MPP-E1180 Lecture 9: Automatic Tables and Static Visualisation

Christopher Gandrud

21 March 2016

Objectives for the week

- Assignment 3/Final Project
- Review
- Static results presentation
  - Automatic table creation
  - Plotting best practices
  - ggplot2 for general graphing
  - Simulations for showing results

Assignment 3

Purpose: Gather, clean, and analyse data
Deadline: 15 April 2016 (note change!)
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.

Collaborative Research Project (1)

Purposes: Pose an interesting research question and try to answer it using data analysis and standard academic practices. Effectively communicate your results to a **variety of audiences** in a **variety of formats**.

Deadline:

- Presentation: In-class Monday 2 May
- Website/Paper: 13 May 2016

Collaborative Research Project (2)

The project can be thought of as a ‘dry run’ for your thesis with multiple presentation outputs.

Presentation: 10 minutes **maximum**. **Engagingly** present your research question and key findings to a general academic audience (fellow students).

Paper: 5,000 words maximum. **Standard academic paper**, properly cited laying out your research question, literature review, data, methods, and findings.

Website: An engaging website designed to convey your research to **a general audience**.

Collaborative Research Project (3)

As always, you should **submit one GitHub repository** with all of the materials needed to **completely reproduce** your data gathering, analysis, and presentation documents.

Note: Because you've had two assignments already to work on parts of the project, I expect **high quality work**.

Collaborative Research Project (3)

Find one other group to be a **discussant** for your presentation.
The discussants will provide a quick (max 2 minute) critique of your presentation–ideas for things you can improve on your paper.

Office hours

I will have normal office hours every week for the rest of the term **except 4 April**.

Please take advantages of this opportunity to **improve your final project**.

Review

- What is the basic R syntax for a regression model?
- What is a model function? What two parts do GLM model functions have?
- 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 a 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:
HertieDataScience/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

```r
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('GRE Score', 'GPA Score',
            '2nd Ranked School', '3rd Ranked School',
            '4th Ranked School', '(Intercept)')

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('GRE Score', 'GPA Score',
            '2nd Ranked School', '3rd Ranked School',
            '4th Ranked School', '(Intercept)')

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

stargazer plain text output

You may want to compare multiple models at once in your R console, use stargazer with type = 'text':

```
stargazer(L1, L2, L3, type = 'text')
```

Showing Results with Figures

Tables **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?

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

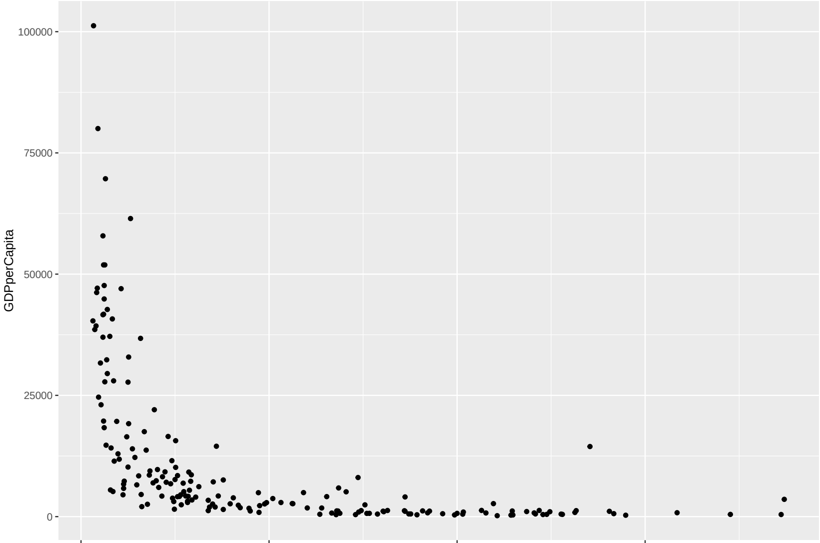
Each plot is made of **layers**. Layers include the coordinate system (x-y), points, labels, etc.
Each layer has **aesthetics** (`aes`) including the x & y, size, shape, and colour.
The **main layer types** are called **geometrics** (`geom`). These include lines, points, density plots, bars, and text.

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"
```

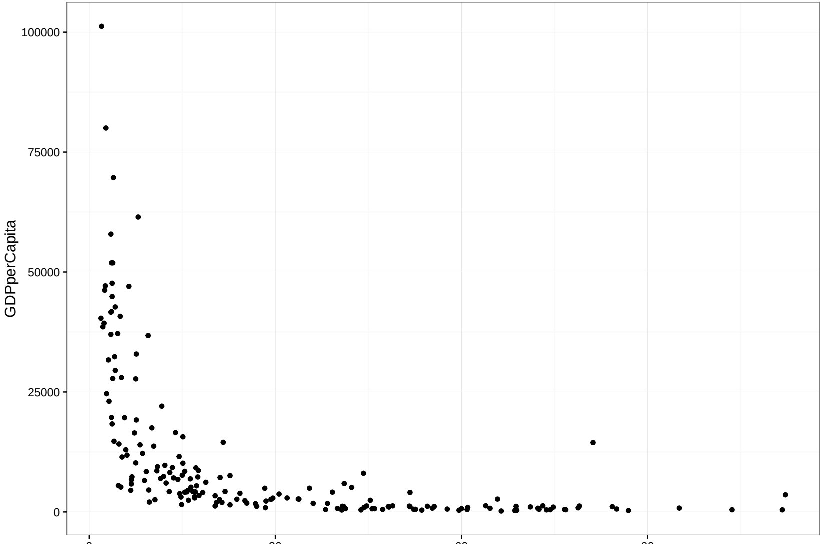
Simple example

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



Simple example with BW theme

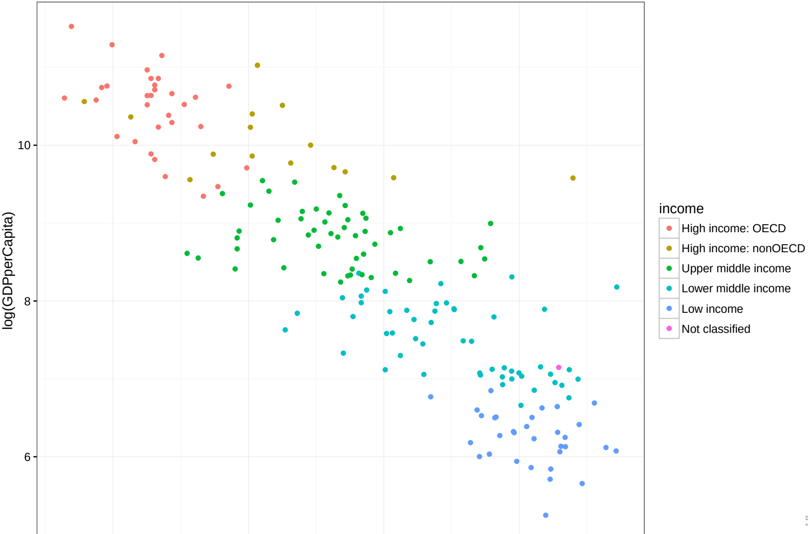
```
ggplot(data = MortalityGDP, aes(x = InfantMortality,
       y = GDPperCapita)) + geom_point() + theme_bw(base_s
```



Colours

There are a number of ways to specify colours in ggplot2.
The simplest way is to let ggplot choose the colours for you.

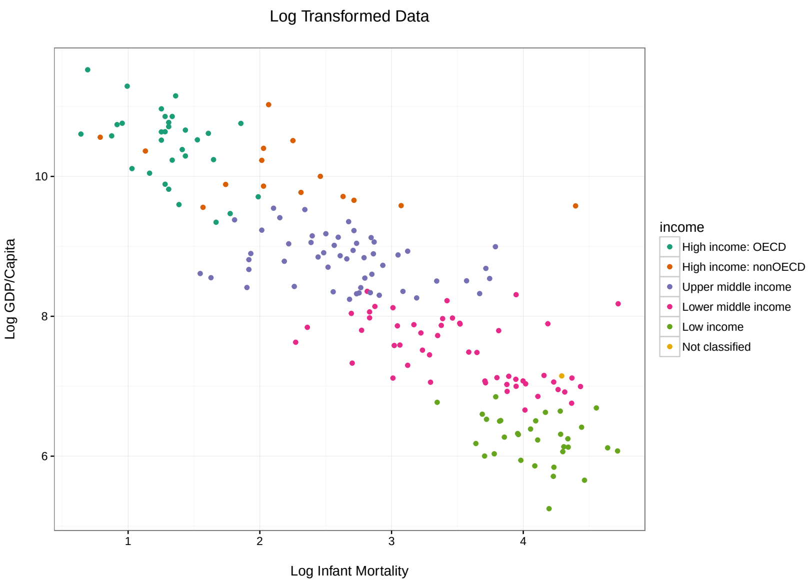
```r
ggplot(data = InfantNoMiss, aes(log(InfantMortality),
                                log(GDPperCapita))) +
    geom_point(aes(colour = income)) +
    theme_bw()
```



Selecting colours

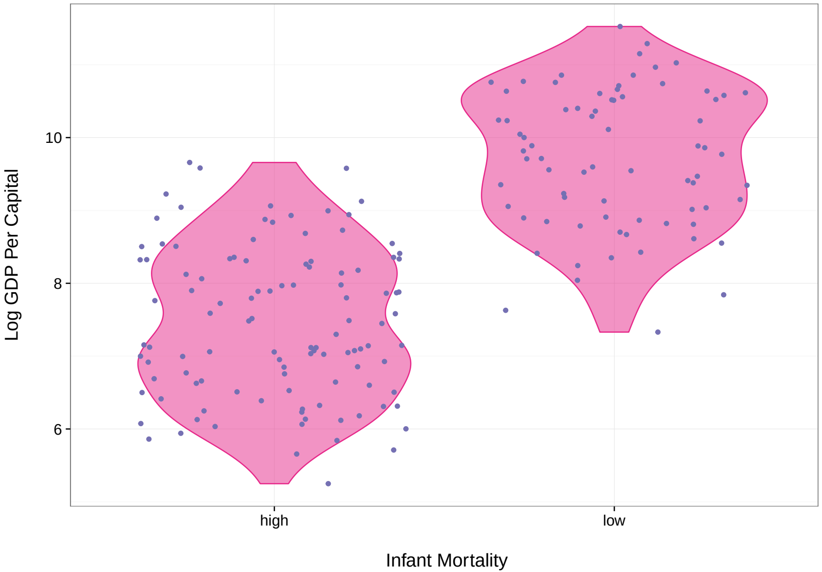
There are many ways to pick specific colors.
In this class we will mainly use **hexadecimal** colours.
This is probably the most commonly used system for choosing colours on the web.
Every colour is given six digits.
A good website for getting hexadecimal colour schemes is:
`http://colorbrewer2.org/`.

```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
Log Infant Mortality
10
8
6
1
2
3
4
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

1. Find the coefficient estimates from an estimated model with `coef`.
2. Find the co-variance matrix with `vcov`.
3. Draw point estimates from the multivariate normal distribution with `mvrnorm`.
4. Calculate the quantity of interest with the draws + fitted values using and plot the results.

Simulations: estimate model

First estimate your model as normal and create fitted values:

```
library(car) # Contains data
M_prest <- lm(prestige ~ education + type,
          data = Prestige)

# Find a range of education values
range(Prestige$education)
```

```
## [1]  6.38 15.97
```

```
edu_range <- 6:16
```

Simulations: extract estimates

Extract point estimates (coefficients) and co-variance matrix:

```
mp_coef <- matrix(coef(M_prest))
mp_vcov <- vcov(M_prest)
```

Now draw 1,000 simulations of your point estimates:

```
library(MASS) # contains the mvrnorm function
drawn <- mvrnorm(n = 1000, mu = mp_coef, Sigma = mp_vcov) %
            data.frame
head(drawn)[1:3, ]
```

```
##   X.Intercept. education  typeprof    typewc
## 1     1.086868  4.354257  6.222224 -9.924401
## 2   -15.620613  6.058029 -2.277837 -9.106983
## 3     1.184108  4.116103  9.412179 -4.955666
```

Simulations: merge in fitted values

Now we can add in our fitted values to the simulation data frame:

```
drawn_sim <- merge(drawn, edu_range)

# Rename the fitted value variable
drawn_sim <- dplyr::rename(drawn_sim, fitted_edu = y)

nrow(drawn)
```

```
## [1] 1000
```

```
nrow(drawn_sim)
```

```
## [1] 11000
```

Simulations: calculate quantity of interest

Using the normal linear regression formula ($\hat{y}_i = \hat{\alpha} + X_{i1}\hat{\beta}_1 + \ldots$) we can find the quantity of interest for white collar workers:

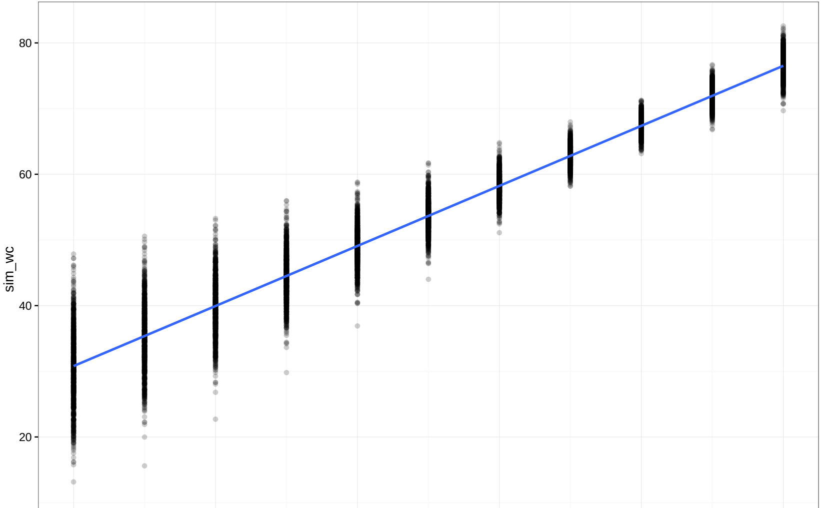
```
names(drawn_sim)
```

```
## [1] "X.Intercept." "education"    "typeprof"     "typewc
## [5] "fitted_edu"
```

```
drawn_sim$sim_wc <- drawn_sim[, 1] + drawn_sim[, 2] * drawn
                        drawn_sim[, 3]
```

Simulations: plot points

```
ggplot(drawn_sim, aes(fitted_edu, sim_wc)) +
        geom_point(alpha = 0.2) + stat_smooth(se = FALSE) -
        theme_bw()
```

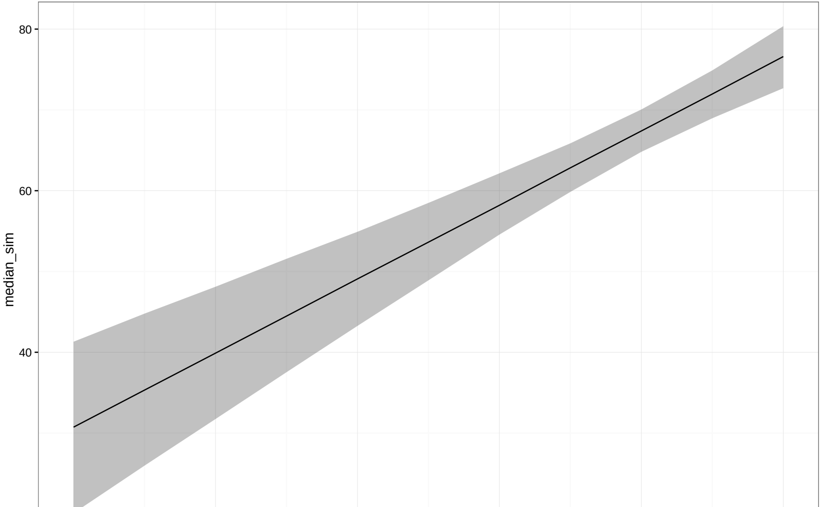


Simulations: find 95% central interval ribbons

```
# Find 95% central interval and median at each fitted valu
central <- drawn_sim %>% group_by(fitted_edu) %>%
           summarise(median_sim = median(sim_wc),
                     lower_95 = quantile(sim_wc, probs = (
                     upper_95 = quantile(sim_wc, probs = (
           )
```

Simulations: plot 95% central interval

```
ggplot(central, aes(fitted_edu, median_sim)) +
    geom_ribbon(aes(ymin = lower_95, ymax = upper_95), alph
    geom_line() + theme_bw()
```



Predictions from logistic regression

Use the same steps for simulating predicted outcomes from logistic regression models. The only difference is that the equation for the quantity of interest is:

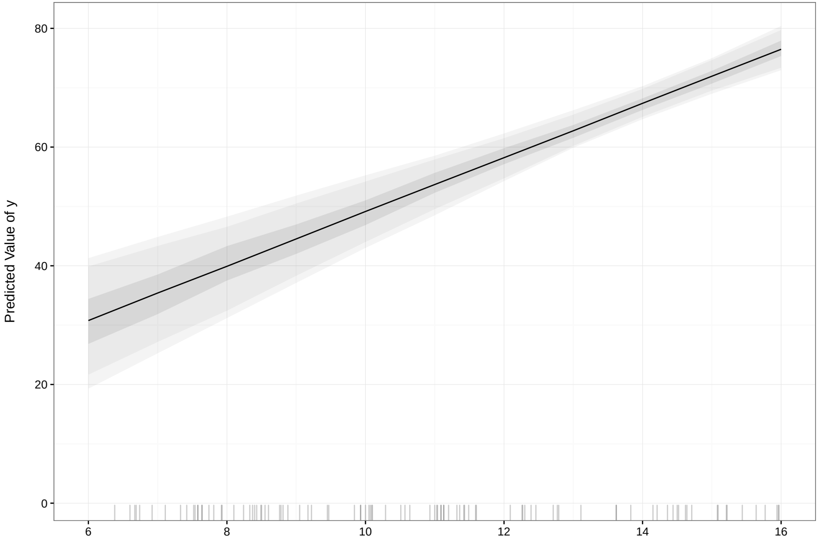
$$P(y_i = 1) = \frac{\exp(\hat{\alpha} + X_{i1}\hat{\beta}_1 + \ldots)}{1 - \exp(\hat{\alpha} + X_{i1}\hat{\beta}_1 + \ldots)}$$

Easier Implementation (1)

Last week I started working on the simGLM package for doing this process with normal linear and logistic regression models.

simGLM

```
fitted_edu <- expand.grid(education = edu_range, typeprof =
simGLM::sim_glm(M_prest, newdata = fitted_edu, x_coef = 'ed
```



simGLM

simGLM is in development. Comments, bug reports welcome!
It can be downloaded with:

```
ghit::install_github('christophergandrud/simGLM')
```

For more examples see: `http://bit.ly/22oSUHW`

Easier Implementation (2)

The Zelig package also streamlines the simulation process.

Zelig (1)

First estimate your regression model using `zelig`.

```r
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)
```

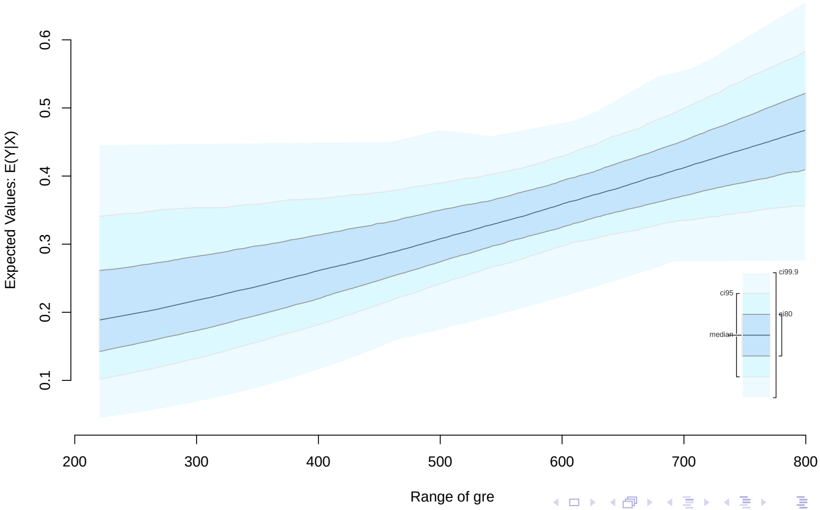
And run the simulations (1,000 by default) with `sim`.

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

Zelig (3)

Plot:

```
ci.plot(simZ1)
```



Seminar

Create **tables** and **visualisations** of **descriptive** and **inferential** for your Assignment 3 in an R Markdown document using the techniques covered in class today.

If you don't have your data set fully cleaned yet, use one of the built-in R data sets for practice.

Bonus help develop simGLM. Test out the examples on the README, suggest other model types to simulate quantities of interest for, and more.

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.