Bayesian Computing

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Experiment no. 4

Aim: To implement a model for a bioassay experiment: consider data from Gelman at al. (2003), where are observers a dose level (in 10 g g/ml). The number of animals and the number of deaths for each of four groups.

Theory:-

Multiparameter Models:-

These are statistical models that involve multiple parameters or unknown quantities. These models are commonly used in various fields, including statistics, machine learning and scientific research, to represent complex relationships between variables and to make predictions or inferences about the parameters.

In Bayesian computing, multiparameter models are analyzed using Bayesian methods which incorporate prior beliefs about the parameters into the analysis and update their beliefs based on observed data. Bayesian inference provides a comprehensive framework for handling uncertainty in multiparameter models.

Logistic Regression:-

Logistic Regression is a statistical model used for binary classification, where the goal is to predict a binary outcome (eg; yes or no, success or failure, etc. based on a set of independent variables.

In Bayesian logistic regression, prior beliefs about the model parameters, such as the regression coeffecients, or incorporated into the analysis using probability distributions. These priors are updated using Bayes rule baud on observed data, resulting in posterior distributions that reflect the updated beliefs about the parameters.

A Bioassay Experiment :

Bioassay experiments are used to determine the dose-response relationship for a biological agents such as drug or toxin. These experiments typically involve exposing a group of organisms to different doses of the agent & measuring the biological responses, such as survival or death. Logistic Regression can be used in a Bayesian framework to analyze bioassay data by modeling probability of a positive response as a function of the dose The model parameters can be interpreted as the dose of at which a certain proportion of population is expected to experience positive response.

Conclusion :

In this experiment, we implemented a Bayesian model for a binary experiment using R. The model fitted the date well, capturing the uncertainty in the parameter estimate. The results demonstrated the utility of Bayesian methods in interpreting bioassay data and the influence of prior information on the posterior distribution.

In conclusion, the experiment provided valuable insights into Bayesian computing and its application in bioassay analysis by modeling & analyzing a bioassay experiment using Bayesian logistic regression.

Department of Computer Engineering

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Batch: C2-1

Subject: Bayesian Computing Laboratory   Semester: VII

Experiment No. 4

Aim:

Implement a model for A Bioassay Experiment: consider data from Gelman et al. (2003), where one observes a dose level (in log g/ml), the number of animals, and the number of deaths for each of four groups.

Code:

Importing Libraries

```
library('LearnBayes')
```

Bayesian fitting of a logistic model using data from a dose-response experiment.

```
x <- c(-0.86, -0.3, -0.05,

0.73) n <- c(5, 5, 5, 5) y <-

c(0, 1, 3, 5) data <- cbind(x,

n, y)


glmdata <- cbind(y, n - y) results <-

glm(glmdata ~ x, family = binomial)

summary(results)


a1.b1 <- beta.select(list(p=.5, x=.2),

          list(p=.9, x=.5)) a2.b2
<- beta.select(list(p=.5, x=.8),
```

```
                list(p=.9, x=.98))


prior <- rbind(c(-0.7, 4.68, 1.12),

c(0.6, 2.10, 0.74)) data.new <-

rbind(data, prior)



plot(c(-1,1), c(0, 1), type="n",

xlab="Dose", ylab="Prob(death)") lines(-

0.7 * c(1, 1), qbeta(c(.25, .75),

a1.b1[1], a1.b1[2]), lwd=4) lines(0.6 *

c(1, 1), qbeta(c(.25, .75),     a2.b2[1],

a2.b2[2]), lwd=4) points(c(-0.7, 0.6),

qbeta(.5, c(a1.b1[1],        a2.b2[1]),

c(a1.b1[2], a2.b2[2])),        pch=19,

cex=2) text(-0.3, .2, "Beta(1.12, 3.56)")

text(.2, .8, "Beta(2.10, 0.74)") response <-

rbind(a1.b1, a2.b2) x <- c(-0.7, 0.6) fit <-

glm(response ~ x, family = binomial)



curve(exp(fit$coef[1] + fit$coef[2] * x) /
(1 + exp(fit$coef[1] + fit$coef[2] * x)),
add=T)
```
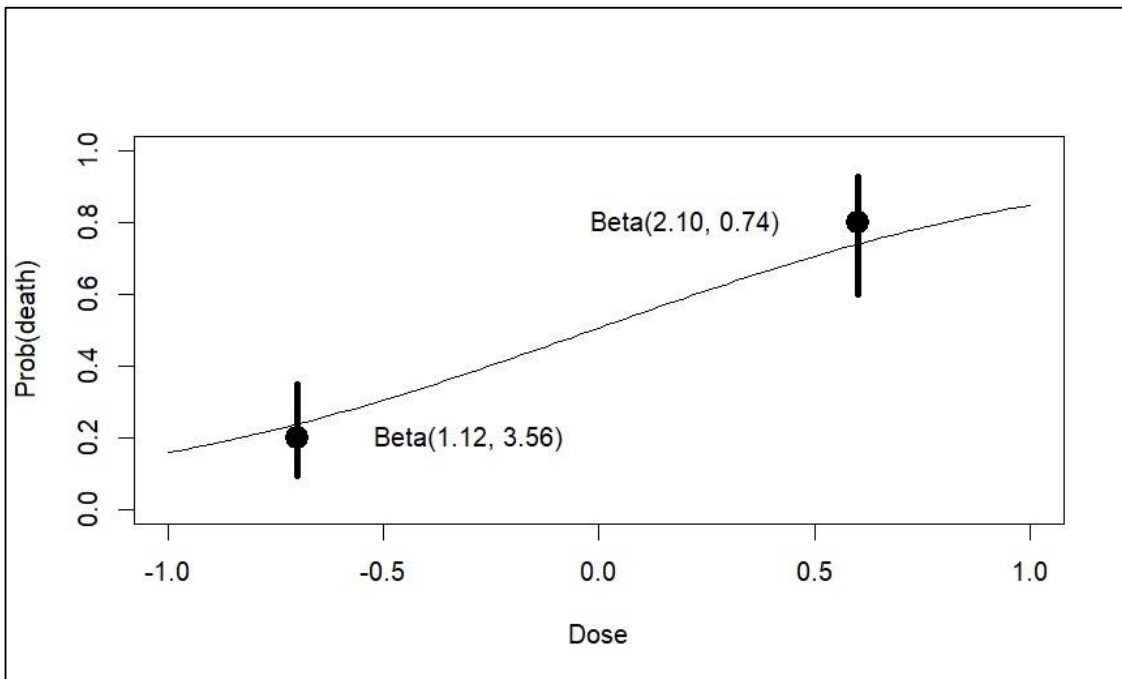
Output:

```
Call:
glm(formula = glmdata ~ x, family = binomial)

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept)   0.8466     1.0191   0.831    0.406
x             7.7488     4.8728   1.590    0.112

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 15.791412  on 3  degrees of freedom
Residual deviance:  0.054742  on 2  degrees of freedom
AIC: 7.9648

Number of Fisher Scoring iterations: 7
```
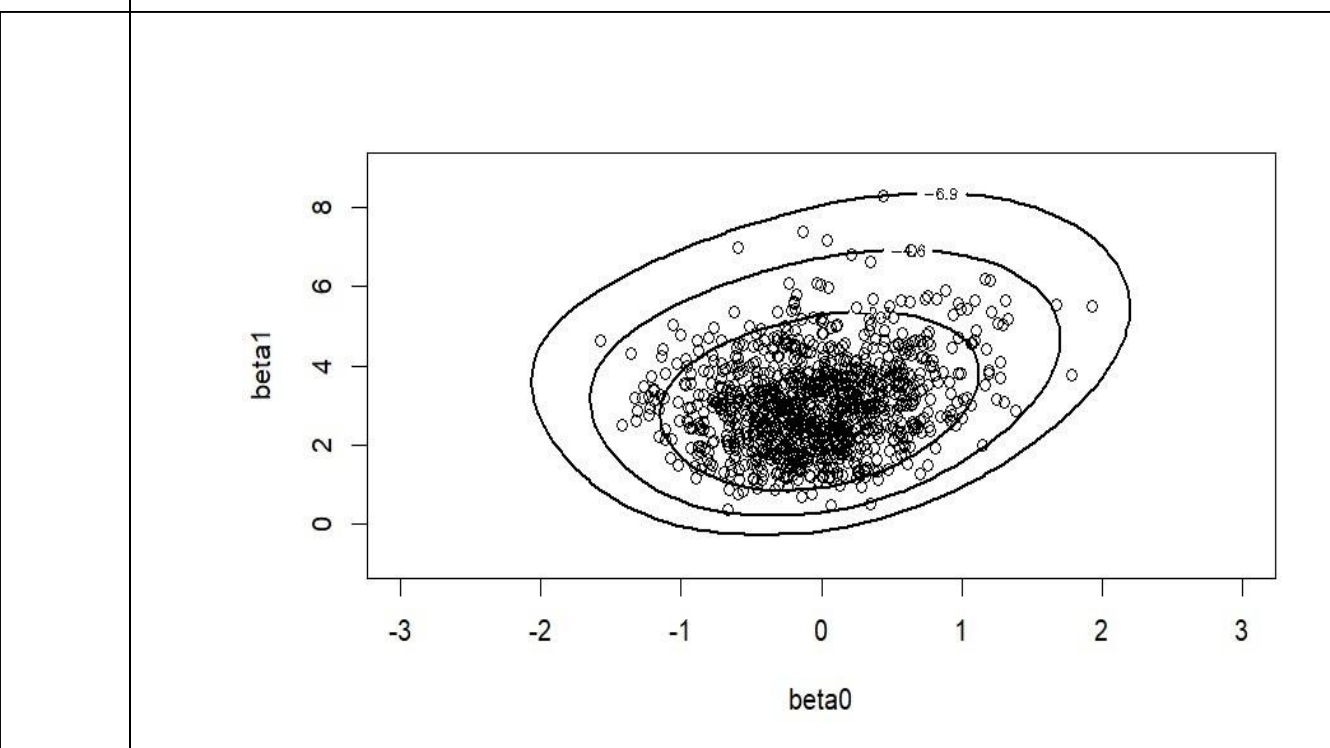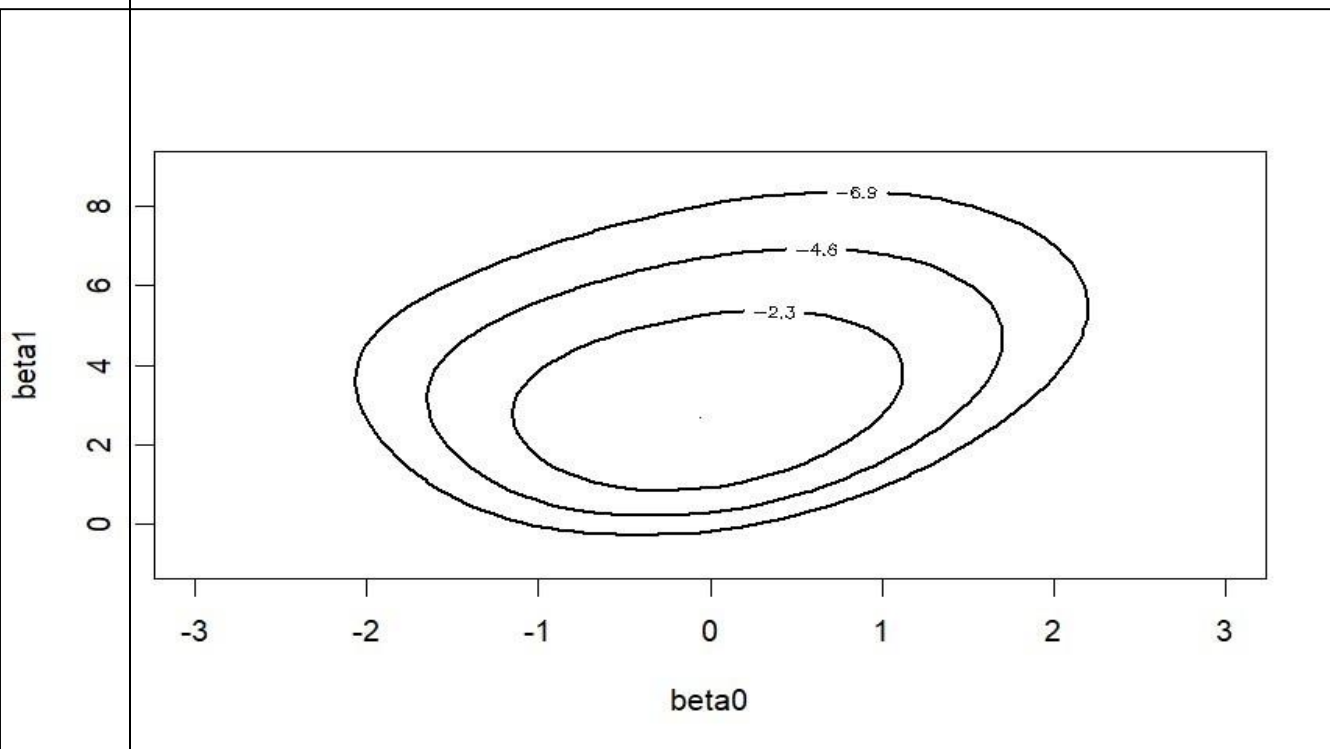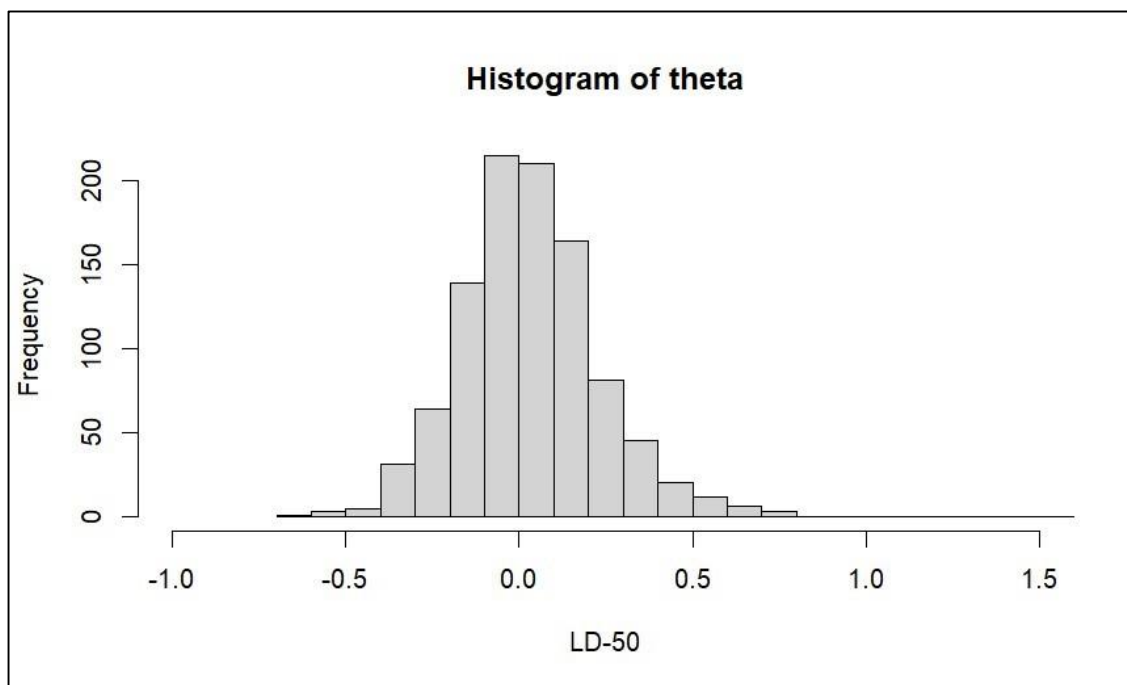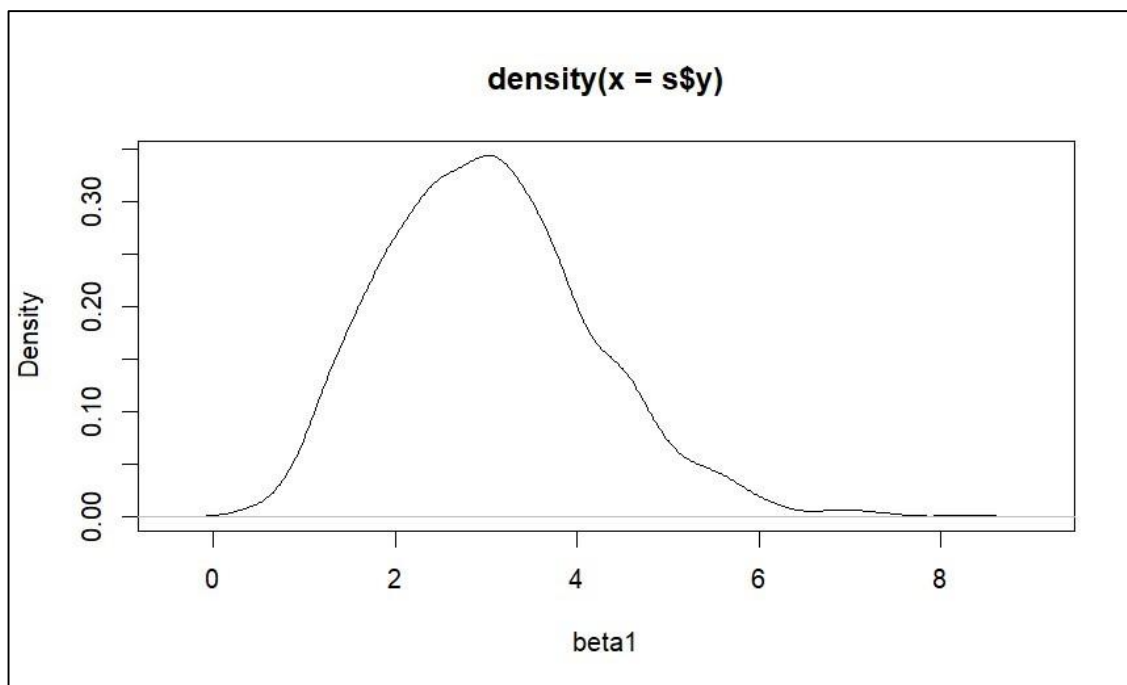
Shri Vile Parle Kelavani Mandal's

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density(x = s$y)

Histogram of theta

```
      2.5%      97.5%
-0.3251418   0.4707840
```