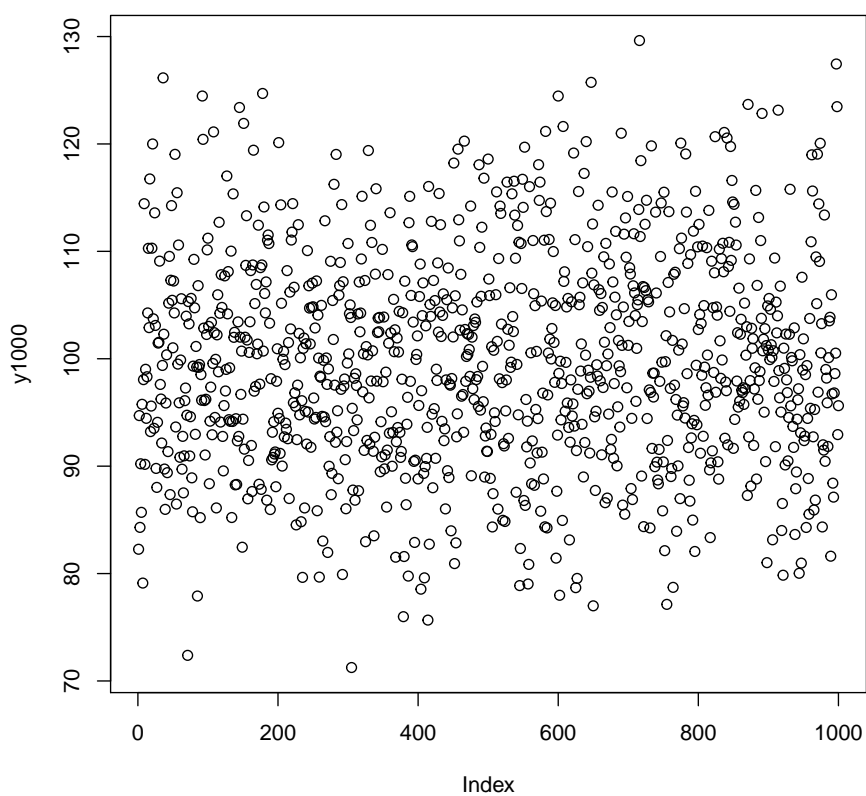


从现在开始我决定认真的学习 Bayesian 方法，以及 R 语言的 LaplacesDemon 包。那么我们就从平均值 mean 开始，慢慢的一步一步的来吧。

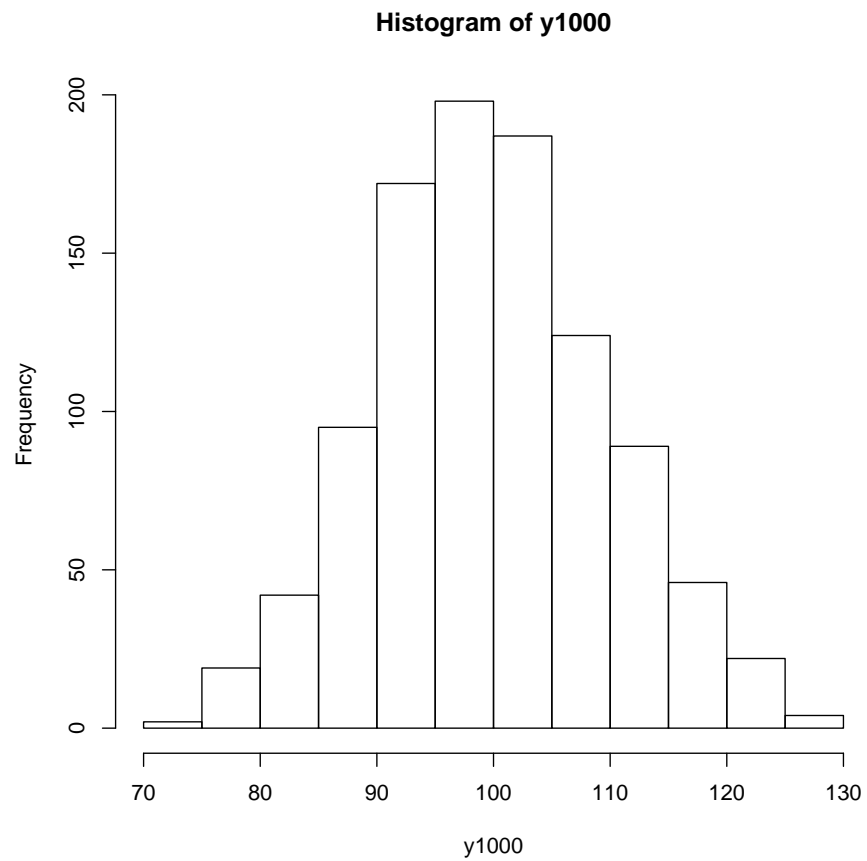
第一章：用暴力的方法求平均数和方差。

1. 创建 y1000，平均值为 100，标准误为 10 的正态数据组，共 1000 个数据。

```
# Simple normal mean model in LaplacesDemon Generate two samples of body  
# mass measurements of male peregrines  
y1000 <- rnorm(n = 1000, mean = 100, sd = 10) # Sample of 1000 birds  
##  
plot(y1000)
```



```
hist(y1000)
```

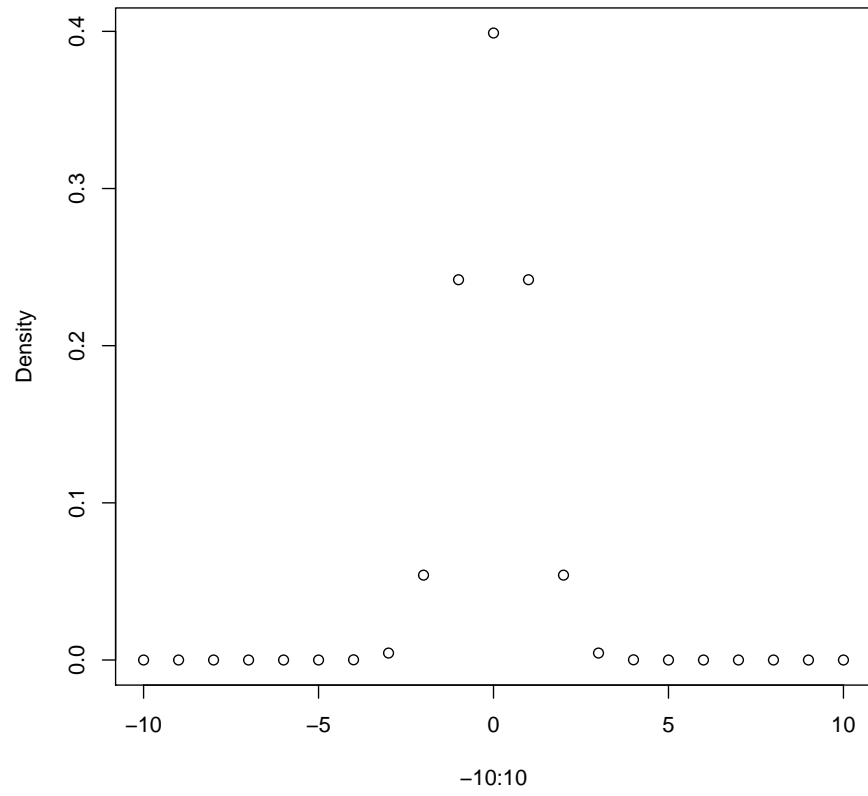


```
##  
mean(y1000)  
## [1] 99.73  
  
sd(y1000)  
## [1] 9.842  
  
##  
lm0 <- lm(y1000 ~ 1)  
summary(lm0)
```

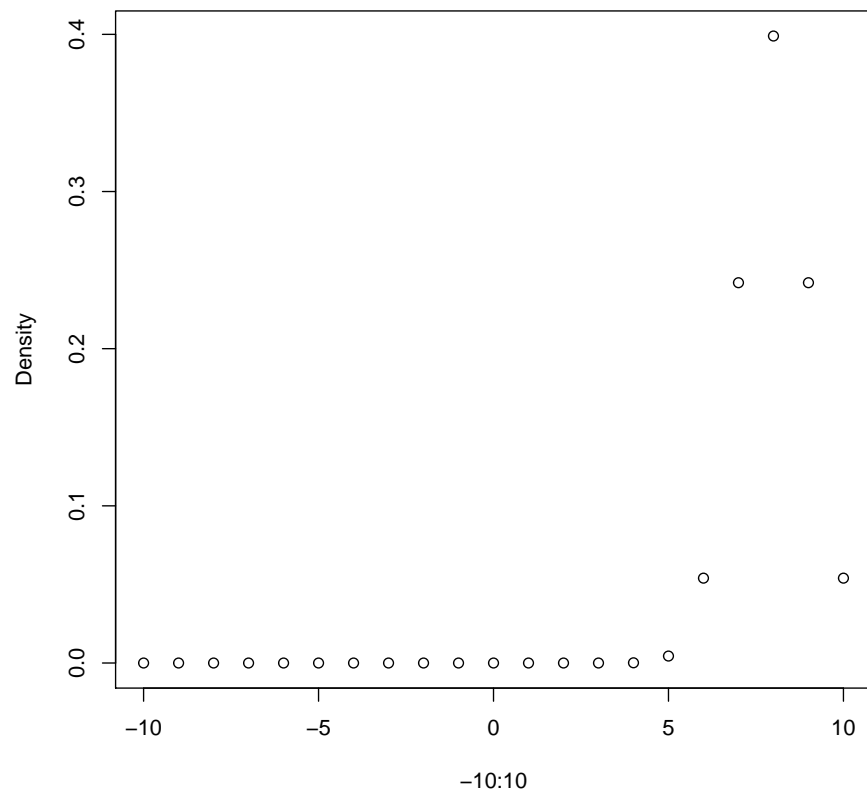
```
##
## Call:
## lm(formula = y1000 ~ 1)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -28.477  -6.959  -0.464   6.205  29.901
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)   99.728     0.311     320   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 9.84 on 999 degrees of freedom
##
```

先了解一下密度函数是怎么一回事

```
plot(x = -10:10, y = dnorm(-10:10, mean = 0, sd = 1), ylab = "Density")
```



```
plot(x = -10:10, y = dnorm(-10:10, mean = 8, sd = 1), ylab = "Density")
```



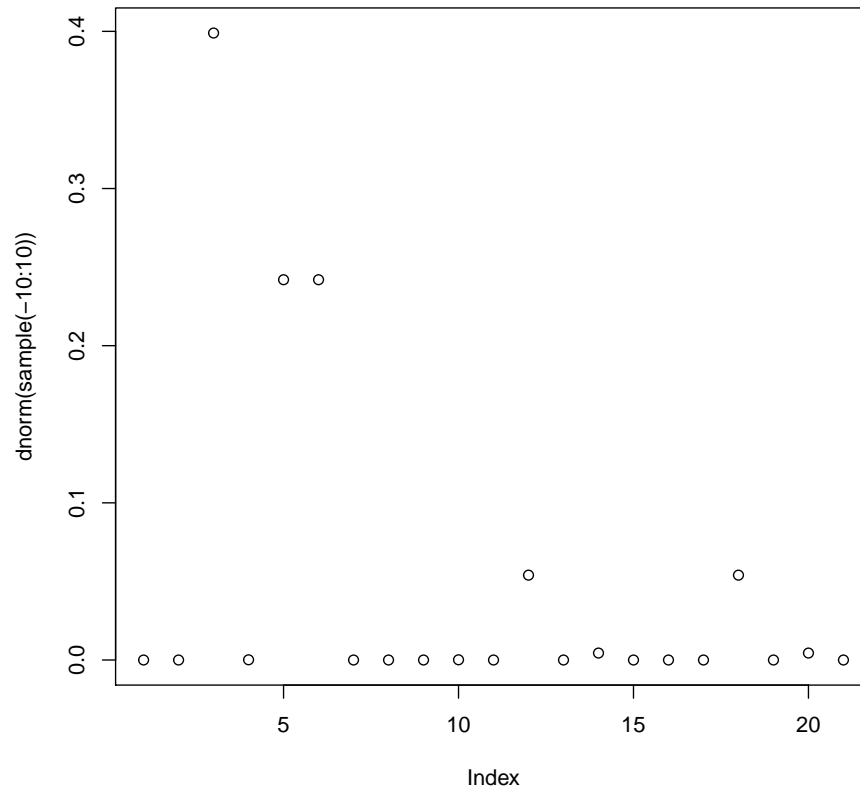
```
sum(dnorm(-10:10, mean = 0, sd = 1))

## [1] 1

sum(dnorm(-10:10, mean = 8, sd = 1))

## [1] 0.9954

#
plot(dnorm(sample(-10:10)))
```



如果假设的正态分布组的方差是 1，平均数是 1:3000，哪个平均数最有可能，使实际数据的密度函数之和最大呢？如果假设的正态分布组的平均数是 100，方差是 1:100，哪个方差最有可能，使实际数据的密度函数之和最大呢？重复 50 次之后的结果是不是可靠呢？

```
population.sd <- 1
for (i in 1:50) {
  mu <- 1:3000
  la00 <- sapply(mu, function(xx) sum(dnorm(y1000, xx, population.sd, log = TRUE)))
  mu <- mu[which.max(la00)]
  population.sd <- 1:100
  d01 <- sapply(population.sd, function(xx) sum(dnorm(y1000, mu, xx, log = TRUE)))
  population.sd <- population.sd[which.max(d01)]
}
```

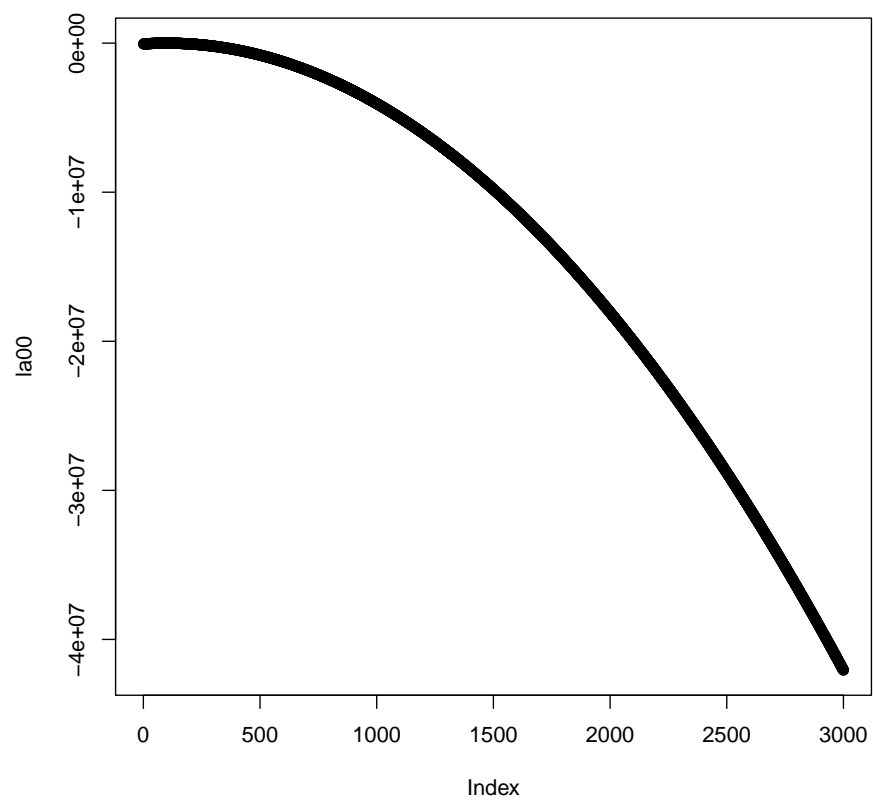
```

}
c(mean = mu, sd = population.sd)

## mean    sd
##   100   10

#
plot(la00)

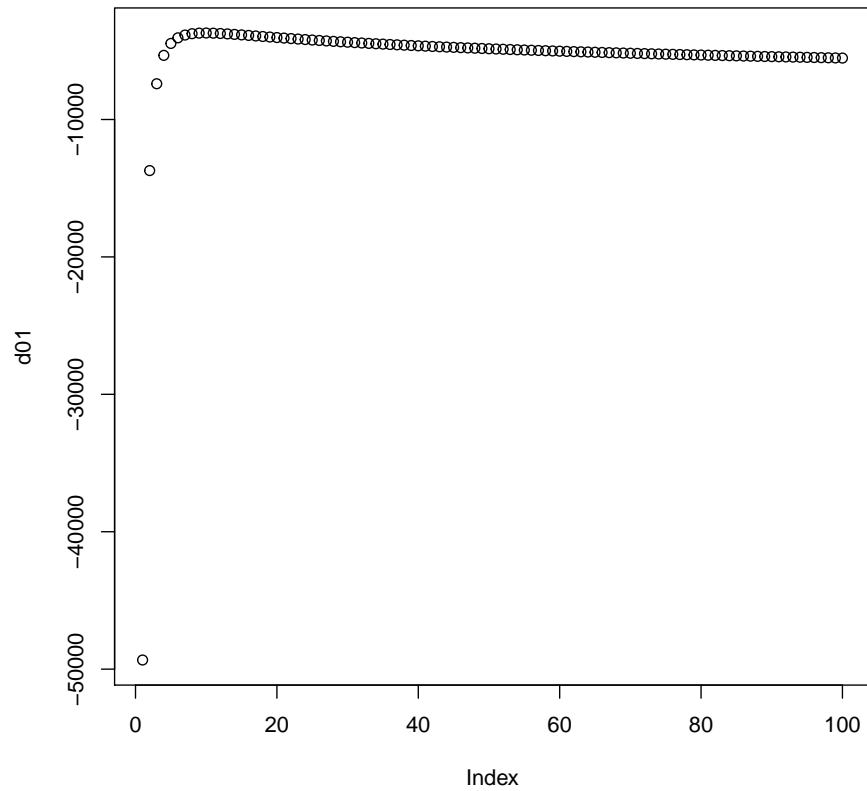
```



```

plot(d01)

```



来看看 R 语言的 LaplacesDemon 包是怎么将暴力进行到底的呢？Model function 就相当于一个 for 循环。那么就让 Model 循环 10000 次吧。

```
# Load library
library(LaplacesDemon)

## Loading required package: parallel

y1000 <- rnorm(n = 1000, mean = 250, sd = 10) # Sample of 1000 birds
## Model specification
Model <- function(parm, Data) {
  # Parameters
  population.mean <- parm[1]
  population.sd <- parm[2]
```



```

    # Prior density
    population.mean.prior <- dunif(population.mean, 0, 5000)
    population.sd.prior <- dunif(population.sd, 0, 100)
    # Log-Likelihood
    mu <- population.mean
    LL <- sum(dnorm(Data$mass, mu, population.sd, log = TRUE))
    # Log-Posterior
    LP <- LL + population.mean.prior + population.sd.prior
    Modelout <- list(LP = LP, Dev = -2 * LL, Monitor = c(LP), yhat = rnorm(Data$N,
        mu, population.sd), parm = parm)
    return(Modelout)
}

# Prepare the data
parm.names <- c("population.mean0", "population.sd0")
Data <- list(mass = y1000, N = length(y1000), mon.names = c("LP"), parm.names = parm.names)
# Initial values
Initial.Values <- c(1000, -250)
# MCMC settings
ni <- 5000 # Number of draws from posterior (for each chain)
st <- 1000 # Steps when status message should be given
nt <- 50 # Thinning rate # Abate autocorrelation
# Run LaplacesDemon
out <- LaplacesDemon(Model, Data = Data, Initial.Values, Iterations = ni, Status = st,
    Thinning = nt)

##
## Laplace's Demon was called on Wed Oct 30 18:04:56 2013
##
## Performing initial checks...

## Warning: NaNs produced
## Warning: NAs produced

## Generating initial values due to a non-finite posterior.

## Warning: NaNs produced
## Warning: NAs produced

```

```
## Warning: NaNs produced
## Warning: NAs produced
## Warning: NaNs produced
## Warning: NAs produced
## Warning: NaNs produced
## Warning: NAs produced
```

```
# Have a look at some summary statistics
out
```

Values,

```

## Covariance Matrix: (NOT SHOWN HERE; diagonal shown instead)
## population.mean0    population.sd0
##           2.835           2.835
##
## Covariance (Diagonal) History: (NOT SHOWN HERE)
## Deviance Information Criterion (DIC):
##           All Stationary
## Dbar      7956      7449.2
## pD      1433069      278.3
## DIC      1441024      7727.5
##
## Delayed Rejection (DR): 0
## Initial Values:
## [1] 42.79 51.29
##
## Iterations: 5000
## Log(Marginal Likelihood): NA
## Minutes of run-time: 0.02
## Model: (NOT SHOWN HERE)
## Monitor: (NOT SHOWN HERE)
## Parameters (Number of): 2
## Periodicity: 5001
## Posterior1: (NOT SHOWN HERE)
## Posterior2: (NOT SHOWN HERE)
## Recommended Burn-In of Thinned Samples: 10
## Recommended Burn-In of Un-thinned Samples: 500
## Recommended Thinning: 400
## Status is displayed every 1000 iterations
## Summary1: (SHOWN BELOW)
## Summary2: (SHOWN BELOW)
## Thinned Samples: 100
## Thinning: 50
##
##
## Summary of All Samples

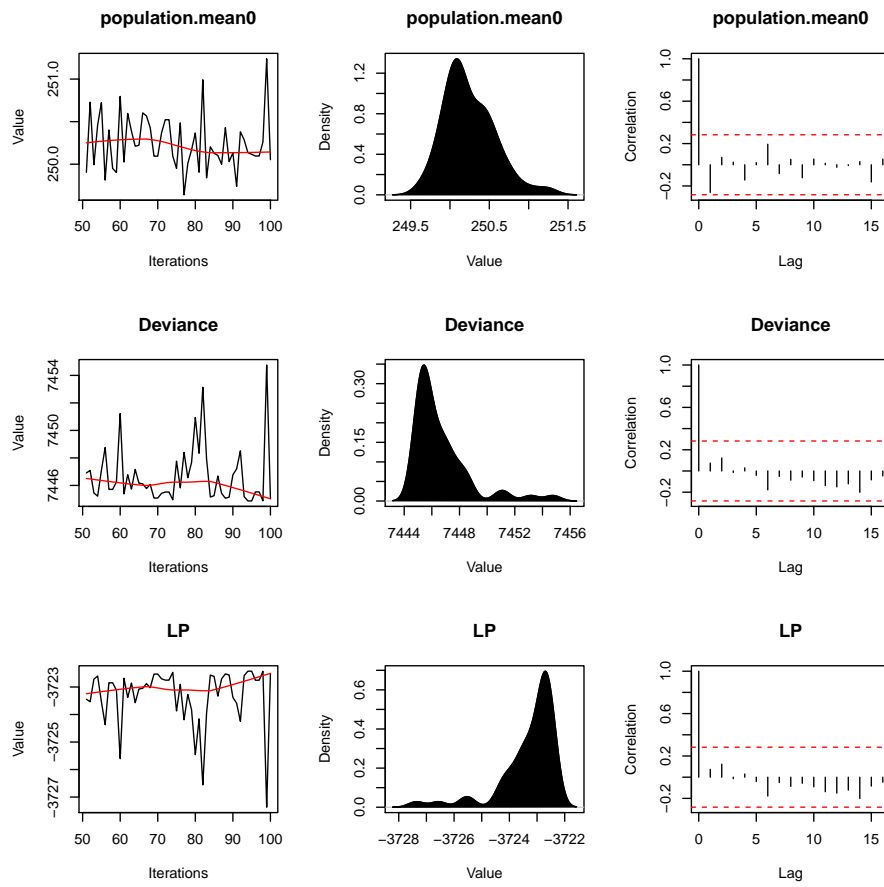
```

```

##              Mean      SD  MCSE   ESS      LB  Median    UB
## population.mean0 239.16 39.27 14.56 7.461 86.407 250.2 250.8
## population.sd0   18.86 28.52 11.47 12.477 9.633 10.1 118.7
## Deviance        7955.58 1692.97 666.52 11.773 7444.874 7446.4 13105.7
## LP              -3977.78 846.49 333.26 11.773 -6552.836 -3723.2 -3722.4
##
##
## Summary of Stationary Samples
##              Mean      SD      MCSE ESS      LB  Median
## population.mean0 250.23 0.4124 0.04023 90 249.668 250.22
## population.sd0   10.11 0.4844 0.05074 90 9.624 10.06
## Deviance        7449.19 23.5941 2.45715 90 7444.873 7446.20
## LP              -3724.59 11.7971 333.26228 90 -3726.344 -3723.09
##              UB
## population.mean0 250.78
## population.sd0   10.58
## Deviance        7452.71
## LP              -3722.43

# Plotting output
plot(out, BurnIn = 50, Data, Params = (".mean0"))

```



第二章：关于平均值、T 检验、线性回归、单变量方差分析、双变量方差分析、协方差分析

数据：mass 生物量, pop 种群, region 范围, hab 栖息地, svl 体长

```
mass <- c(6, 8, 5, 7, 9, 11)
pop <- factor(c(1, 1, 2, 2, 3, 3))
region <- factor(c(1, 1, 1, 1, 2, 2))
hab <- factor(c(1, 2, 3, 1, 2, 3))
svl <- c(40, 45, 39, 50, 52, 57)
```

平均值: $\text{mass}_i = \mu + \epsilon_i, \epsilon_i \sim \text{Normal}(0, \sigma^2)$

```

# mean
lm(mass ~ 1) # massi = + i , i ~ Normal(0, 2)

##
## Call:
## lm(formula = mass ~ 1)
##
## Coefficients:
## (Intercept)
##          7.67

model.matrix(mass ~ 1)

## (Intercept)
## 1          1
## 2          1
## 3          1
## 4          1
## 5          1
## 6          1
## attr(,"assign")
## [1] 0

```

t 检验: $mass_i = + * region_i + i; i \sim Normal(0, 2)$ $mass_i \sim Normal(+ * region, 2)$
 $c(6, 8, 5, 7, 9, 11) = * (1, 1, 1, 1, 1, 1) + * \text{factor}(c(1,1,1,1,2,2)) +$
 $c(1, 2, 3, 4, 5, 6)$

```

# t-test
lm(mass ~ region) #

##
## Call:
## lm(formula = mass ~ region)
##
## Coefficients:
## (Intercept)      region2
##          6.5          3.5

```

```

model.matrix(~region)

##      (Intercept) region2
## 1             1      0
## 2             1      0
## 3             1      0
## 4             1      0
## 5             1      1
## 6             1      1
## attr(,"assign")
## [1] 0 1
## attr(,"contrasts")
## attr(,"contrasts")$region
## [1] "contr.treatment"

summary(lm(mass ~ region))

##
## Call:
## lm(formula = mass ~ region)
##
## Residuals:
##      1      2      3      4      5      6
## -0.5   1.5 -1.5   0.5 -1.0   1.0
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)    6.500     0.661    9.83  0.0006 ***
## region2        3.500     1.146    3.06  0.0378 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.32 on 4 degrees of freedom
## Multiple R-squared:  0.7, Adjusted R-squared:  0.625
## F-statistic: 9.33 on 1 and 4 DF, p-value: 0.0378

# mass_i = + *region_i + _i _i ~ Normal(0, ^2) mass_i ~ Normal(+ *region, ^2)

```

```

# c(6, 8, 5, 7, 9, 11) = * (1, 1, 1, 1, 1, 1) + * factor(c(1,1,1,1,2,2))
# + c(1, 2, 3, 4, 5, 6)
lm(mass ~ region - 1)

##
## Call:
## lm(formula = mass ~ region - 1)
##
## Coefficients:
## region1 region2
##      6.5      10.0

model.matrix(~region - 1)

##   region1 region2
## 1        1        0
## 2        1        0
## 3        1        0
## 4        1        0
## 5        0        1
## 6        0        1
## attr("assign")
## [1] 1 1
## attr("contrasts")
## attr("contrasts")$region
## [1] "contr.treatment"

summary(lm(mass ~ region - 1))

##
## Call:
## lm(formula = mass ~ region - 1)
##
## Residuals:
##      1      2      3      4      5      6
## -0.5   1.5 -1.5   0.5 -1.0   1.0
##

```



```
## Coefficients:
##           Estimate Std. Error t value Pr(>|t|)
## region1      6.500      0.661    9.83 0.00060 ***
## region2     10.000      0.935   10.69 0.00043 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.32 on 4 degrees of freedom
## Multiple R-squared:  0.981, Adjusted R-squared:  0.972
## F-statistic: 105 on 2 and 4 DF, p-value: 0.000347

# 6.5 + 3.5 = 10.0
```

简单线性回归: $mass_i = + * svl_i + \epsilon_i; \epsilon_i \sim Normal(0, \sigma^2)$

```
lm(mass ~ svl)

##
## Call:
## lm(formula = mass ~ svl)
##
## Coefficients:
## (Intercept)          svl
##          -5.56          0.28

model.matrix(~svl)

##   (Intercept) svl
## 1           1  40
## 2           1  45
## 3           1  39
## 4           1  50
## 5           1  52
## 6           1  57
## attr(,"assign")
## [1] 0 1
```

```

#
lm(mass ~ svl - 1)

##
## Call:
## lm(formula = mass ~ svl - 1)
##
## Coefficients:
##      svl
## 0.165

model.matrix(~svl - 1)

##      svl
## 1  40
## 2  45
## 3  39
## 4  50
## 5  52
## 6  57
## attr(,"assign")
## [1] 1

```

单变量方差分解:

$$mass_i = \mu + \alpha_i + \epsilon_i \quad \alpha_i \sim \text{Normal}(0, \sigma^2) \quad \epsilon_i \sim \text{Normal}(0, \sigma^2)$$

Each parameterization is better suited to a different aim: the effects model is better for testing for differences and the means model is better for presentation.

```

# effects model
lm(mass ~ pop)

##
## Call:
## lm(formula = mass ~ pop)

```

```
##
## Coefficients:
## (Intercept)      pop2      pop3
##           7        -1         3

model.matrix(~pop)

##      (Intercept) pop2 pop3
## 1           1     0     0
## 2           1     0     0
## 3           1     1     0
## 4           1     1     0
## 5           1     0     1
## 6           1     0     1
## attr("assign")
## [1] 0 1 1
## attr("contrasts")
## attr("contrasts")$pop
## [1] "contr.treatment"

# means model
lm(mass ~ pop - 1)

##
## Call:
## lm(formula = mass ~ pop - 1)
##
## Coefficients:
## pop1  pop2  pop3
##    7     6    10

model.matrix(~pop - 1)

##      pop1 pop2 pop3
## 1     1     0     0
## 2     1     0     0
## 3     0     1     0
```

```
## 4    0    1    0
## 5    0    0    1
## 6    0    0    1
## attr("assign")
## [1] 1 1 1
## attr("contrasts")
## attr("contrasts")$pop
## [1] "contr.treatment"
```

双变量方差分解: two-way analysis of variance

model 1: $\text{mass}_i = +_j.i * \text{region}_i + +_k.i * \text{hab}_i + +_{i,i} \text{Normal}(0,^2)$

model 2: $\text{mass}_i = +_j.i * \text{region}_i + +_k.i * \text{hab}_i + +_j.k.i * \text{region}_i * \text{hab}_i + +_{i,i} \text{Normal}(0,^2)$

model 3: $\text{mass}_i = +_j.k.i * \text{region}_i * \text{hab}_i + +_{i,i} \text{Normal}(0,^2)$

```
lm(mass ~ region + hab)

##
## Call:
## lm(formula = mass ~ region + hab)
##
## Coefficients:
## (Intercept)      region2        hab2        hab3
##          6.50         3.50         0.25        -0.25

model.matrix(~region + hab) # model 1

## (Intercept) region2 hab2 hab3
## 1          1         0  0  0
## 2          1         0  1  0
## 3          1         0  0  1
## 4          1         0  0  0
## 5          1         1  1  0
## 6          1         1  0  1
## attr("assign")
## [1] 0 1 2 2
## attr("contrasts")
```

```

## attr("contrasts")$region
## [1] "contr.treatment"
##
## attr("contrasts")$hab
## [1] "contr.treatment"

#
lm(mass ~ region * hab)

##
## Call:
## lm(formula = mass ~ region * hab)
##
## Coefficients:
## (Intercept)      region2      hab2      hab3 region2:hab2
##          6.5          6.0          1.5         -1.5          -5.0
## region2:hab3
##              NA

model.matrix(~region * hab) # model 2

## (Intercept) region2 hab2 hab3 region2:hab2 region2:hab3
## 1          1          0  0  0              0              0
## 2          1          0  1  0              0              0
## 3          1          0  0  1              0              0
## 4          1          0  0  0              0              0
## 5          1          1  1  0              1              0
## 6          1          1  0  1              0              1
## attr("assign")
## [1] 0 1 2 2 3 3
## attr("contrasts")
## attr("contrasts")$region
## [1] "contr.treatment"
##
## attr("contrasts")$hab
## [1] "contr.treatment"

```

```

#
lm(mass ~ region * hab - 1 - region - hab)

##
## Call:
## lm(formula = mass ~ region * hab - 1 - region - hab)
##
## Coefficients:
## region1:hab1 region2:hab1 region1:hab2 region2:hab2 region1:hab3
##          6.5          NA          8.0          9.0          5.0
## region2:hab3
##          11.0

model.matrix(~region * hab - 1 - region - hab) # model 3

## region1:hab1 region2:hab1 region1:hab2 region2:hab2 region1:hab3
## 1          1          0          0          0          0
## 2          0          0          1          0          0
## 3          0          0          0          0          1
## 4          1          0          0          0          0
## 5          0          0          0          1          0
## 6          0          0          0          0          0
## region2:hab3
## 1          0
## 2          0
## 3          0
## 4          0
## 5          0
## 6          1
## attr("assign")
## [1] 1 1 1 1 1 1
## attr("contrasts")
## attr("contrasts")$region
## [1] "contr.treatment"
##
## attr("contrasts")$hab
## [1] "contr.treatment"

```

协方差分析: analysis of covariance

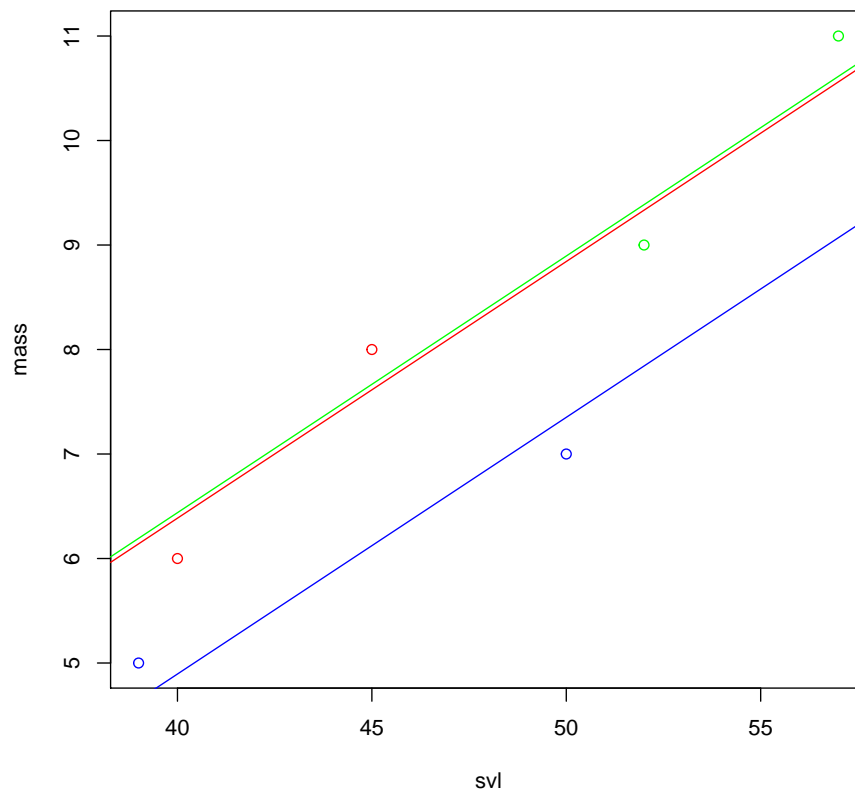
```
#
fm <- lm(mass ~ pop + svl) # Refit model
fm

##
## Call:
## lm(formula = mass ~ pop + svl)
##
## Coefficients:
## (Intercept)      pop2      pop3      svl
##    -3.4386    -1.4912     0.0526     0.2456

model.matrix(~pop + svl)

## (Intercept) pop2 pop3 svl
## 1          1    0    0 40
## 2          1    0    0 45
## 3          1    1    0 39
## 4          1    1    0 50
## 5          1    0    1 52
## 6          1    0    1 57
## attr("assign")
## [1] 0 1 1 2
## attr("contrasts")
## attr("contrasts")$pop
## [1] "contr.treatment"

plot(svl, mass, col = c(rep("red", 2), rep("blue", 2), rep("green", 2)))
abline(fm$coef[1], fm$coef[4], col = "red")
abline(fm$coef[1] + fm$coef[2], fm$coef[4], col = "blue")
abline(fm$coef[1] + fm$coef[3], fm$coef[4], col = "green")
```



```
#
fm <- lm(mass ~ pop * svl) # Refit model
fm

##
## Call:
## lm(formula = mass ~ pop * svl)
##
## Coefficients:
## (Intercept)      pop2      pop3      svl  pop2:svl
## -1.00e+01    7.91e+00   -1.80e+00    4.00e-01   -2.18e-01
##      pop3:svl
## -1.60e-15
```



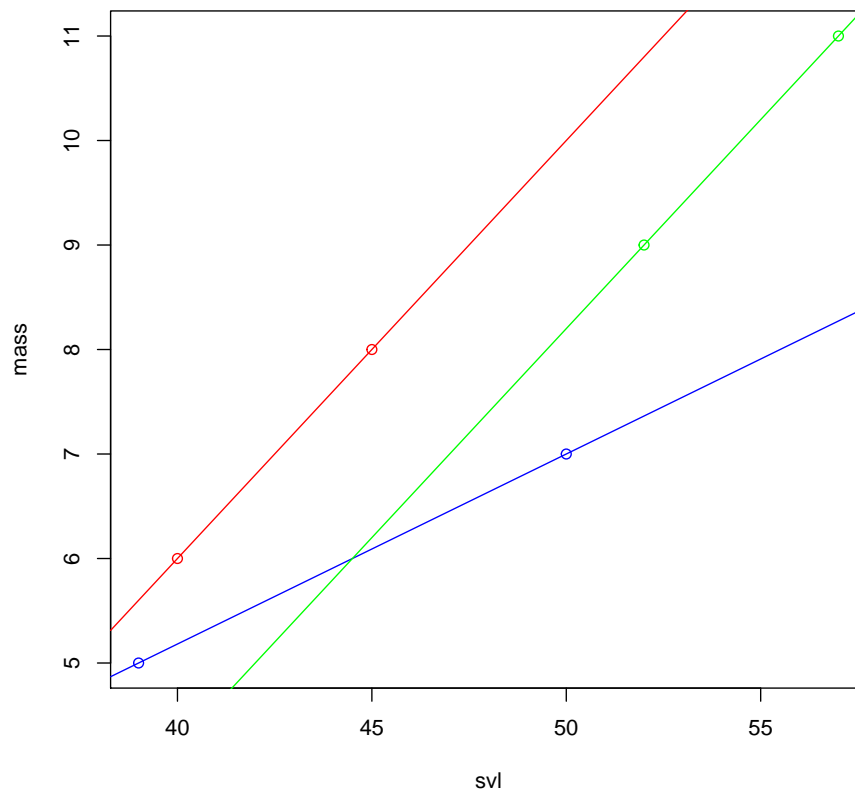
```

model.matrix(~pop * svl)

##      (Intercept) pop2 pop3 svl pop2:svl pop3:svl
## 1             1    0    0 40          0         0
## 2             1    0    0 45          0         0
## 3             1    1    0 39         39         0
## 4             1    1    0 50         50         0
## 5             1    0    1 52          0        52
## 6             1    0    1 57          0        57
## attr("assign")
## [1] 0 1 1 2 3 3
## attr("contrasts")
## attr("contrasts")$pop
## [1] "contr.treatment"

plot(svl, mass, col = c(rep("red", 2), rep("blue", 2), rep("green", 2)))
abline(fm$coef[1], fm$coef[4], col = "red")
abline(fm$coef[1] + fm$coef[2], fm$coef[4] + fm$coef[5], col = "blue")
abline(fm$coef[1] + fm$coef[3], fm$coef[4] + fm$coef[6], col = "green")

```



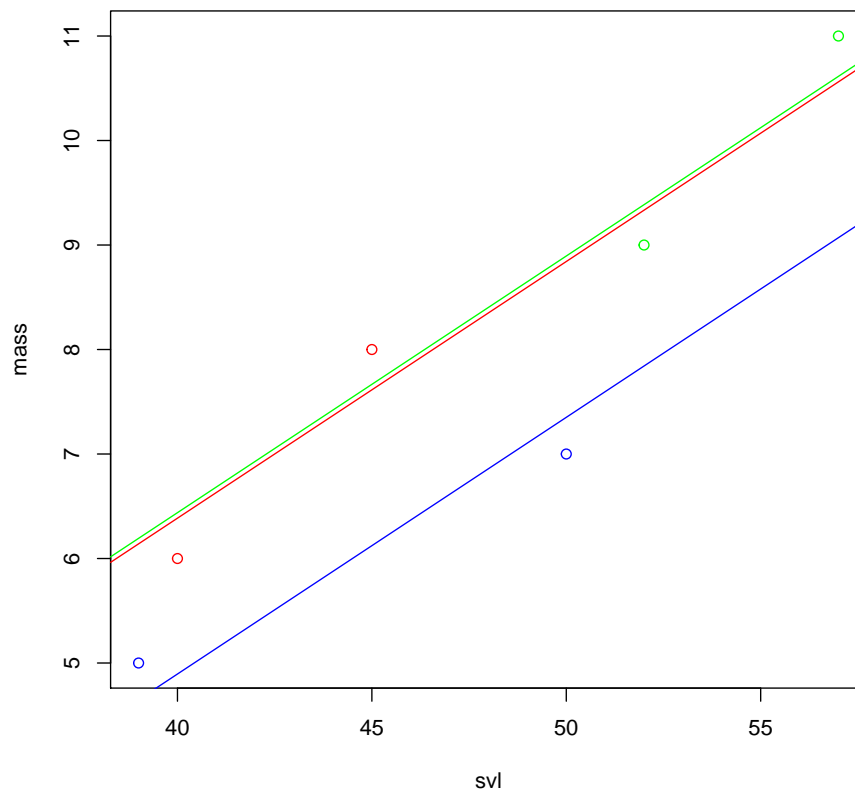
```
#
fm <- lm(mass ~ pop + svl - 1)
fm

##
## Call:
## lm(formula = mass ~ pop + svl - 1)
##
## Coefficients:
##  pop1    pop2    pop3     svl
## -3.439 -4.930 -3.386  0.246

model.matrix(~pop + svl - 1)
```

```
##   pop1 pop2 pop3 svl
## 1    1    0    0  40
## 2    1    0    0  45
## 3    0    1    0  39
## 4    0    1    0  50
## 5    0    0    1  52
## 6    0    0    1  57
## attr(,"assign")
## [1] 1 1 1 2
## attr(,"contrasts")
## attr(,"contrasts")$pop
## [1] "contr.treatment"

plot(svl, mass, col = c(rep("red", 2), rep("blue", 2), rep("green", 2)))
abline(fm$coef[1], fm$coef[4], col = "red")
abline(fm$coef[2], fm$coef[4], col = "blue")
abline(fm$coef[3], fm$coef[4], col = "green")
```



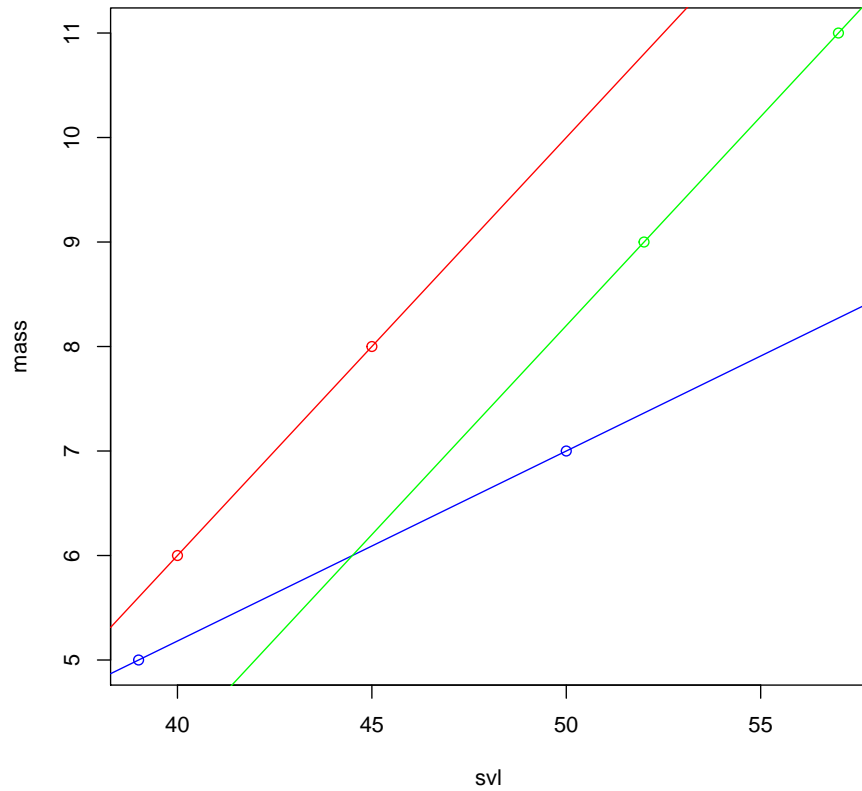
```
#
fm <- lm(mass ~ pop * svl - 1 - svl)
fm

##
## Call:
## lm(formula = mass ~ pop * svl - 1 - svl)
##
## Coefficients:
##      pop1      pop2      pop3  pop1:svl  pop2:svl  pop3:svl
## -10.000   -2.091  -11.800    0.400    0.182    0.400

model.matrix(~pop * svl - 1 - svl)
```

```
##   pop1 pop2 pop3 pop1:svl pop2:svl pop3:svl
## 1    1    0    0      40      0      0
## 2    1    0    0      45      0      0
## 3    0    1    0       0     39      0
## 4    0    1    0       0     50      0
## 5    0    0    1       0      0     52
## 6    0    0    1       0      0     57
## attr("assign")
## [1] 1 1 1 2 2 2
## attr("contrasts")
## attr("contrasts")$pop
## [1] "contr.treatment"

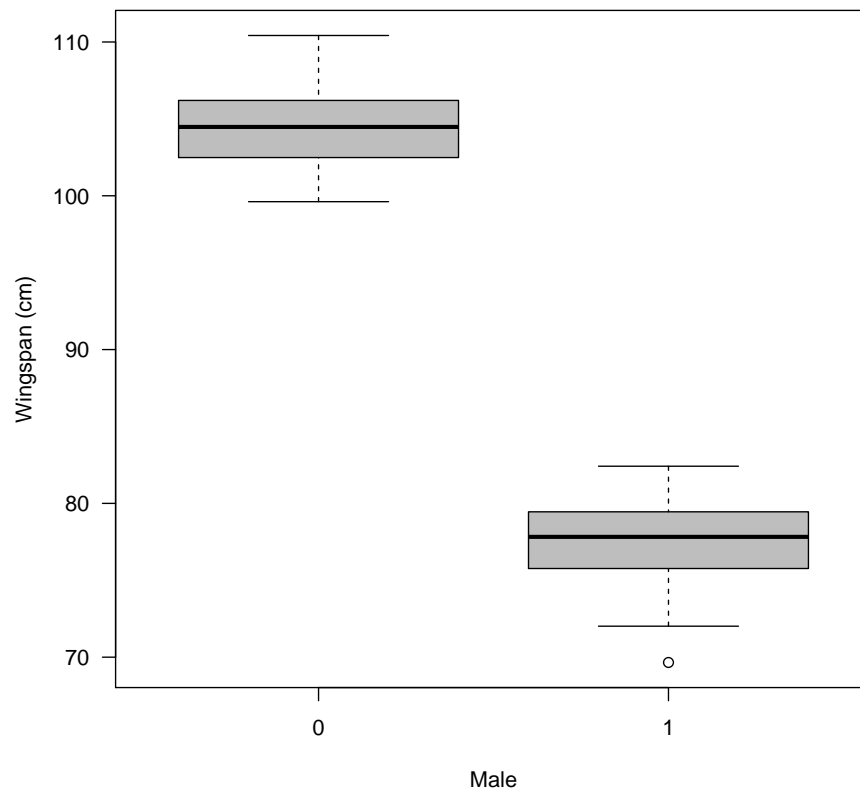
plot(svl, mass, col = c(rep("red", 2), rep("blue", 2), rep("green", 2)))
abline(fm$coef[1], fm$coef[4], col = "red")
abline(fm$coef[2], fm$coef[5], col = "blue")
abline(fm$coef[3], fm$coef[6], col = "green")
```



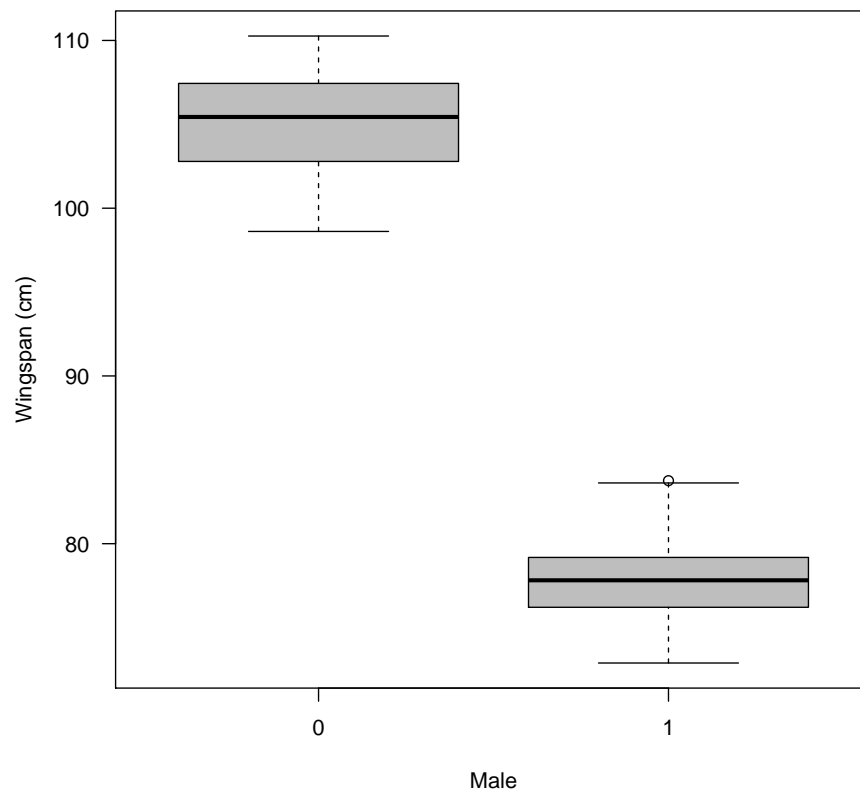
第三章真正的 T 检验

```
# data ~~~~~
n1 <- 60 # Number of females
n2 <- 40 # Number of males
mu1 <- 105 # Population mean of females
mu2 <- 77.5 # Population mean of males
sigma <- 2.75 # Average population SD of both
n <- n1 + n2 # Total sample size
#
y1 <- rnorm(n1, mu1, sigma) # Data for females
y2 <- rnorm(n2, mu2, sigma) # Date for males
y <- c(y1, y2) # Aggregate both data sets
```

```
x <- rep(c(0, 1), c(n1, n2)) # Indicator for male
boxplot(y ~ x, col = "grey", xlab = "Male", ylab = "Wingspan (cm)", las = 1)
```



```
# data
n <- n1 + n2 # Total sample size
alpha <- mu1 # Mean for females serves as the intercept
beta <- mu2 - mu1 # Beta is the difference male female
E.y <- alpha + beta * x # Expectation
y.obs <- rnorm(n = n, mean = E.y, sd = sigma) # Add random variation
boxplot(y.obs ~ x, col = "grey", xlab = "Male", ylab = "Wingspan (cm)", las = 1)
```



```
#
fit1 <- lm(y ~ x) # Analysis of first data set
fit2 <- lm(y.obs ~ x) # Analysis of second data set
summary(fit1)

##
## Call:
## lm(formula = y ~ x)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -7.839  -1.813   0.269   1.845   6.035
##
```



```
## Coefficients:
##           Estimate Std. Error t value Pr(>|t|)
## (Intercept)  104.387      0.348   300.0  <2e-16 ***
## x           -26.892      0.550   -48.9  <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2.69 on 98 degrees of freedom
## Multiple R-squared:  0.961, Adjusted R-squared:  0.96
## F-statistic: 2.39e+03 on 1 and 98 DF,  p-value: <2e-16

summary(fit2)

##
## Call:
## lm(formula = y.obs ~ x)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -6.473 -2.001  0.137  1.973  5.977
##
## Coefficients:
##           Estimate Std. Error t value Pr(>|t|)
## (Intercept)  105.087      0.358   293.6  <2e-16 ***
## x           -27.307      0.566   -48.3  <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2.77 on 98 degrees of freedom
## Multiple R-squared:  0.96, Adjusted R-squared:  0.959
## F-statistic: 2.33e+03 on 1 and 98 DF,  p-value: <2e-16

#
anova(fit1)

## Analysis of Variance Table
##
```

```

## Response: y
##           Df Sum Sq Mean Sq F value Pr(>F)
## x           1  17357   17357    2390 <2e-16 ***
## Residuals 98    712         7
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

anova(fit2)

## Analysis of Variance Table
##
## Response: y.obs
##           Df Sum Sq Mean Sq F value Pr(>F)
## x           1  17896   17896    2329 <2e-16 ***
## Residuals 98    753         8
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

#
model.matrix(fit1)

##      (Intercept) x
## 1             1 0
## 2             1 0
## 3             1 0
## 4             1 0
## 5             1 0
## 6             1 0
## 7             1 0
## 8             1 0
## 9             1 0
## 10            1 0
## 11            1 0
## 12            1 0
## 13            1 0
## 14            1 0
## 15            1 0

```

## 16	1 0
## 17	1 0
## 18	1 0
## 19	1 0
## 20	1 0
## 21	1 0
## 22	1 0
## 23	1 0
## 24	1 0
## 25	1 0
## 26	1 0
## 27	1 0
## 28	1 0
## 29	1 0
## 30	1 0
## 31	1 0
## 32	1 0
## 33	1 0
## 34	1 0
## 35	1 0
## 36	1 0
## 37	1 0
## 38	1 0
## 39	1 0
## 40	1 0
## 41	1 0
## 42	1 0
## 43	1 0
## 44	1 0
## 45	1 0
## 46	1 0
## 47	1 0
## 48	1 0
## 49	1 0
## 50	1 0

## 51	1 0
## 52	1 0
## 53	1 0
## 54	1 0
## 55	1 0
## 56	1 0
## 57	1 0
## 58	1 0
## 59	1 0
## 60	1 0
## 61	1 1
## 62	1 1
## 63	1 1
## 64	1 1
## 65	1 1
## 66	1 1
## 67	1 1
## 68	1 1
## 69	1 1
## 70	1 1
## 71	1 1
## 72	1 1
## 73	1 1
## 74	1 1
## 75	1 1
## 76	1 1
## 77	1 1
## 78	1 1
## 79	1 1
## 80	1 1
## 81	1 1
## 82	1 1
## 83	1 1
## 84	1 1
## 85	1 1

```

## 86      1 1
## 87      1 1
## 88      1 1
## 89      1 1
## 90      1 1
## 91      1 1
## 92      1 1
## 93      1 1
## 94      1 1
## 95      1 1
## 96      1 1
## 97      1 1
## 98      1 1
## 99      1 1
## 100     1 1
## attr("assign")
## [1] 0 1

model.matrix(fit2)

##      (Intercept) x
## 1      1 0
## 2      1 0
## 3      1 0
## 4      1 0
## 5      1 0
## 6      1 0
## 7      1 0
## 8      1 0
## 9      1 0
## 10     1 0
## 11     1 0
## 12     1 0
## 13     1 0
## 14     1 0
## 15     1 0

```

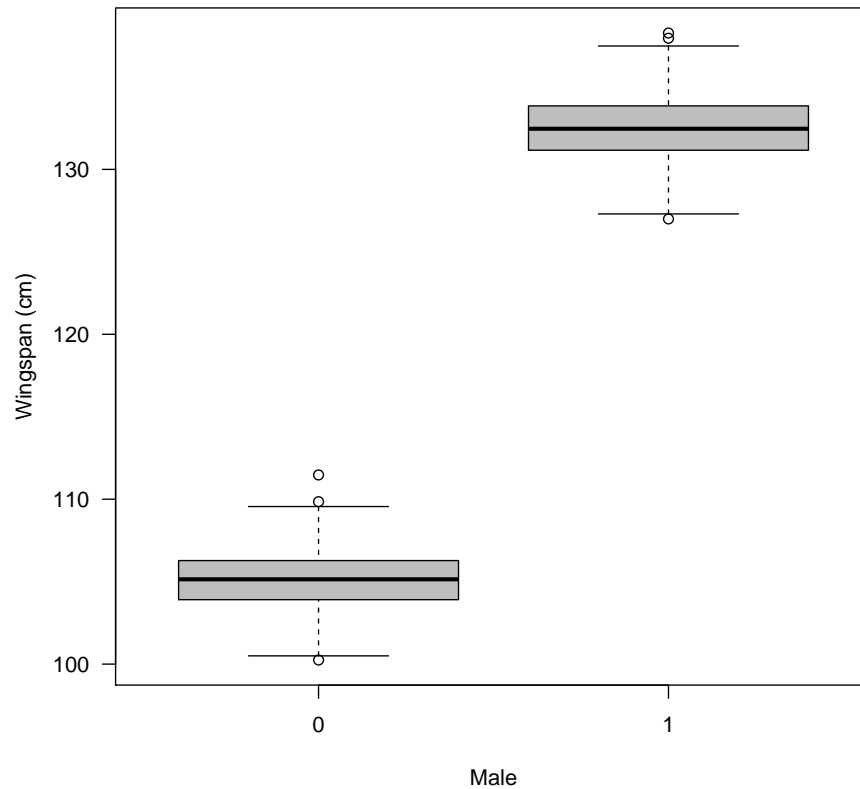
## 16	1 0
## 17	1 0
## 18	1 0
## 19	1 0
## 20	1 0
## 21	1 0
## 22	1 0
## 23	1 0
## 24	1 0
## 25	1 0
## 26	1 0
## 27	1 0
## 28	1 0
## 29	1 0
## 30	1 0
## 31	1 0
## 32	1 0
## 33	1 0
## 34	1 0
## 35	1 0
## 36	1 0
## 37	1 0
## 38	1 0
## 39	1 0
## 40	1 0
## 41	1 0
## 42	1 0
## 43	1 0
## 44	1 0
## 45	1 0
## 46	1 0
## 47	1 0
## 48	1 0
## 49	1 0
## 50	1 0

## 51	1 0
## 52	1 0
## 53	1 0
## 54	1 0
## 55	1 0
## 56	1 0
## 57	1 0
## 58	1 0
## 59	1 0
## 60	1 0
## 61	1 1
## 62	1 1
## 63	1 1
## 64	1 1
## 65	1 1
## 66	1 1
## 67	1 1
## 68	1 1
## 69	1 1
## 70	1 1
## 71	1 1
## 72	1 1
## 73	1 1
## 74	1 1
## 75	1 1
## 76	1 1
## 77	1 1
## 78	1 1
## 79	1 1
## 80	1 1
## 81	1 1
## 82	1 1
## 83	1 1
## 84	1 1
## 85	1 1

```
## 86      1 1
## 87      1 1
## 88      1 1
## 89      1 1
## 90      1 1
## 91      1 1
## 92      1 1
## 93      1 1
## 94      1 1
## 95      1 1
## 96      1 1
## 97      1 1
## 98      1 1
## 99      1 1
## 100     1 1
## attr("assign")
## [1] 0 1
```

现在来看一下如何使用 bayesian 方法实现呢？

```
## 2.2 Data ~~~~~
require(LaplacesDemon)
##### data ~~~~~
n1 <- 600 # Number of females
n2 <- 400 # Number of males
mu1 <- 105 # Population mean of females
mu2 <- 77.5 # Population mean of males
sigma <- 1.75 # Average population SD of both
#
n <- n1 + n2 # Total sample size
alpha <- mu1 # Mean for females serves as the intercept
beta <- mu1 - mu2 # Beta is the difference male female
x <- rep(c(0, 1), c(n1, n2))
E.y <- alpha + beta * x # Expectation
y.obs <- rnorm(n = n, mean = E.y, sd = sigma) # Add random variation
boxplot(y.obs ~ x, col = "grey", xlab = "Male", ylab = "Wingspan (cm)", las = 1)
```

```
#####
parm.names <- as.parm.names(Initial.Values)

## Error: replacement has length zero

mon.names <- c("LP00")
Data <- MyData <- list(N = n, mon.names = mon.names, parm.names = parm.names,
  x = x, y = y.obs)
## 2.3. Model ~~~~~
Model <- function(parm, Data) {
  ### Parameters
  alpha <- parm[1]
  beta <- parm[2]
```

```

sigma <- parm[3]
### Log(Prior Densities)
alpha.prior <- dnorm(x = alpha, mean = 0, var = 1000, log = TRUE)
beta.prior <- dnorm(x = beta, mean = 0, sd = sigma, log = TRUE)
sigma.prior <- dhalfcauchy(x = sigma, scale = 25, log = TRUE)
### Log-Likelihood
mu <- alpha + beta * Data$x
LL <- sum(dnorm(x = Data$y, mean = mu, sd = sigma, log = TRUE))
### Log-Posterior
LP <- LL + alpha.prior + beta.prior + sigma.prior
Modelout <- list(LP = LP, Dev = -2 * LL, Monitor = c(LP), yhat = rnorm(length(mu),
mu, sigma), parm = parm)
return(Modelout)
}

## 2.4. Initial Values ~~~~~
parm <- Initial.Values <- c(alpha_11 = 100, beta_11 = 20, sigma_11 = 1)

## 2.5 MCMC ~~~~~ MCMC settings
ni <- 10000 # Number of draws from posterior (for each chain)
st <- 4000 # Steps when status message should be given
nt <- 50 # Thinning rate # Abate autocorrelation
# Run LaplacesDemon
out <- LaplacesDemon(Model, Data = MyData, Initial.Values, Iterations = ni,
Status = st, Thinning = nt)

##
## Laplace's Demon was called on Wed Oct 30 18:04:59 2013
##
## Performing initial checks...
## WARNING: The length of Initial Values differed from Data$parm.names.

## Warning: NAs produced

## Generating initial values due to a non-finite posterior.

## Warning: NAs produced
## Warning: NAs produced
## Warning: NAs produced

```


[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

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[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

```
## Warning: NAs produced
## Warning: NAs produced
## Warning: NAs produced
## Warning: NAs produced
## Warning: NAs produced
## Warning: NAs produced
## Warning: NAs produced
## Warning: NAs produced
## Warning: NAs produced
## Warning: NAs produced
## Warning: NAs produced
## Warning: NAs produced
## Warning: NAs produced
## Warning: NAs produced
## Warning: NAs produced
## Warning: NAs produced
## Warning: NAs produced
## Warning: NAs produced
## Warning: NAs produced
```

```
## Warning: NAs produced
```

```
## Error: The deviance is a missing value!
```

```
# Have a look at some summary statistics
out
```

.Values,

```

## population.mean0    population.sd0
##                2.835                2.835
##
## Covariance (Diagonal) History: (NOT SHOWN HERE)
## Deviance Information Criterion (DIC):
##           All Stationary
## Dbar      7956      7449.2
## pD      1433069      278.3
## DIC      1441024      7727.5
##
## Delayed Rejection (DR): 0
## Initial Values:
## [1] 42.79 51.29
##
## Iterations: 5000
## Log(Marginal Likelihood): NA
## Minutes of run-time: 0.02
## Model: (NOT SHOWN HERE)
## Monitor: (NOT SHOWN HERE)
## Parameters (Number of): 2
## Periodicity: 5001
## Posterior1: (NOT SHOWN HERE)
## Posterior2: (NOT SHOWN HERE)
## Recommended Burn-In of Thinned Samples: 10
## Recommended Burn-In of Un-thinned Samples: 500
## Recommended Thinning: 400
## Status is displayed every 1000 iterations
## Summary1: (SHOWN BELOW)
## Summary2: (SHOWN BELOW)
## Thinned Samples: 100
## Thinning: 50
##
##
## Summary of All Samples
##           Mean      SD    MCSE    ESS      LB  Median      UB

```



```

## population.mean0 239.16 39.27 14.56 7.461 86.407 250.2 250.8
## population.sd0 18.86 28.52 11.47 12.477 9.633 10.1 118.7
## Deviance 7955.58 1692.97 666.52 11.773 7444.874 7446.4 13105.7
## LP -3977.78 846.49 333.26 11.773 -6552.836 -3723.2 -3722.4
##
##
## Summary of Stationary Samples
## Mean SD MCSE ESS LB Median
## population.mean0 250.23 0.4124 0.04023 90 249.668 250.22
## population.sd0 10.11 0.4844 0.05074 90 9.624 10.06
## Deviance 7449.19 23.5941 2.45715 90 7444.873 7446.20
## LP -3724.59 11.7971 333.26228 90 -3726.344 -3723.09
## UB
## population.mean0 250.78
## population.sd0 10.58
## Deviance 7452.71
## LP -3722.43

# alpha= 105, beta= 27.5, sigma= 1.75 Plotting output
plot(out, BurnIn = 50, Data, PDF = F)

```

