Exploratory data analysis using the tidyverse and ggplot2

Introduction

What is the tidyverse?

A 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

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

```
1  library(mosaicData)
2  library(tidyverse)
3
4  data(Gestation)
5  count(Gestation) # just like nrow()
```

```
# A tibble: 1 × 1
      n
  <int>
1  1236
```

Summarising grouped data

- Can also count for a given grouping variable

```
1 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

```
1  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
```

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

```
1 Gestation_grouped_by_race <- group_by(Gestation, race)
2 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 fet… live b… 1964-11-11       284 male    120      1 asian    27
 2    20 single fet… live b… 1965-02-07       282 male    113      2 white    33
 3    58 single fet… live b… 1965-04-25       279 male    128      1 white    28
 4    61 single fet… live b… 1965-02-12        NA male    123      2 white    36
 5    72 single fet… live b… 1964-11-25       282 male    108      1 white    23
 6   100 single fet… live b… 1965-07-31       286 male    136      4 white    25
 7   102 single fet… live b… 1964-12-19       244 male    138      4 black    33
 8   129 single fet… live b… 1965-04-11       245 male    132      2 black    23
 9   142 single fet… live b… 1964-11-08       289 male    120      3 white    25
10   148 single fet… live b… 1965-04-17       299 male    143      3 white    30
# ℹ 1,226 more rows
# ℹ 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.
```

Summarising data

- We can summarise multiple variables (`.vars`) with the same function(s) (`.funs`)

```
summarise_at(Gestation,
             .vars = vars(gestation, wt, age),
             .funs = mean, na.rm = T)
```

```
# A tibble: 1 × 3
  gestation    wt   age
      <dbl> <dbl> <dbl>
1      279.  120.  27.3
```

Summarising data

- We can even do multiple summaries across multiple variables by specifying
  - which `.vars` we want to summarise, and
  - a list of which z we wish to summarise with

```
summarise_at(Gestation,
             .vars = vars(gestation, wt, age),
             .funs = list(mean = mean,sd = sd),
             na.rm = T)
```

```
# A tibble: 1 × 6
  gestation_mean wt_mean age_mean gestation_sd wt_sd age_sd
           <dbl>   <dbl>    <dbl>        <dbl> <dbl>  <dbl>
1           279.    120.     27.3         16.0  18.2   5.78
```

Summarising grouepd data

- All `summarise\*()` respects the grouping structure

```
summarise_at(Gestation_grouped_by_race,
             .vars = vars(gestation, wt, age),
             .funs = list(mean = mean), na.rm = T)
```

```
# A tibble: 6 × 4
  race  gestation_mean wt_mean age_mean
  <chr>          <dbl>   <dbl>    <dbl>
1 asian           274.    110.     29.4
2 black           274.    113.     27.6
3 mex             278.    124.     26.5
4 mixed           279.    120.     26.4
5 white           281.    122.     27.1
6 <NA>            280     117.     30.7
```

Rows and columns

Operating on columns

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

```
1 Gestation <- mutate(Gestation, race = str_to_title(race))
2 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
```

Choosing columns

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

```
1 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
# ℹ 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>
```

```
1 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
# ℹ 1,226 more rows
```

Choosing and renaming columns

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

```
1 names(Gestation)
```

```
 [1] "id"         "plurality"  "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"
```

```
1 Gestation <- rename(Gestation, Cigs.smoked = number)
2
3 names(Gestation)
```

```
 [1] "id"          "plurality"   "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         = number)
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
# ℹ 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?

```
1 slice_min(Gestation2, `Birthweight (oz)`)
```

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

```
1 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

Long and wide tidy data

- Tidy data frames consist of a number of observations (rows) of variables (columns), they can be either wide or long (Wickham 2014)
- We can pivot between wide and long format with tidyr's `pivot\_\*()` functions
- Pivoting to a longer data frame helps put data in key-value pairs, useful for ggplot2
- The value is the value of the named variable for a given id

Long and wide tidy data

To make this pivot, we specify

- which cols are to be converted from being `k` columns of length `n` to one column of length `n×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`

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

```
1 Gestation_long <- pivot_longer(Gestation_igwa, -id)
2 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
```

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

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)
```

```
# 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

- 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

Summary

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 ggplot2

Why do we visualise?

“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 x and y axes of the plot
- State geometry we're using to show variables

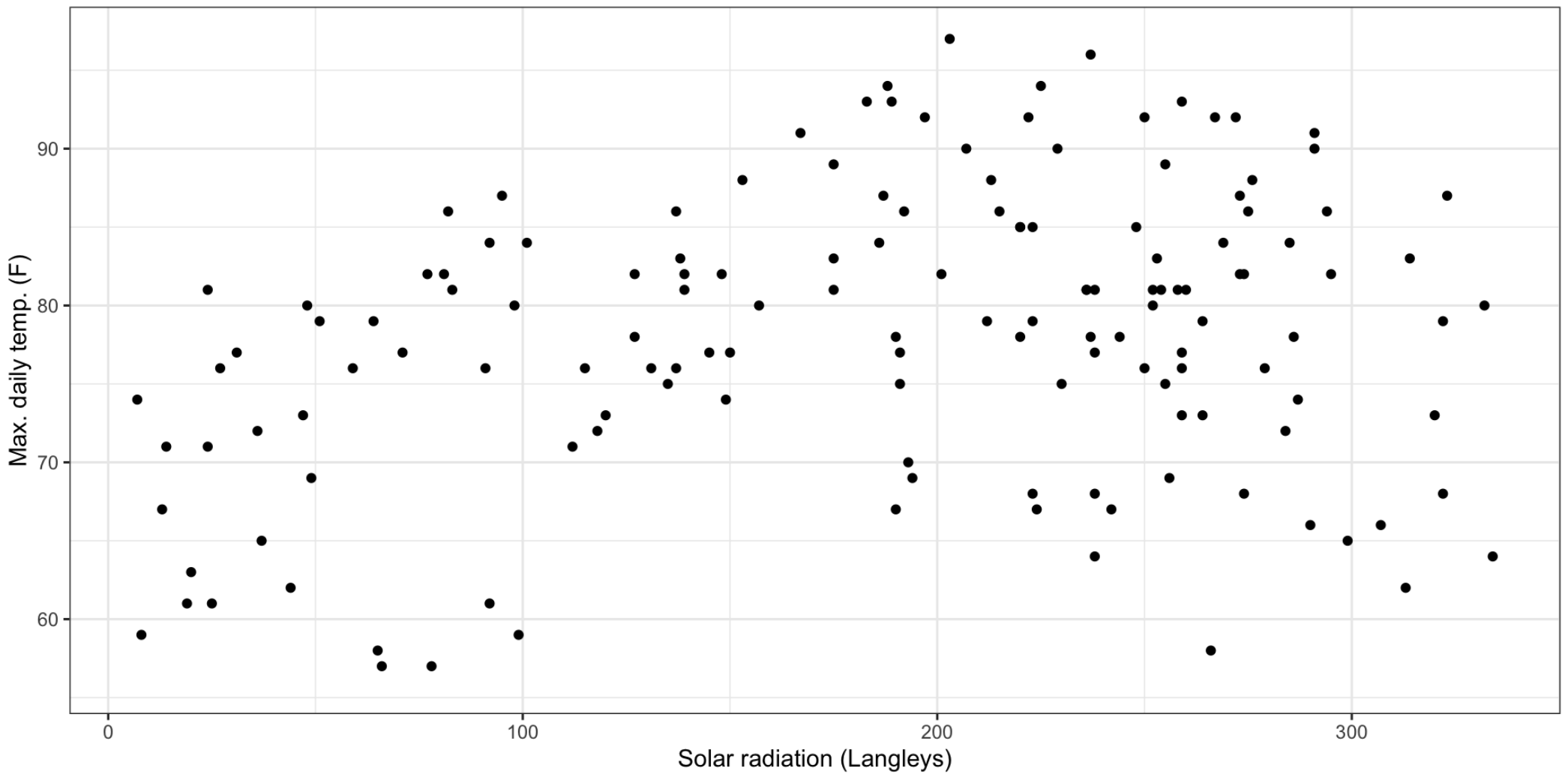
Building plots

- 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



Some more geometries

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

```
1 airquality_plot
```

Line plot

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

```
1  airquality_plot +
2    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

More on aesthetics

Aesthetic	What it affects
size	points, lines
shape	points
linetype	lines
colour	points, lines, boundary
alpha	transparency
fill	interior
group	recreates geometry by group

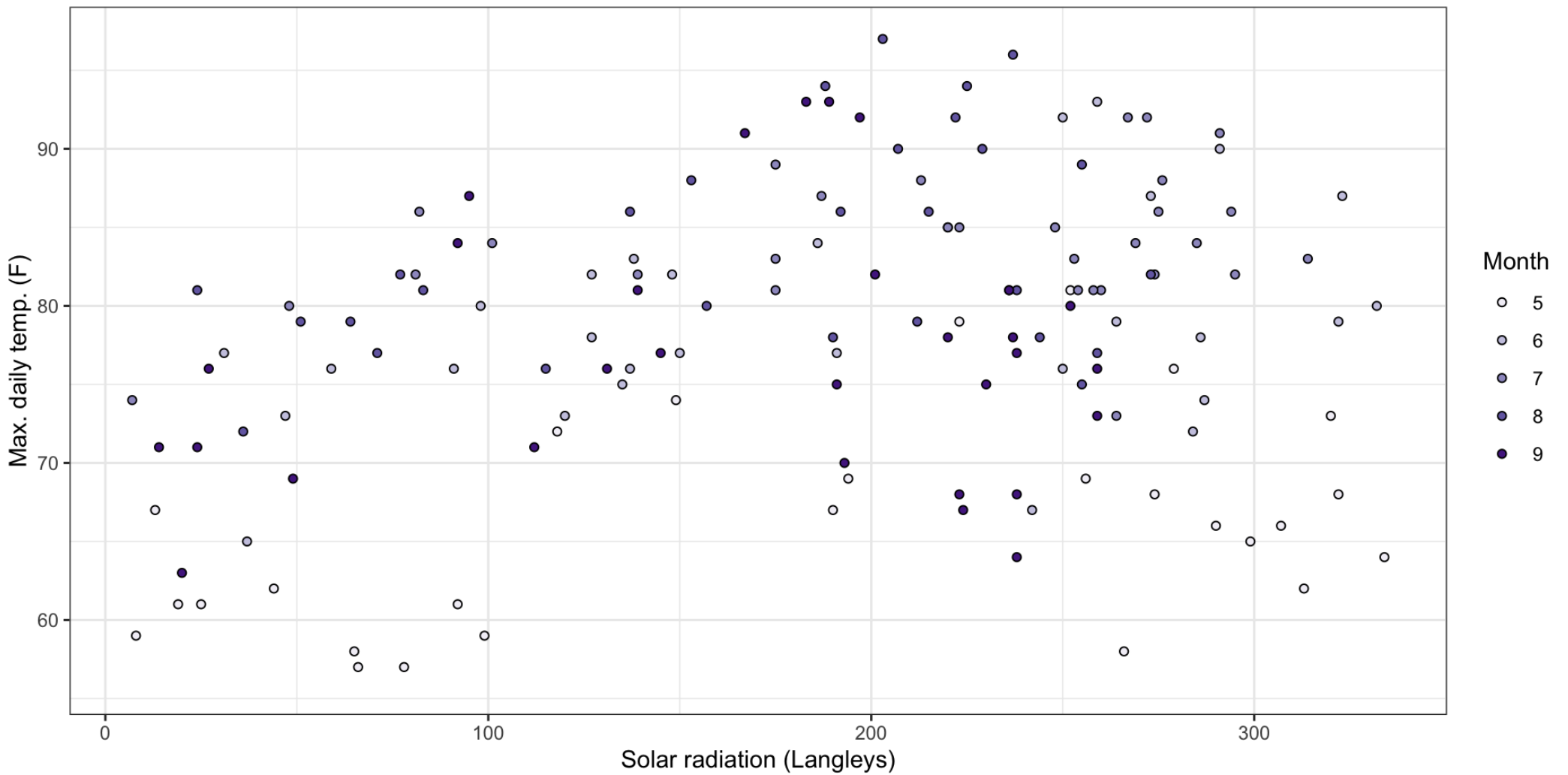
- If these (except group) are outside aes() they fix the value for all parts of that geometry
- Aesthetics specified inside ggplot() are inherited by all geometries for that plot
- Not all geometries accept all aesthetics (e.g. geom_line() has no fill)
- Some point shapes admit a colour and a fill

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

```
1 solar_temp_plot_colored
```



Small multiples

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

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

Small multiples

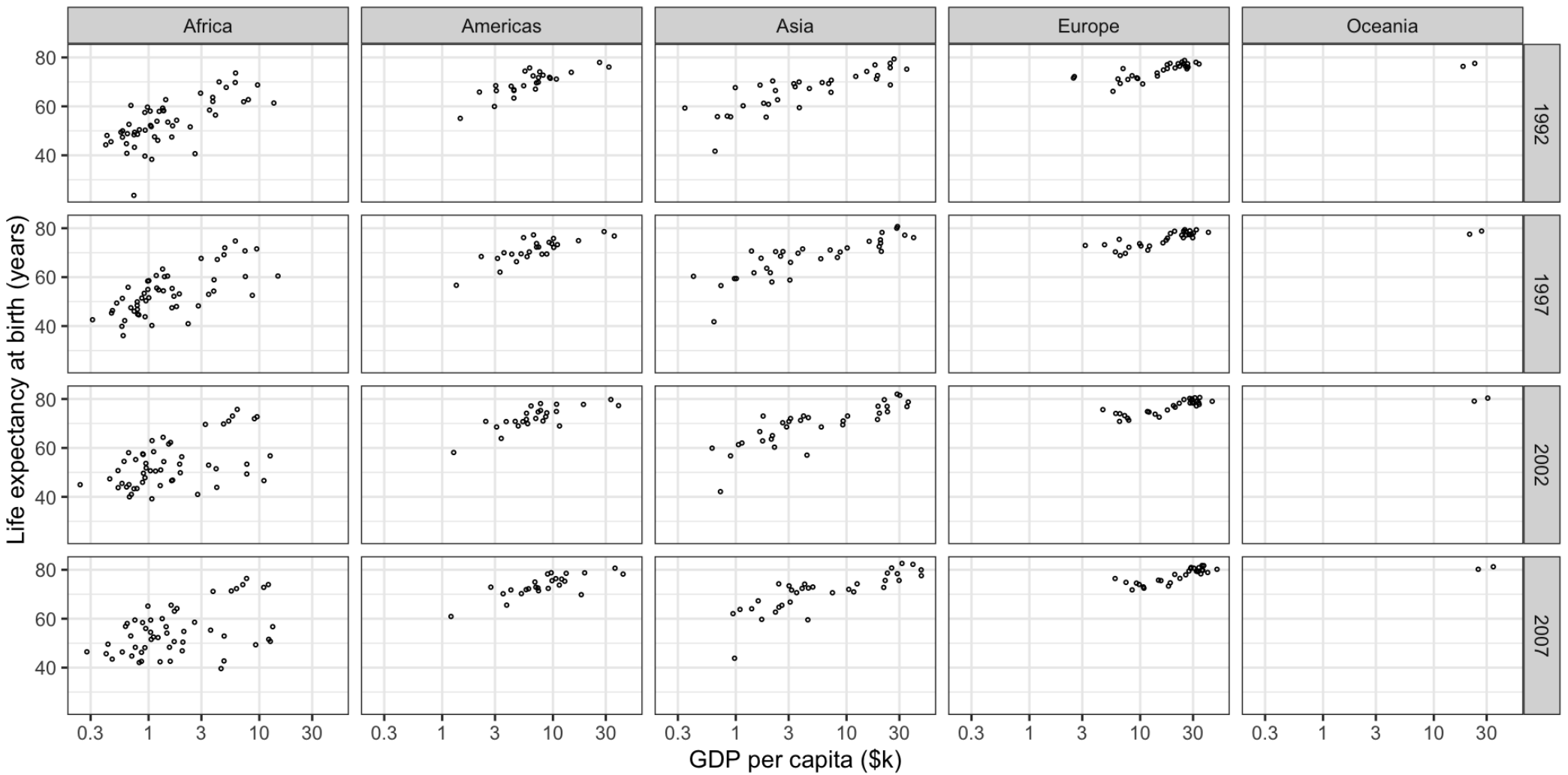
We can also use facet_grid() to repeat the aesthetic and geometries for specified rows and cols variables

```
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

```
1 gapminder_plot
```



Summary

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

Further reading

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)

References

Chang, Winston. 2017. R Graphics Cookbook: Practical Recipes for Visualizing Data. 2nd ed. O'Reilly Media. http://www.cookbook-r.com/Graphs/.

Friendly, M. 2005. "Milestones in the History of Data Visualization: A Case Study in Statistical Historiography." In Classification: The Ubiquitous Challenge, edited by C. Weihs and W. Gaul, 34–52. New York: Springer. http://www.math.yorku.ca/SCS/Papers/gfkl.pdf.

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Kibirige, Hassan. 2020. A Grammar of Graphics for Python. https://plotnine.readthedocs.io/en/stable/index.html.

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