MPP-E1180 Lecture 9: Automatic Tables and Static Visualisation

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Objectives for the week

- Assignment 3
- Review
- Static results presentation
  - Automatic table creation
  - Plotting best practices
  - ggplot2 for general graphing
  - Zelig simulations for showing results

Assignment 3

Purpose: Gather, clean, and analyse data

Deadline: 14 November 2014

You will submit a GitHub repo that:

- Gathers web-based data from at least **two sources**. Cleans and merges the data so that it is ready for statistical analyses.
- Conducts basic descriptive and inferential statistics with the data to address a relevant research question.
- Briefly describes the results including with dynamically generated tables and figures.
- Has a write up of 1,500 words maximum that describes the data gathering and analysis and uses literate programming.

Assignment 3

Note: I will be traveling/at a conference/not able to check my email much on the **13th** and **14th**.

So try to ask all of your **questions by the 12th (Wednesday)**.

I will have **normal office hours** on Wednesday.

Review

- How do you find a function's help file?
- What is the basic R syntax for a regression model?
- What is a model function?
- How do you find a 95% confidence interval for a parameter point estimate (both mathematically and in R)?
- What is one good way to interpret and present results from a logistic regression to both an statistical and general audience?

Motivation

Today we will learn how to **communicate your research findings** with automatically generated tables and static plots.

Why automatically generate?

- **Saves time**: don't have to re-enter numbers by hand into a table or restyle a graph each time you change the data/analysis.
- Easier to **find and correct errors**: all source code that created all tables and figures is linked and output updated when corrections are made.
- **More reproducible**: everything is clearly linked together.

General process

In general include the functions to create the tables/figures in a code chunk.

Include in the **code chunk head** `echo=FALSE, warning=FALSE, error=FALSE, message=FALSE`.

You may need to also include `results='asis` for some table functions.

See previous weeks 4 and 5 for figure code chunk options.

Automatic table generation

There are a number of tools for automatically generating tables in R/R Markdown.

- `kable` in the knitr package
- xtable package
- texreg package
- stargazer package

Today

We will focus on `kable` and `stargazer`.

- `kable` is a good, **simple** tool for creating tables from **data frames** (or matrices).
- `stargazer` is useful for creating more complex tables of **regression model output**.

Example Docs:
HertieDataScience2014/Examples/PaperWithRegressionTables

kable example: predicted probabilities

Set up from Lecture 8:

```r
# Load data
URL <- 'http://www.ats.ucla.edu/stat/data/binary.csv'
Admission <- read.csv(URL)

# Estimate model
Logit1 <- glm(admit ~ gre + gpa + as.factor(rank),
              data = Admission, family = 'binomial')

# Create fitted data
fitted <- with(Admission,
               data.frame(gre = mean(gre),
                          gpa = mean(gpa),
                          rank = factor(1:4)))
```

kable example: predicted probabilities

```
library(knitr)
fitted$predicted <- predict(Logit1, newdata = fitted,
                            type = 'response')
kable(fitted)
```

gre	gpa	rank	predicted
587.7	3.3899	1	0.5166016
587.7	3.3899	2	0.3522846
587.7	3.3899	3	0.2186120
587.7	3.3899	4	0.1846684

kable example: predicted probabilities

You can stylise the table.

```
kable(fitted, align = 'c', digits = 2,
      caption = 'Predicted Probabilities for Fitted Values
```

Table 2: Predicted Probabilities for Fitted Values

gre	gpa	rank	predicted
587.7	3.39	1	0.52
587.7	3.39	2	0.35
587.7	3.39	3	0.22
587.7	3.39	4	0.18

Note

Don't showing more digits to the right of the decimal than are statistically and substantively meaningful.

A rule of thumb: more than one or two digits are rarely meaningful.

See also: `http://andrewgelman.com/2012/07/02/moving-beyond-hopeless-graphics/`

Show regression output with `stargazer`

`kable` is limited if we want to create regression output tables, especially for multiple models.

`stargazer` is good for this.

stargazer example

Estimate models

```
L1 <- glm(admit ~ gre,
              data = Admission, family = 'binomial')

L2 <- glm(admit ~ gre + gpa,
              data = Admission, family = 'binomial')

L3 <- glm(admit ~ gre + gpa + as.factor(rank),
              data = Admission, family = 'binomial')
```

stargazer example HTML

When you are creating a table for an HTML doc with stargazer use:

- type = 'html'

```
# Create cleaner covariate labels
labels <- c('(Intercept)', 'GRE Score', 'GPA Score',
            '2nd Ranked School', '3rd Ranked School',
            '4th Ranked School')

stargazer::stargazer(L1, L2, L3, covariate.labels = labels,
    title = 'Logistic Regression Estimates of Grad School A
    digits = 2, type = 'html')
```

`stargazer` example HTML

stargazer example PDF

When you are creating a PDF use the arguments:

- `type = 'latex'`
- `header = FALSE`

```
# Create cleaner covariate labels
labels <- c('(Intercept)', 'GRE Score', 'GPA Score',
            '2nd Ranked School', '3rd Ranked School',
            '4th Ranked School')

stargazer::stargazer(L1, L2, L3, covariate.labels = labels,
    title = 'Logistic Regression Estimates of Grad School A
    digits = 2, type = 'latex', header = FALSE)
```

`stargazer` output in PDF

Showing Results with Figures

Tables are **are important** to include so that readers can **explore details**, but are **usually not the best way** to show your results.

Figures are often more effective.

General principles

(A Selection of) Tufte's Principles for Excellent Statistical Graphics (2001, 13):

- Show the data
- Encourage the eye to compare **differences** in the data
- Serve a clear purpose
- Avoid distorting the data
- Be closely integrated with the text

Show the data

Show the data, not other things like silly graphics or unnecessary words.

Have a high **data ink** ratio.

$$\text{Data Ink Ratio} = \frac{\text{data} - \text{ink}}{\text{total ink}}$$

Encourage the eye to compare differences

How did the budgets change? (Orange is 2013, Blue is 2012)

A little better

Even better

Avoid distorting the data: special case circles

In general: Avoid using the **size** of a circle to mean something!

So, avoid:

- bubble charts
- pie charts

Why avoid circles?

Circles can distort data.

- It is difficult to compare their size.
- The Ebbinghause Illusion!

Order the circles from smallest to largest.

The circles are on a scale of 0-100, so what are their values?

Order the circles from smallest to largest.

The circles are on a scale of 0-100, so what are their values?

Ebbinghause Illusion

Which circle is bigger?

Colours and Data Distortions

Which square is darkest?

Colour Principles

Only give graphical features (e.g. bars in a bar chart) different colours if it **means something** in the data.

Colour Principles

Colours should be used to:

- highlight particular data,
- group items,
- encode quantitative values
  - Values of continuous variables should be represented using **increasing hues of the same colour**.
  - Categorical variables should be represented with **different colours**. (rule of thumb: avoid using more than about 7 colours in a plot)

Bad

Good

Colours and accessibility

Color Blindness

People who are colour blind can have difficulty distinguishing between **red-green** and **blue-yellow**.

About 5-8% of men are colour blind.

We need to choose colour schemes for our graphics that are **colour blind friendly**.

For more information see `http://www.usability.gov/get-involved/blog/2010/02/color-blindness.html`.

Selecting colors

Color Brewer is a great resource for selecting colours: `http://colorbrewer2.org/`.

A more systematic introduction to ggplot2

"gg" means "Grammar of Graphics".

"2" just means that it is the second one.

ggplot2 syntax

Each plot is made of **layers**. Layers include the coordinate system (x-y), points, labels, etc.

Each layer has **aesthetics** (`aes`) including the x & y, size, shape, and colour.

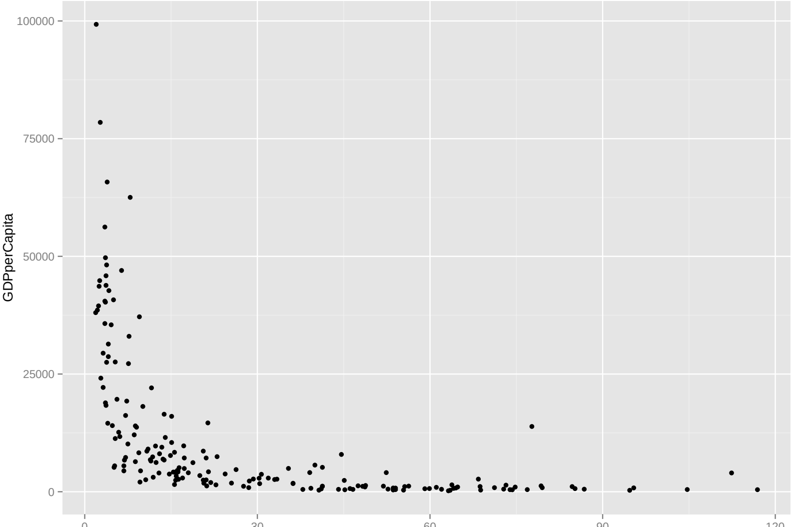
The **main layer types** are called **geometrics** (`geom`). These include lines, points, density plots, bars, and text.

ggplot2 examples setup

```
library(devtools)
library(ggplot2)

source_url("http://bit.ly/OTWEGS")

# Create data with no missing values of infant mortality
InfantNoMiss <- subset(MortalityGDP,
                       !is.na(InfantMortality))

# Create High/Low Income Variable
InfantNoMiss$DumMort[InfantNoMiss$InfantMortality
                    >= 15] <- "high"
InfantNoMiss$DumMort[InfantNoMiss$InfantMortality
                    < 15] <- "low"
```

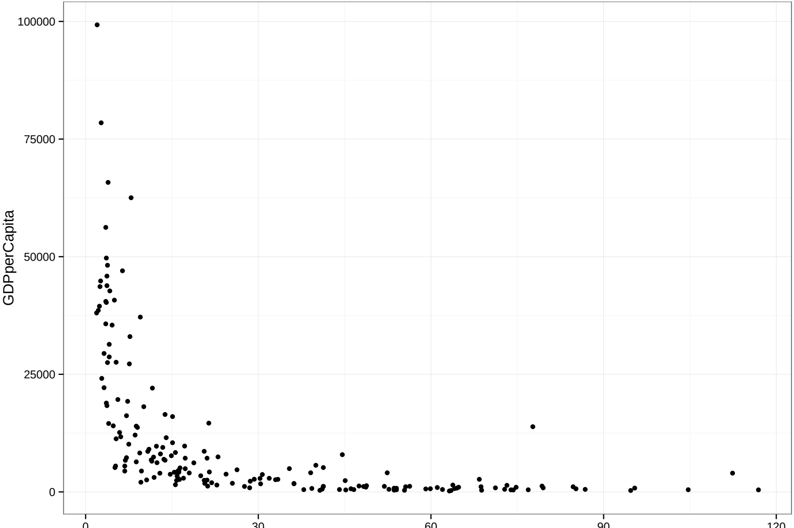
Simple example

```
ggplot(data = MortalityGDP, aes(x = InfantMortality,
       y = GDPperCapita)) + geom_point()
```



Simple example with BW theme

```
ggplot(data = MortalityGDP, aes(x = InfantMortality,
       y = GDPperCapita)) + geom_point() + theme_bw(base_s
```

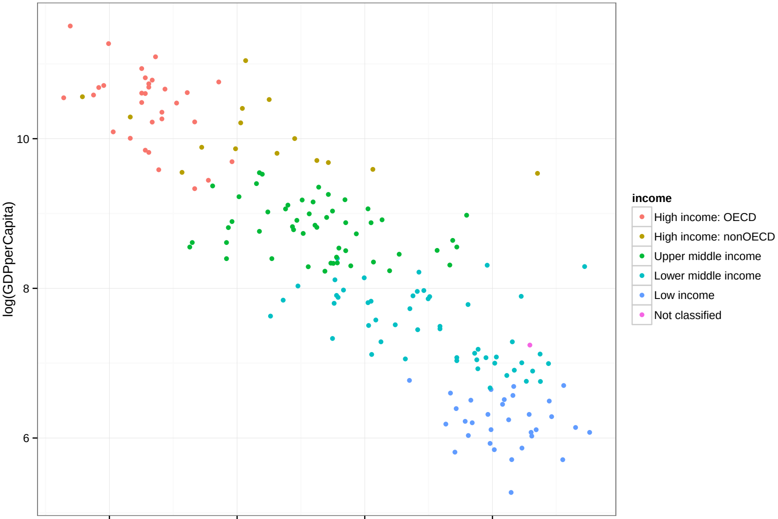


Colours

There are a number of ways to specify colours in ggplot2.

The simplest way is to let ggplot choose the colours for you.

```
ggplot(data = InfantNoMiss, aes(log(InfantMortality),
                                log(GDPperCapita))) +
    geom_point(aes(colour = income)) +
    theme_bw()
```



Selecting colours

There are many ways to pick specific colors.

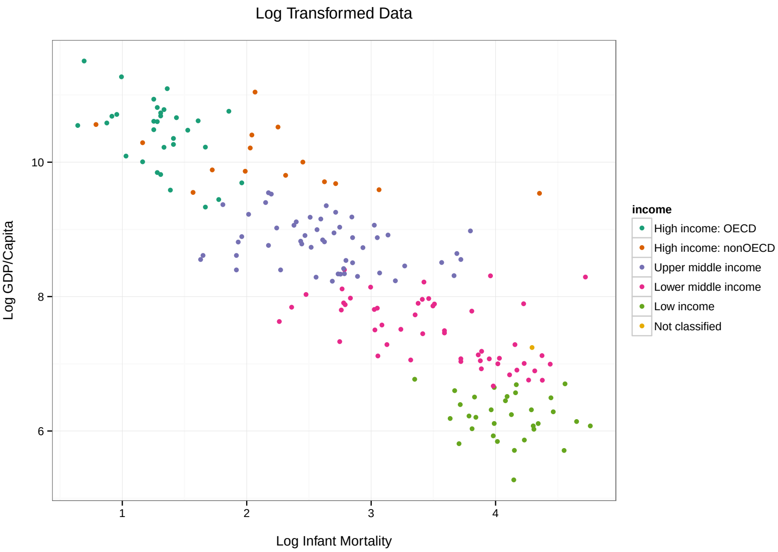
In this class we will mainly use **hexadecimal** colours.

This is probably the most commonly used system for choosing colours on the web.

Every colour is given six digits.

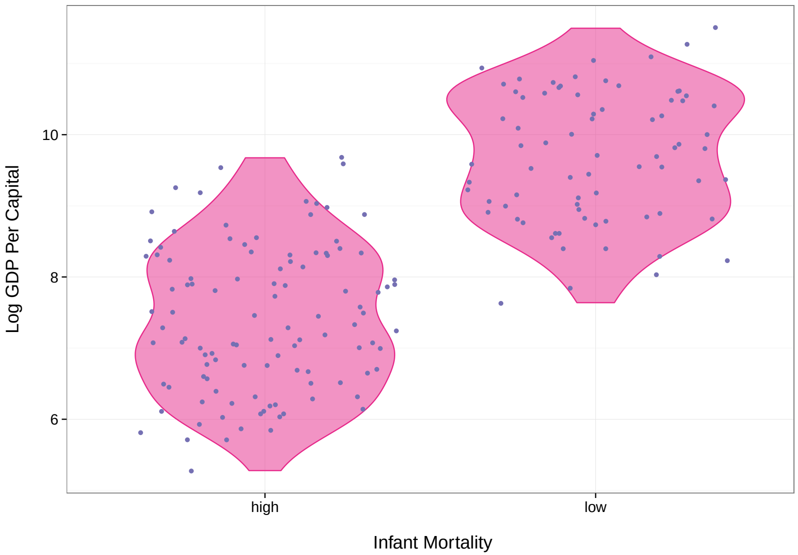
A good website for getting hexadecimal colour schemes is: `http://colorbrewer2.org/`.

```r
# Create colour vector
Colours <- c("#1B9E77", "#D95F02", "#7570B3",
             "#E7298A", "#66A61E", "#E6AB02")

# Create graph
ggplot(data = InfantNoMiss,
                  aes(log(InfantMortality),
                      log(GDPperCapita))) +
       geom_point(aes(colour = income)) +
       scale_color_manual(values = Colours) +
       xlab("\nLog Infant Mortality") +
       ylab("Log GDP/Capita\n") +
       ggtitle("Log Transformed Data\n") +
       theme_bw()
```


Log Transformed Data
Log GDP/Capita
10
8
6
1
2
3
4
Log Infant Mortality
income
High income: OECD
High income: nonOECD
Upper middle income
Lower middle income
Low income
Not classified

ggplot2 is very flexible

```
# Create a violin Plot
ggplot(InfantNoMiss, aes(factor(DumMort),
                        log(GDPperCapita))) +
        geom_violin(fill = "#E7298A",
                    colour = "#E7298A",
                    alpha = I(0.5)) +
        geom_jitter(color = "#7570B3") +
        xlab("\n Infant Mortality") +
        ylab("Log GDP Per Capital\n") +
        theme_bw(base_size = 16)
```


Log GDP Per Capital
10
8
6
high
low
Infant Mortality

Showing results from regression models

King, Tomz, and Wittenberg (2001) argue that **post estimation simulations** can be used to effectively communicate **results from regression models**.

Steps

1. Estimate our parameters' point estimates for $\hat{\beta}_{1 \ldots k}$.
2. Draw n values of the point estimates from multivariate normal distributions with means $\bar{\beta}_{1 \ldots k}$ and variances specified by the parameters' estimated co-variance.
3. Use the simulated values to calculate quantities of interest (e.g. predicted probabilities).
4. Plot the simulated distribution using **visual weighting**.

Notes

Post-estimation simulations allow us to effectively communicate our estimates and the **uncertainty around them**.

This method is broadly similar to a fully Bayesian approach with Markov-Chain Monte Carlo or bootstrapping. Just differ on **how the parameters are drawn**.

Implementation

It is relatively easy to find the coefficient estimates from an estimated model with `coef`.

You can find the co-variance matrix with `vcov`.

Then draw the values from the multivariate normal distribution with `mvrnorm`.

Finally, calculate the quantity of interest with the draws + fitted values using and plot the results.

Easier Implementation

The Zelig package streamlines this process.

Zelig (1)

First estimate your regression model using `zelig`.

```
library(Zelig)

# Have to explicitly declare rank as factor
Admission$rank <- as.factor(Admission$rank)

Z1 <- zelig(admit ~ gre + gpa + rank, cite = FALSE,
              data = Admission, model = 'logit')
```

Zelig (2)

Then set the fitted values with `setx`.

```
setZ1 <- setx(Z1, gre = 220:800)
```

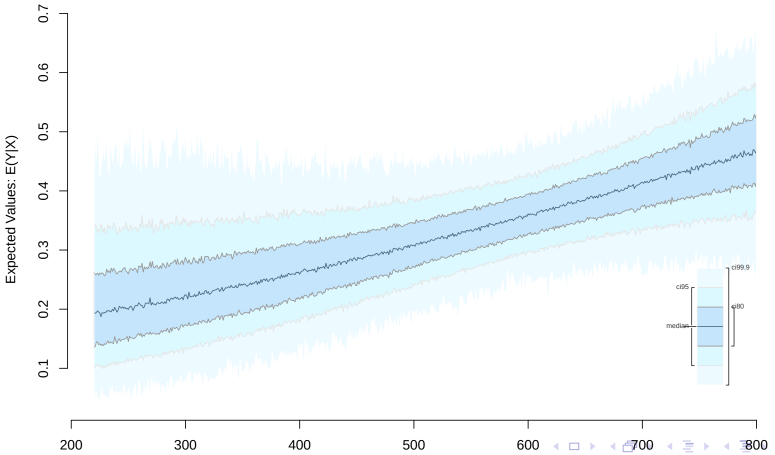
And run the simulations (1,000 by default) with `sim`.

```
simZ1 <- sim(Z1, x = setZ1)
```

Zelig (3)

Plot:

```r
plot(simZ1)
```



Seminar

Create descriptive and inferential visualisations for your Assignment 3 using the techniques covered in class today.

References

King, Gary, Micheal Tomz, and Jason Wittenberg. 2001. "Making the Most of Statistical Analyses: Improving Interpretation and Presentation." *American Journal of Political Science* 22 (4): 341–255.

Tufte, Edward R. 2001. *The Visual Display of Quantitative Information*. 2nd ed. Cheshire, CT: Graphics Press.