

Bayesian Hierarchical Modeling for the Social Sciences

Running Regular Bayesian Regression Models

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Example: Poverty Among the Elderly, Europe

- ▶ Governments often worry about the economic condition of senior citizens for political and social reasons.
- ▶ Typically in a large industrialized society, a substantial portion of these people obtain the bulk of their income from government pensions.
- ▶ An important question is whether there is enough support through these payments to provide subsistence above the poverty rate.
- ▶ To see if this is a concern, the European Union (EU) looked at this question in 1998 for the (then) 15 member countries with two variables:
 1. the median (EU standardized) income of individuals age 65 and older as a percentage of the population age 0–64,
 2. the percentage with income below 60% of the median (EU standardized) income of the national population.

Example: Poverty Among the Elderly, Europe

- ▶ The data from the European Household Community Panel Survey are:

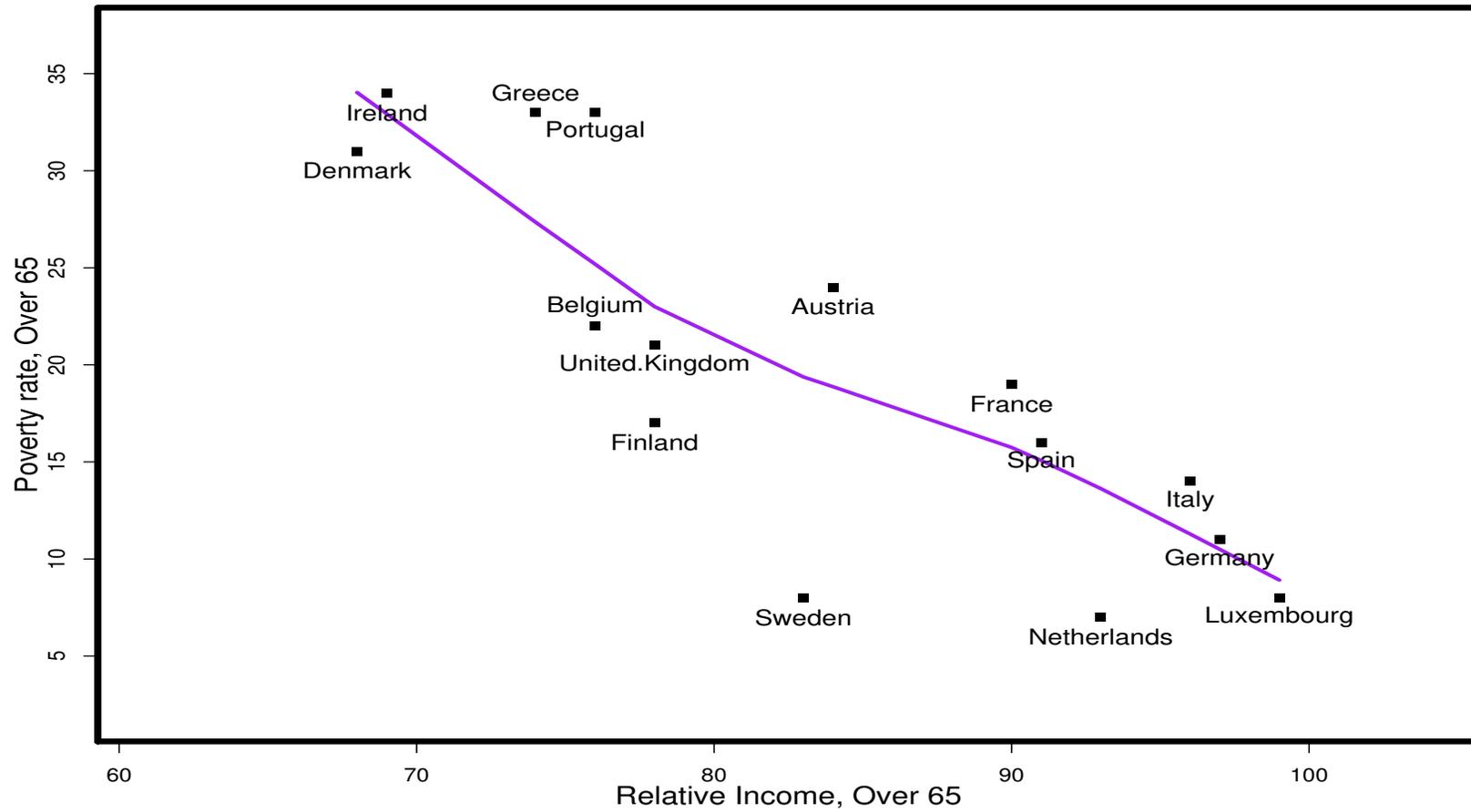
Nation	Relative Income	Poverty Rate
Netherlands	93.00	7.00
Luxembourg	99.00	8.00
Sweden	83.00	8.00
Germany	97.00	11.00
Italy	96.00	14.00
Spain	91.00	16.00
Finland	78.00	17.00
France	90.00	19.00
United.Kingdom	78.00	21.00
Belgium	76.00	22.00
Austria	84.00	24.00
Denmark	68.00	31.00
Portugal	76.00	33.00
Greece	74.00	33.00
Ireland	69.00	34.00

Lowess Smooth: Poverty Among the Elderly, Europe

```
eu.pov <- read.table("http://JeffGill.org/data/inc.pov.dat", row.names=1)
names(eu.pov) <- c("relative income", "poverty rate")
eu.pov <- eu.pov[-1,]

par(mfrow=c(1,1), mar=c(4,4,2,2), lwd=5)
plot(eu.pov, pch=15, xlab="", ylab="", ylim=c(2,37), xlim=c(61,104))
lines(lowess(eu.pov), col="purple", lwd=3)
text.loc <- cbind(eu.pov[,1], (eu.pov[,2]-1))
text.loc[14,2] <- text.loc[14,2] +2
text.loc[10,2] <- text.loc[10,2] +2
text(text.loc, dimnames(eu.pov)[[1]], cex=1.2)
mtext(side=1, cex=1.3, line=2, "Relative Income, Over 65")
mtext(side=2, cex=1.3, line=2, "Poverty rate, Over 65")
```

Example: Poverty Among the Elderly, Europe



Simple Linear Bayesian Specification: Poverty Among the Elderly, Europe

- ▶ For basic regressions the **arm** package by Andrew Gelman, Yu-Sung Su, Daniel Lee, and Aleks Jakulin works nicely.
- ▶ Load the package and run a linear regression at the defaults:
- ▶ A useful function in this package is **bayesglm**, which is functionally equivalent to the regular **glm**.

```
library(arm)
eu.pov.out <- bayesglm(eu.pov[,2] ~ eu.pov[,1], prior.mean=0, prior.df=1,
  prior.df.for.intercept=0, prior.mean.for.intercept=1)
```

Simple Linear Bayesian Specification: Poverty Among the Elderly, Europe

Deviance Residuals:

Min	1Q	Median	3Q	Max
-12.218	-3.306	1.488	3.929	7.429

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	83.6859	12.2525	6.830	1.21e-05
eu.pov[, 1]	-0.7647	0.1458	-5.246	0.000158

(Dispersion parameter for gaussian family taken to be 31.48377)

Null deviance: 1275.73 on 14 degrees of freedom
Residual deviance: 409.29 on 13 degrees of freedom
AIC: 98.164

Non-Bayesian Specification: Poverty Among the Elderly, Europe

```
x.y.fit <- lm(eu.pov[,2] ~ eu.pov[,1])  
summary(x.y.fit)
```

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	83.6928	12.2526	6.831	1.21e-05
eu.pov[, 1]	-0.7647	0.1458	-5.246	0.000158

Residual standard error: 5.611 on 13 degrees of freedom

Multiple R-Squared: 0.6792, Adjusted R-squared: 0.6545

F-statistic: 27.52 on 1 and 13 DF, p-value: 0.0001580

Prior Sensitivity: Poverty Among the Elderly, Europe

```
eu.pov.out2 <- bayesglm(eu.pov[,2] ~ eu.pov[,1], prior.mean=50, prior.df=100,  
  prior.df.for.intercept=-50, prior.mean.for.intercept=100)  
summary(eu.pov.out2)
```

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	83.6578	12.2526	6.828	1.21e-05
eu.pov[, 1]	-0.7642	0.1458	-5.243	0.000159

(Dispersion parameter for gaussian family taken to be 31.48379)

Null deviance: 1275.73 on 14 degrees of freedom

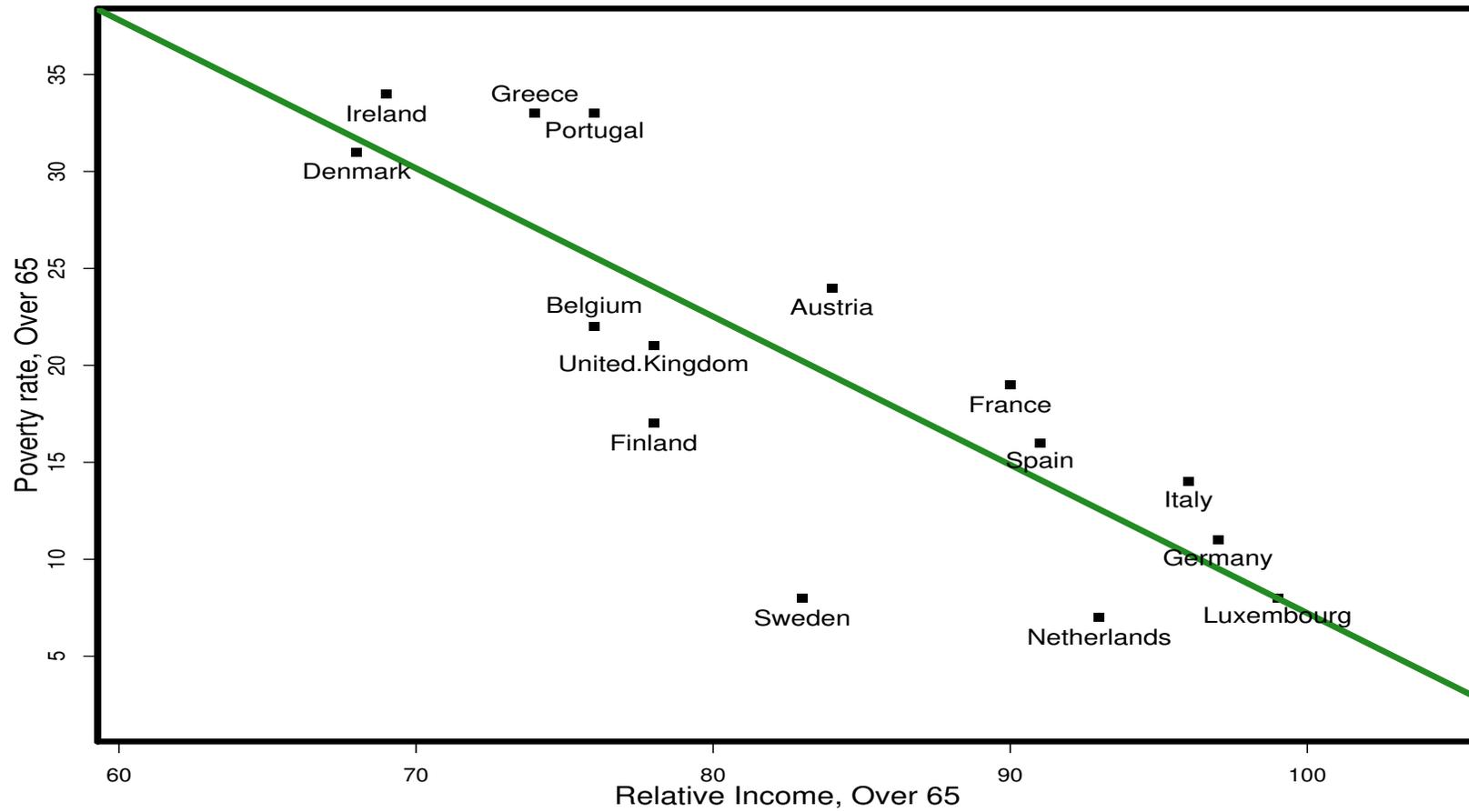
Residual deviance: 409.29 on 13 degrees of freedom

AIC: 98.164

Graphing: Poverty Among the Elderly, Europe

```
par(mfrow=c(1,1),mar=c(4,4,2,2),lwd=5)
plot(eu.pov,pch=15,xlab="",ylab="",ylim=c(2,37),xlim=c(61,104))
abline(eu.pov.out$coefficients,col="forest green")
text.loc <- cbind(eu.pov[,1],(eu.pov[,2]-1))
text.loc[14,2] <- text.loc[14,2] +2
text.loc[10,2] <- text.loc[10,2] +2
text(text.loc,dimnames(eu.pov)[[1]],cex=1.2)
mtext(side=1,cex=1.3,line=2,"Relative Income, Over 65")
mtext(side=2,cex=1.3,line=2,"Poverty rate, Over 65")
```

Graphing: Poverty Among the Elderly, Europe



Data Exercise 4: Model Comparison: Poverty Among the Elderly, Europe

- ▶ Replicate the model just shown using the poverty data.
- ▶ Run the same model with different hyperparameter values.
- ▶ Run a regular non-Bayesian alternative.
- ▶ Compare the coefficient results numerically and graphically (be creative).

ANES Data from 2012

- ▶ Suppose we are interested in survey “mode effects” such as whether face-to-face versus internet responses differ.
- ▶ To analyze the potential consequences of mode effects on the uncertainty that surrounds public opinion data, we examine the American National Election Studies 2012 Time Series Study.
- ▶ The ANES 2012 study is the 29th installment in a longstanding series of election studies that go back to 1948.
- ▶ The 2012 edition differs from its predecessors significantly, and lends itself exceptionally well to our analysis because it is the first ANES study that implements a dual-mode design by incorporating a traditional ANES face-to-face sample as well as a separate sample interviewed on the Internet.
- ▶ Both samples were independently drawn and data collection was conducted independently in the two modes as well.

ANES Data from 2012

- ▶ Download the data in R:

```
f2f.anes <- read.table("http://JeffGill.org/data/f2f.anes.1.dat")  
inet.anes <- read.table("http://JeffGill.org/data/inet.anes.1.dat")
```

```
dim(f2f.anes)  
[1] 2054 54  
> dim(inet.anes)  
[1] 3860 54
```

ANES Data from 2012

► Look at the variables:

```
names(f2f.anes)
[1] "weight_ftf"          "presvote2012_x"    "gender_respondent_x" "dem_edu"
[5] "dem_birthy"         "dem_racecps_white" "dem_racecps_black"  "dem_hisp"
[9] "dem_marital"       "pid_x"            "libcpres_self"      "interest_attention"
[13] "candrel_dpc"       "cses_econ"        "ftcasi_illegal"     "egal_worryless"
[17] "interest_voted2008" "prmedia_atinews"  "prmedia_wktvnws"    "prmedia_attvnws"
[21] "prmedia_atpprnews" "prevote_regist_addr" "prevote_intpreswho" "prevote_intpresst"
[25] "congapp_job"       "presapp_track"    "presapp_job"        "presapp_econ"
[29] "presapp_foreign"   "presapp_health"   "presapp_war"        "ft_dpc"
[33] "ft_rpc"           "ft_dvpc"          "ft_rvpc"            "ft_dem"
[37] "ft_rep"           "finance_finfam"   "finance_finpast"    "finance_finnext"
[41] "health_insured"    "health_2010hcr"   "health_self"        "health_smokeamt"
[45] "likelypct_whatpct1" "campfin_limcorp"  "ineq_incgap_x"      "effic_complicrev"
[49] "effic_carerev"     "econ_ecpast_x"    "econ_unpast_x"      "preswin_dutychoice_x"
[53] "war_terror"       "gun_control"
```

Some 2 and 3 Point Items

Variable Name	Variable Description
<code>cses_econ</code>	State of Economy
<code>campfin_banads</code>	Ban Corporate/Union Ads
<code>ineqinc_ineqreduc</code>	Gov't Reducing Income Inequality
<code>econ_ecpast</code>	National Economy: Better/Worse
<code>econ_unpast</code>	Unemployment: Better/Worse
<code>mip_prob2pty</code>	Best Party to Handle MIP #2
<code>iran_nuksite</code>	Bombing Iran's Nuclear Sites
<code>auth_consid</code>	Important for Child: Considerate or Well-Behaved
<code>finance_finpast</code>	Better/Worse Off Than Year Ago
<code>interest_wherevote</code>	Know Where to Vote
<code>tea_suppln</code>	Tea Party: Leaning Towards Support/Opposition
<code>preswin_dutyst</code>	Voting as Duty: Feeling Strength
<code>fedspend_schools</code>	Public Schools: More or Less Spending

Some 4 and 5 Point Items

Variable Name	Variable Description
resent_deserve	Blacks: Gotten Less Than Deserved
cses_govtact	Gov't Reducing Income Inequality
resent_try	Blacks: Must Try Harder
ecperil_payhlthcst	Able to Pay Health Care
egal_worryless	Worry Less About Equality
ctrain_dpccare	Dem Cand: Cares About People Like Me
ecblame_pres	Blame President for Economy
ctrain_rpclead	Rep Cand: Strong Leadership
ctrain_dpcmoral	Dem Cand: Is Moral
ctrain_rpcmoral	Rep Cand: Is Moral
finance_finpast_x	Better/Worse Off Than Year Ago (5 point scale)
likelypct_howlikvt1	Likelihood of Voting
trustgov_trustgstd	Trust Gov't in Washington
cses_diffvote	Vote Makes a Difference
gayrt_discstd_x	Favor Laws Against Gays/Lesbian Job Discrim
egal_equal	Provide Equal Opportunities

Some 7 and 11 Point Items

Variable Name	Variable Description
<code>cses_dptylike</code>	Democratic Party Like (0-10)
<code>cses_rptylike</code>	Republican Party Like (0-10)
<code>cses_rpclike</code>	Republican Pres Cand Like (0-10)
<code>cses_rptyleft</code>	Left-Right Republican Party (0-10)
<code>cses_dpclike</code>	Democratic Pres Cand Like (0-10)
<code>cses_rpclike</code>	Republican Pres Cand Like (0-10)
<code>wpres_gdbd_x</code>	Good/Bad: Woman Pres
<code>women_bond_x</code>	Working Mother's Bond with Child
<code>abort_sex_x</code>	Legal Abortion to Select Child Gender
<code>budget_deficit_x</code>	Favor Reducing Budget Deficit
<code>scourt_remove_x</code>	Possibility to Remove Sup Court Judges

Some 101 Point Items

Variable Name	Variable Description
<code>ftgr_unions</code>	FT: Unions
<code>ftgr_fedgov</code>	FT: Federal Government
<code>ftcasi_illegal</code>	FT: Illegal Immigrants
<code>ft_dpc</code>	FT: Democratic Presidential Candidate
<code>ft_rpc</code>	FT: Republican Presidential Candidate
<code>ft_dvpc</code>	FT: Democratic Vice Presidential Candidate
<code>ft_rvpc</code>	FT: Republican Vice Presidential Candidate
<code>ft_dpcsp</code>	FT: Spouse of Democratic Presidential Candidate

ANES Data, Linear Model

- ▶ Run a linear regression on the face-to-face subset:

```
f2f.linear.out <- bayesglm(ft_dpc ~ health_insured + interest_voted2008 + gun_control
+ congapp_job + dem_racecps_black,
prior.mean=0, prior.df=1, prior.df.for.intercept=0, prior.mean.for.intercept=1,
data=f2f.anes, weights=weight_ftf)
summary(f2f.linear.out)
```

ANES Data, Linear Model

► Face-to-face results:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	84.9985	4.2595	19.955	<2e-16
health_insured	4.0757	1.7892	2.278	0.0228
interest_voted2008	-0.2391	1.4213	-0.168	0.8664
gun_control	-9.0931	0.6507	-13.974	<2e-16
congapp_job	-9.9348	1.4983	-6.631	4.26e-11
dem_racecps_black	30.1378	1.8654	16.157	<2e-16

(Dispersion parameter for gaussian family taken to be 805.6735)

Null deviance: 2173744 on 2053 degrees of freedom

Residual deviance: 1650019 on 2048 degrees of freedom

AIC: 20579

ANES Data, Linear Model

- ▶ Consider the outcome variable of feeling thermometers (0-100) for the Democratic party candidate for president.
- ▶ Now run a linear regression on the internet subset:

```
inet.linear.out <- bayesglm(ft_dpc ~ health_insured + interest_voted2008 + gun_control  
  + congapp_job + dem_racecps_black,  
  prior.mean=0, prior.df=1, prior.df.for.intercept=0, prior.mean.for.intercept=1,  
  data=inet.anes, weights=weight_web)  
summary(inet.linear.out)
```

ANES Data, Linear Model

► Internet subset results:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	82.8155	3.2436	25.532	<2e-16
health_insured	2.8211	1.3852	2.037	0.0418
interest_voted2008	0.4189	1.1946	0.351	0.7259
gun_control	-11.5795	0.5036	-22.995	<2e-16
congapp_job	-8.5299	1.1919	-7.156	9.87e-13
dem_racecps_black	34.2749	1.4854	23.074	<2e-16

(Dispersion parameter for gaussian family taken to be 904.4944)

Null deviance: 4674189 on 3859 degrees of freedom

Residual deviance: 3485921 on 3854 degrees of freedom

AIC: 38634

Data Exercise 5: ANES Data/Model

- ▶ Using the ANES data, respecify to see if you can get a bigger difference in face-to-face and internet samples.
- ▶ You can change the mix of covariates or the model specification.
- ▶ Consider a different outcome variable.

Logit Model for Survey Responses in Scotland

- ▶ These data come from the British General Election Study, Scottish Election Survey, 1997 (ICPSR Study Number 2617).
- ▶ These data contain 880 valid cases, each from an interview with a Scottish national after the election.
- ▶ Our outcome variable of interest is their party choice in the UK general election for Parliament where we collapse all non-Conservative party choices (abstention, Labour, Liberal Democrat, Scottish National, Plaid Cymru, Green, Other, Referendum) to one category, which produces 104 Conservative votes.
- ▶ For a logit model the `prior.scale` is `2.5`, and for a probit model the prior scale is `2.5*1.6` (typical assumptions are `1` and `1.6`).

Logit Model for Survey Responses in Scotland, Explanatory Variables

- ▶ **POLITICS**, which asks how much interest the respondent has in political events (increasing scale: none at all, not very much, some, quite a lot, a great deal).
- ▶ **READPAP**, which asks about daily morning reading of the newspapers (yes=1 or no=0).
- ▶ **PTYTHNK**, how strong that party affiliation is for the respondent (categorical by party name).
- ▶ **IDSTRNG** (increasing scale: not very strong, fairly strong, very strong).
- ▶ **TAXLESS** asks if “it would be better if everyone paid less tax and had to pay more towards their own healthcare, schools and the like” (measured on a five point increasing Likert scale).
- ▶ **DEATHPEN** asks whether the UK should bring back the death penalty ((measured on a five point increasing Likert scale).
- ▶ **LORDS** queries whether the House of Lords should be reformed (asked as *remain as is* coded as zero and *change is needed* coded as one).
- ▶ **SCENGBEN** asks how economic benefits are distributed between England and Scotland with the choices: England benefits more = -1 , neither/both lose = 0 , Scotland benefits more = 1 .

Logit Model for Survey Responses in Scotland, Explanatory Variables

- ▶ **INDPAR** asks which of the following represents the respondent's view on the role of the Scottish government in light of the new parliament: (1) Scotland should become independent, separate from the UK and the European Union, (2) Scotland should become independent, separate from the UK but part of the European Union, (3) Scotland should remain part of the UK, with its own elected parliament which has some taxation powers, (4) Scotland should remain part of the UK, with its own elected parliament which has no taxation powers, and (5) Scotland should remain part of the UK without an elected parliament.
- ▶ **SCOTREF1** asks "should there be a Scottish parliament within the UK? (yes=1, no=0).
- ▶ **RSEX**, the respondent's sex.
- ▶ **RAGE**, the respondent's age.
- ▶ **RSOCCLA2**, the respondents social class (7 category ascending scale).
- ▶ **TENURE1**, whether the respondent rents (0) or owns (1) their household.
- ▶ **PRESBm** a categorical variable for church affiliation, measurement of religion is collapsed down to one for the dominant historical religion of Scotland (Church of Scotland/Presbyterian) and zero otherwise and designated

Logit Model for Survey Responses in Scotland

- ▶ Run a probit model for the conservative/not-conservative outcome with these covariates:
- ▶ Results give across two slides...

```
scot.mat <- read.table("http://JeffGill.org/data/scotland.dat", sep=",", header=TRUE)
scot.out <- bayesglm(VOTE ~ POLITICS + READPAP + PTYTHNK + IDSTRNG + TAXLESS + DEATHPEN
  + LORDS + SCENGBEN + SCOPREF1 + RSEX + RAGE + RSOCCLA2
  + TENURE1 + PRESB + IND.PAR,
  data=scot.mat, family=binomial(link="logit"))
summary(scot.out)
```

Logit Model for Survey Responses in Scotland, Results

	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	-1.520579	1.026848	-1.481	0.13865
POLITICS	0.369950	0.141111	2.622	0.00875
READPAP	0.412143	0.333149	1.237	0.21604
PTYTHNK	-0.987682	0.171090	-5.773	7.79e-09
IDSTRNG	0.384849	0.141462	2.721	0.00652
TAXLESS	0.219942	0.134571	1.634	0.10218
DEATHPEN	0.168560	0.104639	1.611	0.10721
LORDS	-0.798360	0.287346	-2.778	0.00546
SCENGBEN	0.586385	0.200590	2.923	0.00346
SCOPREF1	-1.651397	0.339557	-4.863	1.15e-06
RSEX	0.705948	0.310589	2.273	0.02303
RAGE	0.019811	0.007722	2.566	0.01030
RSOCCLA2	-0.246593	0.108432	-2.274	0.02296
TENURE1	0.851254	0.336873	2.527	0.01151
PRESB	-0.225592	0.304528	-0.741	0.45882
IND.PAR	0.568041	0.349059	1.627	0.10366

Logit Model for Survey Responses in Scotland, Results

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 639.38 on 879 degrees of freedom
Residual deviance: 340.64 on 864 degrees of freedom
AIC: 372.64

Deviance Residuals:

Min	1Q	Median	3Q	Max
-2.2572	-0.2931	-0.1577	-0.0627	3.3411

Objects Produced

```
names(scot.out)
[1] "coefficients"  "residuals"      "fitted.values"  "effects"        "R"
[6] "rank"          "qr"             "family"         "linear.predictors" "deviance"
[11] "aic"           "null.deviance"  "iter"           "weights"         "prior.weights"
[16] "df.residual"   "df.null"        "y"              "converged"       "boundary"
[21] "prior.mean"    "prior.scale"    "prior.df"       "prior.sd"        "dispersion"
[26] "model"         "call"           "formula"        "terms"           "data"
[31] "offset"        "control"        "method"         "contrasts"       "xlevels"
[36] "keep.order"    "drop.baseline"
```

Percent Predicted Correctly

```
scot.pred <- scot.out$fitted.values  
scot.pred[scot.pred < 0.5] <- 0  
scot.pred[scot.pred > 0.5] <- 1  
table(scot.pred, scot.mat$VOTE)
```

```
scot.pred 0 1  
0 750 49  
1 26 55
```

```
sum(diag(table(scot.pred, scot.mat$VOTE)))/nrow(scot.mat)  
[1] 0.9147727
```

Percent Predicted Correctly

```
mean(scot.pred)
[1] 0.09204545
scot.pred <- scot.out$fitted.values
scot.pred[scot.pred < mean(scot.pred)] <- 0
scot.pred[scot.pred > mean(scot.pred)] <- 1
table(scot.pred, scot.mat$VOTE)

scot.pred 0 1
  0 667 12
  1 109 92

sum(diag(table(scot.pred, scot.mat$VOTE)))/nrow(scot.mat)
[1] 0.8625
```

Data Exercise 6: Modeling the Scotland Data

- ▶ Using the Scotland data, respecify more parsimonious model.
- ▶ Consider a different model specification, including the link function.
- ▶ Is your model robust to small changes in variable selection?
- ▶ What is the default prior selection for `bayesglm`?

Application: Poisson Model of Military Coups.

- ▶ Sub-Saharan Africa has experienced a disproportionately high proportion of regime changes due to the military takeover of government for a variety of reasons, including ethnic fragmentation, arbitrary borders, economic problems, outside intervention, and poorly developed governmental institutions.
- ▶ These data, selected from a larger set given by Bratton and Van De Walle (1994), look at potential causal factors for counts of military coups (ranging from 0 to 6 events) in 33 sub-Saharan countries over the period from each country's colonial independence to 1989.
- ▶ Included are 99 variables describing governmental, economic, and social conditions for the 47 cases. Also provided are data from 106 presidential and 185 parliamentary elections, including information about parties, turnout, and political openness.
- ▶ Seven explanatory variables are chosen here to model the count of military coups: **Military Oligarchy** (the number of years of this type of rule); **Political Liberalization** (0 for no observable civil rights for political expression, 1 for limited, and 2 for extensive); **Parties** (number of legally registered political parties); **Percent Legislative Voting**; **Percent Registered Voting**; **Size** (in one thousand square kilometer units); and **Population** (given in millions).

Application: Poisson Model of Military Coups.

- ▶ The focus here is an outcome variable included in Bratton and Van De Walle's work (1994, p. 479), but not featured as a modeled result: regime change through military coups.
- ▶ This is a well-studied issue (Bienen 1979; Decalo 1976a and 1976b; Feit 1968; Jackman, et al. 1986; Johnson, et al. 1984), but not necessarily so from a *statistical perspective*.
- ▶ **Military Coups** is operationalized as the successful number of military coups for a country over the period from independence to 1989 (ranging from zero to six events). This outcome variable is defined only over a positive integer sample space and therefore requires a generalized linear model link function appropriate to counts.

Application: Poisson Model of Military Coups.

- ▶ A generalized linear model for these data with the Poisson link function is specified as:

$$g^{-1}(\boldsymbol{\theta}) = g^{-1}(\mathbf{X}\boldsymbol{\beta}) = \exp[\mathbf{X}\boldsymbol{\beta}] = \mathbb{E}[\mathbf{Y}] = \mathbb{E}[\mathbf{Military Coups}].$$

- ▶ In this specification, the systematic component is $\mathbf{X}\boldsymbol{\beta}$, the stochastic component is $\mathbf{Y} = \mathbf{Military Coups}$, and the link function is $\boldsymbol{\theta} = \log(\boldsymbol{\mu})$.
- ▶ We can re-express this model by moving the link function to the left-hand side exposing the linear predictor: $g(\boldsymbol{\mu}) = \log(\mathbb{E}[\mathbf{Y}]) = \mathbf{X}\boldsymbol{\beta}$ (although this is now a less intuitive form for understanding the outcome variable).
- ▶ Left out of the discussion above are the prior distributions: again we will assume Student's-t for the coefficients.

Getting Data and a Function

- ▶ Get the data:

```
africa.dat <- read.table("http://JeffGill.org/data/africa.dat")
```

- ▶ Get my substitute function for `summary`:

```
connect1 <- url("http://JeffGill.org/Models/graph.summary.R")  
source(connect1)  
close(connect1)
```

Summary Function

```
function (in.object, alpha = 0.05, digits=3)
{
  lo <- in.object$coefficient - qnorm(1-alpha/2) * summary(in.object)$coef[,2]
  hi <- in.object$coefficient + qnorm(1-alpha/2) * summary(in.object)$coef[,2]
  out.mat <- round(cbind(in.object$coefficient, summary(in.object)$coef[,2], lo, hi),digits)
  blanks <- "
                                "
  dashes <- "-----"
  bar.plot <- NULL
  scale.min <- floor(min(out.mat[,3])); scale.max <- ceiling(max(out.mat[,4]))
  for (i in 1:nrow(out.mat)) {
    ci.half.length <- abs(out.mat[i,1]-out.mat[i,3])
    ci.start <- out.mat[i,1] - ci.half.length
    ci.stop <- out.mat[i,1] + ci.half.length
    bar <- paste("|",substr(dashes,1,ci.half.length), "o", substr(dashes,1,ci.half.length), "|", sep="", collapse="")
    start.buf <- substr(blanks,1,round(abs(scale.min - ci.start)))
    stop.buf <- substr(blanks,1,round(abs(scale.max - ci.stop)))
    bar.plot <- rbind( bar.plot, paste(start.buf,bar, stop.buf, sep="", collapse="") )
  }
}
```

Summary Function, Continued

```
out.df <- data.frame( matrix(NA,nrow=nrow(out.mat),ncol=ncol(out.mat)), bar.plot[1:length(bar.plot)] )
out.df[1:nrow(out.mat),1:ncol(out.mat)] <- out.mat
CI.label <- paste( "CIs:", substr(blanks,1,abs(scale.min)-2-4),"ZE+R0",
  substr(blanks,1,abs(scale.max)-2), sep="", collapse="" )
dimnames(out.df)[[1]] <- dimnames(summary(in.object)$coef)[[1]]
dimnames(out.df)[[2]] <- c("Coef","Std.Err.", paste(1-alpha,"Lower"),paste(1-alpha,"Upper"),CI.label)
if (substr(in.object$call[1],1,2) == "gl") print(in.object$family)
if (substr(in.object$call[1],1,2) == "lm") cat("\nFamily: gaussian\nLink function: identity\n\n")
print(out.df)
cat("\n")
if (substr(in.object$call[1],1,2) == "gl") {
  cat( paste("N:", length(in.object$y)," log-likelihood:",round(ncol(out.mat)-in.object$aic/2,digits),
    " AIC:",round(in.object$aic,digits),
    " Dispersion Parameter:",summary(in.object)$dispersion,"\n" ) )
  cat( paste(" Null deviance:",round(in.object$null.deviance,digits),"on",in.object$df.null,"degrees of freedom\n" ) )
  cat( paste("Residual deviance: ",round(in.object$deviance,digits),"on",in.object$df.residual,"degrees of freedom\n" ) )
}
if (substr(in.object$call[1],1,2) == "lm") {
  cat( paste("N:",length(in.object$fitted.values)," Estimate of Sigma:",round(summary(in.object)$sigma,digits),"\n" ) )
}
}
```

Looking At the Variables

```
names(africa.dat)
```

```
[1] "CNTRYCDE" "REGION" "POP" "SIZE" "COLONIAL" "BORDERS"  
[7] "DATEINDP" "GNPPC" "GROWTH" "ENERGY" "MANUF" "AGLABOR"  
[13] "INFLATN" "ADJPROGS" "AIDFLOWS" "DEBT" "SERVICE" "URBAN"  
[19] "ETHNIC" "PCTTRAD" "PCTCATH" "PCTPROT" "PCTMUSL" "RADIOS89"  
[25] "TELEV89" "PARTY75" "PARTY89" "PARTY93" "UNION89" "BUSIN75"  
[31] "BUSIN89" "CHURSCH" "CHURMED" "DAILY75" "DAILY89" "DAILY93"  
[37] "PERIOD75" "PERIOD89" "PERIOD93" "PUBLIS75" "PUBLIS89" "PUBLIS93"  
[43] "CONSTIT" "DICTATOR" "MILITARY" "PLBSCTRY" "COMPTIVE" "SETTLER"  
[49] "POLYACHY" "NUMREGIM" "REGCHANG" "MILTCOUP" "NUMELEC" "NUMLEGS"  
[55] "NUMPRES" "COMPELEC" "YRSCOMP" "DATELAST" "PARTYLEG" "PCTSEAT"  
[61] "MEANSEAT" "PCTTURN" "MEANTURN" "PCTVOTE" "MEANVOTE" "MEANPRES"  
[67] "PROTFREQ" "PROTEST" "REPRESS" "POLLIB" "MANIP" "OPPCOH"  
[73] "GOVTCOH" "MILTROLE" "INTLPR" "NATCON" "PRESELEC" "PRESDATE"  
[79] "PRESCAND" "PRESVOTS" "PRESTURN" "LEGSELEC" "LEGSDATE" "LEGSCAND"  
[85] "LEGSPRTY" "LEGSEATS" "LEGSTURN" "FREEFAIR" "INCBOUST" "LOSERACC"  
[91] "PROTBEG" "POLLIBEG" "TRANSEND" "LIBCHANG" "BACKSLID" "OUTCOME"  
[97] "DEMCHANG" "DEMLEVEL"
```

Results: Poisson Model of Military Coups.

- ▶ The R language GLM call for this model is:

```
africa.out <- bayesglm(MILTCOUP ~ MILITARY + POLLIB + PARTY93 + PCTVOTE + PCTTURN
+ SIZE*POP + NUMREGIM*NUMELEC, family=poisson, data=africa.dat)
```

- ▶ Summarize the model fit: `graph.summary(africa.out)`

	Coef	Std.Err.	0.95 Lower	0.95 Upper	CIs:ZE+R0
(Intercept)	1.739	1.177	-0.566	4.045	--o--
MILITARY	0.113	0.038	0.038	0.187	o
POLLIB	-0.465	0.298	-1.049	0.120	o
PARTY93	0.024	0.011	0.003	0.045	o
PCTVOTE	0.039	0.017	0.006	0.072	o
PCTTURN	-0.025	0.011	-0.047	-0.002	o
SIZE	-0.001	0.000	-0.002	0.000	o
POP	-0.055	0.025	-0.105	-0.006	o
SIZE:POP	0.000	0.000	0.000	0.000	o
NUMREGIM	-0.427	0.363	-1.138	0.285	o
NUMELEC	-0.272	0.150	-0.566	0.022	o
NUMREGIM:NUMELEC	0.104	0.050	0.007	0.201	o

Comments: Poisson Model of Military Coups.

- ▶ Note that the two interaction terms are specified by using the multiplication character. The iteratively weighted least squares algorithm converged in only four iterations using Fisher scoring, and the results are provided in the table.
- ▶ The model appears to fit the data quite well:
 - ▷ an improvement from the null deviance of 62 on 32 degrees of freedom to a residual deviance of 7.5 on 21 degrees of freedom
 - ▷ evidence that the model does not fit would be supplied by a model deviance value in the tail of a χ_{n-k}^2 distribution
 - ▷ and nearly all the coefficients have 95% confidence intervals bounded away from zero and therefore appear reliable in the model.