Data Science for Economists

Lecture 1: Introduction

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University of North Carolina | ECON 370

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✱ Slides adapted from Alex Marsh's ECON 370 and Grant McDermott's EC 607 at University of Oregon.

Prologue

Introductions

Me

- Drew Van Kuiken
- drew.van.kuiken@unc.edu
- Office Hours: MTh 2:15-3:15PM (Does this work for people?)
- I'm from New Jersey
- Now: Fourth Year Economics PhD Student (Empirical IO, Innovation, Industrial Policy)
- Extremely novice whittler

Syllabus Highlights

(Read the full document here.)

Why this course?

Fill in the gaps left by traditional econometrics and methods classes.

- Practical skills that tools that will complement your other econometric courses.
- Neglected skills like how to actually find datasets in the wild and clean them.
- This stuff kills in an interview.
- It also matters for your job! (sometimes)

Data science skills are largely distinct from (and complementary to) the core 'metrics curriculum familiar to economists.

- Data viz, cleaning and wrangling; programming; cloud computation; relational databases; machine learning; etc.

Grading

Component	Weight
5 × homework assignments	60%
1 × final project	30%
Participation	10%

- Number of homework assignments might change.
  - Regardless, will be equally weighted.
  - Individual weight = 60/n.
- Homework assignments may be done in groups of at most 3.
  - If done in groups *all group members are still expected to program on their own.*
  - If done in groups, *please submit only one assignment.*
- I will be requiring you to submit assignments with an R Markdown file and an R script.
  - Discuss details when the first assignment comes up.
- Final Project
  - Details TBD.
  - Individual project, short presentations during our final period.

Course Overview

Course Goals

1. Teach students how to competently program in R with good style,
2. Teach students how to think and approach problems from a computational perspective,
3. Teach students basic data science skills including data visualization and basic models,
4. Imbue students with a desire to learn more about econometrics and data science.

Course Overview

Learning Objectives

1. Be able to write functioning, readable, and aesthetically pleasing code in the R programming language,
2. Give raw data, be able to manipulate the data into the correct format needed for an analysis,
3. Given data and a research question, be able to create a exploratory data visualization in the right format to get at answering the question,
4. Be able to communicate results to a non-technical audience.

Lecture outline

Introduction

- Introduction: Motivation, software installation, and data visualization
- R language basics (will take some time)

Applications of Numerical Programming

Topics here are good to know but are mostly to practice programming

- Simulation
- Optimization

Data skills

- data.table and dplyr
- Merging

Lecture Outline (Cont.)

Basics of Data Science

- Data Visualization
- Regression
- Classification

Speakers

- We will have a few speakers from industry come throughout the semester
- TBD

Textbooks and Resources

I will be pulling from various books that are publicly available.

- *R for Data Science (2e)* by Hadley Wickham, Mine Cetinkaya-Rudel, and Garrett Grolemund
- *Hands-On Programming with R* by Garrett Grolemun
- *An Introduction to Statistical Learning with Applications in R* by Gareth James, Daniela Witten, Trevor Hastie, and Robert Tibshirani

Additional Books and Resources

- *Learning R* by Richard Cotton
- *Advanced R* by Hadley Wickham
- Swirl: Learn R, in R -- Great resource to learn the basics of R within R

Other Ways to Learn Programming

- More than anything else, learning to code is done via trial and error

1. StackOverflow:
    - Online message board, truly incredible number of questions and answers to comb through
    - I've never posted on StackOverflow, but you might want to! If you do, make sure you follow their rules
    - Usually, a couple different threads will pertain to your question - review all of them to get a sense of how to solve your issue
2. LLMs
    - I use Claude to help me code all the time! I am too lazy to fully learn regular expressions, Claude is not.
    - Claude sometimes sucks at coding. Check the AI's work!
    - Make sure you understand why something works
3. Various presentations and blog posts on the internet
    - e.g., Comparison of dplyr and data.table
    - Avoid TowardsDataScience, websites with tons of ads

Getting started

Software installation and registration

1. Download R.

2. Download RStudio.

If you had trouble completing any of these steps, please raise your hand.

- See Appendix A of *Hands-On Programming with R*

Some OS-specific extras

I'll detail further software requirements as and when the need arises. However, to help smooth some software installation issues further down the road, please also do the following (depending on your OS):

- **Windows:** Install Rtools.
- **Mac:** Might need to install Xcode later. This can take awhile, so I will let you know.
- **Linux:** None (you should be good to go).

Checklist

☑ Do you have the most recent version of R?

```
version$version.string
```

```
## [1] "R version 4.4.1 (2024-06-14)"
```

☑ Do you have the most recent version of RStudio? (The preview version is fine.)

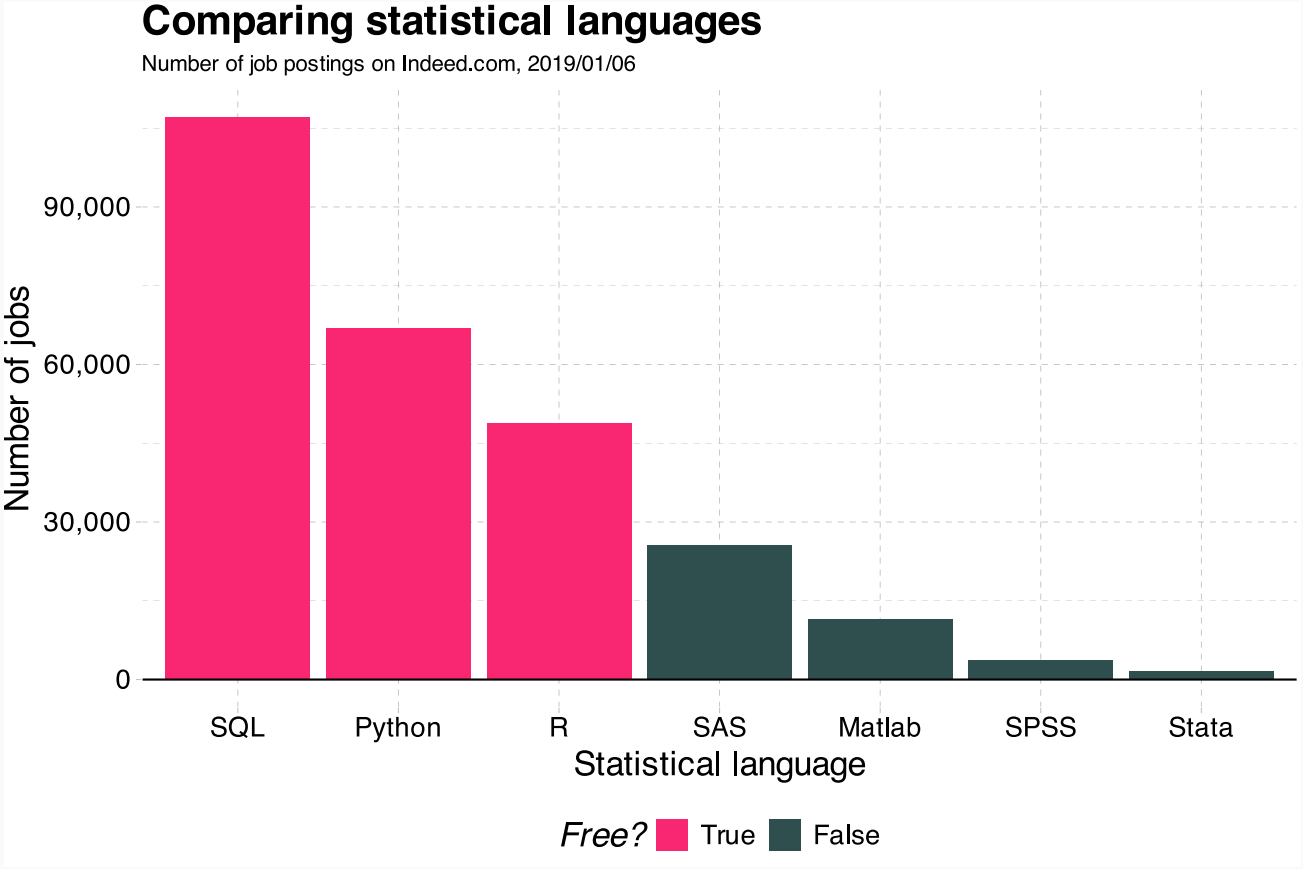
```
RStudio.Version()$version
## Requires an interactive session but should return something like "[1] '2024.4.2..
```

☑ Have you updated all of your R packages?

```
update.packages(ask = FALSE, checkBuilt = TRUE)
```

R for data science

Why R and RStudio? (cont.)



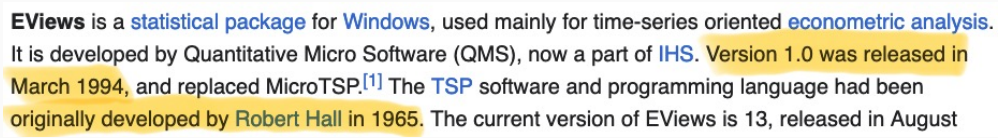
Why This Course? Why R? My Experience:

- What I "learned" in college: R, Java, Eviews

EViews is a statistical package for Windows, used mainly for time-series oriented econometric analysis. It is developed by Quantitative Micro Software (QMS), now a part of IHS. Version 1.0 was released in March 1994, and replaced MicroTSP.[1] The TSP software and programming language had been originally developed by Robert Hall in 1965. The current version of EViews is 13, released in August

Why This Course? Why R? My Experience:

- What I "learned" in college: R, Java, Eviews
- What I used at work: Stata, R, Python



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- What I use now: R, Matlab, Stata
- Languages change over time: for now, R is probably your best bet
- Being flexible is most valuable - ultimately, you want to learn how computers think

Why R and RStudio? (cont.)

Data science positivism

- Alongside Python, R has become the *de facto* language for data science.
  - See: *The Impressive Growth of R*, *The Popularity of Data Science Software*
- Open-source (free!) with a global user-base spanning academia and industry.
  - LLMs are good at it! (rip Matlab)

Bridge to applied economics and other tools

- Already has all of the statistics and econometrics support, and is amazingly adaptable as a "glue" language to other programming languages and APIs.
- The RStudio IDE and ecosystem allow for further, seemless integration.

Pros and Cons of R

✓ Syntax is fairly basic for those with a math background.

✓ Great community with lots of support.

✓ Free.

✓ RStudio.

✓ Beautiful Graphics (better than Python ☺).

✓ Data wrangling.

✕ Slow.

✕ Demanding on RAM.

✕ Dependency on packages.

R vs Python

Both R and Python are common data science languages.

However, Python is arguably the more important language in industry.

So why not learn Python for this class?

1. I think R is the easier of the two to get started learning.
2. There is much commonality between the two with just a few quirks.
3. R is better for learning statistics as it is ultimately a programming language designed with statistical computing in mind.
4. Python is sort of a mess. Package stuff is worse (imo), numpy is a scourge.

R is a language for statistics whereas Python is a language that can do statistics.

Laptops in Class

We'll be using our laptops a lot in class this semester. This is the best way to learn how to code!

In my intro to CS class in college, I watched a woman play Bloons Tower Defense 4 twice a week for five months. In another class, a guy watched Netflix all

It was ***incredibly*** distracting. ***Please!!!!!!!*** do not do this.

If you are unable to control yourself, ***please*** sit in the back of the classroom

I reserve the right to take participation points off if you're making life harder for your classmates.

A Note on File Structure

It has come to my attention that many college students do not use folders

When I was a college student, I did not use folders

I have lost everything I did in college

A Suggested File Structure

Desktop → 2024 → econ370 → hw1, final project, books, slides, etc.

For any coding project (and, e.g., within the hw1 folder) use the following subfolders (trust me on this):

- data
- raw_data
- scripts
- output
- temp

Notes on folders:

- No spaces in folder names!!!
- Within folders like scripts, create subfolders named _old. Don't delete old files, just move them to _old
- When creating files, I often begin filenames with the date I created that file. I use YYYY.MM.DD_filename

A Lay of the Land

R is a coding language. If you want, you can just open your computer's terminal and start typing in R.*

When we open RStudio, we can start typing R code into the console and make our computer do stuff.

Nowadays, there are three paradigms people use to write R code:

1. Using base R
2. Using the tidyverse (a *package* with a huge set of functions for writing code)
3. Using data.table (another *package* with a huge, different set of functions for writing code)

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1. Using base R
    - Section 1 is in base R
    - Think of this as an introduction to coding itself. You likely won't write much base R going forward, but the principles we learn here will pop up everywhere
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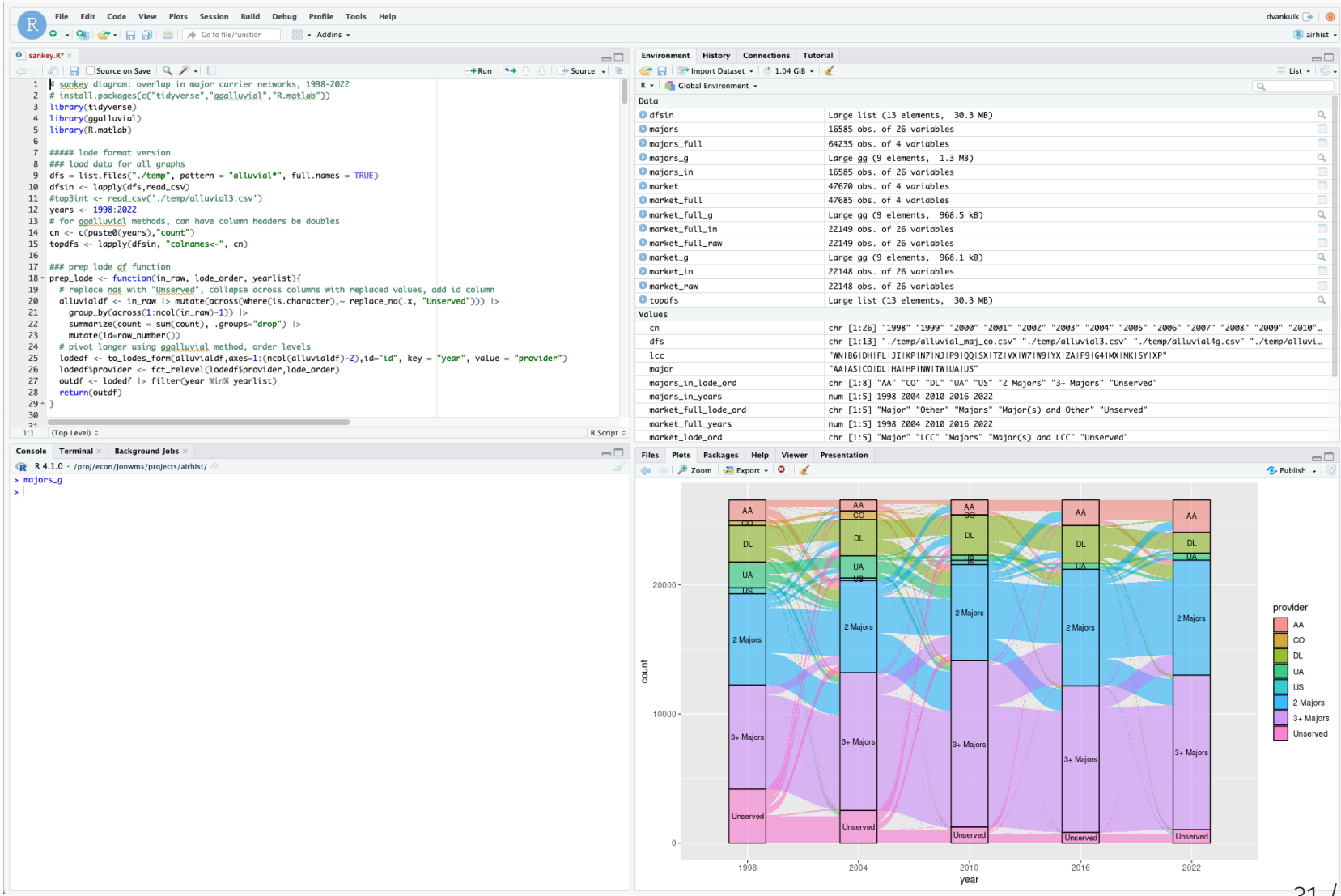
2. Using the tidyverse (a *package* with a huge set of functions for writing code)
3. Using data.table (another *package* with a huge, different set of functions for writing code)
    - Section 2 will introduce the **tidyverse** and **data.table** packages
    - I suggest you write most of your code using the **tidyverse**. It's easy to pick up and very readable
    - You'll see lots of internet code using **data.table**. It's probably more powerful on net than the **tidyverse**, so it's important you're familiar with it

A Lay of the Land (Virtual)



Some R basics

1. Everything is an object.
2. Everything has a name.
3. You do things using functions.
4. Functions come pre-written in packages (i.e. "libraries"), although you can — and should — write your own functions too.

Points 1. and 2. can be summarized as an object-oriented programming (OOP) approach.

- This may sound super abstract now, but we'll see *lots* of examples over the coming weeks that will make things clear.

R code example (linear regression)

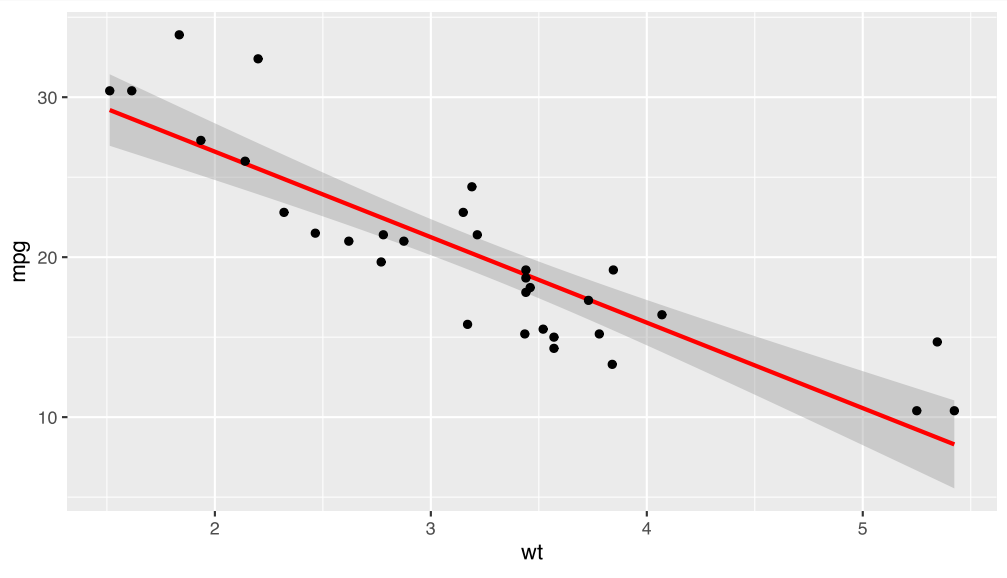
```
fit = lm(mpg ~ wt, data = mtcars)
summary(fit)
```

```
##
## Call:
## lm(formula = mpg ~ wt, data = mtcars)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -4.5432 -2.3647 -0.1252  1.4096  6.8727
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  37.2851     1.8776  19.858  < 2e-16 ***
## wt           -5.3445     0.5591  -9.559 1.29e-10 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 3.046 on 30 degrees of freedom
## Multiple R-squared:  0.7528,    Adjusted R-squared:  0.7446
## F-statistic: 91.38 on 1 and 30 DF,  p-value: 1.294e-10
```

ggplot2

```
library(ggplot2)
ggplot(data = mtcars, aes(x = wt, y = mpg)) +
  geom_smooth(method = "lm", col = "red") +
  geom_point()
```

```
## `geom_smooth()` using formula = 'y ~ x'
```



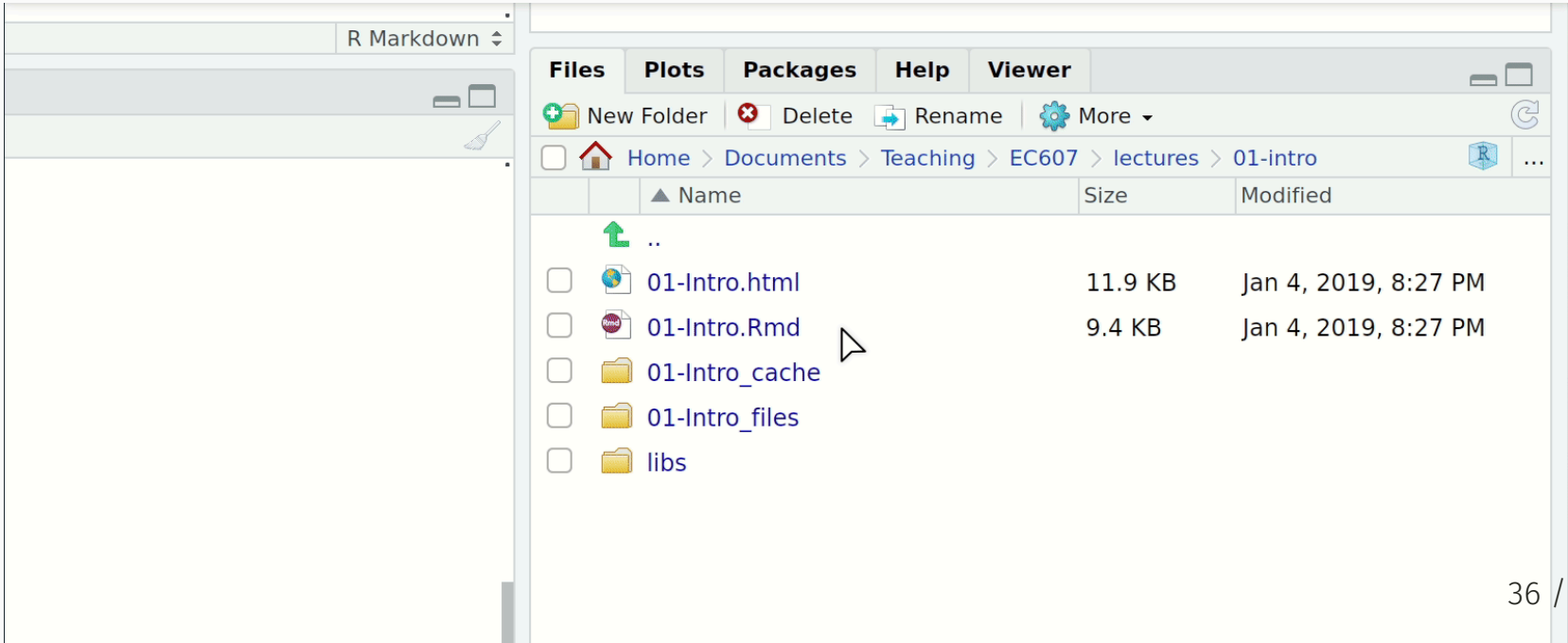
More ggplot2

Install and load

Open up your laptops. For the remainder of this first lecture, we're going continue playing around with ggplot2 (i.e. livecoding).

If you don't have them already, install the `ggplot2` and `gapminder` packages via either:

- **Console:** Enter `install.packages(c("ggplot2", "gapminder"), dependencies=T)`.
- **RStudio:** Click the "Packages" tab in the bottom-right window pane. Then click "Install" and search for these two packages.



Install and load (cont.)

Once the packages are installed, load them into your R session with the `library()` function.

```
library(ggplot2)
library(gapminder) ## We're just using this package for the gapminder data
```

Notice too that you don't need quotes around the package names any more. Reason: R now recognises these packages as defined objects with given names. ("Everything in R is an object and everything has a name.")

PS — A convenient way to combine the package installation and loading steps is with the pacman package's `p_load()` function. If you run `pacman::p_load(ggplot, gapminder)` it will first look to see whether it needs to install either package before loading them. Clever.

- We'll get to this next week, but if you want to run a function from an (installed) package without loading it, you can use the `PACKAGE::package_function()` syntax.

Brief aside: The gapminder dataset

Because we're going to be plotting the gapminder dataset, it is helpful to know that it contains panel data on life expectancy, population size, and GDP per capita for 142 countries since the 1950s.

```
gapminder
```

```
## # A tibble: 1,704 × 6
##    country     continent  year lifeExp      pop gdpPercap
##    <fct>       <fct>     <int>   <dbl>    <int>     <dbl>
##  1 Afghanistan Asia       1952    28.8  8425333      779.
##  2 Afghanistan Asia       1957    30.3  9240934      821.
##  3 Afghanistan Asia       1962    32.0 10267083      853.
##  4 Afghanistan Asia       1967    34.0 11537966      836.
##  5 Afghanistan Asia       1972    36.1 13079460      740.
##  6 Afghanistan Asia       1977    38.4 14880372      786.
##  7 Afghanistan Asia       1982    39.9 12881816      978.
##  8 Afghanistan Asia       1987    40.8 13867957      852.
##  9 Afghanistan Asia       1992    41.7 16317921      649.
## 10 Afghanistan Asia       1997    41.8 22227415      635.
## # ℹ 1,694 more rows
```

Elements of ggplot2

Hadley Wickham's ggplot2 is one of the most popular packages in the entire R canon.

- It also happens to be built upon some deep visualization theory: i.e. Leland Wilkinson's *The Grammar of Graphics*.

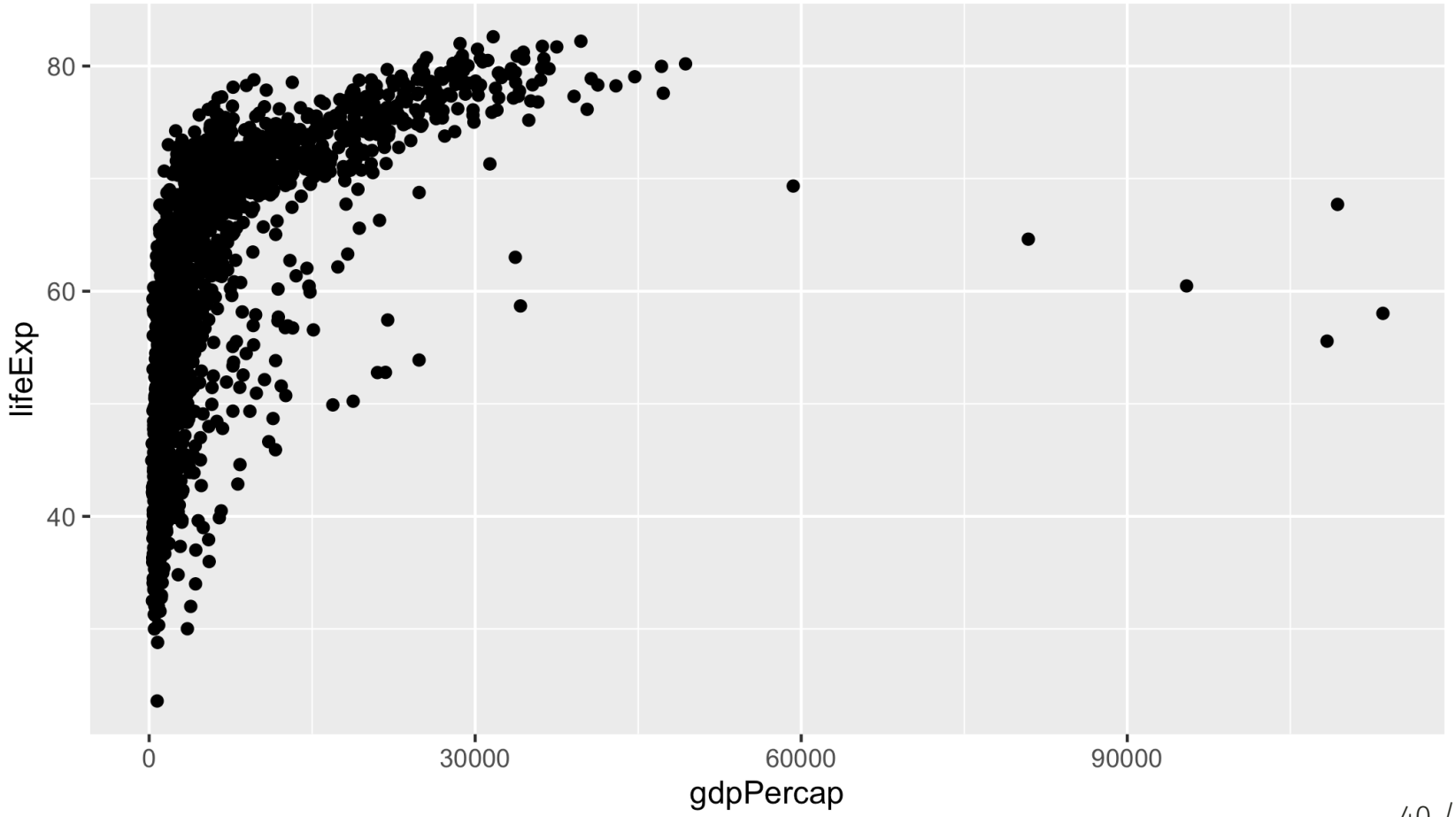
There's a lot to say about ggplot2's implementation of this "grammar of graphics" approach, but the three key elements are:

1. Your plot ("the visualization") is linked to your variables ("the data") through various **aesthetic mappings**.
2. Once the aesthetic mappings are defined, you can represent your data in different ways by choosing different **geoms** (i.e. "geometric objects" like points, lines or bars).
3. You build your plot in **layers**.

That's kind of abstract. Let's review each element in turn with some actual plots.

1. Aesthetic mappings

```
ggplot(data = gapminder, mapping = aes(x = gdpPercap, y = lifeExp)) +
  geom_point()
```



1. Aesthetic mappings (cont.)

```
ggplot(data = gapminder, mapping = aes(x = gdpPercap, y = lifeExp)) +
  geom_point()
```

Focus on the top line, which contains the initialising `ggplot()` function call. This function accepts various arguments, including:

- Where the data come from (i.e. `data = gapminder`).
- What the aesthetic mappings are (i.e. `mapping = aes(x = gdpPercap, y = lifeExp)`).

The aesthetic mappings here are pretty simple: They just define an x-axis (GDP per capita) and a y-axis (life expectancy).

- To get a sense of the power and flexibility that comes with this approach, however, consider what happens if we add more aesthetics to the plot call...

1. Aesthetic mappings (cont.)

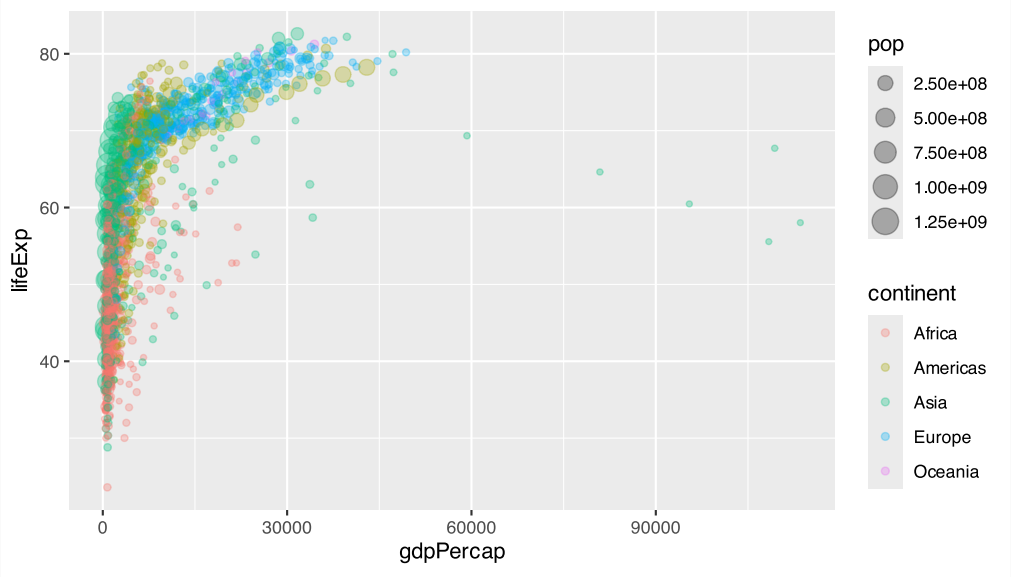
```
ggplot(data = gapminder, aes(x = gdpPercap, y = lifeExp, size = pop, col = continent))
  geom_point(alpha = 0.3) ## "alpha" controls transparency. Takes a value between 0 a
```

Note that I've dropped the "mapping =" part of the ggplot call. Most people just start with "aes(...)", since `ggplot2` knows the order of the arguments.

1. Aesthetic mappings (cont.)

We can specify aesthetic mappings in the geom layer too.

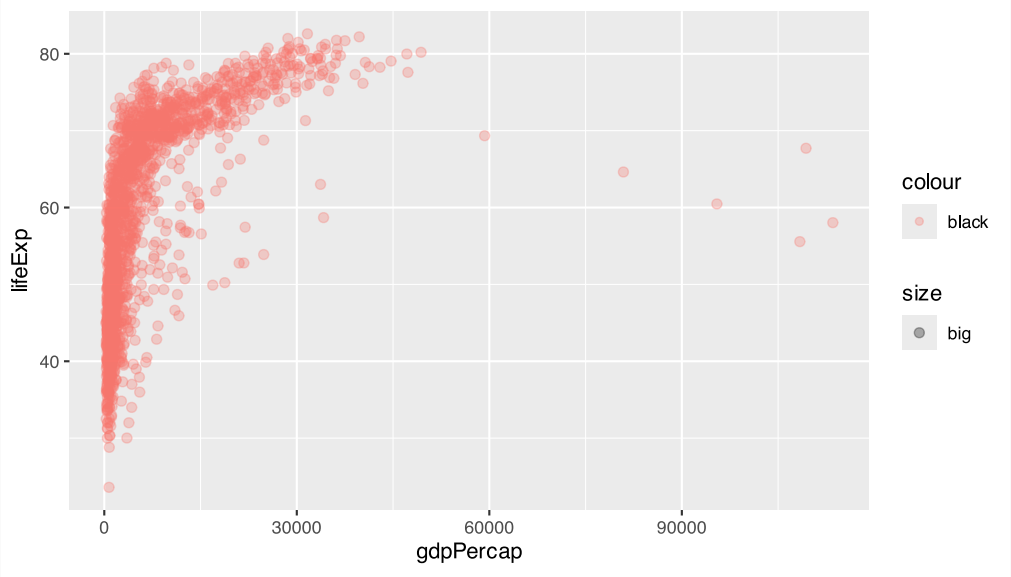
```
ggplot(data = gapminder, aes(x = gdpPercap, y = lifeExp)) + ## Applicable to all geoms
  geom_point(aes(size = pop, col = continent), alpha = 0.3) ## Applicable to this geom
```



1. Aesthetic mappings (cont.)

Oops. What went wrong here?

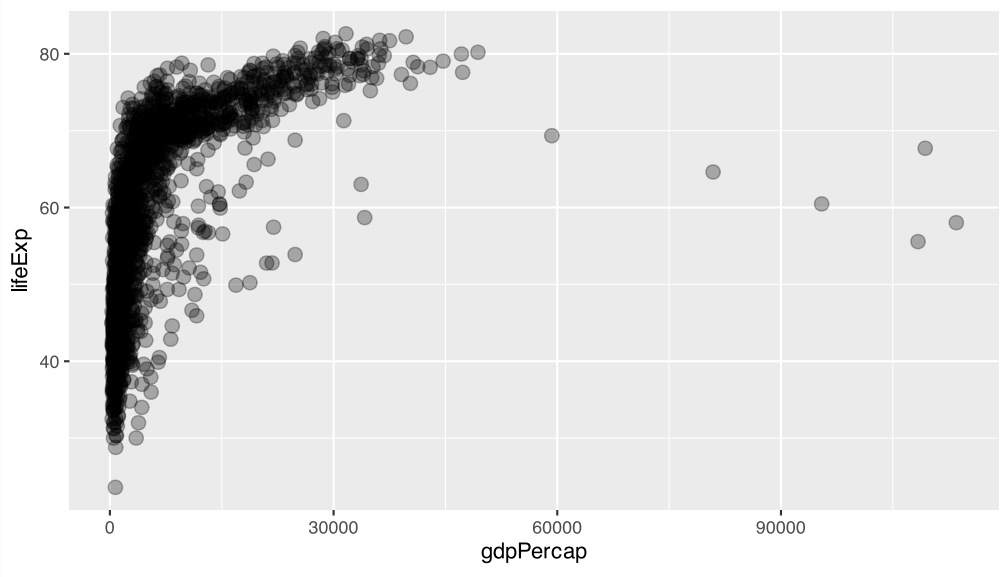
```
ggplot(data = gapminder, aes(x = gdpPercap, y = lifeExp)) +
  geom_point(aes(size = "big", col="black"), alpha = 0.3)
```



1. Aesthetic mappings (cont.)

This is what we wanted to do!

```
ggplot(data = gapminder, aes(x = gdpPercap, y = lifeExp)) +
  geom_point(size = 3, col="black", alpha = 0.3)
```

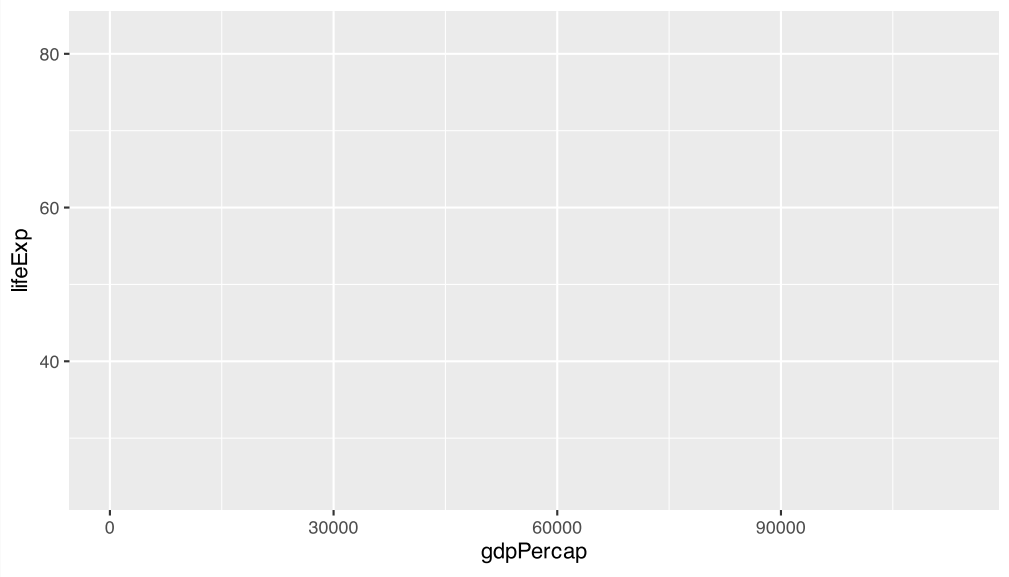


Note: `size` must take a numeric argument, not a character.

1. Aesthetic mappings (cont.)

At this point, instead of repeating the same ggplot2 call every time, it will prove convenient to define an intermediate plot object that we can re-use.

```
p = ggplot(data = gapminder, aes(x = gdpPercap, y = lifeExp))
p
```

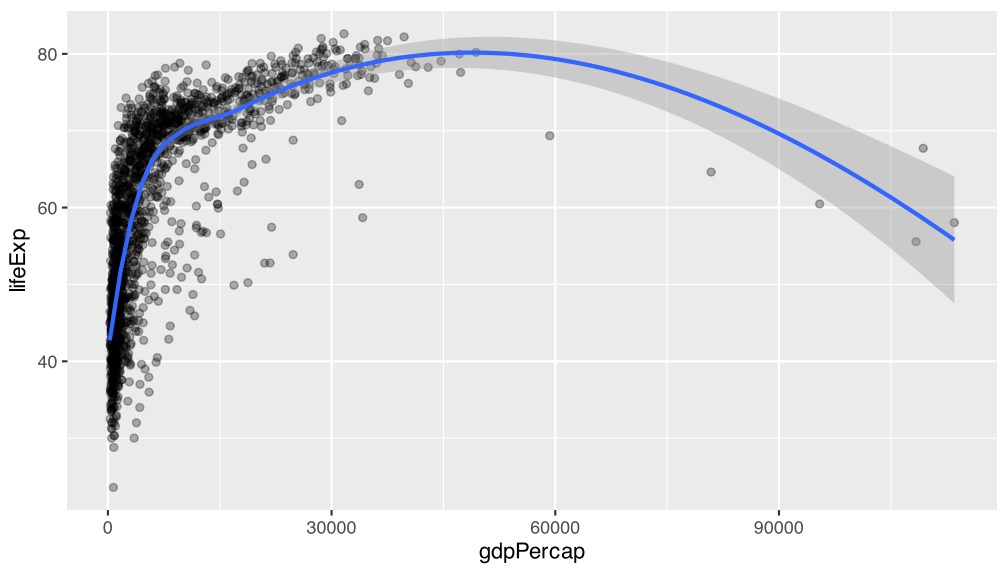


2. Geoms

Once your variable relationships have been defined by the aesthetic mappings, you can invoke and combine different geoms to generate different visulaizations.

```
p + geom_point(alpha = 0.3)  +
  geom_smooth(method = "loess")
```

```
## `geom_smooth()` using formula = 'y ~ x'
```

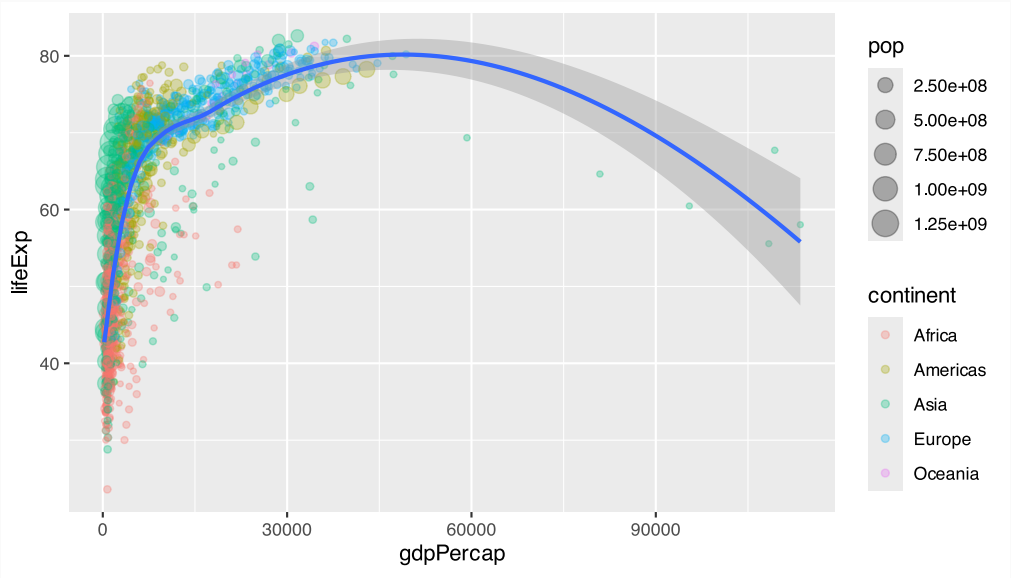


2. Geoms (cont.)

Aesthetics can be applied differentially across geoms.

```
p + geom_point(aes(size = pop, col = continent), alpha = 0.3)  +
  geom_smooth(method = "loess")
```

```
## `geom_smooth()` using formula = 'y ~ x'
```



2. Geoms (cont.)

The previous plot provides a good illustration of the power (or effect) that comes from assigning aesthetic mappings "globally" vs in the individual geom layers.

- Compare: What happens if you run the below code chunk?

```
p_bad = ggplot(data = gapminder,
               aes(x = gdpPercap, y = lifeExp, size = pop, col = continent)) +
  geom_point(alpha = 0.3)  +
  geom_smooth(method = "loess")
```

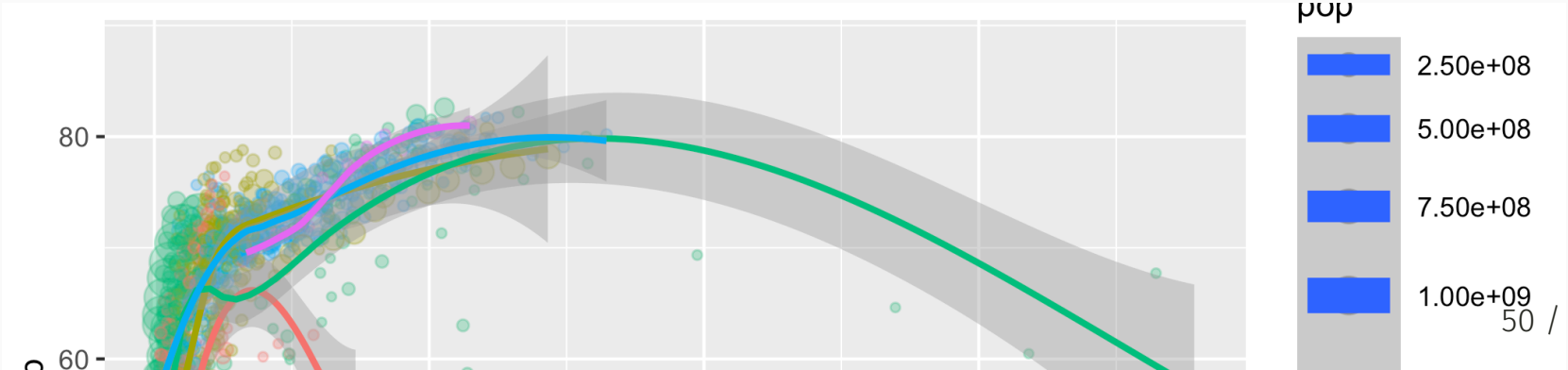
2. Geoms (cont.)

```
p_bad
```

```
## Warning: Using `size` aesthetic for lines was deprecated in ggplot2 3.4.0.
## ℹ Please use `linewidth` instead.
## This warning is displayed once every 8 hours.
## Call `lifecycle::last_lifecycle_warnings()` to see where this warning was
## generated.

## `geom_smooth()` using formula = 'y ~ x'

## Warning: The following aesthetics were dropped during statistical transformation: size.
## ℹ This can happen when ggplot fails to infer the correct grouping structure in
##   the data.
## ℹ Did you forget to specify a `group` aesthetic or to convert a numerical
##   variable into a factor?
```



2. Geoms (cont.)

Similarly, note that some geoms only accept a subset of mappings. E.g. `geom_density()` doesn't know what to do with the "y" aesthetic mapping.

```
p + geom_density()
```

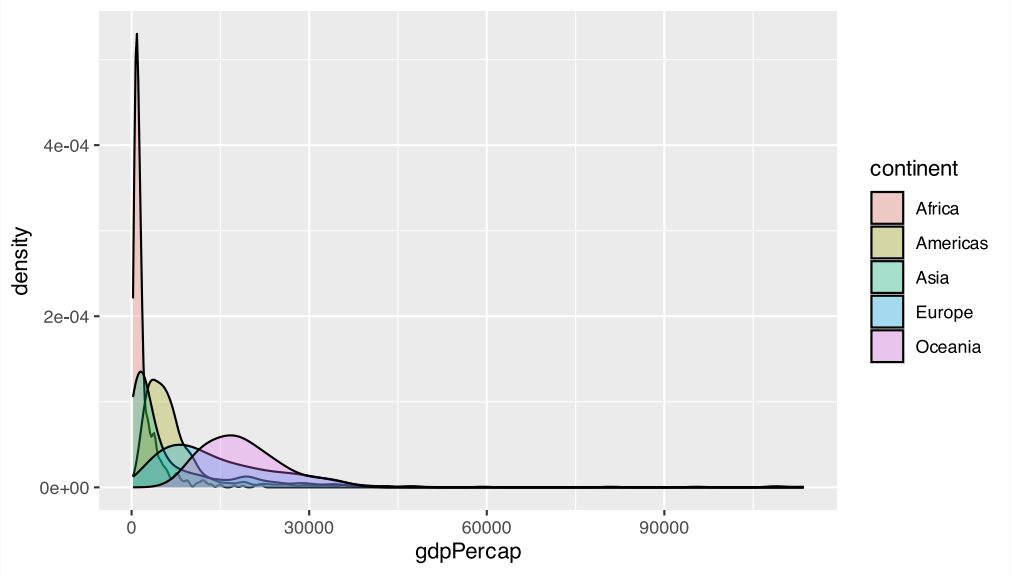
```
## Warning: The following aesthetics were dropped during statistical transformation: y.
## ℹ This can happen when ggplot fails to infer the correct grouping structure in
##   the data.
## ℹ Did you forget to specify a `group` aesthetic or to convert a numerical
##   variable into a factor?
```

```
## Error in `geom_density()`:
## ! Problem while setting up geom.
## ℹ Error occurred in the 1st layer.
## Caused by error in `compute_geom_1()`:
## ! `geom_density()` requires the following missing aesthetics: y.
```

2. Geoms (cont.)

We can fix that by being more careful about how we build the plot.

```
ggplot(data = gapminder) + ## i.e. No "global" aesthetic mappings"
  geom_density(aes(x = gdpPercap, fill = continent), alpha=0.3)
```



3. Build your plot in layers

We've already seen how we can chain (or "layer") consecutive plot elements using the `+` connector.

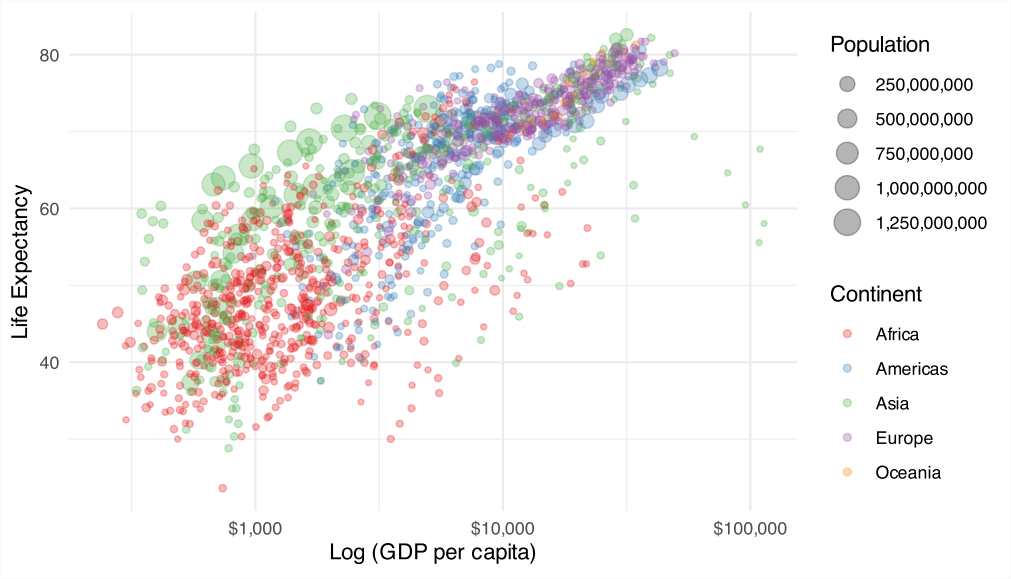
- The fact that we can create and then re-use an intermediate plot object (e.g. "p") is testament to this.

But it bears repeating: You can build out some truly impressive complexity and transformation of your visualization through this simple layering process.

- You don't have to transform your original data; ggplot2 takes care of all of that.
- For example (see next slide for figure).

```
p2 =
  p +
  geom_point(aes(size = pop, col = continent), alpha = 0.3) +
  scale_color_brewer(name = "Continent", palette = "Set1") + ## Different colour scal
  scale_size(name = "Population", labels = scales::comma) + ## Different point (i.e.
  scale_x_log10(labels = scales::dollar) + ## Switch to logarithmic scale on x-axis. (
  labs(x = "Log (GDP per capita)", y = "Life Expectancy") + ## Better axis titles
  theme_minimal() ## Try a minimal (b&w) plot theme
```

3. Build your plot in layers (cont.)



What else?

We have barely scratched the surface of ggplot2's functionality... let alone talked about the entire ecosystem of packages that has been built around it.

- Here's are two quick additional examples to whet your appetite

Note that you will need to install and load some additional packages if you want to recreate the next two figures on your own machine. A quick way to do this:

```
if (!require("pacman")) install.packages("pacman")
```

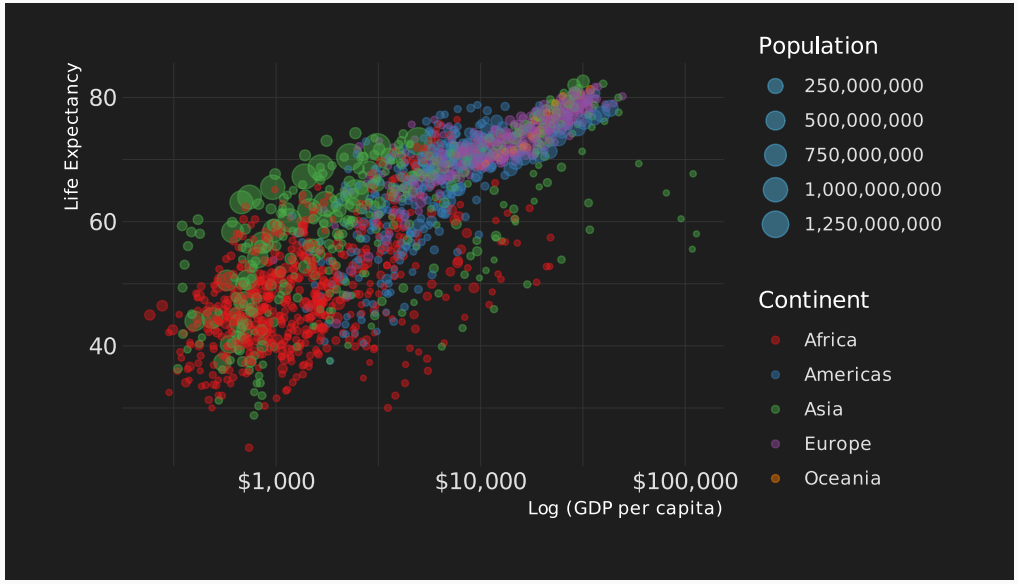
```
## Loading required package: pacman
```

```
pacman::p_load(hrbrthemes, gganimate)
```

What else? (cont.)

Simple extension: Use an external package theme.

```
# library(hrbrthemes)
p2 + theme_modern_rc() + geom_point(aes(size = pop, col = continent), alpha = 0.2)
```



What else? (cont.)

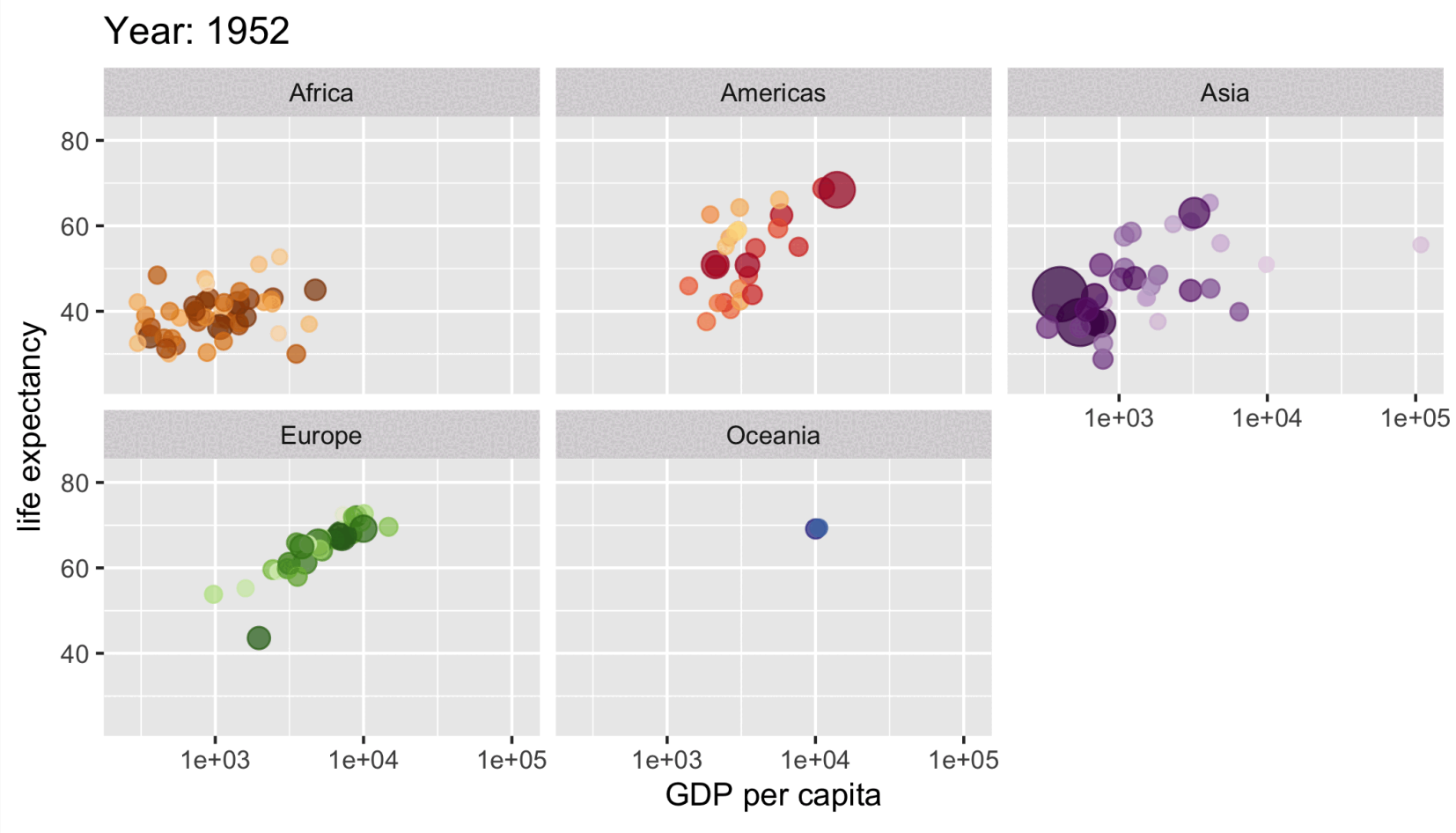
Elaborate extension: Animation! (See the next slide for the resulting GIF.)

```
library(gganimate)
library(magick)

ggplot(gapminder, aes(gdpPercap, lifeExp, size = pop, colour = country)) +
  geom_point(alpha = 0.7, show.legend = FALSE) +
  scale_colour_manual(values = country_colors) +
  scale_size(range = c(2, 12)) +
  scale_x_log10() +
  facet_wrap(~continent) +
  # Here comes the gganimate specific bits
  labs(title = 'Year: {frame_time}', x = 'GDP per capita', y = 'life expectancy') +
  transition_time(year) +
  ease_aes('linear')
```

What else? (cont.)

```
## Warning: package 'magick' was built under R version 4.3.3
```



Very cool. Also very useful!

What else? (cont.)

There's a lot more to say, but I think we'll stop now for today's lecture.

We also haven't touched on ggplot2's relationship to "tidy" data.

- It actually forms part of a suite of packages collectively known as the tidyverse.
- We will get back to this in later lectures.

Rest assured, you will be using ggplot2 throughout the rest of this course and developing your skills along the way.

In the meantime, I want you to do some reading and practice on your own. Pick either of the following (or choose among the litany of online resources) and work through their examples:

- Chapter 3 of *R for Data Science* by Hadley Wickham and Garett Grolemund.
- *Data Visualization: A Practical Guide* by Kieran Healy.
- Designing ggplots by Malcom Barrett.

Next lecture: Getting started with R.

Appendix

R vs Stata

If you're coming from Stata, some additional things worth emphasizing:

- Multiple objects (e.g. data frames) can exist happily in the same workspace.
    - No more `keep`, `preserve`, `restore` hackery. (Though, props to Stata 16.)
    - This is a direct consequence of the OOP approach.
- You will load packages at the start of every new R session. Make peace with this.
    - "Base" R comes with tons of useful in-built functions. It also provides all the tools necessary for you to write your own functions.
    - However, many of R's best data science functions and tools come from external packages written by other users.
- R easily and infinitely parallelizes. For free.
    - Compare the cost of a Stata/MP license, nevermind the fact that you effectively pay per core...
- You don't need to `tset or xtset` your data. (Although you can too.)

Base R plot

```
par(mar = c(4, 4, 1, .1)) ## Just for nice plot margins on this slide deck
plot(mtcars$wt, mtcars$mpg)
abline(fit, col = "red")
```