

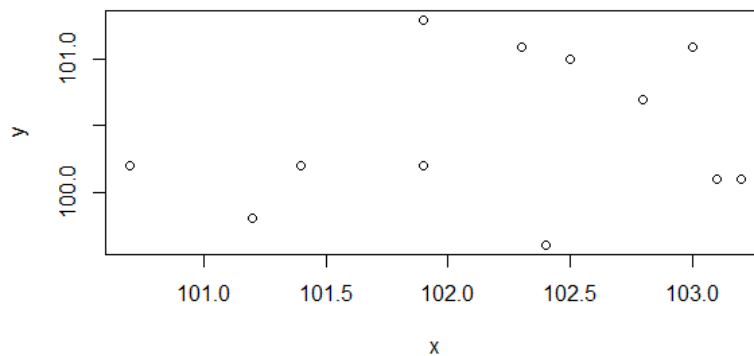
# Midterm Math525

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Part a:

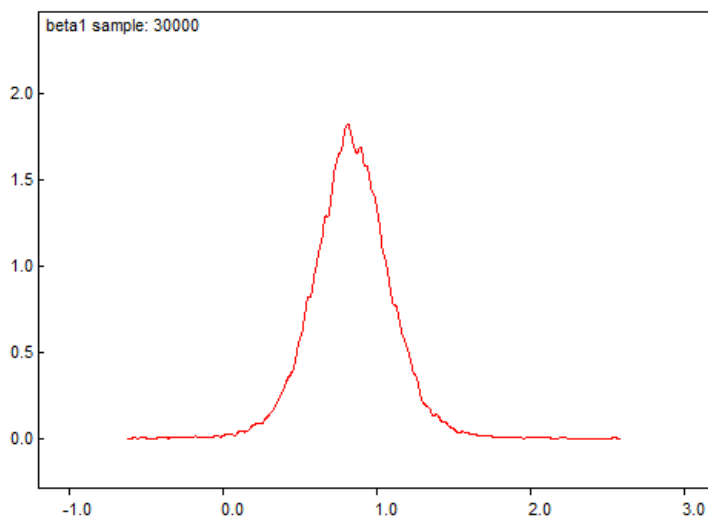
I plotted the raw data in R and that yielded:



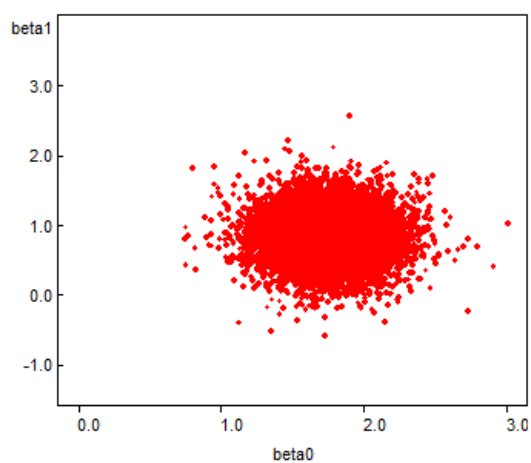
The linear model doesn't appear plausible for the first look at the raw data plot, but we need a "goodness-of-fit" measure (like  $R^2$ ) to make a better decision; running a standard linear regression of Z on the X-mean(x) returns an  $R^2 = 0.5987$ ; so I conclude that a linear model is plausible.

Part b:

Fitting the given SLR model in WinBUGS (after finding the  $Z_i$  values in R), and running 30'000 iterations after 1000 burn-ins, I got the following posterior for  $\beta_1$ :



And a bi-variate scatter plot for the joint posterior of  $\beta = (\beta_0, \beta_1)$  :

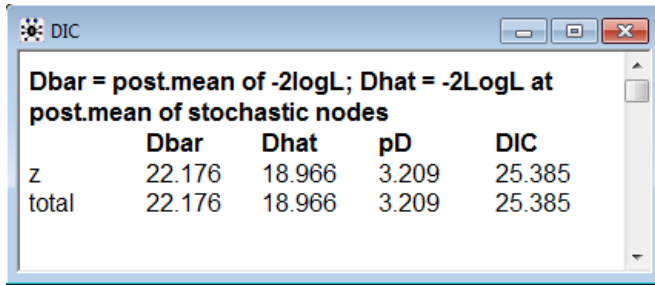


There's no correlation between  $\beta_0$  and  $\beta_1$  because the X's are already centered around their mean in our simple linear regression model.

WinBUGS also gives us the 95% of  $\beta_1$  which was: (0.3481,1.338), with  $\beta_1$  mean: 0.8407 and standard deviation: 0.2491.

I can't set a  $H_0 : \beta_1 = 0$  and reject it to confirm the investigators' suggestion because I set a vague flat prior on  $\beta_1$ , so testing the  $R_{01}$  will give 1; not useful. But by running: `cor(x,y)` in R, I had: 0.223615; a positive correlation means the higher x is, the higher z will be; so according to that I confirm the investigators' suggestion that reduction in temperature is related to the initial temperature.

For the DIC and the  $P_D$ , WinBUGS returned:  $P_D = 3.209$  and DIC=25.385



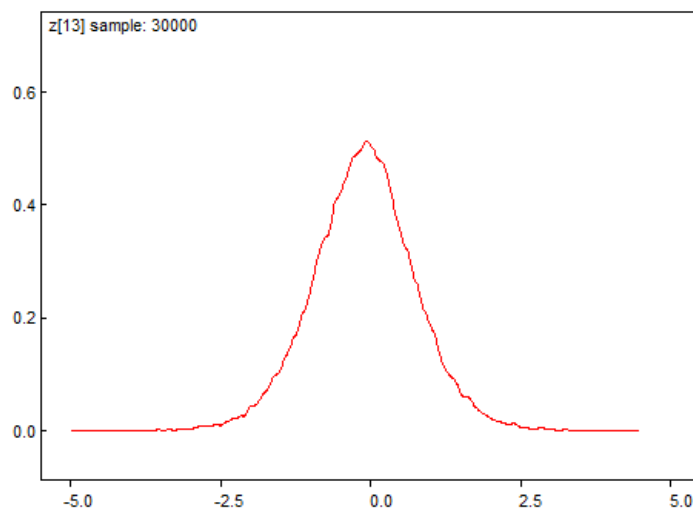
The image shows a screenshot of the WinBUGS DIC (Deviance Information Criterion) window. The window title is 'DIC'. The text inside the window reads: 'Dbar = post.mean of -2logL; Dhat = -2LogL at post.mean of stochastic nodes'. Below this, there is a table with five columns: 'z', 'Dbar', 'Dhat', 'pD', and 'DIC'. The table has two rows: 'z' and 'total'. The values for 'z' are: Dbar=22.176, Dhat=18.966, pD=3.209, DIC=25.385. The values for 'total' are: Dbar=22.176, Dhat=18.966, pD=3.209, DIC=25.385.

	Dbar	Dhat	pD	DIC
z	22.176	18.966	3.209	25.385
total	22.176	18.966	3.209	25.385

Part c:

I predicted Z after the arrival of the new  $x_{n+1}$  in WinBUGS for 30'000 iterations after 1000 burn-ins and monitored Z. (code below).

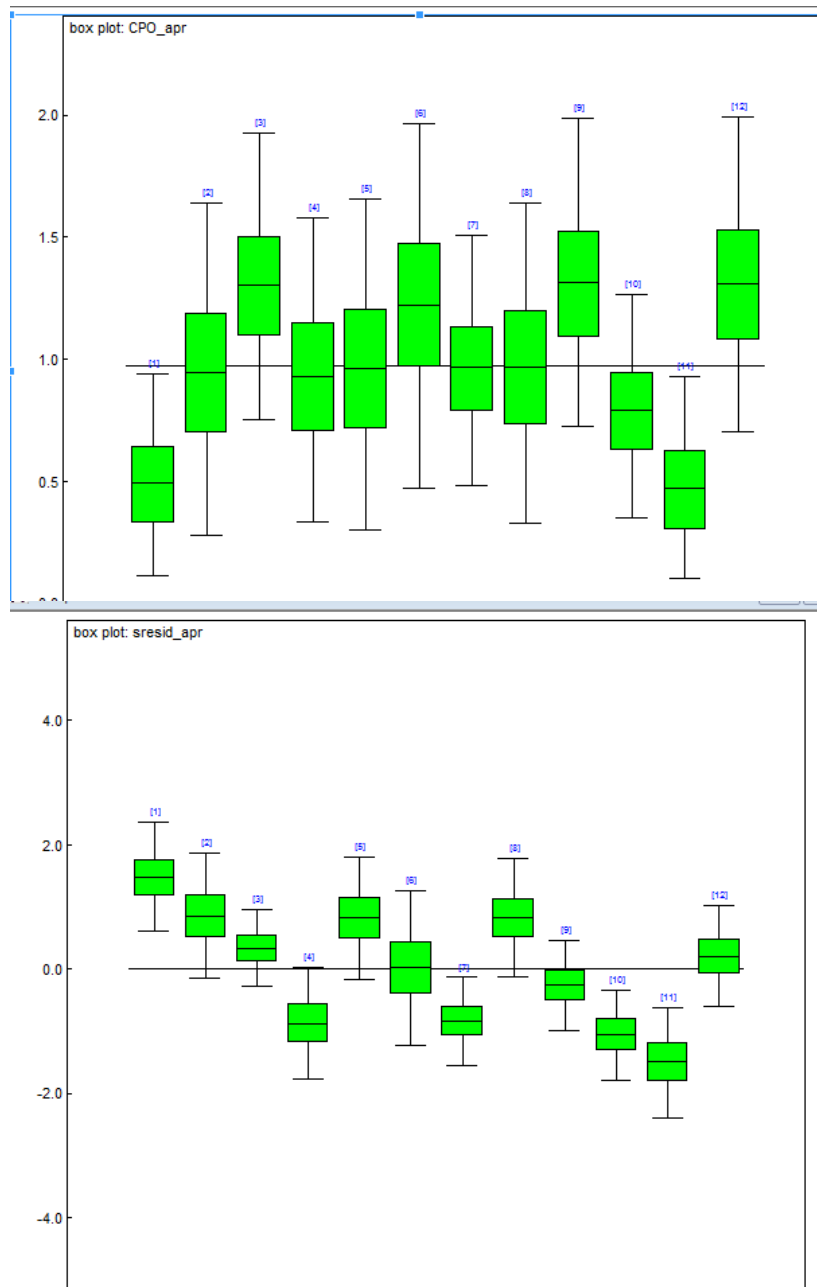
The density of  $z_{13}$  and the mean and standard deviation (the point estimates) as WinBUGS returned are:



Node statistics							
node	mean	sd	MC error	2.5%	median	97.5%	start sample
z[13]	-0.1071	0.8653	0.004992	-1.828	-0.09843	1.619	1001 30000

Part d:

Following the book's code in WinBUGS again, but I modified it by finding the standardized X's and Z's in R instead and used them in WinBUGS data directly, then ran 20'000 iterations after 1000 burn-ins. I got the following Box-plots:



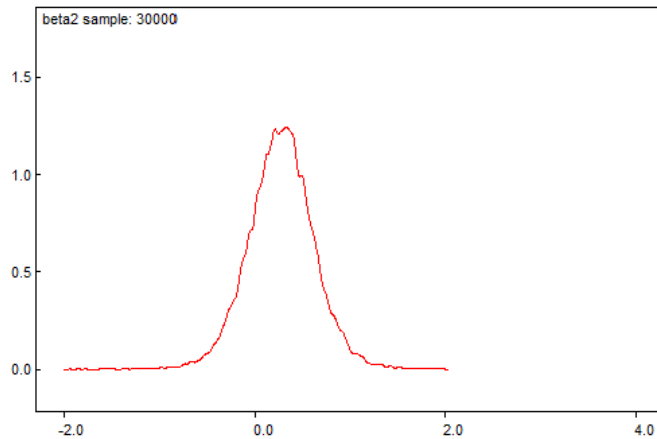
I don't recognize any astray outliers, but most of them on the far end (I tried to change from step=1.5 to step=2 in the WinBUGS code and got similar results); we need more data, I assume this is not enough sample size to decide on outliers.

Checking DIC and  $p_D$  again, gives: DIC=28.683 and  $p_D$ =3.193

Part e:

The model is now:  $Z_i = \beta_0 + \beta_1(x_i - \bar{x}) + \beta_2(x_i - \bar{x})^2 + \epsilon_i$

Running this in WinBUGS for 30'000 iterations after 1000 burn-ins gave this posterior density for  $\beta_2$ :

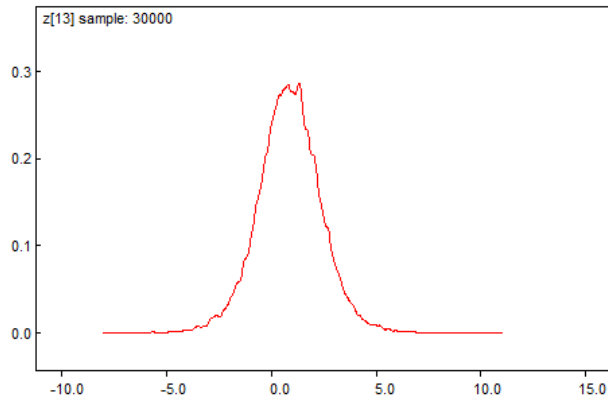


It's normal distribution with mean:0.2769 and sd:0.3475. As I did for  $\beta_1$  earlier, I took the coda from WinBUGS and put it in R and fitted the distribution to normal and it returned the same mean and standard deviation I got in WinBUGS.

Using the DIC tool in WinBUGS, I got:  $p_D=4.338$  and  $DIC=26.867$

Lower number for DIC than the previous model means the model has enhanced, we have a better fitting model to our data after adding the quadratic term; the data justifies that because we have some entries a little far from the mean, and the new squared distance included them in the model, (both the over and below the line).

To see how that impacts Part c, I predicted  $z_{13}$  again for  $x_{n+1} = 100$  under this new SLR model; and that done in WinBUGS and checked in R (code below) gave the following normal density and statistics:



Node statistics								
node	mean	sd	MC error	2.5%	median	97.5%	start	sample
z[13]	0.868	1.513	0.008822	-2.173	0.8645	3.885	1001	30000

Yes, the second prediction is the justified by the data because I got a positive (mean) reduction in temperature, which accords with the rest of the Z vector  $z_1 \dots z_{12}$ , while the first prediction yielded a negative number (negative mean, with small sd) for  $z_{13}$  which doesn't make sense, since it means the patient temperature (most likely) went up after taking aspirin; and that is contradicted by the rest of the Z vector values.

### The codes used:

```
##R code for Part a:
#-----
rm(list=ls())
data<-read.table("aspirin_data.txt")
x<-data$V2
y<-data$V3
n<-length(x)
plot(x,y)
#####
#####
##WinBUGS code for Part b:
#-----
model{
  for( i in 1:n) {
    xmean[i] <- (x[i]-mean(x[]))
    z[i] ~ dnorm(mu[i] , tau)

    mu[i] <- beta0+ beta1*xmean[i]
  }

  # beta0 ~ dnorm(0, 0.001)    # for later use
  # beta1 ~ dnorm(0, 0.001)

  beta0 ~ dflat()           # for max comparability to frequentest results
  beta1 ~ dflat()

  tau ~ dgamma(0.1, 0.1)    # p-D = 3.203,    DIC = 25.365
  sigma <- 1/sqrt(tau)
} # end of BUGS code

#Data:
list(x = c( 102.4, 103.2, 101.9, 103.0,
101.2, 100.7, 102.5, 103.1, 102.8, 102.3,
101.9, 101.4),
z=c(2.8, 3.1, 1.7, 1.9, 1.4, 0.5, 1.5, 3.0,
2.1, 1.2, 0.6, 1.2),
n = 12)
```



```

# Inits:
list( beta0 = 0, beta1 = 1, tau = 1)    # for gamma prior on tau

#####
#R code for fitting beta1 posterior:
#-----
b1post<-read.table("b1post.txt")
library(MASS)
ppost<-b1post$v2
fitdistr(ppost,"normal")
#same as we got in WinBUGS
#####
##WinBUGS code for Part c:
#-----

model{
  for( i in 1:n) {
    xmean[i] <- (x[i]-mean(x[]))
    z[i] ~ dnorm(mu[i] , tau)

    mu[i] <- beta0+ beta1*xmean[i]

  }

  beta0 ~ dflat()      # for max comparability to frequentist results
  beta1 ~ dflat()

  tau ~ dgamma(0.1, 0.1)  # p-D = 3.203,   DIC = 25.365
  sigma <- 1/sqrt(tau)

} # end of BUGS code

#Data:
list(x = c( 102.4, 103.2, 101.9, 103.0, 101.2,
100.7, 102.5, 103.1, 102.8, 102.3, 101.9, 101.4, 100),
z=c(2.8, 3.1, 1.7, 1.9, 1.4, 0.5, 1.5, 3.0, 2.1,
1.2, 0.6, 1.2, NA),

```

```

n = 13)

# Inits:

list( beta0 = 0, beta1 = 1, tau = 1)  # for gamma prior on tau

#Note about carrying out the model here and in prediction in Part d:
#for some reason, it didn't accept the initials, so I generated ones,
#updated for 1000 iterations as burn-ins, then loaded these initials
#and monitored Z, updated for 30'000 iterations and collected
#information as usual.

#####
#R code for distribution of z13:
#-----
#predictive was found in WinBUGS
partc<-read.table("part-c-prediction.txt")
newz<-partc$V2
library(MASS)
fitdistr(newz,"normal")
#it's indeed normal. results are consistant with what found in WinBUGS
z13<-pnorm(0.0001,-0.120042920,0.868969448)
z13
#####
##WinBUGS code for Part d:
#-----
#standardizing the data in R:
#-----
lz<-c(scale(z))
lx<-c(scale(x))
lx
lz

#now the WinBUGS code:
#-----
#the new data set is the standardized data found in R
#from the linear regression model we find these:

```

```

beta1<- beta1 / sd(x)
beta0 <- beta0 - b1 * mean(x)

model{
  for( i in 1:n) {
    z[i]~dnorm(mu[i],tau)
    mu[i]<-beta0+beta1*x[i]
  }

# beta0 ~ dnorm(0, 0.001)    # for later use
# beta1 ~ dnorm(0, 0.001)

  beta0 ~ dflat()           # for max comparability to frequentist results
  beta1 ~ dflat()

  tau ~ dgamma(0.1, 0.1)    # p-D = 3.203,    DIC = 25.365
  sigma <- 1/sqrt(tau)

  for( i in 1:n) {
    # standardized residuals without the "leave-one-out", and taking the
    # the *ratio* before posterior averaging.
    #Results tend to be too close to 0.
    sresid_apr[i] <- (z[i] - mu[i]) / sigma

# flag observations with sresid_apr values bigger than 1.5 as outliers:
    outlier_apr[i] <- step(sresid_apr[i] - 1.5) +
      step(-(sresid_apr[i] +1.5) )
# approximate CPO:
    CPO_apr[i] <-sqrt(tau)* exp(-tau/2* (z[i] - mu[i])* (z[i] -mu[i]))
  }
} # end of BUGS code

#Data:
list(x = c( 0.2503559, 1.2517794, -0.3755338, 1.0014235,
-1.2517794, -1.8776690, 0.3755338, 1.1266014, 0.7510676, 0.1251779,
-0.3755338, -1.0014235),
z=c(1.20805061, 1.55320793, -0.05752622, 0.17257866,

```

```

-0.40268354, -1.43815549, -0.28763110, 1.43815549,
0.40268354, -0.63278842, -1.32310305, -0.63278842),
n = 12)

# Inits:
list( beta0 = 0, beta1 = 1, tau = 1) # for gamma prior on tau
#####
#####
###WinBUGS code for Part e:
#-----

model{
  for( i in 1:n) {
    xmean[i] <- (x[i]-mean(x[]))
    z[i] ~ dnorm(mu[i] , tau)

    mu[i] <- beta0+ beta1*xmean[i] +beta2*(xmean[i]*xmean[i])

  }

  beta0 ~ dflat() # for max comparability to frequentist results
  beta1 ~ dflat()
  beta2 ~ dflat()

  tau ~ dgamma(0.1, 0.1) # p-D = 3.203, DIC = 25.365
  sigma <- 1/sqrt(tau)

} # end of BUGS code

#Data:
list(x = c( 102.4, 103.2, 101.9, 103.0, 101.2, 100.7,
102.5, 103.1, 102.8, 102.3, 101.9, 101.4),
z=c(2.8, 3.1, 1.7, 1.9, 1.4, 0.5, 1.5, 3.0,
2.1, 1.2, 0.6, 1.2),
n = 12)

# Inits:
list( beta0 = 0, beta1 = 1, beta2 = 1, tau = 1) #for gamma prior on tau

```

```

#####
##WinBUGS code for Part e – predicting z13:
#-----

model{
  for( i in 1:n) {
    xmean[i] <- (x[i]-mean(x[]))
    z[i] ~ dnorm(mu[i] , tau)

    mu[i] <- beta0+ beta1*xmean[i] +beta2*(xmean[i]*xmean[i])

  }

# beta0 ~ dnorm(0, 0.001)
# beta1 ~ dnorm(0, 0.001)
# beta2 ~ dnorm(0, 0.001)

  beta0 ~ dflat()
  beta1 ~ dflat()
  beta2 ~ dflat()

  tau ~ dgamma(0.1, 0.1) # p-D = 3.203, DIC = 25.365
  sigma <- 1/sqrt(tau)

} # end of BUGS code

#Data:
list(x = c( 102.4, 103.2, 101.9, 103.0, 101.2, 100.7,
102.5, 103.1, 102.8, 102.3, 101.9, 101.4, 100),
z=c(2.8, 3.1, 1.7, 1.9, 1.4, 0.5, 1.5, 3.0, 2.1,
1.2, 0.6, 1.2, NA),
n = 13)

# Inits:

```

```

list( beta0 = 0, beta1 = 1, beta2 = 1, tau = 1) #for gamma prior on tau
#####
#R code for Part 2, fitting posteriors:
#for beta2:
b2post<-read.table("b2post-part-e.txt")
library(MASS)
#by looking at b2post from the -working environement-:
b2<-b2post$V2
fitdistr(b2,"normal")

#for the z13 prediction:
z13e<-read.table("part-e-prediction.txt")
library(MASS)
zz<-z13e$V2
fitdistr(zz,"normal")
#####

```