Workshop: How to Write a Quantitative Research Paper

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Introductions

About myself

- Data Scientist at Looping Studios in Berlin
- Postdoc at Hertie from May 2015 to Dec 2017
- PhD in PolSci (Uni Mannheim)
- Research on parties, legislative politics, electoral behavior
- Authored several journal articles and book chapters
- Programming with R since 2011 (switched from STATA)

Contact:

- mh@looping.group

About yourself

- Who are you?
- Why did you take this workshop?
- What are your expectations?

Plan for Today

10:00 - 11:45 Session 1: Elements and Style of a Quantitative Paper

11:45 - 12:15 Lunch break

12:15 - 14:00 Session 2: The Principles of Scientific Visualizations

14:15 - 16:00 Session 3: Visualizing Data and Results with R

Slides and additional content are on Moodle and GitHub

Things we (unfortunately) can't cover

- Research design
- How to get, process, and analyze data
- Help with STATA

Session 1: Elements and Style of a Quantitative Paper

Structure of a quantitative research paper

Whose mind are you going to change about what?

1. Abstract
2. Introduction
    - motivation, state of the art, results, contribution
3. Theory and hypotheses
4. Research Design
5. Data and Methods
6. Results
7. Discussion and Conclusion
8. References
9. Appendix

Content and structure of a Method Section

1. Intention and Goal of the Analysis
2. Description and Justification of the Data Selection
3. Description and Operationalization of the Dependent and Independent Variables
   - descriptive statistics, distribution, etc.
4. Description of the Methodology
5. Presentation of the Results
6. Discussion of the Results
   - including robustness checks

Things to remember about Style (King 2006)

"The best way to understand how to organize a paper is to imagine that your readers will randomly fall asleep at any time for five minutes and yet keep turning pages; when they wake up, they should know exactly where they are from your subheadings alone."

- Your paper should be rigorously structured and organized into sections and subsections
- Heading titles should be clear, contain no acronyms, and should summarize the key point in the section
- You are writing for busy people looking for a way to finish the thankless task of reviewing your paper as quickly as possible
- You need to make reading your paper as easy as possible

Things to remember about Style (King 2006)

- The overall structure of the paper, and all the key points you want to make, should make sense in terms of accomplishing *your* goal
- Keep revising the list of section headings until it looks like a table of contents that conveys your key point well even if one does not read the paper
- Do not try to hide weaknesses in your paper. Be so forthright with potential problems

Math

- Write down your statistical model and likelihood function
- Use only as many decimal places as you have precision
- Mathematics is always in italics and Greek letters
- e.g. not yhat = beta-b + gamma-w *X + e but
  $\widehat{\gamma}_i = \beta^b + \gamma^w X_i + \epsilon_i$
- Larger equations should be set with equation numbers, and be referred to as with this example of Bayes Theorem:

$$P(\theta|\gamma) = \frac{P(\gamma|\theta)P(\theta)}{P(\gamma)}, \tag{1}$$

where θ is an unknown parameter and γ is a data vector.

Language

- Do not say that quantities are “statistically significant” unless you have a very good substantive reason to do so
- Avoid saying “this proves that”. You are not a physicist!
- Focus the discussion on the direction and substantive effect of your key predictors
- Use active (“We ran a least squares regression.”) rather than passive (“A least squares regression was run.”)

Tables and Figures

- Tables and figures should be included to make specific points, and to draw readers' attention to these points
- All tables and figures should be fully documented
- In most cases, a figure is better than a table
- Number the figures and tables (separately) consecutively
- Refer to each in the text by number (e.g., see Figure 4)
- When explaining the content of a figure, it is good practice to devote one paragraph to the setup—the horizontal and vertical axis measurements, the unit of analysis, etc.—and then to start a new paragraph that explains your results

Describing your Analysis

- Provide sufficient information about your analysis so that it is possible for someone who reads your paper to replicate the analysis.
- Be very precise about coding rules, where the data came from, how indices were computed, what the unit of analysis is, etc

Final Thought

Find a publication in a top 3 academic journal and model your paper after it!

Session 2: The Principles of Scientific Visualizations

Why Visualization is Important

"At their best, graphics are instruments for reasoning about quantitative information." Tufte (1983)

"There is no statistical tool that is as powerful as a well-chosen graph." Chambers et al. (1983)

"Diagrams prove nothing, but bring outstanding features readily to the eye." Fisher (1925)

"Graphics should report the results of careful data analysis—rather than be an attempt to replace it." Tukey (1993)

Graphics are used to communicate discoveries

- Discovery goals:
  - Giving an overview—a qualitative sense of what is in a dataset
  - Conveying the sense of the scale and complexity of a dataset
- Communication goals:
  - Communication to self and others: Displaying information from the dataset in a readily understandable way
  - Telling a story
  - Attracting attention and stimulating interest

Interpreting a graph depends on expectations

- If readers have a lot of background knowledge, they will view the graphic differently don't assume you already have the reader's interest and involvement
- Making graphics attractive can help motivate readers to understand them

Graphics are part of a story

- A graphic does not live on its own
- There can be annotations, a legend, a title, a caption, accompanying text, an overall story, and a headline

Seven Rules for Better Figures (Rougier et al. 2014)

1. Know your audience
    - Who is the figure for?
2. Identify your message
    - What is the role of the figure?
3. Captions are not optional
    - Always use captions, explaining how to read a figure
4. Use color effectively
    - Color can be your greatest ally or your worst enemy (Tufte 1983)

Seven Rules for Better Figures (Rougier et al. 2014)

5. Do not mislead the reader
   - A scientific figure is tied to the data
6. Avoid chartjunk
   - Get rid of any unnecessary non-data-ink
7. Get the right tool
   - Use R!

Session 3: Visualizing Data and Results with R

Install Packages

```r
my_packages <- c("tidyverse", "broom", "gapminder",
                 "hrbrthemes", "margins", "MASS",
                 "scales", "stargazer", "survival")
install.packages(my_packages, repos = "http://cran.rstudio.com")
```

Load Packages

```r
library(tidyverse) # Core data science package
library(broom) # Tidy Model output
library(extrafont) # Custom fonts package
loadfonts() # Register custom fonts
library(gapminder) # Example GDP dataset
library(hrbrthemes) # Custom theme package
theme_set(theme_ipsum()) # Enable custom theme
library(margins) # Compute marginal effects
library(MASS) # Statistical models package
library(scales) # Adjust scales
library(stargazer) # Produce beautiful tables
library(survival) # For survival models
```

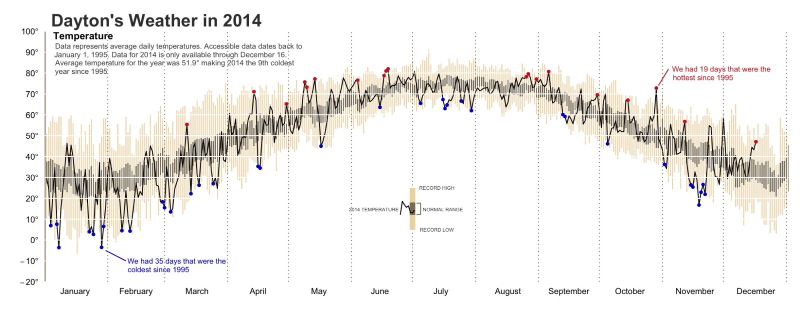
Why use R?

- Open source: makes it highly customizable and easily extensible
- Over 7,500 packages and counting
- Used by many social scientists interested in data analysis
- Powerful tool to generate elegant and effective plots
- Command-line interface and scripts favors reproducibility
- Excellent documentation and online help resources

ggplot2

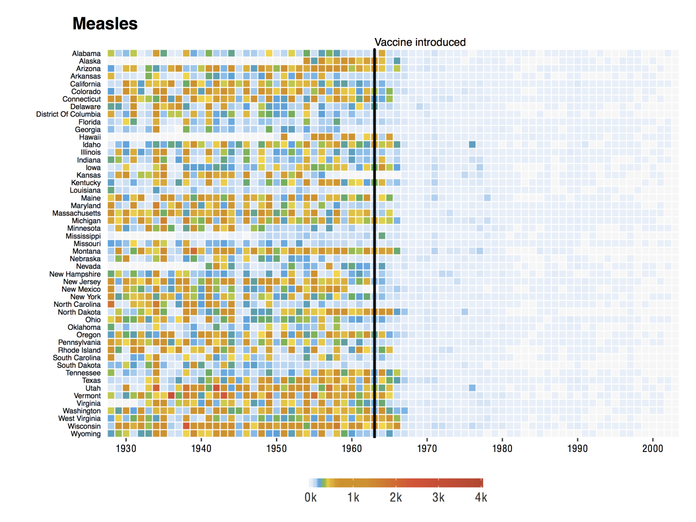
R has several systems for making graphs, but `ggplot2` is one of the most elegant and most versatile. `ggplot2` implements the grammar of graphics, a coherent system for describing and building graphs.

ggplot2 examples



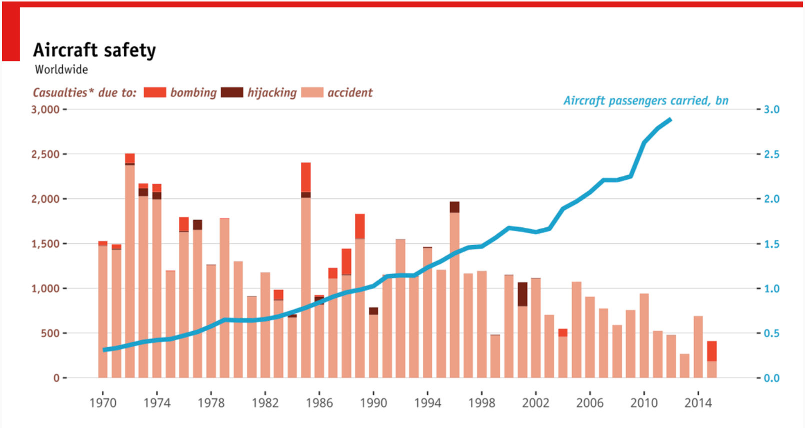
Source

ggplot2 examples



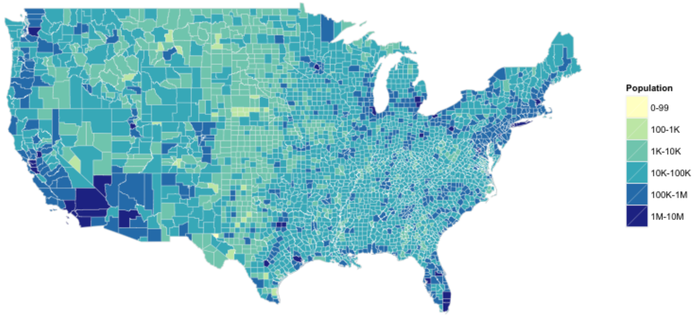
Source

ggplot2 examples



Source

ggplot2 examples



Source

The grammar of graphics

- Each plot is made of layers. Layers include the coordinate system (x-y), points, labels, etc.
- Each layer has aesthetics (`aes`) including x & y, size, shape, and color.
- The main layer types are called geometrics(`geom`) and include lines, points, etc.

The grammar of graphics

A `ggplot` is build piece by piece

1. Tidy Data

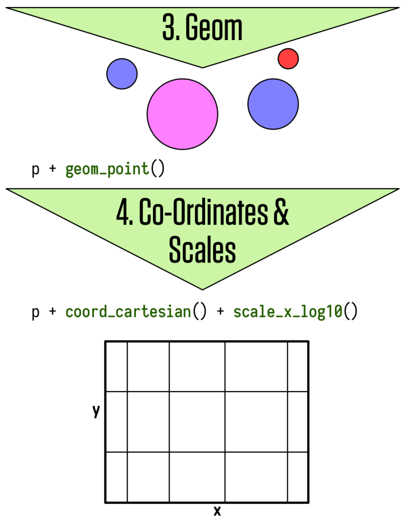
```
p <- ggplot(data = gapminder, ...
```

gdp	lifexp	pop	continent
340	65	31	Euro
227	51	200	Amer
909	81	80	Euro
126	40	20	Asia

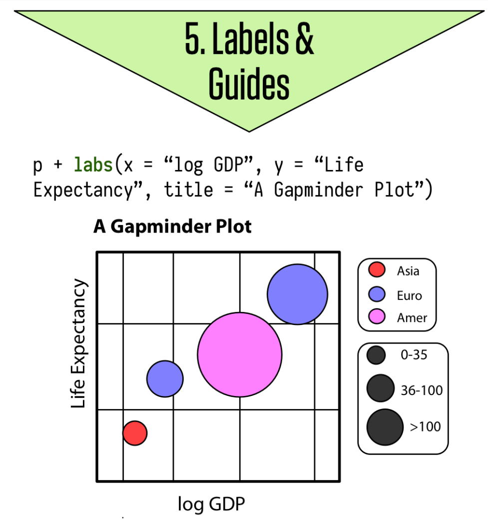
2. Mapping

```
p <- ggplot(data = gapminder, mapping =
         aes(x = gdp, y = lifexp, size = pop,
             color = continent))
```

The grammar of graphics



The grammar of graphics



ggplot workflow

1. Tell the `ggplot()` function what your data are.
2. Tell `ggplot` what relationships we want to see.
3. Tell `ggplot` how you want to see the relationships in your data.
4. Add additional layers to the p object one at a time.
5. Use additional functions to adjust scales, labels, tick marks.

Components of a ggplot2 graph

- data: Variables mapped to aesthetic attributes
- aesthetic: Visual property of the plot objects
- geom: Geometrical object used to represent data
- stats: Statistical transformations of the data
- scales: Values mapped to aesthetic attributes
- coord: Coordinate system
- facets: Subplots that each display one subset of the data

Tidy data

`ggplot` requires data to be tidy, with observations in rows and variables grouped in *key* | *value* columns.

Person	treatmentA	treatmentB
John Smith		2
Jane Doe	16	11

Person	treatment	result
John Smith	a	
Jane Doe	a	16
John Smith	b	2
Jane Doe	b	11

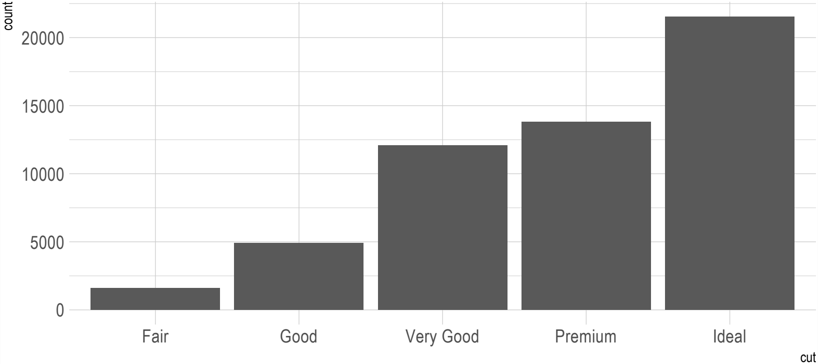
Plotting Distributions

Variation

- Variation is the difference between expected output to observed output.
- Visualization of the distribution is different for categorical (`fctr`, `chr`) and continuous (`dbl`, `int`, `dttm`) variables

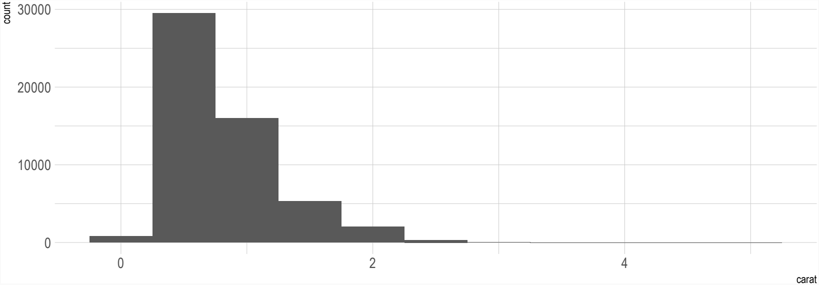
Distributions of categorical data

```
ggplot(data=diamonds) +
  geom_bar(mapping = aes(x = cut))
```



Distributions of continuous data

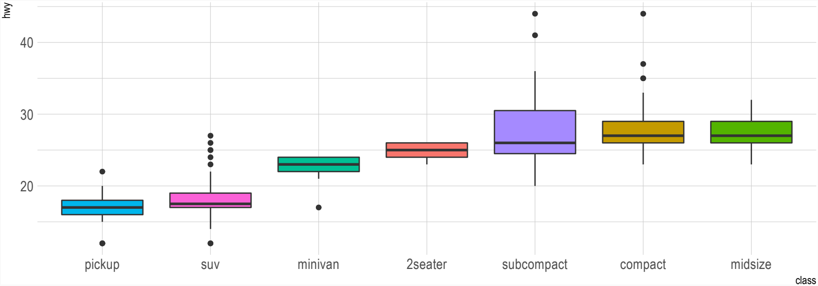
```
ggplot(data=diamonds) +
  geom_histogram(mapping = aes(x = carat),
                 binwidth = 0.5)
```



Boxplot

We can use geom_boxplot() to plot covariation between continuous and catagorical variables

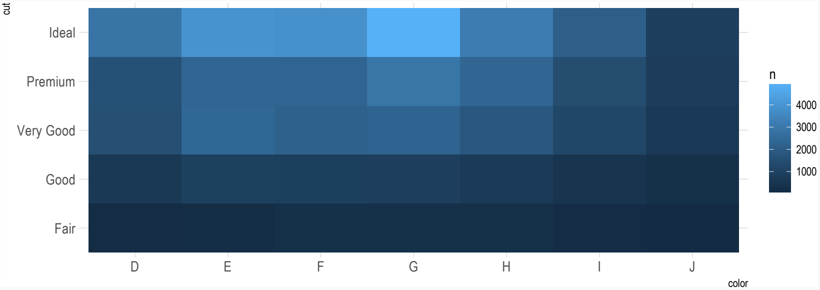
```
ggplot(data = mpg, aes(x = class, y = hwy, fill = class)) +
  geom_boxplot(aes(x=reorder(class, hwy,FUN = median),
                   y = hwy)) +
  theme(legend.position = "none")
```



Tile Plot

We can use `geom_tile` to plot the covariation between two categorical variables

```
diamonds %>%
  count(color, cut) %>%
  ggplot(mapping = aes(x = color, y = cut)) +
    geom_tile(mapping = aes(fill = n))
```



Scatter Plots

The easiest way to visualize the covariation between two continuous variables is to draw a scatterplot with `geom_point()`.

```
p <- ggplot(data=gapminder, mapping = aes(x = gdpPercap,
                                          y = lifeExp)) +
  geom_point() +
  scale_x_log10(labels = scales::dollar) +
  labs(x = "GDP Per Capita",
       y = "Life Expectancy in Years",
       title = "Economic Growth and Life Expectancy",
       subtitle = "Data points are country-years",
       caption = "Source: Gapminder.")
```

Scatter Plots

Presenting model-based graphics

Goals

1. Show how `ggplot` can use various modeling techniques directly within geoms
2. Tidily extract and plot estimates of models that we fit ourselves

OLS vs. Robust Regression

- The geom_smooth() function can take a range of method arguments to fit LOESS, OLS, and robust regression lines
- geom_smooth() can also be instructed to use different formulas to produce their fits

```
p_ols <- p + geom_smooth(color = "tomato", fill="tomato",
                         method = MASS::rlm) +
  geom_smooth(color = "steelblue", fill="steelblue",
              method = "lm")
```

OLS vs. Robust Regression

Polynominal fit

```r
p_poly <- p + geom_smooth(color = "tomato",
                          method = "lm", size = 1.2,
                formula = y ~ splines::bs(x, 3),
                se = FALSE)
```

Polynominal fit

Plot Model Output

- Figures based on statistical models face all the ordinary challenges of effective data visualization
- The more complex the model,a the trickier it becomes to convey this information effectively

Another Look at the Gapminder Data

```
## # A tibble: 1,704 x 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.
## # ... with 1,694 more rows
```

Linear Model of Life Expectancy

```r
out <- lm(formula = lifeExp ~ gdpPercap + pop +
            continent, data = gapminder)
summary(out)
```

```
##
## Call:
## lm(formula = lifeExp ~ gdpPercap + pop + continent, data = gapminder
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -49.161  -4.486   0.297   5.110  25.175
##
## Coefficients:
##                       Estimate Std. Error t value Pr(>|t|)
## (Intercept)          4.781e+01  3.395e-01 140.819  < 2e-16 ***
## gdpPercap            4.495e-04  2.346e-05  19.158  < 2e-16 ***
## pop                  6.570e-09  1.975e-09   3.326 0.000901 ***
## continentAmericas    1.348e+01  6.000e-01  22.458  < 2e-16 ***
```

Present your findings in substantive terms

- Show results in context where other variables are held at sensible values (e.g. mean or median)
- For continuous variables, generate predicted values that cover some meaningful range of the distribution (e.g. 25th to the 75th percentile)
- For unordered categorical variables, predicted values might be presented with respect to the modal category
- Use a scale that readers can easily understand, e.g. use predicted probabilities if your model reports log-odds
- Show confidence intervals and measures of model fit when you present your results

Tidy Data

- we can use the `tidy` function from the `broom` packages to turn our model object into a data frame that we can plot with `ggplot`

```
out_tidy <- tidy(out, conf.int = TRUE)
```

Export Tables to Word

To export tables to Word, follow these general steps:

1. Create a table or data.frame in R.
2. Write this table to a comma-separated .txt file using write.table().
3. Copy and paste the content of the .txt file into Word.
4. In Word,
   - select the text you just pasted from the .txt file
   - go to Table → Convert → Convert Text to Table...
   - make sure "Commas" is selected under "Separate text at", click OK

Export Tables to Word

```
write.table(out_tidy, file = "model_out.txt",
            sep = ";", quote = FALSE,
            row.names = FALSE)
```

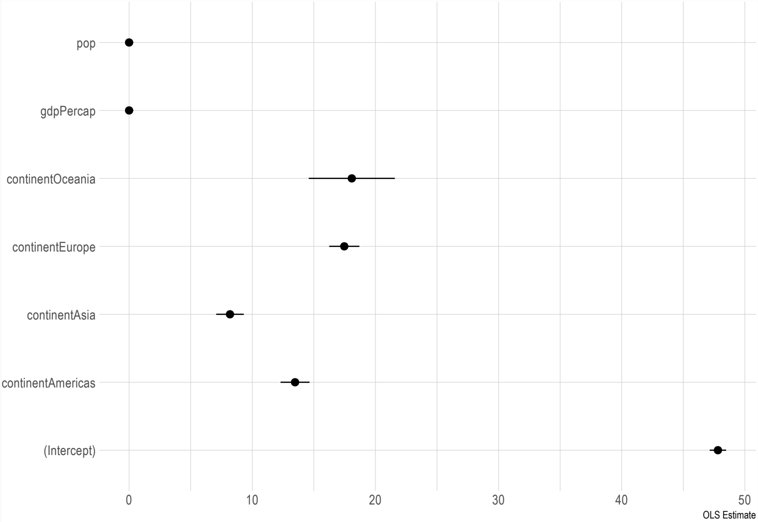
Export with Stargazer

```r
stargazer(out, align = TRUE) # Latex
stargazer(out, type = "text", align = TRUE) # Word
```

Coefficient Plot

```r
p <- ggplot(out_tidy, mapping = aes(x = term,
                                    y = estimate,
                                    ymin = conf.low,
                                    ymax = conf.high)) +
  geom_pointrange() +
  coord_flip() +
  labs(x="", y="OLS Estimate")
```

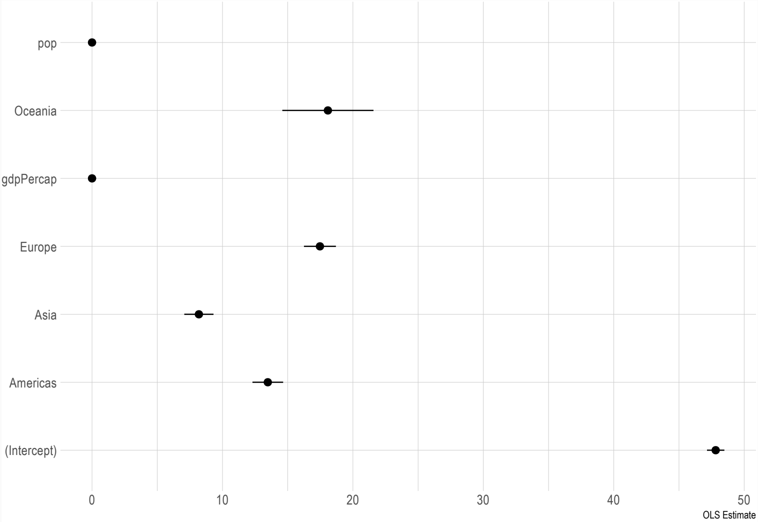
Coefficient Plot



Coefficient Plot even better

```r
out_tidy <- out_tidy %>%
  mutate(term = gsub("continent", "", term))
p <- ggplot(out_tidy, mapping = aes(x = term,
                                    y = estimate,
                                    ymin = conf.low,
                                    ymax = conf.high)) +
  geom_pointrange() +
  coord_flip() +
  labs(x="", y="OLS Estimate")
```

Coefficient Plot even better



Predictions

- Use predictions to get a picture of the estimates your model produces over the range of some particular variable, holding other covariates constant at some sensible values
- For example, predict `gdpPercap` from minimum to maximum, holding `pop` constant at its median and letting `continent` take all of its five available values

Prepare Data For Predictions

```
min_gdp <- min(gapminder$gdpPercap)
max_gdp <- max(gapminder$gdpPercap)
med_pop <- median(gapminder$pop)

pred_df <- expand.grid(gdpPercap =
                         (seq(from = min_gdp,
                              to = max_gdp,
                              length.out = 100)),
                       pop = med_pop,
                       continent = c("Africa",
                                     "Americas",
                                     "Asia", "Europe",
                                     "Oceania"))
```

Generate Predictions

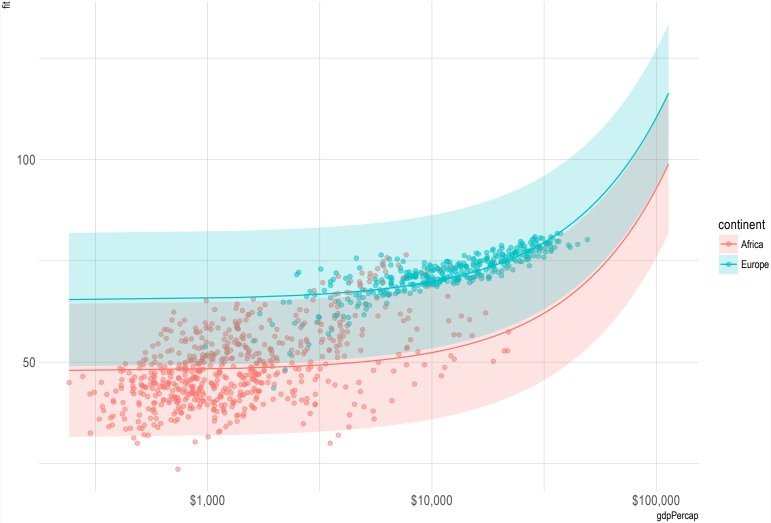
- we can use `predict()` withmour new data and model to calculate the fitted values for every row in the data frame and merge the results with `pred_df`

```
pred_out <- predict(object = out,
                    newdata = pred_df,
                    interval = "predict") # 95% CI
pred_full <- cbind(pred_df, pred_out)
```

Plot Predictions For Europe and Africa

```
p <- ggplot(data = subset(pred_full,
                          continent %in% c("Europe", "Africa")),
            aes(x = gdpPercap, y = fit, ymin = lwr,
                ymax = upr,
                color = continent, fill = continent,
                group = continent)) +
  geom_point(data = subset(gapminder,
                           continent %in% c("Europe", "Africa")),
             aes(x = gdpPercap, y = lifeExp,
                 color = continent),
             alpha = 0.5,
             inherit.aes = FALSE) +
    geom_line() +
    geom_ribbon(alpha = 0.2, color = FALSE) +
    scale_x_log10(labels = scales::dollar)
```

Plot Predictions For Europe and Africa



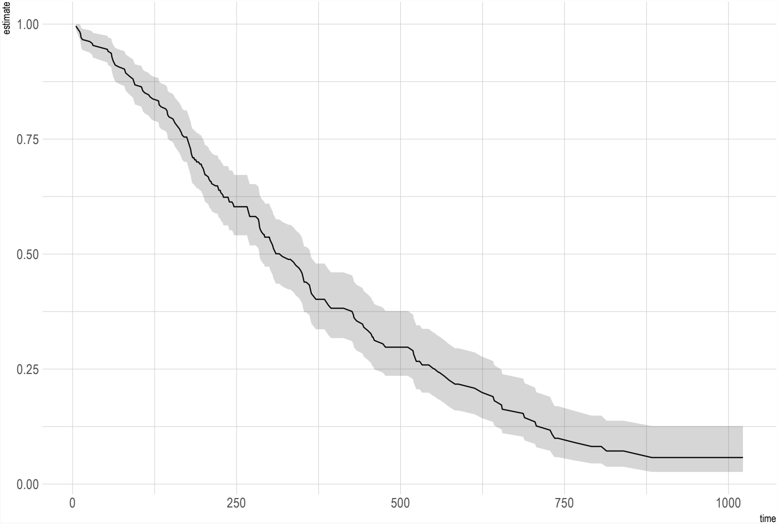
Tidy Results from a Survival Model

```
out_cph <- coxph(Surv(time, status) ~ age + sex,
                 data = lung)
out_surv <- survfit(out_cph)
out_tidy <- tidy(out_surv)
```

Plot Survival Model Output

```r
p <- ggplot(data = out_tidy,
            mapping = aes(time, estimate)) +
  geom_line() +
  geom_ribbon(mapping = aes(ymin = conf.low,
                             ymax = conf.high),
              alpha = .2)
```

Plot Survival Model Output



Generate Marginal Effects

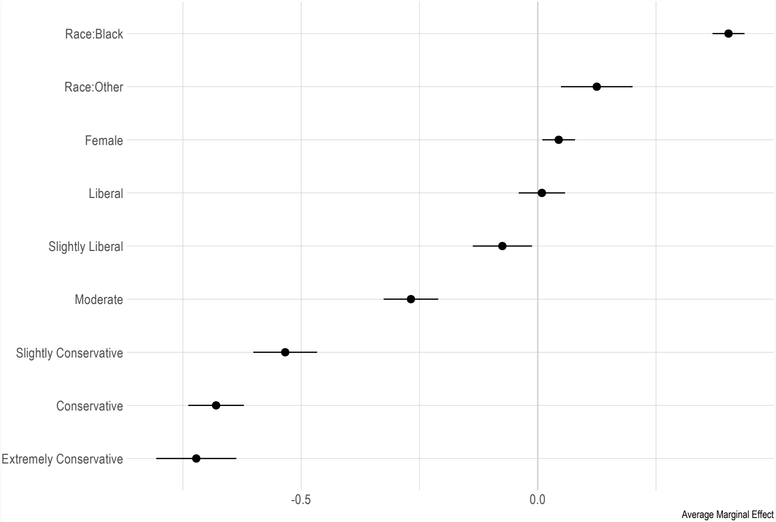
- Using the General Social Survey data let's fit a logistic regression on `obama`, with `age`, `polviews`, `race`, and `sex` as predictors.

```
load("gss.RData")
gss_sm$polviews_m <- relevel(gss_sm$polviews,
                             ref = "Moderate")
out_bo <- glm(obama ~ polviews + sex*race,
              family = "binomial", data = gss_sm)
bo_m <- margins(out_bo)
bo_gg <- as.tibble(summary(bo_m)) %>%
  mutate(factor = gsub("polviews|sex", "", factor)) %>%
  mutate(factor = gsub("race", "Race:", factor))
```

Plot Marginal Effects

```
p <- ggplot(data = bo_gg, aes(x = reorder(factor, AME),
                              y = AME, ymin = lower,
                              ymax = upper)) +
  geom_hline(yintercept = 0, color = "gray80") +
  geom_pointrange() + coord_flip() +
  labs(x = NULL, y = "Average Marginal Effect")
```

Plot Marginal Effects



Need Help

ggplot Cheat Sheet

That's it. Thank you for your attention.