# **ADVANCED** BAYESIAN MODELING

# Bread and Peace Example: Posterior Inference

Recall Bread and Peace model data for U.S. presidential elections (1952 to 2004)

 $y_i$  = incumbent two-party vote % in election i

 $x_i$  = weighted-average per capita real income % growth (previous term)

Consider simple linear regression

$$y_i \mid \theta, X \sim \text{indep. N}(\beta_1 + \beta_2 x_i, \sigma^2)$$
  $i = 1, \dots, 14$ 

### > bp <- read.table("breadandpeace.txt", header=TRUE)</pre>

>	bp		
	Election	${\tt IncumbentPct}$	${\tt IncomeGrowth}$
1	1952	44.6	2.4
2	1956	57.8	2.9
3	1960	49.9	0.8
4	1964	61.3	4.2
5	1968	49.6	3.0
6	1972	61.8	3.6
7	1976	49.0	1.1
8	1980	44.7	-0.4
9	1984	59.2	3.9
10	1988	53.9	2.3
11	1992	46.5	0.4
12	1996	54.7	1.0
13	3 2000	50.3	2.4
14	2004	51.2	1.9

Classical linear regression in R is performed with function 1m:

> mod <- lm(IncumbentPct ~ IncomeGrowth, data=bp)</pre>

The first argument is a *formula*, which defines y and X.

```
> ( X <- model.matrix(mod) )</pre>
   (Intercept) IncomeGrowth
                          2.4
                          2.9
                          0.8
                          4.2
                          3.0
                          3.6
                          1.1
                         -0.4
                          3.9
10
                          2.3
11
                          0.4
12
                          1.0
13
                          2.4
14
                          1.9
attr(,"assign")
[1] 0 1
```

Classical inference is available using summary and other R functions, but we will just extract what we need:  $\hat{\beta}$ ,  $s^2$ ,  $V_{\beta}$ , and n-k.

- > betahat <- coef(mod)</pre>
- > smod <- summary(mod)</pre>
- > s.2 <- smod\$sigma^2
- > Vbeta <- smod\$cov.unscaled</pre>
- > n.minus.k <- df.residual(mod)</pre>

# Posterior Simulation

We simulate directly from the posterior, with the help of a function for simulating multivariate normal variates, from package MASS:

```
> library(MASS) # provides mvrnorm
> Nsim <- 1000
> post.sigma.2.sim <- n.minus.k * s.2 / rchisq(Nsim, n.minus.k)
> post.beta.sim <- matrix(NA, Nsim, length(betahat))
> for(s in 1:Nsim)
+ post.beta.sim[s,] <- mvrnorm(1, betahat, post.sigma.2.sim[s] * Vbeta)</pre>
```

### Can approximate posterior intervals and probabilities as usual:

```
> quantile(post.sigma.2.sim, c(0.025,0.975)) # posterior interval
    2.5% 97.5%
 8.29754 42.93682
> apply(post.beta.sim, 2, quantile, c(0.025,0.975)) # posterior intervals
          \lceil .1 \rceil \qquad \lceil .2 \rceil
2.5% 41.56126 1.520744
97.5% 49.74621 4.897986
> confint(mod) # exact classical intervals, for comparison
                 2.5 % 97.5 %
(Intercept) 41.450056 50.178157
IncomeGrowth 1.403473 4.908561
> mean(post.beta.sim[,2] > 0) # posterior prob. slope is positive
[1] 0.999
```

A note on R function apply:

```
apply(mat, 2, fun, ...)
applies function fun to each column of matrix mat, returning the results as a
vector or matrix (if needed).
(... allows additional arguments to fun.)
apply(mat, 1, fun, ...)
does the same for each row of mat instead.
```

## Prediction

We wish to predict the incumbent (Republican) vote % for the 2008 election.

It was known (prior to the election) that the real income growth in the previous term was 0.75%.

We start by simulating from the posterior predictive distribution:

Approximate the posterior predictive interval as usual, and compare with the classical prediction interval:

```
> quantile(post.pred.y.sim, c(0.025,0.975)) # posterior predictive interval
    2.5% 97.5%
38.89235 56.79167
> predict(mod, data.frame(IncomeGrowth=0.75), interval="prediction")
    fit lwr upr
1 48.18112 38.86593 57.49631
> # exact 95% classical interval
```

For reference, the actual Republican two-party vote share for 2008 was 46.3%.

Can also approximate the posterior predictive probability of a 2008 incumbent (Republican) victory:

```
> mean(post.pred.y.sim > 50) # post. pred. prob. of incumbent victory
[1] 0.342
```