

# CSSS 510: Lab 3

## Logistic Regression

2017-10-13

### 0. Agenda

1. Deriving a likelihood function for the logistic regression model
2. Fitting a logit model using `optim()` and `glm()`
3. Simulating predicted values and confidence intervals
4. Simulating first differences

### 1. Deriving a likelihood function for the logistic regression model

Recall from lecture the logit model:

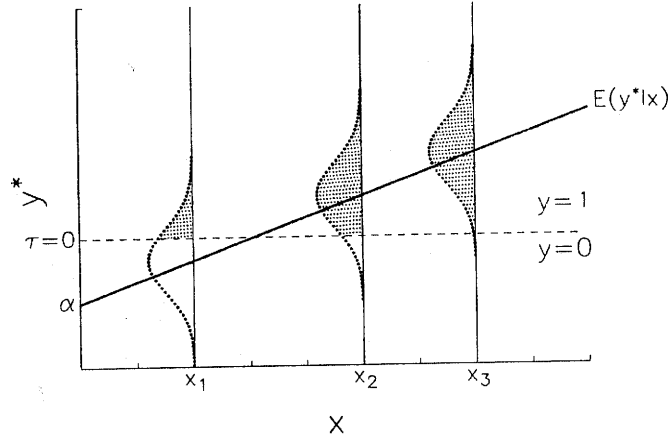
$$\begin{aligned}y_i &\sim \text{Bern}(\pi_i) \\ \pi_i &= \text{logit}^{-1}(\mathbf{x}_i\boldsymbol{\beta}) \\ \pi_i &= \frac{\exp(\mathbf{x}_i\boldsymbol{\beta})}{1 + \exp(\mathbf{x}_i\boldsymbol{\beta})} = \frac{1}{1 + \exp(-\mathbf{x}_i\boldsymbol{\beta})}\end{aligned}$$

In the simple case, this stems from the latent variable model:

$$y^* = \beta_0 + \beta_1 x + \epsilon$$

where the relationship between latent variable  $y^*$  and the explanatory variable  $x$  is modeled using simple linear regression, and the binary outcome  $y$  is a function of the sign of  $y^*$ :

$$y = \begin{cases} 1, & \text{if } y^* > 0 \\ 0, & \text{if } y^* \leq 0 \end{cases} \quad (1)$$



**Figure 3.2.** The Distribution of  $y^*$  Given  $x$  in the Binary Response Model

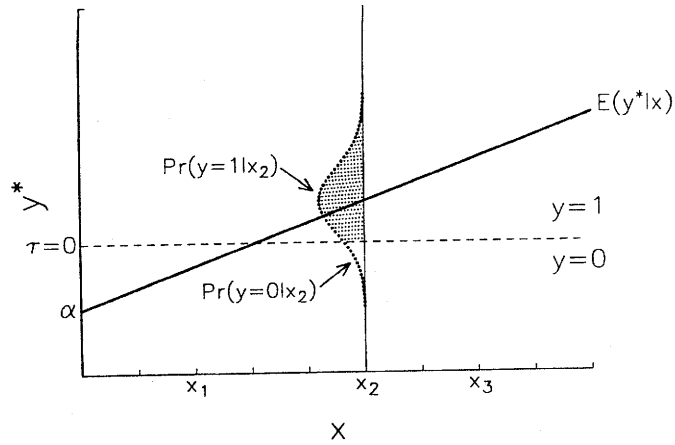
The logistic regression model is obtained if we assume the errors of this latent variable model follow a standard logistic distribution. Recall that the pdf and cdf of the standard logistic distribution are as follows:

$$f(t) = \frac{\exp(t)}{(1 + \exp(t))^2}$$

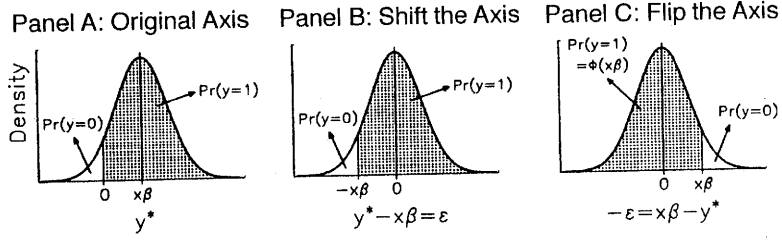
$$F(t) = \frac{\exp(t)}{1 + \exp(t)}$$

We therefore have the following:

$$\begin{aligned} \Pr(y = 1|x) &= \Pr(y^* > 0|x) \\ &= \Pr(\beta_0 + \beta_1 x + \epsilon > 0|x) \\ &= \Pr(\epsilon > -(\beta_0 + \beta_1 x)) \\ &= \Pr(\epsilon < \beta_0 + \beta_1 x) \\ &= F(\beta_0^L + \beta_1^L x) \end{aligned}$$



**Figure 3.4.** Probability of Observed Values in the Binary Response Model



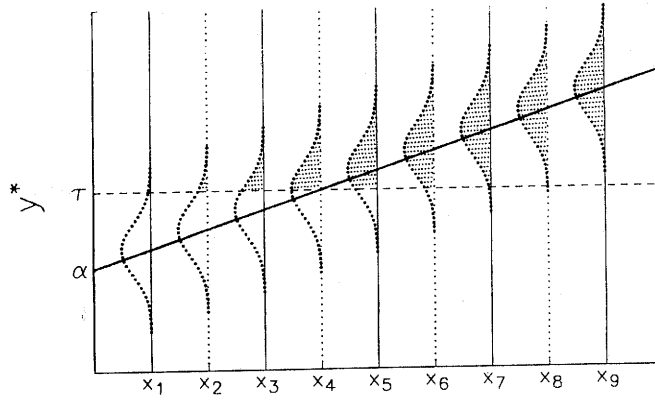
**Figure 3.5.** Computing  $\Pr(y = 1 | x)$  in the Binary Response Model

Since we assume the errors follow a standard logistic distribution, we have

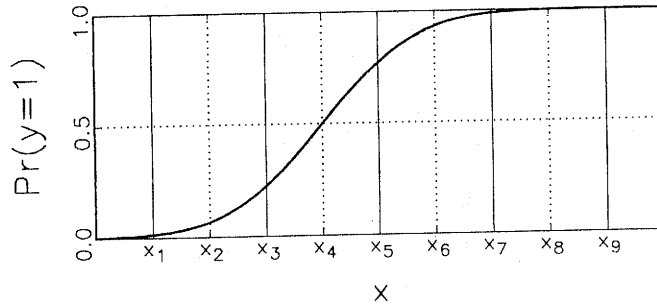
$$\Pr(y = 1|x) = F(\beta_0^L + \beta_1^L x) = \frac{\exp(\beta_0^L + \beta_1^L x)}{1 + \exp(\beta_0^L + \beta_1^L x)}$$

and  $E(\epsilon)=0$  and  $\text{Var}(\epsilon) = \frac{\pi^2}{3}$ .

Panel A: Plot of  $y^*$



Panel B: Plot of  $\Pr(y=1|x)$



**Figure 3.6.** Plot of  $y^*$  and  $\Pr(y = 1 | x)$  in the Binary Response Model

The logit function is the inverse of the logistic function:

$$\text{logit}(p) = \log \frac{p}{1-p}$$

or

$$\text{logit}^{-1}(p) = \frac{\exp(x)}{1 + \exp(x)}$$

We therefore have the following

$$\Pr(y = 1|x) = \text{logit}^{-1}(\beta_1^L + \beta_1^L x)$$

or

$$\text{logit}(\Pr(y = 1|x)) = \beta_1^L + \beta_1^L x$$

or

$$\log \frac{\Pr(y = 1|x)}{\Pr(y = 0|x)} = \beta_0^L + \beta_1^L x.$$

Recall from lecture that a Bernoulli distribution has the following pdf:

$$\Pr(y_i = 1|\pi_i) = \pi_i^{y_i} (1 - \pi_i)^{1-y_i}$$

And the likelihood function can be derived from the joint probability:

$$\begin{aligned}\mathcal{L}(\boldsymbol{\pi}|\mathbf{y}) &\propto \prod_{i=1}^n \pi_i^{y_i} (1 - \pi_i)^{1-y_i} \\ \mathcal{L}(\boldsymbol{\beta}|\mathbf{y}) &\propto \prod_{i=1}^n \left( \frac{1}{1 + \exp(-\mathbf{x}_i \boldsymbol{\beta})} \right)^{y_i} \left( 1 - \frac{1}{1 + \exp(-\mathbf{x}_i \boldsymbol{\beta})} \right)^{1-y_i} \\ \mathcal{L}(\boldsymbol{\beta}|\mathbf{y}) &\propto \prod_{i=1}^n (1 + \exp(-\mathbf{x}_i \boldsymbol{\beta}))^{-y_i} (1 + \exp(-\mathbf{x}_i \boldsymbol{\beta}))^{-(1-y_i)} \\ \log \mathcal{L}(\boldsymbol{\beta}|\mathbf{y}) &\propto \sum_{i=1}^n -y_i \log(1 + \exp(-\mathbf{x}_i \boldsymbol{\beta})) - (1 - y_i) \log(1 + \exp(\mathbf{x}_i \boldsymbol{\beta}))\end{aligned}$$

## 2. Fitting a logit model using `optim()` and `glm()`

```
rm(list = ls()) # clear up the memory

#install and load the packages needed
#from CRAN: install.packages("MASS", dependencies = TRUE)
library(MASS)
library(RColorBrewer)

#download simcf and tile packages from- http://faculty.washington.edu/cadolph/software
# don't unzip the archive (tar) file
library(simcf)
library(tile)
```

```
## Loading required package: grid
```

```

# Load data
file <- "nes00a.csv"
data <- read.csv(file, header=TRUE)

# attach(data)

# Estimate logit model using optim()
# Construct variables and model objects
y <- data$vote00
x <- cbind(data$age,data$hsdeg,data$coldeg)

# Likelihood function for logit
llk.logit <- function(param,y,x) {
  os <- rep(1,length(x[,1])) # constant
  x <- cbind(os,x) # constant+covariates
  b <- param[ 1 : ncol(x) ]
  # number of parameters to be estimated equals number of columns in x
  # (i.e, one for constant and one for each covariates : total 4)
  xb <- x%*%b
  sum( y*log(1+exp(-xb)) + (1-y)*log(1+exp(xb))) # log-likelihood function for logit model
  # (based on our choice of standard logistic cdf as the systematic component)
  # optim is a minimizer, so use -lnL here
}

# Fit logit model using optim
ls.result <- lm(y~x) # use ls estimates as starting values (for convenience)
stval <- ls.result$coefficients # initial guesses
logit.result.opt <- optim(stval,llk.logit,method="BFGS",hessian=T,y=y,x=x)
# call minimizer procedure or max by adding control=list(fnscale=-1)
pe.opt <- logit.result.opt$par # point estimates
vc.opt <- solve(logit.result.opt$hessian) # var-cov matrix
se.opt <- sqrt(diag(vc.opt)) # standard errors
ll.opt <- -logit.result.opt$value # likelihood at maximum

logit.optim<-data.frame(cbind(round(pe.opt,3), round(se.opt,3)))
rownames(logit.optim)<-c("intercept", "age", "highschool" , "college")
colnames(logit.optim)<-c("pe", "std.err")
logit.optim

##           pe std.err
## intercept -2.149  0.257
## age       0.031  0.003
## highschool 1.213  0.179
## college   1.102  0.130

#p-value based on t-statistics
2*pt(abs(logit.optim$pe/logit.optim$std.err), df=length(y)-length(pe.opt) , lower.tail = FALSE)

## [1] 1.229175e-16 2.393414e-24 1.668155e-11 4.780627e-17

# Estimate logit model using glm()

# Run logit & extract results using glm.
# GLM solves the likelihood equations with a common numeric algorithm
# called iteratively re-weighted least squares (IRWLS).

```

```
logit.result <- glm(vote00~age +hsdeg+coldeg, family=binomial, data=data)
# family "binomial" calls logit transformation (log(pi/1-pi)) as a "link function"
# corresponding to logistic distribution.
# Link function transforms pi so that it follows a linear model.
# (So although pi itself is dependent on covariates in a non-linear way,
# logit transformed pi is dependent on covariates in a linear way.)
```

```
summary(logit.result)
```

```
##
## Call:
## glm(formula = vote00 ~ age + hsdeg + coldeg, family = binomial,
##      data = data)
##
## Deviance Residuals:
##      Min       1Q   Median       3Q      Max
## -2.4487  -1.1347   0.6360   0.8973   1.8854
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept) -2.147997   0.256608  -8.371  < 2e-16 ***
## age          0.030885   0.003386   9.121  < 2e-16 ***
## hsdeg        1.212882   0.179447   6.759 1.39e-11 ***
## coldeg       1.102465   0.130426   8.453  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##      Null deviance: 2293.5  on 1782  degrees of freedom
## Residual deviance: 2076.0  on 1779  degrees of freedom
## AIC: 2084
##
## Number of Fisher Scoring iterations: 4
```

```
# now a new model adding age^2
```

```
model <- vote00 ~ age + I(age^2) + hsdeg + coldeg
```

```
mdata <- extractdata(model, data, na.rm=TRUE) # needs library(simcf)
```

```
logit.result <- glm(model, family=binomial, data=mdata)
```

```
summary(logit.result)
```

```
##
## Call:
## glm(formula = model, family = binomial, data = mdata)
##
## Deviance Residuals:
##      Min       1Q   Median       3Q      Max
## -2.2045  -1.1145   0.6335   0.8743   1.9841
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept) -3.0193891  0.4181899  -7.220 5.19e-13 ***
## age          0.0747252  0.0168440   4.436 9.15e-06 ***
```

```
## I(age^2)      -0.0004427  0.0001655  -2.674  0.00749 **
## hsdeg        1.1243908  0.1800069   6.246  4.20e-10 ***
## coldeg       1.0795702  0.1312113   8.228  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##      Null deviance: 2293.5  on 1782  degrees of freedom
## Residual deviance: 2069.0  on 1778  degrees of freedom
## AIC: 2079
##
## Number of Fisher Scoring iterations: 4

pe <- logit.result$coefficients # point estimates
vc <- vcov(logit.result)       # var-cov matrix

pe

##      (Intercept)          age      I(age^2)          hsdeg          coldeg
## -3.0193890720  0.0747251922 -0.0004427014  1.1243907749  1.0795702357
sqrt(diag(vc))

##      (Intercept)          age      I(age^2)          hsdeg          coldeg
## 0.4181899367 0.0168440337 0.0001655466 0.1800068893 0.1312113265
```

### 3. Simulating predicted values and confidence intervals

```
# Simulate parameter distributions
sims <- 10000
simbetas <- mvrnorm(sims, pe, vc) #needs library(MASS) # draw 10000 sets of simulated
# parameter (beta) estimates from a multivariate normal distribution with
# mean pe and variance-covariance vc

# Now let's plan counterfactuals: We will have three sets of counterfactuals based
# on education level (less than hs edu, hs edu, college or higher edu), and for each set
# we will make age varies between 18 years old and 97 years old.

# Set up counterfactuals: all ages, each of three educations
xhyp <- seq(18,97,1) # create age vector
nscen <- length(xhyp) # we will have total 80 different age scenarios for each education level

nohsScen <- hsScen <- collScen <- cfMake(model, mdata, nscen) #this is just to initialize
# 80 scenarios for each education level. As default, all covariate values are set at the mean.

# Create three sets of education counterfactuals

for (i in 1:nscen) {
  # No High school scenarios (loop over each age, total 80 scenarios)
  nohsScen <- cfChange(nohsScen, "age", x = xhyp[i], scen = i)
  nohsScen <- cfChange(nohsScen, "hsdeg", x = 0, scen = i) # no hs degree
```

```

nohsScen <- cfChange(nohsScen, "coldeg", x = 0, scen = i) # no college degree

# HS grad scenarios (loop over each age, total 80 scenarios)
hsScen <- cfChange(hsScen, "age", x = xhyp[i], scen = i)
hsScen <- cfChange(hsScen, "hsdeg", x = 1, scen = i) # has hs degree
hsScen <- cfChange(hsScen, "coldeg", x = 0, scen = i) # no college degree

# College grad scenarios (loop over each age, total 80 scenarios)
collScen <- cfChange(collScen, "age", x = xhyp[i], scen = i)
collScen <- cfChange(collScen, "hsdeg", x = 1, scen = i) # has hs degree
collScen <- cfChange(collScen, "coldeg", x = 1, scen = i) # has college degree
}

# # Now given the counterfactual covariates (nohsScen/hsScen/collScen) and simulated
# parameters (simbetas), we can calculate expected value of the response.
# In this case, expected probability of voting!

head(nohsScen$x) #we will fit the counterfactual data

##      vote00 age hsdeg coldeg
## 1 0.6567583  18     0      0
## 2 0.6567583  19     0      0
## 3 0.6567583  20     0      0
## 4 0.6567583  21     0      0
## 5 0.6567583  22     0      0
## 6 0.6567583  23     0      0

nohsScen$model # in the model specification

## vote00 ~ age + I(age^2) + hsdeg + coldeg

nohsSims <- logitsimev(nohsScen, simbetas, ci=0.95) # using simulated betas to get expected values.
# Built-in function "logitsimev" calculates the expected value
# for every individual scenario you created.

nohsSims #reports lower and upper confidence intervals as well as expected probabilities

## $pe
## [1] 0.1417779 0.1488721 0.1561558 0.1636213 0.1712596 0.1790610 0.1870151
## [8] 0.1951105 0.2033353 0.2116768 0.2201221 0.2286573 0.2372687 0.2459420
## [15] 0.2546627 0.2634164 0.2721885 0.2809647 0.2897306 0.2984721 0.3071756
## [22] 0.3158277 0.3244153 0.3329260 0.3413478 0.3496693 0.3578795 0.3659681
## [29] 0.3739254 0.3817424 0.3894105 0.3969219 0.4042691 0.4114455 0.4184449
## [36] 0.4252617 0.4318906 0.4383271 0.4445670 0.4506066 0.4564424 0.4620716
## [43] 0.4674916 0.4727000 0.4776949 0.4824745 0.4870375 0.4913825 0.4955084
## [50] 0.4994144 0.5030998 0.5065639 0.5098062 0.5128264 0.5156242 0.5181992
## [57] 0.5205514 0.5226807 0.5245868 0.5262699 0.5277300 0.5289670 0.5299810
## [64] 0.5307722 0.5313407 0.5316867 0.5318106 0.5317124 0.5313928 0.5308521
## [71] 0.5300910 0.5291101 0.5279102 0.5264922 0.5248574 0.5230070 0.5209424
## [78] 0.5186655 0.5161781 0.5134825
##
## $lower
## [1] 0.09377019 0.09995426 0.10615759 0.11282169 0.11936489 0.12599243
## [7] 0.13290005 0.13998294 0.14699995 0.15399886 0.16125492 0.16887393
## [13] 0.17604341 0.18370299 0.19104135 0.19852122 0.20566449 0.21293749

```



```
## [19] 0.22050125 0.22783540 0.23524999 0.24231595 0.24951070 0.25701438
## [25] 0.26431594 0.27179384 0.27927945 0.28639534 0.29352660 0.30066459
## [31] 0.30798652 0.31504087 0.32207452 0.32941351 0.33651606 0.34331545
## [37] 0.34952665 0.35629996 0.36273621 0.36926549 0.37557788 0.38151130
## [43] 0.38779827 0.39321460 0.39863360 0.40361107 0.40837775 0.41300197
## [49] 0.41761840 0.42158495 0.42556816 0.42893753 0.43243801 0.43527081
## [55] 0.43735744 0.43883358 0.44017221 0.44174674 0.44246663 0.44273335
## [61] 0.44237669 0.44191833 0.44043658 0.43825657 0.43539030 0.43204555
## [67] 0.42823800 0.42486057 0.42078292 0.41697679 0.41121037 0.40554511
## [73] 0.39954056 0.39306410 0.38579637 0.37859680 0.37054944 0.36242260
## [79] 0.35417954 0.34484440
##
## $upper
## [1] 0.2023818 0.2101062 0.2176362 0.2256744 0.2342587 0.2428356 0.2513252
## [8] 0.2611398 0.2702617 0.2796697 0.2891085 0.2986075 0.3085844 0.3186677
## [15] 0.3280763 0.3379936 0.3480507 0.3580141 0.3676791 0.3770160 0.3865661
## [22] 0.3960088 0.4055202 0.4142995 0.4235429 0.4327804 0.4420366 0.4508130
## [29] 0.4591295 0.4670002 0.4748582 0.4825155 0.4896542 0.4968459 0.5035823
## [36] 0.5103394 0.5165632 0.5227099 0.5284014 0.5339872 0.5390787 0.5437367
## [43] 0.5486379 0.5531580 0.5577996 0.5618355 0.5662450 0.5698467 0.5737313
## [50] 0.5768879 0.5804261 0.5840182 0.5877341 0.5910140 0.5944436 0.5974188
## [57] 0.6010396 0.6040960 0.6066435 0.6102348 0.6127903 0.6161255 0.6190451
## [64] 0.6219877 0.6255116 0.6293252 0.6325501 0.6355493 0.6392818 0.6426057
## [71] 0.6455647 0.6493698 0.6539092 0.6573798 0.6606825 0.6637474 0.6672634
## [78] 0.6707484 0.6744996 0.6779163
```

```
# same thing for two other sets of sceneraios
hsSims <- logitsimev(hsScen, simbetas, ci=0.95)
collSims <- logitsimev(collScen, simbetas, ci=0.95)
```

```
# Get 3 nice colors for traces
col <- brewer.pal(3,"Dark2")
```

```
# Set up lineplot traces of expected probabilities
```

```
#Traces are elements of tile : lines, labels, legends...
```

```
# no hs
```

```
nohsTrace <- lineplot(x=xhyp, # age on x-axis
  y=nohsSims$pe, #expected probability on y-axis
  lower=nohsSims$lower, # lower confidence interval
  upper=nohsSims$upper, #upper confidence interval
  col=col[1], #color choice
  extrapolate=list(data=mdata[,2:ncol(mdata)],
    #actual covariates (i.e., values in your data)
    cfact=nohsScen$x[,2:ncol(hsScen$x)],#counterfactual covariates
    omit.extrapolated=FALSE), #don't show extrapolated values
  plot=1)
```

```
# hs but no college
```

```
hsTrace <- lineplot(x=xhyp,
  y=hsSims$pe,
  lower=hsSims$lower,
  upper=hsSims$upper,
```

```

        col=col[2],
        extrapolate=list(data=mdata[,2:ncol(mdata)],
                        cfact=hsScen$x[,2:ncol(hsScen$x)],
                        omit.extrapolated=FALSE),

        plot=1)

#college
collTrace <- lineplot(x=xhyp,
                    y=collSims$pe,
                    lower=collSims$lower,
                    upper=collSims$upper,
                    col=col[3],
                    extrapolate=list(data=mdata[,2:ncol(mdata)],
                                    cfact=collScen$x[,2:ncol(hsScen$x)],
                                    omit.extrapolated=FALSE),

                    plot=1)

# Set up traces with labels
labelTrace <- textTile(labels=c("Less than HS", "High School", "College"),
                      x=c( 55,    49,    30),
                      y=c( 0.26, 0.56, 0.87),
                      col=col,
                      plot=1)

# For legend
legendTrace <- textTile(labels=c("Logit estimates:", "95% confidence", "interval is shaded"),
                       x=c(82, 82, 82),
                       y=c(0.2, 0.16, 0.12),
                       plot=1)

#options(device="quartz")

# Plot traces using tile
voting<-tile(nohsTrace,
            hsTrace,
            collTrace,
            labelTrace,
            legendTrace,
            limits=c(18,94,0,1),
            xaxis=list(at=c(20,30,40,50,60,70,80,90)),
            yaxis=list(label.loc=-0.5, major=FALSE),
            xaxistitle=list(labels="Age of Respondent"),
            yaxistitle=list(labels="Probability of Voting"),
            width=list(null=5,yaxistitle=4,yaxis.labelspace=-0.5)
            #,output=list(file="educationEV",width=5.5)
)

## Loading required package: WhatIf
## Loading required package: lpSolve
## #####

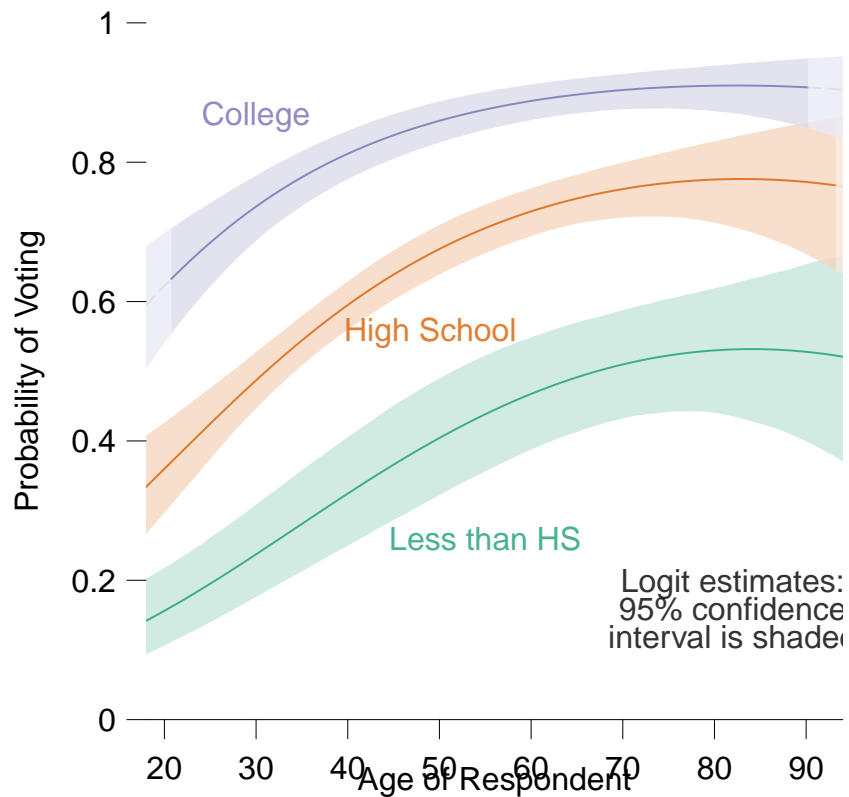
```

```

## ##
## ## WhatIf (Version 1.5-6, built 2014-01-06)
## ## Complete documentation available from http://gking.harvard.edu/whatif
## ##
## #####

## [1] "Running whatif"
## [1] "Preprocessing data ..."
## [1] "Performing convex hull test ..."
## [1] "Calculating distances ...."
## [1] "Calculating the geometric variance..."
## [1] "Calculating cumulative frequencies ..."
## [1] "Finishing up ..."
## [1] "Whatif finished; returning to tile"
## [1] "Running whatif"
## [1] "Preprocessing data ..."
## [1] "Performing convex hull test ..."
## [1] "Calculating distances ...."
## [1] "Calculating the geometric variance..."
## [1] "Calculating cumulative frequencies ..."
## [1] "Finishing up ..."
## [1] "Whatif finished; returning to tile"
## [1] "Running whatif"
## [1] "Preprocessing data ..."
## [1] "Performing convex hull test ..."
## [1] "Calculating distances ...."
## [1] "Calculating the geometric variance..."
## [1] "Calculating cumulative frequencies ..."
## [1] "Finishing up ..."
## [1] "Whatif finished; returning to tile"

```



#### 4. Simulating first differences

```
#####
#
# Now consider a new specification adding the variable
# "ever married", or marriedo
#
# We will estimate this new model with glm(), then
# simulate new scenarios for marrieds and non-marrieds

# Estimate logit model using glm()

# Set up a new model formula and model specific data frame

model2 <- vote00 ~ age + I(age^2) + hsdeg + coldeg + marriedo
mdata2 <- extractdata(model2, data, na.rm=TRUE)

# Run logit & extract results
logit.m2 <- glm(model2, family=binomial, data=mdata2)
pe.m2 <- logit.m2$coefficients # point estimates
vc.m2 <- vcov(logit.m2)       # var-cov matrix

# Simulate parameter distributions
```

```

sims <- 10000
simbetas.m2 <- mvrnorm(sims, pe.m2, vc.m2)

# Set up counterfactuals: all ages

xhyp <- seq(18,97,1)
nscen <- length(xhyp)
marriedScen <- cfMake(model2, mdata2, nscen)
for (i in 1:nscen) {

  # - we will use the marriedScen counterfactuals in FDs and RRs as well as EVs
  # Note below the careful use of before scenarios (xpre) and after scenarios (x)
  # :i.e., use of the same age range (18-97) for both x and xpre, only marriedo values differ.

  # Married (loop over each age)
  marriedScen <- cfChange(marriedScen, "age", x = xhyp[i], xpre= xhyp[i], scen = i)
  marriedScen <- cfChange(marriedScen, "marriedo", x = 1, xpre= 0, scen = i)

  # Not Married (loop over each age)
  notmarrScen <- cfChange(notmarrScen, "age", x = xhyp[i], scen = i)
  notmarrScen <- cfChange(notmarrScen, "marriedo", x = 0, scen = i)
}

# Simulate expected probabilities for all age scenarios for married and not married respectively
marriedSims <- logitsimev(marriedScen, simbetas.m2, ci=0.95)
notmarrSims <- logitsimev(notmarrScen, simbetas.m2, ci=0.95)

# Simulate first difference of voting wrt marriage: E(y/married)-E(y/notmarried)
marriedFD <- logitsimfd(marriedScen, simbetas.m2, ci=0.95)

# Simulate relative risk of voting wrt marriage: E(y/married)/E(y/notmarried)
marriedRR <- logitsimrr(marriedScen, simbetas.m2, ci=0.95)

## Make plots using tile

# Get 3 nice colors for traces
col <- brewer.pal(3,"Dark2")

# Set up lineplot traces of expected probabilities
marriedTrace <- lineplot(x=xhyp,
                        y=marriedSims$pe,
                        lower=marriedSims$lower,
                        upper=marriedSims$upper,
                        col=col[1],
                        extrapolate=list(data=mdata2[,2:ncol(mdata2)],
                                         cfact=marriedScen$x[,2:ncol(marriedScen$x)],
                                         omit.extrapolated=TRUE),
                        plot=1)

notmarrTrace <- lineplot(x=xhyp,

```

```

        y=notmarrSims$pe,
        lower=notmarrSims$lower,
        upper=notmarrSims$upper,
        col=col[2],
        ci = list(mark="dashed"),
        extrapolate=list(data=mdata2[,2:ncol(mdata2)],
                        cfact=notmarrScen$x[,2:ncol(notmarrScen$x)],
                        omit.extrapolated=TRUE),

        plot=1)

# Set up traces with labels and legend
labelTrace <- textTile(labels=c("Currently Married", "Not Married"),
                      x=c( 35,    53),
                      y=c( 0.8,  0.56),
                      col=col,
                      plot=1)

legendTrace <- textTile(labels=c("Logit estimates:", "95% confidence", "interval is shaded"),
                      x=c(80, 80, 80),
                      y=c(0.2, 0.15, 0.10),
                      cex=0.9,
                      plot=1)

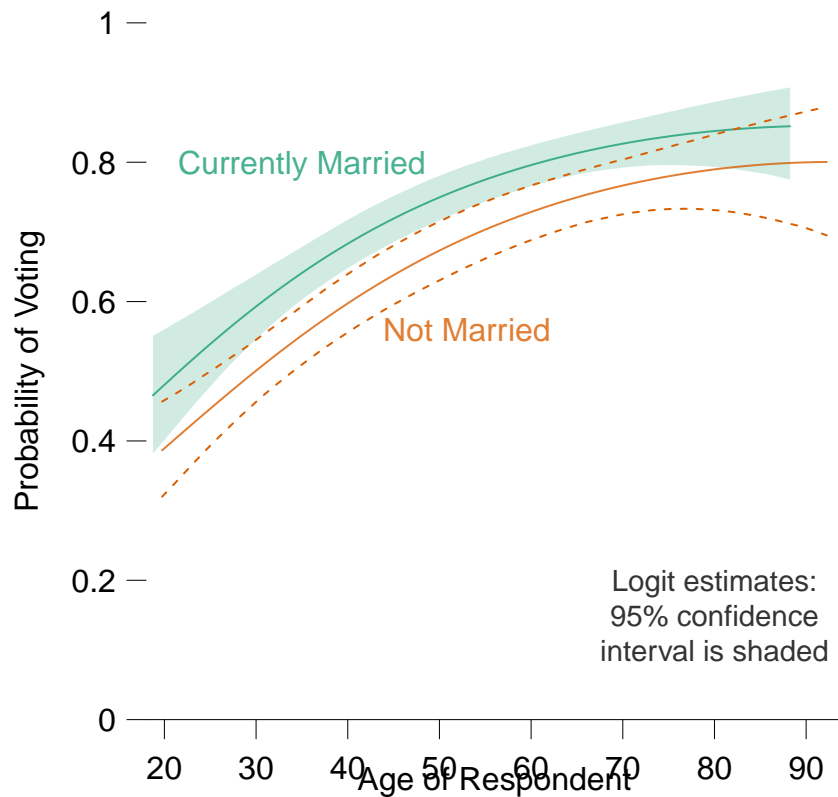
# Plot traces using tile
tile(marriedTrace,
     notmarrTrace,
     labelTrace,
     legendTrace,
     limits=c(18,94,0,1),
     xaxis=list(at=c(20,30,40,50,60,70,80,90)),
     yaxis=list(label.loc=-0.5, major=FALSE),
     xaxistitle=list(labels="Age of Respondent"),
     yaxistitle=list(labels="Probability of Voting"),
     width=list(null=5,yaxistitle=4,yaxis.labelspace=-0.5)
     #,output=list(file="marriedEV",width=5.5)
)

```

```

## [1] "Running whatif"
## [1] "Preprocessing data ..."
## [1] "Performing convex hull test ..."
## [1] "Calculating distances ...."
## [1] "Calculating the geometric variance..."
## [1] "Calculating cumulative frequencies ..."
## [1] "Finishing up ..."
## [1] "Whatif finished; returning to tile"
## [1] "Running whatif"
## [1] "Preprocessing data ..."
## [1] "Performing convex hull test ..."
## [1] "Calculating distances ...."
## [1] "Calculating the geometric variance..."
## [1] "Calculating cumulative frequencies ..."
## [1] "Finishing up ..."
## [1] "Whatif finished; returning to tile"

```



```
# Plot First Difference

# Set up lineplot trace of first difference
marriedFDTrace <- lineplot(x=xhyp,
  y=marriedFD$pe,
  lower=marriedFD$lower,
  upper=marriedFD$upper,
  col=col[1],
  extrapolate=list(data=mdata2[,2:ncol(mdata2)],
    cfact=marriedScen$x[,2:ncol(marriedScen$x)],
    omit.extrapolated=TRUE),
  plot=1)

# Set up baseline: for first difference, this is 0
baseline <- linesTile(x=c(18,94),
  y=c(0,0),
  plot=1)

# Set up traces with labels and legend
labelFDTrace <- textTile(labels=c("Married compared \n to Not Married"),
  x=c( 40),
  y=c( 0.20),
  col=col[1],
  plot=1)

legendFDTrace <- textTile(labels=c("Logit estimates:", "95% confidence", "interval is shaded"),
```

```

x=c(80, 80, 80),
y=c(-0.02, -0.05, -0.08),
cex=0.9,
plot=1)

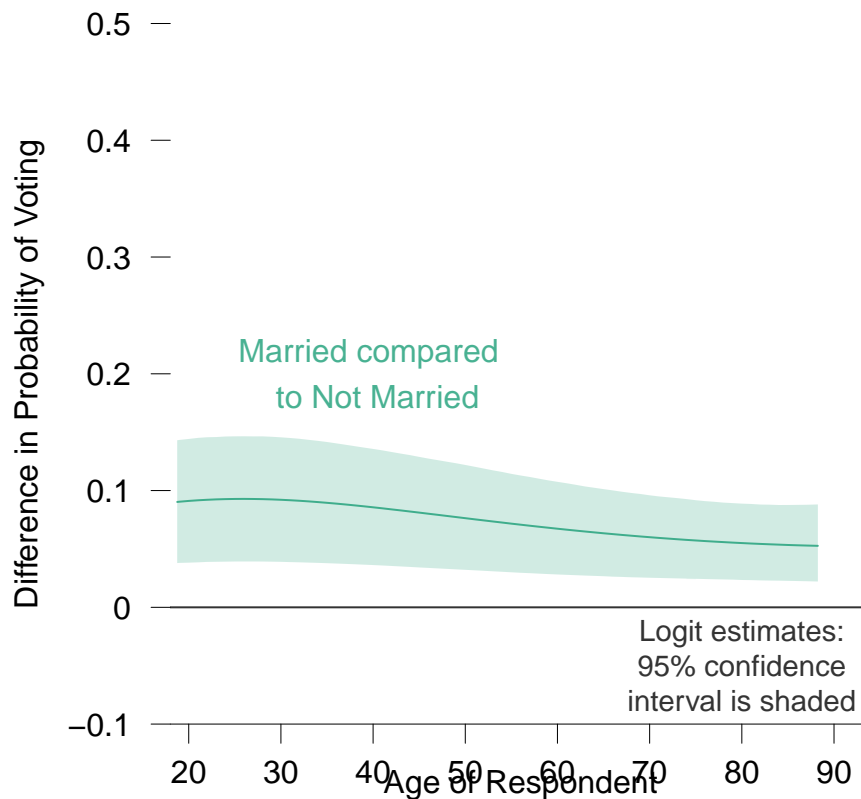
# Plot traces using tile
tile(marriedFDTrace,
     labelFDTrace,
     legendFDTrace,
     baseline,
     limits=c(18,94,-0.1,0.5),
     xaxis=list(at=c(20,30,40,50,60,70,80,90)),
     yaxis=list(label.loc=-0.5, major=FALSE),
     xaxistitle=list(labels="Age of Respondent"),
     yaxistitle=list(labels="Difference in Probability of Voting"),
     width=list(null=5,yaxistitle=4,yaxis.labelspace=-0.5)
     #,output=list(file="marriedFD",width=5.5)
)

```

```

## [1] "Running whatif"
## [1] "Preprocessing data ..."
## [1] "Performing convex hull test ..."
## [1] "Calculating distances ...."
## [1] "Calculating the geometric variance..."
## [1] "Calculating cumulative frequencies ..."
## [1] "Finishing up ..."
## [1] "Whatif finished; returning to tile"

```





```

# Plot Relative Risk

# Set up lineplot trace of relative risk
marriedRRTrace <- lineplot(x=xhyp,
                           y=marriedRR$pe,
                           lower=marriedRR$lower,
                           upper=marriedRR$upper,
                           col=col[1],
                           extrapolate=list(data=mdata2[,2:ncol(mdata2)],
                                             cfact=marriedScen$x[,2:ncol(marriedScen$x)],
                                             omit.extrapolated=TRUE),
                           plot=1)

# Set up baseline: for relative risk, this is 1
baseline <- linesTile(x=c(18,94),
                      y=c(1,1),
                      plot=1)

# Set up traces with labels and legend
labelRRTrace <- textTile(labels=c("Married compared \n to Not Married"),
                         x=c( 55),
                         y=c( 1.25),
                         col=col[1],
                         plot=1)

legendRRTrace <- textTile(labels=c("Logit estimates:", "95% confidence", "interval is shaded"),
                          x=c(80, 80, 80),
                          y=c(0.98, 0.95, 0.92),
                          cex=0.9,
                          plot=1)

# Plot traces using tile
tile(marriedRRTrace,
     labelRRTrace,
     legendRRTrace,
     baseline,
     limits=c(18,94,0.9,1.5),
     xaxis=list(at=c(20,30,40,50,60,70,80,90)),
     yaxis=list(label.loc=-0.5, major=FALSE),
     xaxis.title=list(labels="Age of Respondent"),
     yaxis.title=list(labels="Relative Risk of Voting"),
     width=list(null=5,yaxis.title=4,yaxis.labelspace=-0.5)
     #,output=list(file="marriedRR",width=5.5)
)

## [1] "Running whatif"
## [1] "Preprocessing data ..."
## [1] "Performing convex hull test ..."
## [1] "Calculating distances ..."
## [1] "Calculating the geometric variance..."
## [1] "Calculating cumulative frequencies ..."
## [1] "Finishing up ..."

```

```
## [1] "Whatif finished; returning to tile"
```

