JAGS Examples from Kery's book Introduction to WinBugs

Code in Kery's book can be downloaded from here:

http://www.mbr/-
pwrc.usgs.gov/software/kerybook/R/_WB/_code.txt

JAGS Examples from Kery's book Introduction to WinBugs

Code in Kery's book can be downloaded from here:

http://www.mbr/-
pwrc.usgs.gov/software/kerybook/R/_WB/_code.txt

Most of the code will run, with a few modifications, using JAGS. In particular, we have to add `BUGSoutput` when referencing any of the output from JAGS.

- In Kery's booK: `plot(out$mean$predicted, out$mean$residual)`
- We need to use: `plot(out$BUGSoutput$mean$predicted, out$BUGSoutput$mean$residual)`.

Trends in Wallcreeper Counts

- Proportion of sample quadrats where the bird is observed
- Assume deviations from a linear trend are normally distributed

Ch 8: Linear regression

Prior and likelihood is very similar to what we have already seen.

```
linreg<-function(){

# Priors
 alpha ~ dnorm(0,0.001)
 beta ~ dnorm(0,0.001)
 sigma ~ dunif(0, 100)

# Likelihood
 for (i in 1:n) {
    y[i] ~ dnorm(mu[i], tau)
    mu[i] <- alpha + beta*x[i]
 }
```

Derived quantities

```
# Derived quantities
 tau <- 1/ (sigma * sigma)
 p.decline <- 1-step(beta)      # Probability of decline
```

Step() = 1 if what is in the "()" is > 0 (and 0 otherwise). So, this calculates the probability that $\beta < 0$.

Residuals

```
for (i in 1:n) {
   residual[i] <- y[i]-mu[i]        # Residuals for observed data
   predicted[i] <- mu[i]        # Predicted values
   sq[i] <- pow(residual[i], 2)    # Squared residuals for observed d
```

Note: we will get `n.iter` residuals for each data point! Why?

Residuals

```
for (i in 1:n) {
   residual[i] <- y[i]-mu[i]       # Residuals for observed data
   predicted[i] <- mu[i]       # Predicted values
   sq[i] <- pow(residual[i], 2)    # Squared residuals for observed d
```

Note: we will get `n.iter` residuals for each data point! Why?

Residual: r[i] = $y_i - (alpha + beta * x[i])$.

Residuals

```
for (i in 1:n) {
   residual[i] <- y[i]-mu[i]       # Residuals for observed data
   predicted[i] <- mu[i]       # Predicted values
   sq[i] <- pow(residual[i], 2)    # Squared residuals for observed d
```

Note: we will get `n.iter` residuals for each data point! Why?

Residual: r[i] = $y_i - (alpha + beta * x[i])$.

We generate n_{MCMC} values of alpha and beta, so n_{MCMC} values of r[i]!

Bayesian p-value

- Generate new ("ideal") data: `y.new[i] ~ dnorm(mu[i], tau)`
  - Using the assumed model
  - Using parameters drawn from the posterior distribution (accounts for parameter uncertainty)

Bayesian p-value

- Generate new (“ideal”) data: `y.new[i] ~ dnorm(mu[i], tau)`
  - Using the assumed model
  - Using parameters drawn from the posterior distribution (accounts for parameter uncertainty)
- Calculate measure of “fit” (or lack of fit) for for the observed data and simulated data
  - `fit <- sum(sq[])` sum of squared residuals for the observed data
  - `fit.new <- sum(sq.new[])` (same for simulated data)

Bayesian p-value

If the model fits the data well: “goodness-of-fit” statistics for real and simulated data should be similar

Bayesian p-value

If the model fits the data well: “goodness-of-fit” statistics for real and simulated data should be similar

If the model does not fit the data well

- sum of squared residuals for the observed data > sum of squared residuals for the simulated data

Bayesian p-value

If the model fits the data well: “goodness-of-fit” statistics for real and simulated data should be similar

If the model does not fit the data well

- sum of squared residuals for the observed data > sum of squared residuals for the simulated data

```
test <- step(fit.new - fit)
```

Bayesian p-value

If the model fits the data well: “goodness-of-fit” statistics for real and simulated data should be similar

If the model does not fit the data well

- sum of squared residuals for the observed data > sum of squared residuals for the simulated data

```
test <- step(fit.new - fit)
```

- test = 1 if SS(simulated data) > SS(observed data), i.e., the model fits the observed data better than the simulated data.

Bayesian p-value

If the model fits the data well: "goodness-of-fit" statistics for real and simulated data should be similar

If the model does not fit the data well

- sum of squared residuals for the observed data > sum of squared residuals for the simulated data

```
test <- step(fit.new - fit)
```

- test = 1 if SS(simulated data) > SS(observed data), i.e., the model fits the observed data better than the simulated data.
- `bpvalue <- mean(test)` (how often does the model fit observed data better than the simulated data)
- Want bpvalue to be large (can't conclude there is a lack of fit).

Kery's code: Predictions = CI for the line = $E[Y|X]$

We have n_{MCMC} = `n.chains`(`n.iter - n.burn`) draws from the posterior distribution of (α, β, σ).

Kery's code: Predictions = CI for the line = $E[Y|X]$

We have n_{MCMC} = `n.chains`(`n.iter - n.burn`) draws from the posterior distribution of (α, β, σ).

For each value of $X = x$ (loop), he generates n_{MCMC} predictions.

```
for(i in 1:length(x)){
   predictions[i,] <- out$BUGSoutput$sims.list$alpha +
     out$BUGSoutput$sims.list$beta*x[i]
}
```

Kery's code: Predictions = CI for the line = $E[Y|X]$

We have n_{MCMC} = `n.chains(n.iter - n.burn)` draws from the posterior distribution of (α, β, σ).

For each value of $X = x$ (loop), he generates n_{MCMC} predictions.

```
for(i in 1:length(x)){
   predictions[i,] <- out$BUGSoutput$sims.list$alpha +
     out$BUGSoutput$sims.list$beta*x[i]
}
```

- Gives us n_{MCMC} draws of $E[Y|X = x] = \alpha + x\beta$. What does this tell us?

Kery's code: Predictions = CI for the line = $E[Y|X]$

We have n_{MCMC} = `n.chains(n.iter - n.burn)` draws from the posterior distribution of (α, β, σ).

For each value of $X = x$ (loop), he generates n_{MCMC} predictions.

```
for(i in 1:length(x)){
   predictions[i,] <- out$BUGSoutput$sims.list$alpha +
     out$BUGSoutput$sims.list$beta*x[i]
}
```

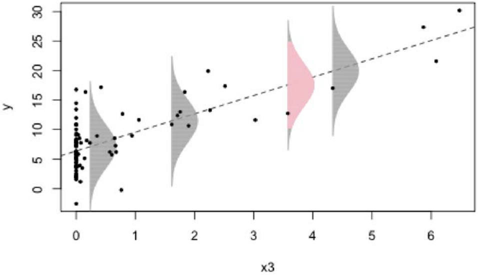
- Gives us n_{MCMC} draws of $E[Y|X = x] = \alpha + x\beta$. What does this tell us?
- This is the posterior distribution of the fitted line (tells us about the line and its uncertainty)

Prediction Intervals

What about prediction intervals? Intervals that are likely to contain a new observation, if collected?

Prediction Intervals

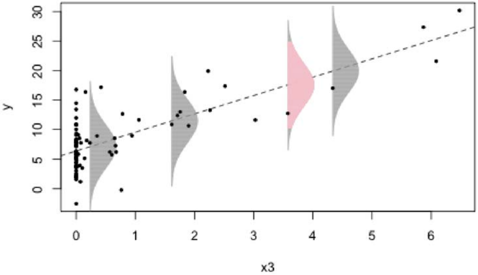
What about prediction intervals? Intervals that are likely to contain a new observation, if collected?



- Requires we also consider the variability about the line

Prediction Intervals

What about prediction intervals? Intervals that are likely to contain a new observation, if collected?



- Requires we also consider the variability about the line
- This variability is described by the errors $\sim N(0, \sigma^2)$.

Exercise 1: Bayesian prediction intervals

Start with the posterior for the line:

- We have n_{MCMC} values of $E[Y|X = x] = \alpha + x\beta$

Exercise 1: Bayesian prediction intervals

Start with the posterior for the line:

- We have n_{MCMC} values of $E[Y|X = x] = \alpha + x\beta$

We need to add…

- random normal deviates

Exercise 1: Bayesian prediction intervals

Start with the posterior for the line:

- We have n_{MCMC} values of $E[Y|X = x] = \alpha + x\beta$

We need to add…

- random normal deviates
- add: rnorm(n_{MCMC}, mean = 0, sd = reference posterior for σ)

Exercise 1: Bayesian prediction intervals

Start with the posterior for the line:

- We have n_{MCMC} values of $E[Y|X = x] = \alpha + x\beta$

We need to add...

- random normal deviates
- add: rnorm(n_{MCMC}, mean = 0, sd = reference posterior for σ)
- gives us the posterior of $Y_{new}|X$ (rather than $E[Y|X]$)

Exercise 1: Bayesian prediction intervals

Start with the posterior for the line:

- We have n_{MCMC} values of $E[Y|X = x] = \alpha + x\beta$

We need to add…

- random normal deviates
- add: rnorm(n_{MCMC}, mean = 0, sd = reference posterior for σ)
- gives us the posterior of $Y_{new}|X$ (rather than $E[Y|X]$)
- Try to modify Kery's code to do this! Hint: to figure out n_{MCMC}, inspect the dimension of `out$BUGSoutput$sims.list$alpha`

Bayesian prediction intervals

Note: we could have added the normal random deviates within our `linreg` function.

Bayesian prediction intervals

Note: we could have added the normal random deviates within our `linreg` function.

Actually, we did do this when we generated y.new.

Bayesian prediction intervals

Note: we could have added the normal random deviates within our `linreg` function.

Actually, we did do this when we generated y.new.

We could have just added `y.new` to our "parameters.to.save" vector and then summarized the quantiles of the jags output to get the prediction intervals.

Exercise 2: Prediction Intervals (frequentist)

For linear models fit in R, we can generate confidence and prediction intervals using the `predict` function, and more specifically, `predict.lm`

- Look up the help file for `predict.lm` and examples at bottom
- Calculate these intervals for the fitted linear model.
- Plot these intervals using the `lines` function along with Bayesian prediction intervals

Chapter 11: ANCOVA model (importance of priors and scaling)

Relationship between Body Mass and Body Length

- Asp viper's from 3 populations (Pyrenees, Massif Central, Jura Mountains) in Switzerland
- Interested in population-specific differences in the body-mass relationship

Linear regression model

$$y_i = \alpha_0 + \beta_1 x_i + \epsilon_i$$

- y_i = body mass of individual i
- x_i = body length of snake i

How dow we capture “population-specific differences in the body-mass relationship”?

Linear regression model

$$y_i = \alpha_0 + \beta_1 x_i + \epsilon_i$$

- y_i = body mass of individual i
- x_i = body length of snake i

How dow we capture "population-specific differences in the body-mass relationship"?

Include interactions!

Example CH 11.2

Effects parameterization:

$$y_i = \alpha_{pyr} + \beta_1 I_{MC,i} + \beta_2 I_{Jura,i} + \beta_3 x_i + \beta_4 x_i I_{MC,i} + \beta_5 x_i I_{Jur,i} + \epsilon_i$$

Example CH 11.2

Effects parameterization:

$$y_i = \alpha_{pyr} + \beta_1 I_{MC,i} + \beta_2 I_{Jura,i} + \beta_3 x_i + \beta_4 x_i I_{MC,i} + \beta_5 x_i I_{Jur,i} + \epsilon_i$$

Means parameterization:

$$y_i = \alpha_{j(i)} + \beta_{j(i)} x_i + \epsilon_i$$

Example CH 11.2

Effects parameterization:

$$y_i = \alpha_{pyr} + \beta_1 I_{MC,i} + \beta_2 I_{Jura,i} + \beta_3 x_i + \beta_4 x_i I_{MC,i} + \beta_5 x_i I_{Jur,i} + \epsilon_i$$

Means parameterization:

$$y_i = \alpha_{j(i)} + \beta_{j(i)} x_i + \epsilon_i$$

Identify the parameters used in the simulation:

- Effects model (α and $\beta_1 - \beta_5$)
- Means model (α and β) for each population.

Parameters

Effects parameterization

- α = -250
- β_1 = 150
- β_2 = 200
- β_3 = 6
- β_4 -3
- β_5 -4

Means parameterization

- Pyrenees: α = -250, β = 6
- Massif: α = -100, β = 3
- Jura: α = -50, β = 2

What happened?

Kery shows that standardizing works. Centering would also help. Why?

What happenened?

Kery shows that standardizing works. Centering would also help. Why?

Lets look at the prior distributions for $\alpha \sim N(0, 0.001)$. Plot this distribution.

What happened?

Kery shows that standardizing works. Centering would also help. Why?

Lets look at the prior distributions for $\alpha \sim N(0, 0.001)$. Plot this distribution.

```r
curve(dnorm(x, 0,sqrt(1/0.001)), from=-250, to=250)
```