

#Assignment-1

#STP 530: Applied Regression Analysis

#Part 1

#a

```
x = c(1, 0, 2, 0, 3, 1, 0, 1, 2, 0)
```

```
y = c(16, 9, 17, 12, 22, 13, 8, 15, 19, 11)
```

```
z=lm(y~x) #estimated regression function
```

```
abline(y~x)
```

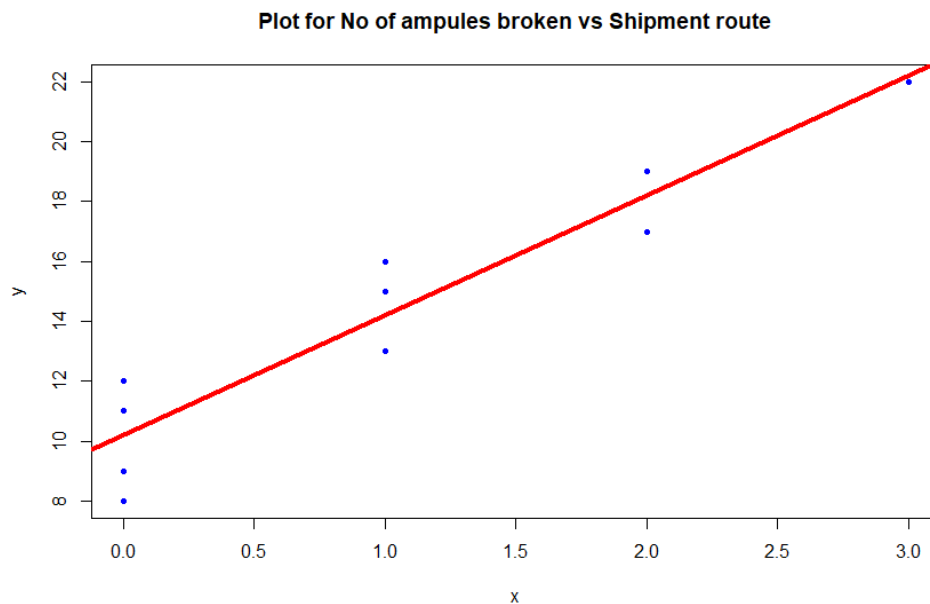
```
plot(y~x, col="blue", pch=20, main="Plot for No of ampules broken vs Shipment route")
```

```
line = lm(y~x)
```

```
summary(line)
```

```
abline(line, col="Red", lwd=4)
```

#the linear regression function does appear to give a good fit here because all the data are around the linear regression function like p-value of 2.75e-05 shows that it is statistically significant and Multiple R-squared is 0.9009 as well.



#b

```
coefficients(lm(y~x))
```

```
(Intercept)          x  
      10.2         4.0
```

```
a=data.frame(x=1)
```

```
predict(z,a)
```

#expected no of broken ampules are 14.2 when x=1 transfer is made

#c

```
coefficients(lm(y~x))
```

```
b=data.frame(x=2)
```

```
predict(z,b)
```

```
predict(z,b) - predict(z,a)
```

#increase in no of broken ampules is 4 when there are 2 transfers as compared to 1 transfer

#d

```
xbar = mean(x)
```

```
ybar = mean(y)
```

```
xbar
```

```
ybar
```

```
a=data.frame(x=1)
```

```
predict(z,a)
```

#thus on inputting values of xbar as 1, we get ans as ybar which is 14.2. Thus it passes through (xbar, ybar)

#Part 2

#a

```
GPAdata=read.table("D:\\ASU Stuff\\SEM-1\\STP 530\\120 students.txt")
```

```
ACT=GPAdata$V2
```

```
GPA=GPAdata$V1
```

```
z1=lm(GPA~ACT)
```

```
coef=coefficients(z1)
```

```
coef
```

```
(Intercept)      ACT  
 2.11404929  0.03882713
```

```
#thus the model is 2.114+0.00388x
```

#b

```
z1=lm(GPA~ACT)
```

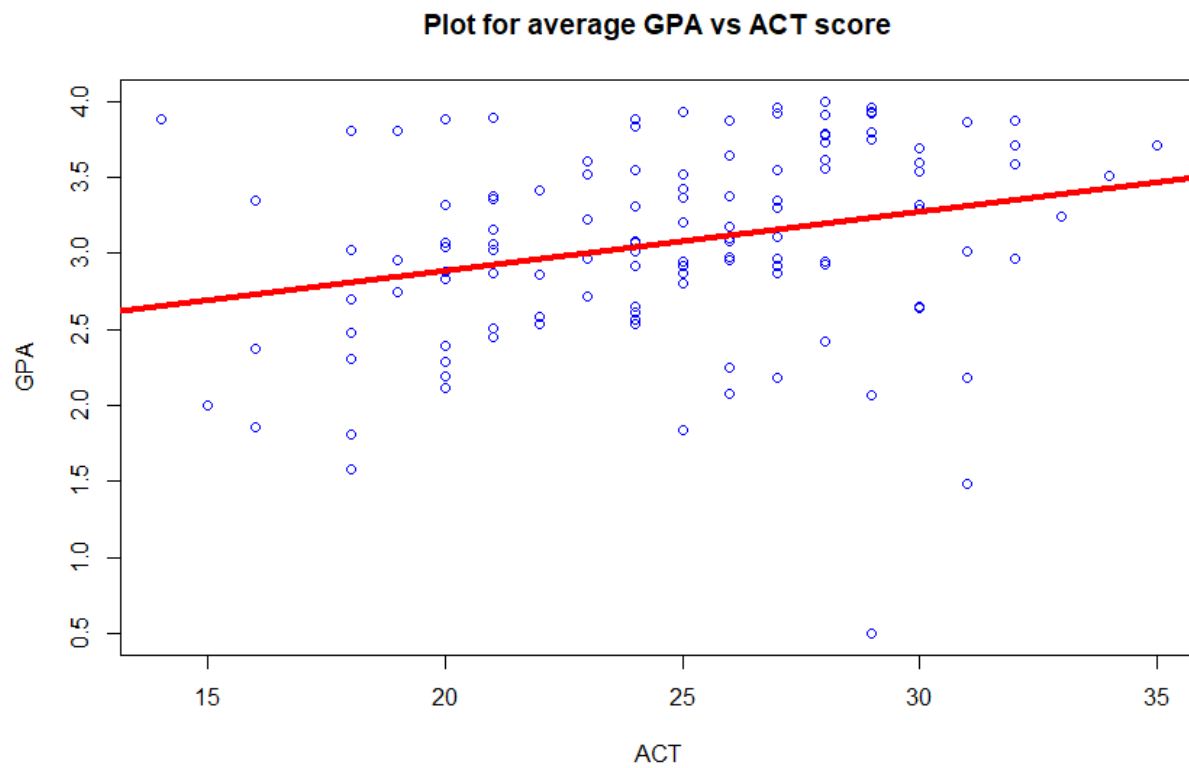
```
summary(z1)
```

```
line=(z1)
```

```
plot(GPA~ACT, main="Plot for average GPA vs ACT score", col="blue")
```

```
abline(z1, col="red", lwd=4)
```

```
#the line doesn't fit the data properly because there is no particular shape in data through which a line can pass
```



#c

```
meangpa=data.frame(ACT=30)
```

```
predict(z1,meangpa)
```

#point estimate of mean is 3.2788 when ACT is 30

#d

```
meangpa1=data.frame(ACT=31)
```

```
predict(z1,meangpa1) #point estimate of mean is 3.3176 when ACT is 31
```

```
predict(z1,meangpa1) - predict(z1,meangpa)
```

#point estimate of the change of the mean response is 0.0388

#e

```
zresid=resid(z1)
```

```
zresid
```

```
sum(zresid)
```

#from the result, it is very much clear that the value doesn't sum up to zero

#f

MSE = sum(zresid^2)/(length(zresid)-2) #value of sigma square

sigma = sqrt(MSE) #value of sigma

sigma

#value of sigma is 0.6231

#Part 3

musclemass=read.table("D:\\ASU Stuff\\SEM-1\\STP 530\\60 students.txt")

age=musclemass\$V2

measure=musclemass\$V1

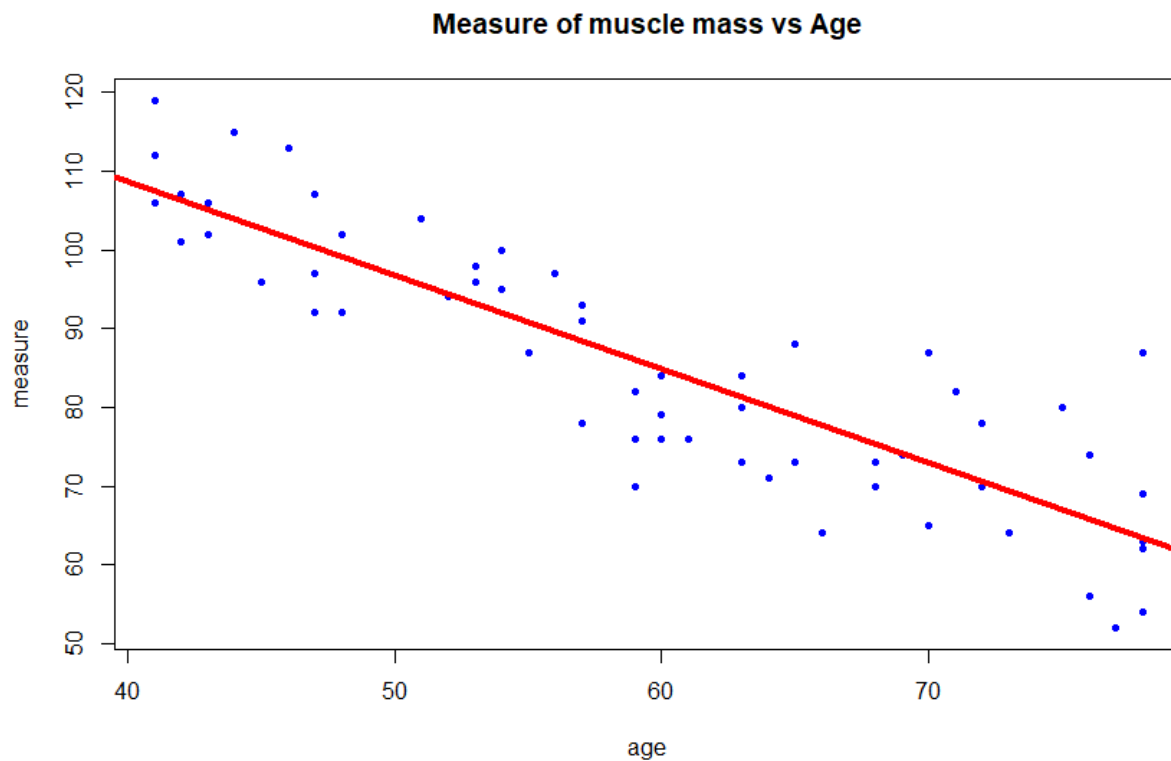
#a

z2=lm(measure~age) #function is 156.3466-1.1900*age

plot(measure~age, col="blue", pch=20, main="Measure of muscle mass vs Age")

abline(z2, col="red", lwd=4)

summary(z2)



#Yes, it does appear that the model does seem to give a good fit here as the R-squared is 0.7501 and the plot clearly shows that the muscle mass decreases with age

#b

#1

```
z2$coefficients[2]
```

#mean muscle mass difference for women differing in age by one year is -1.1899

#2

```
z2$coefficients[1] + z2$coefficients[2]*60
```

#point estimate for women aged 60 years is 84.9468

#3

```
Residuals=resid(z2)
```

#thus the residual at eighth value is 4.4432

#4

```
MSE = sum(Residuals^2)/(length(Residuals)-2)
```

```
#point estimate sigma^2 is 66.8008
```

#Part 4

#a

```
manuscript=c(7,12,4,14,25,30)
```

```
errors=c(128,213,75,250,446,540)
```

```
sumx=sum(manuscript)
```

```
sumy=sum(errors)
```

```
sumxx=sum(manuscript*manuscript)
```

```
sumyy=sum(errors*errors)
```

```
sumxy=sum(manuscript*errors)
```

```
lm(errors~manuscript)
```

```
Call:
```

```
lm(formula = errors ~ manuscript)
```

```
Coefficients:
```

```
(Intercept)      manuscript  
      1.597         17.852
```

#a

```
likelihood=function(errors, manuscript, beta1)
```

```
{
```

```
  lf=c()
```

```
  for ( i in 1:length(errors))
```

```
  {
```

```
    lf[i]=(1/(sqrt(32*pi)))*exp((-1/32)*(errors[i]-beta1*manuscript[i])^2) #likelihood function for six observations
```

```
  }
```

```
  likefunction=prod(lf)
```

```
  return(likefunction)
```

```
}
```

#b

```
likelihood(errors, manuscript, 17) # 9.45133e-30
```

```
likelihood(errors, manuscript, 18) # 2.649043e-07
```

```
likelihood(errors, manuscript, 19) # 3.047285e-37
```

#c

```
b1 = sumxy/sumxx # 17.928
```

#d

```
beta1val=seq(17,19, by=0.01)
```

```
lf1=c()
```

```
for (i in 1:length(beta1val)) {
```

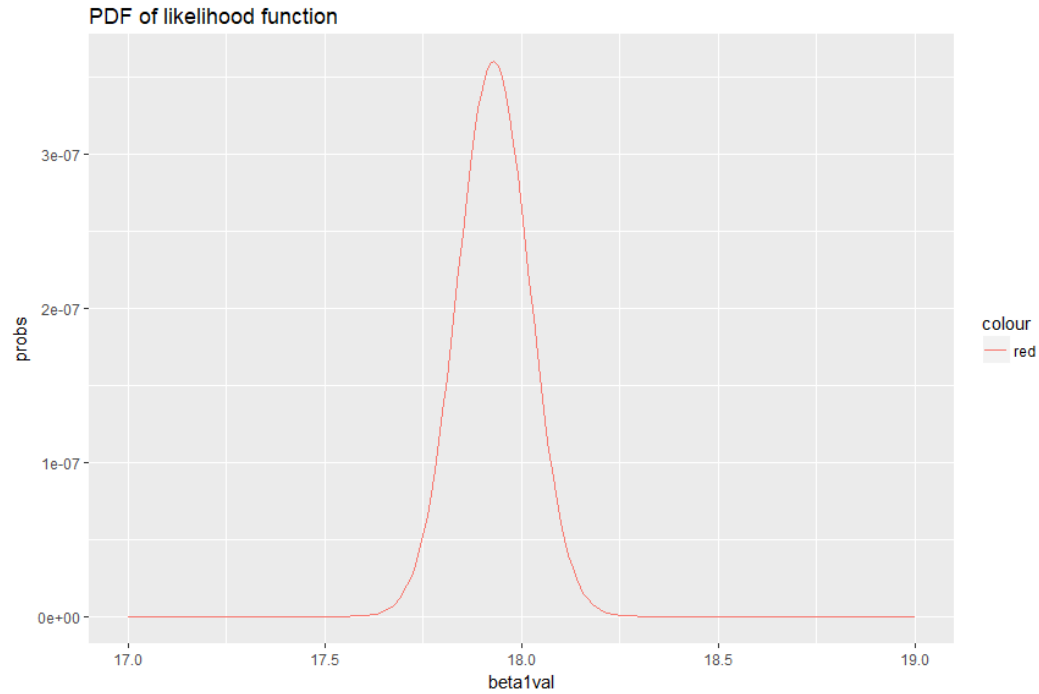
```
  lf1[i]=likelihood(errors, manuscript, beta1val[i])
```

```
}
```

```
lf1=data.frame(beta1val,lf1)
```

```
colnames(lf1)=c("beta1", "probs")
```

```
qplot(beta1val, probs, data=lf1, geom="line", col="red", main="PDF of likelihood function")
```

#thus the plot shows that the max. value of likelihood function is slightly less than 18 which is consistent with our max. likelihood estimate in part c.

#Part 5

#a

```
likelihood1=function(errors, manuscript, beta0, beta1)
{
  lf2=c()
  for ( i in 1:length(errors))
  {
    lf2[i]=(1/(sqrt(32*pi)))*exp((-1/32)*(errors[i]-beta0-(beta1*manuscript[i]))^2) #likelihood function for six
    observations
  }
  likefunction1=prod(lf2)
  return(likefunction1)
}
```

#b

```
coefficients(lm(errors~manuscript))
```

```
#beta0=1.5969 #beta1=17.8523
```

#c

```
b0val=seq(-10,10, by=0.05)
```

```
b1val=seq(17,19, by=0.05)
```

```
f=function(b0val,b1val) {
```

```
(32*pi)^(-3)*exp(-19387.31-60.3125*b1val^2-0.1875*b0val^2+2162.24*b1val+103.25*b0val-5.75*b0val*b1val)
```

```
}
```

```
z=outer(b0val, b1val, f)
```

```
persp(b0val, b1val, z, col="red", theta=120, phi=30, zlab="Likelihood value")
```

