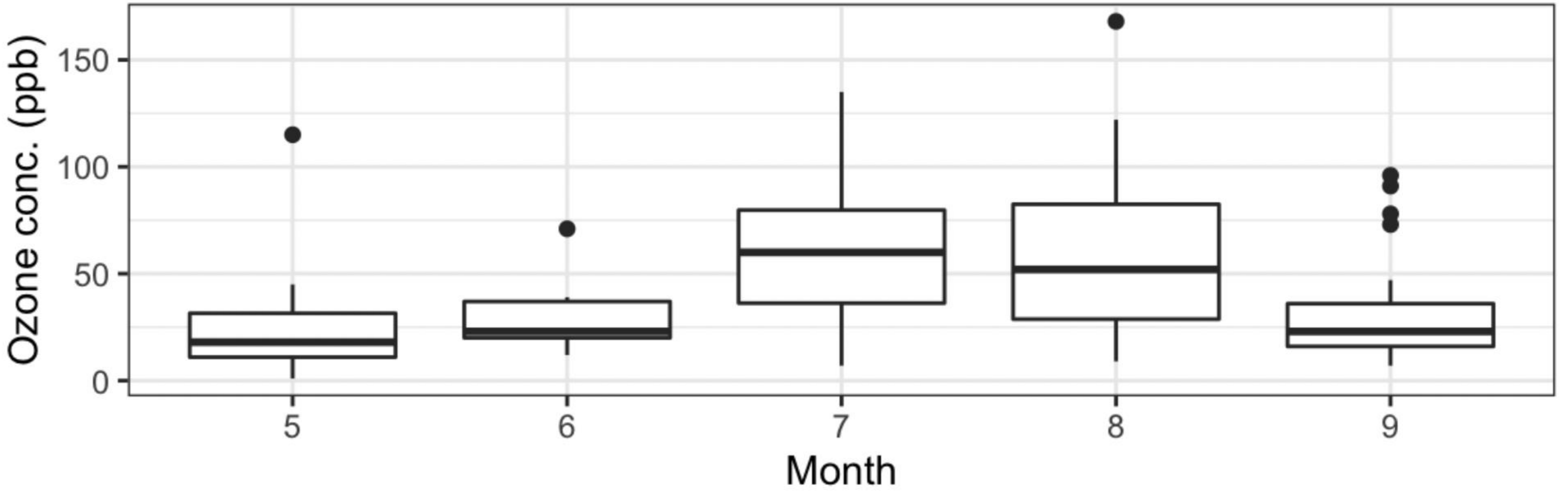
```
airquality_plot + geom_point() + geom_smooth()
```



Boxplot

- continuous y, discrete x
- outliers (> 1.5 IQR from median) shown as points automatically

```
ggplot(data = airquality, aes(x = factor(Month), y = Ozone)) +
  geom_boxplot() + theme_bw() +
  labs(y = 'Ozone conc. (ppb)', x = 'Month')
```

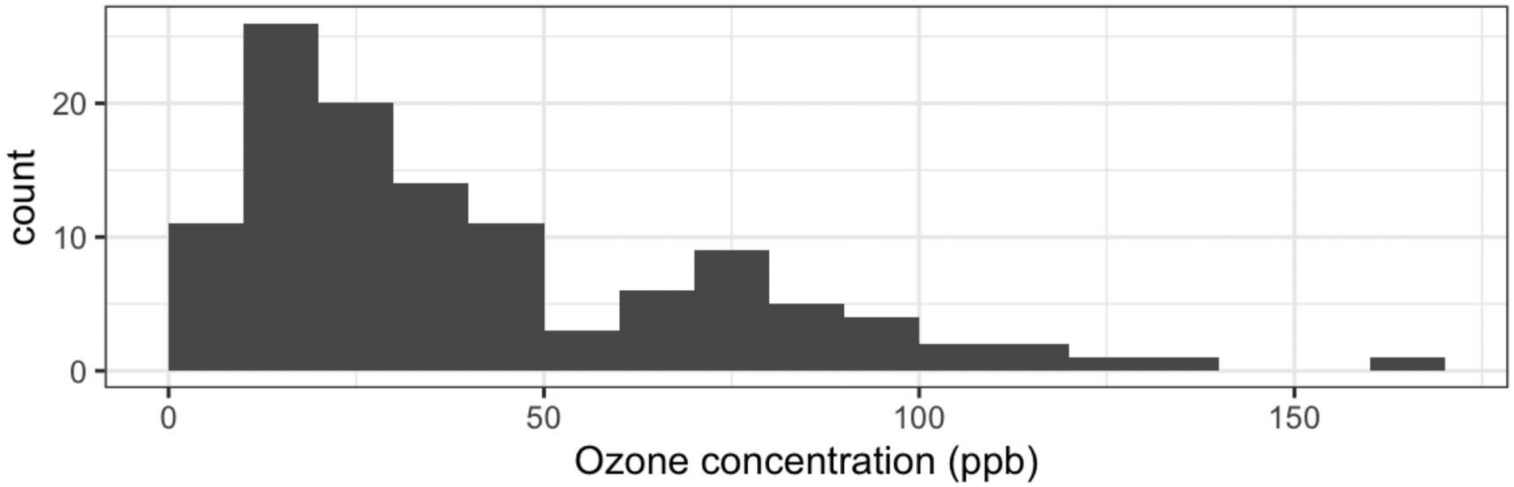


Histograms

- univariate graphical summary needs only one aesthetic, `x`

```
ozone_hist <- ggplot(data = airquality, aes(x = Ozone)) +
  geom_histogram(binwidth = 10, boundary = 0) +
  labs(x = 'Ozone concentration (ppb)') + theme_bw()

ozone_hist
```

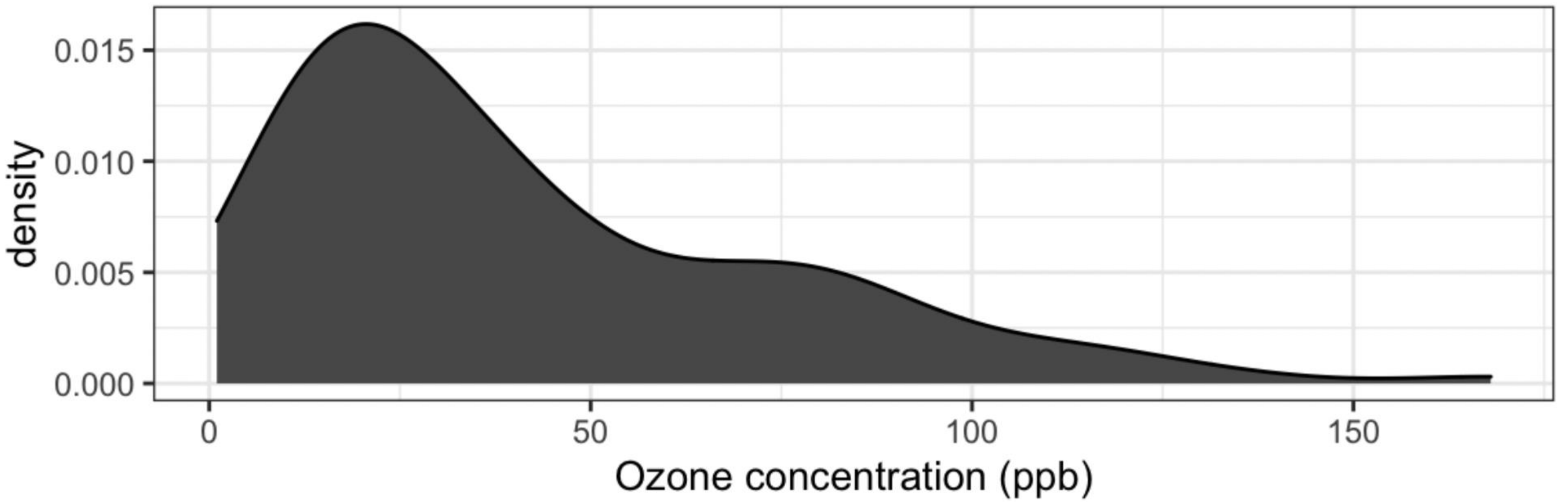


Density plots

- Kernel smoothing (continuous analogue of histogram)

```
ozone_dens <- ggplot(data = airquality, aes(x = Ozone)) +
  geom_density(fill = 'grey35') +
  labs(x = 'Ozone concentration (ppb)') + theme_bw()

ozone_dens
```



More on aesthetics

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More on aesthetics

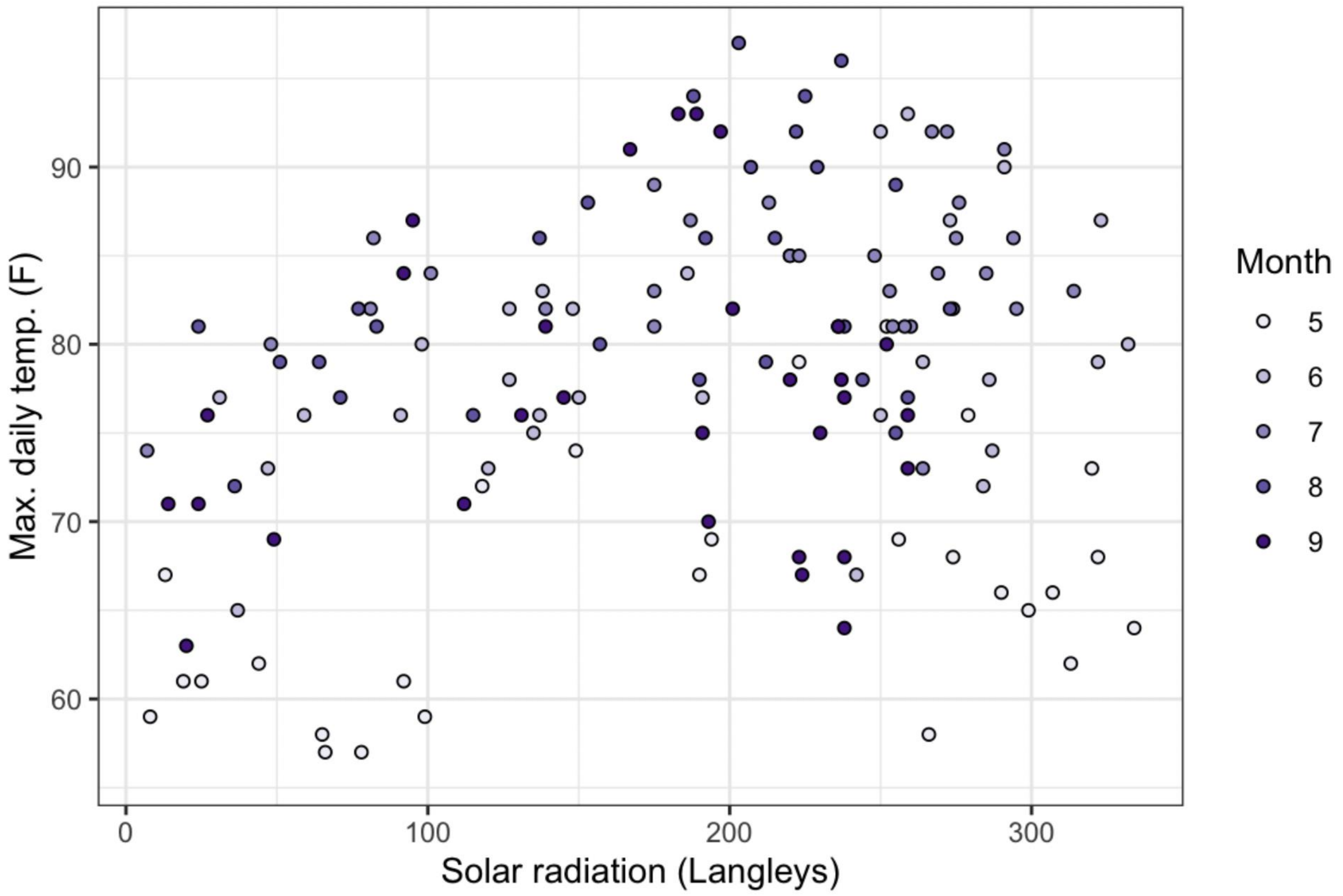
Aesthetic	What it effects
`size`	points, lines
`shape`	points
`linetype`	lines
`colour`	points, lines, boundary
`alpha`	transparency
`fill`	interior
`group`	repeats geometry

- If these (except group) are *outside* `aes()` they fix the value for all parts of that geometry
- Aesthetics specified inside `ggplot()` are inherited by all geometries for that plot
- Not all geometries accept all aesthetics (e.g. `geom_line()` has no fill)
- Some point shapes admit a `colour` and a `fill`

More on aesthetics

```
data(airquality)
solar_temp_plot_colored <-
  ggplot(data = airquality,
         aes(x = Solar.R, y = Temp)) +
  geom_point(aes(fill = factor(Month)),
             shape = 21,
             color = 'black')  +
  labs(x = 'Solar radiation (Langleys)',
       y = 'Max. daily temp. (F)') +
  theme_bw() +
  scale_fill_brewer(palette = "Purples",
                    name    = 'Month')
```

More on aesthetics



Small multiples

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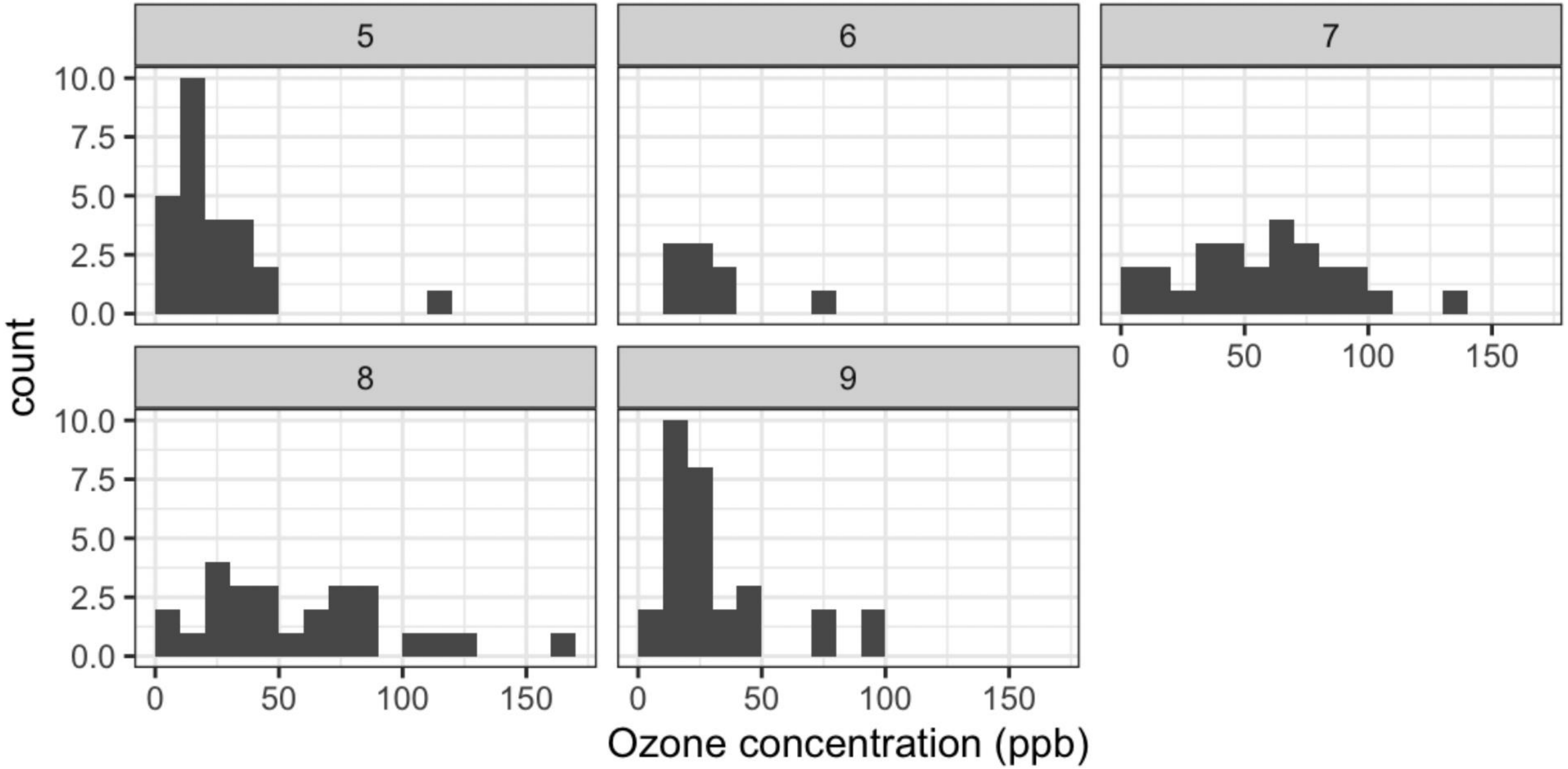
Small multiples

- Group a plot by some categorical variable
- Repeat a basic graph for groups in the data
    - air quality data has information about, e.g. months
- Can view 3-5 dimensions in the data on a 2D page
    - Often a better alternative to 3D, since it doesn’t distort comparisons
    - Inner axes relate to the smallest X-Y plots
    - Outer axes relate to the grouping variables
- Avoids writing loops

Small multiples

- Repeat histogram for each value of `Month`, one per facet

```
ozone_hist + facet_wrap( ~ Month)
```



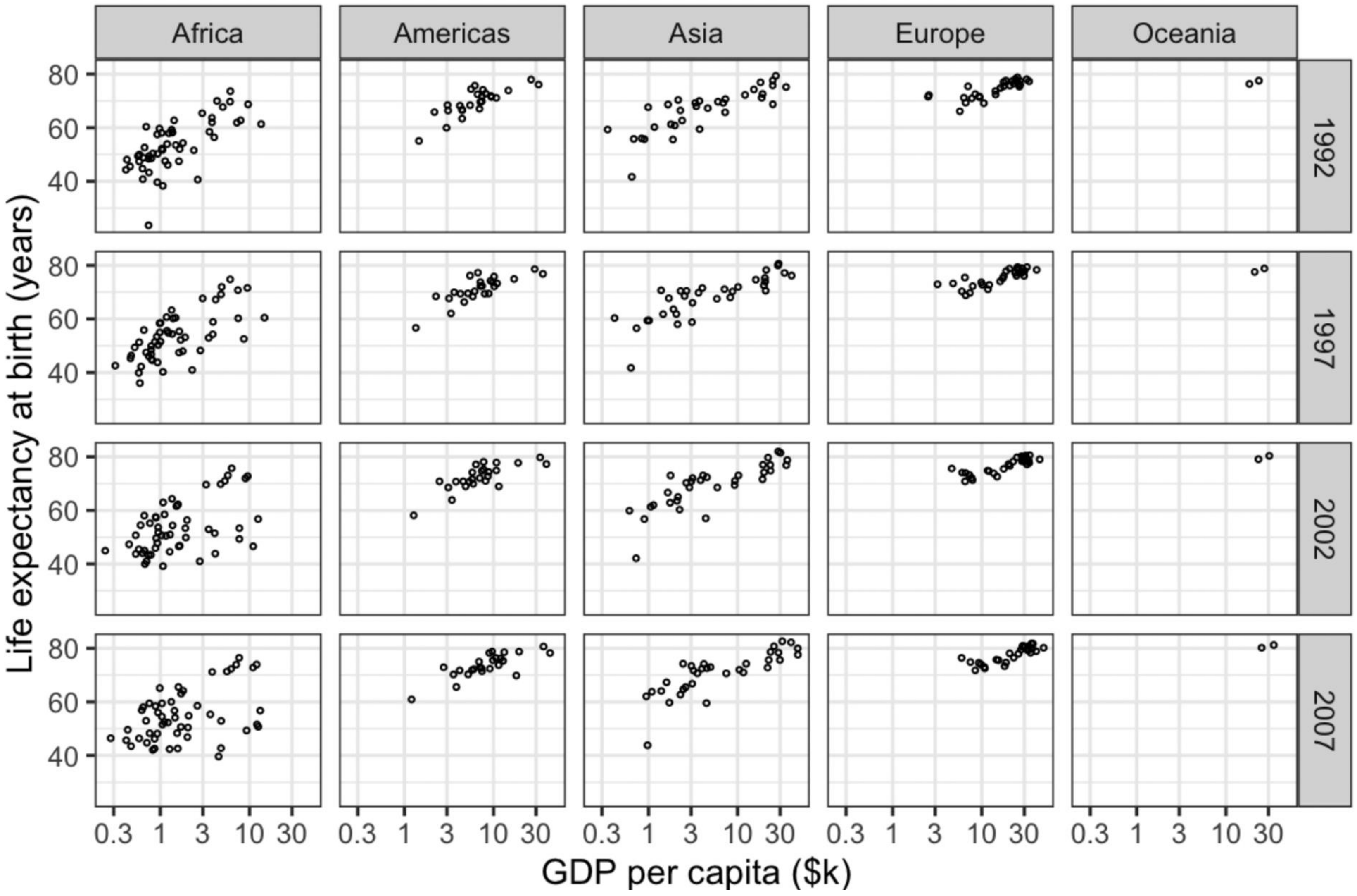
Small multiples

We can also use `facet_grid()` to repeat the aesthetic and geometries for specified `rows` and `cols` variables

```
library(gapminder)
data(gapminder)

gapminder_plot <-
  ggplot(data = subset(gapminder, year >= 1992),
       aes(x = gdpPercap/1e3,
           y = lifeExp)) +
    geom_point(shape = 1, size = 0.5) +
    facet_grid(rows = vars(year),
               cols = vars(continent)) +
    scale_x_log10(labels = ~sprintf("%g", .)) +
  xlab("GDP per capita ($k)") +
  ylab("Life expectancy at birth (years)") +
  theme_bw() +
  theme(panel.grid.minor.x = element_blank())
```

Small multiples



Summary

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Summary

- We make graphs to tell a story with data
- Should draw reader in and explain what they're seeing
- Plots are built from
    - geometric objects
    - axis scales
    - coordinate systems (linear or logarithmic scale, 2D, 3D, etc.)
    - annotations (e.g. heading in small multiples)

Summary

- Successively building a plot with a grammar of graphics allows development of complex plots from simple elements and small changes

- Choose a plotting geometry that helps tell the story

- Meaningful labels remove ambiguity and confusion

- Be careful not to put too much in

Summary

- The `#r4ds` community have TidyTuesday which makes use of the ideas in Wickham and Grolemund (2017)
- History of visualisation
  - Friendly (2005)
  - Friendly (2006)
- Visualisation to help decision making
  - Tufte (1997)
- ggplot2 resources
  - RStudio (2021)
  - Chang (2017)

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