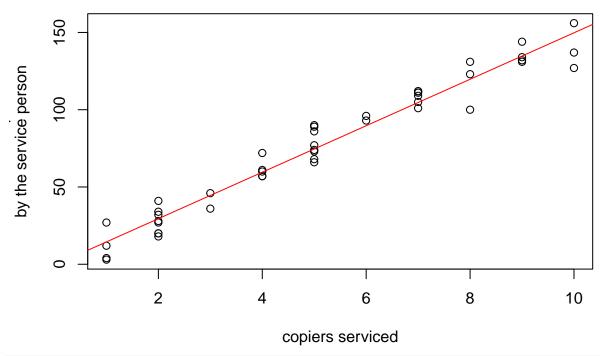
GR5205_HW4

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```
Problem 1.
setwd("/Users/jenniferlieu/Desktop/Linear Regression Models Data 1")
hw4 <- read.table("HW4Problem1.txt", header=T, sep='')</pre>
  i.
copierslm \leftarrow lm(hw4\$y\sim hw4\$x)
summary(copierslm)
##
## Call:
## lm(formula = hw4$y ~ hw4$x)
##
## Residuals:
##
       Min
                  1Q Median
                                    ЗQ
                                            Max
## -22.7723 -3.7371 0.3334 6.3334 15.4039
## Coefficients:
               Estimate Std. Error t value Pr(>|t|)
## (Intercept) -0.5802
                        2.8039 -0.207
                                              0.837
                           0.4831 31.123
## hw4$x
                15.0352
                                             <2e-16 ***
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
## Residual standard error: 8.914 on 43 degrees of freedom
## Multiple R-squared: 0.9575, Adjusted R-squared: 0.9565
## F-statistic: 968.7 on 1 and 43 DF, p-value: < 2.2e-16
  ii.
```

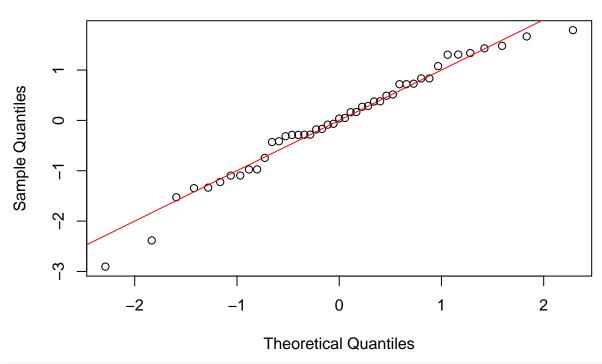
```
# scatter plot + linear model
plot(hw4$x, hw4$y, main = " preventive maintenance service", xlab= "copiers serviced", ylab= "minutes service person")
abline(-0.5802 ,15.0352, col="red")
```

preventive maintenance service



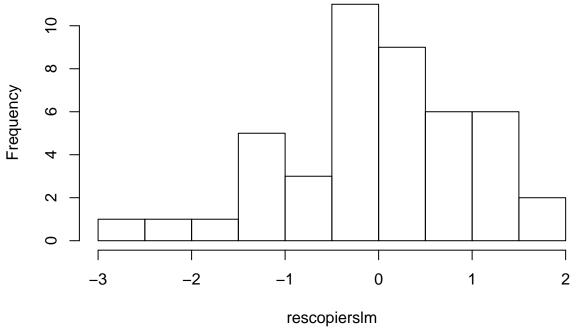
```
# deleted residuals
rescopierslm <- rstudent(copierslm)
# QQ plot of deleted residuals
qqnorm(rescopierslm)
abline(0,1, col="red")</pre>
```

Normal Q-Q Plot



histogram of deleted residuals
hist(rescopierslm)

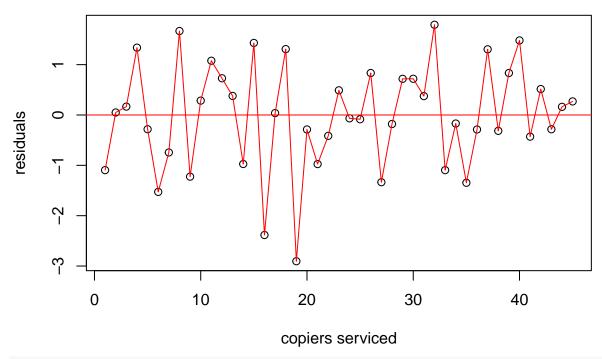
Histogram of rescopiersIm



#line plots of deleted residuals
plot(1:45,rescopierslm, main="deleted residuals", xlab="copiers serviced", ylab="residuals")

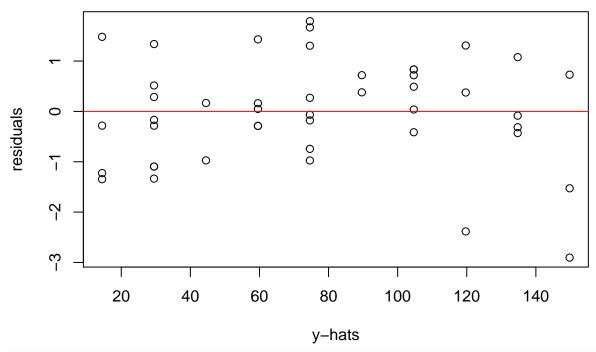
```
lines(1:45, rescopierslm, col="red")
abline(0,0, col="red")
```

deleted residuals



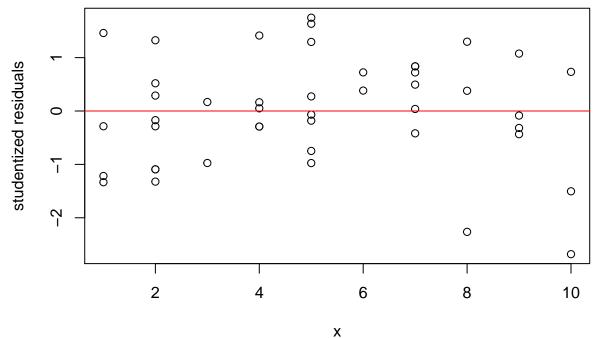
#the studentized deleted residuals verses predicted values ^y
plot(-0.5802+15.0352*hw4\$x,rescopierslm, main="deleted residuals", xlab="y-hats", ylab="residuals")
abline(0,0, col="red")

deleted residuals



#studentized residuals vs. predictor variable x
studres <-rstandard(copierslm)
plot(hw4\$x,studres, main=" studentized residuals", xlab="x", ylab="studentized residuals")
abline(0,0, col="red")</pre>

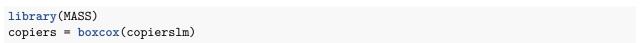
studentized residuals

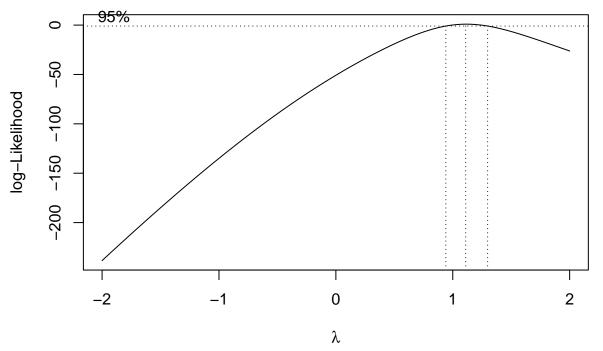


the linear model, we notice that the linear model seems to fit the data proposed. According to the QQ plot,

it seems that the model has a little bit of a left skew, which means that the variance is not constant. The histogram verifies that the distribution is almost-normal with a left skew. The line plot looks like there is a specific pattern to it, so it is not necessarily a linear model. Especially because we have discrete values, rather than continuous for the x. The last two residual plots look random, however, there are less negative values randomly placed near the center which suggests that the model might not be linear.

iii.





```
copiers.lambda = copiers$x[which(copiers$y==max(copiers$y))]
copiers.lambda
```

[1] 1.111111

The lambda is close to 1, so we know that a linear model is appropriate.

Problem 2.

```
hw42 <- read.table("1_22.txt", header=F, sep = "")
time <- hw42$V2
hardness <- hw42$V1

n <- length(hardness)
c <- 4
sse.R <- anova(lm(hardness~time))[[2]][2]
fac.x <- factor(time)
sse.F <- anova(lm(hardness~fac.x))[[2]][2]
f.calc <- ((sse.R-sse.F)/(c-2))/(sse.F/(n-c))
1-pf(f.calc,c-2,n-c)</pre>
```

[1] 0.4621597

We fail to reject the null hypothesis that linearity is not satisfied for the data.

4.

```
i.
x < c(10,20,30,40,50)
e \leftarrow rnorm(5,mean = 0,sd = (.8*x)^{.5})
y<-20+10*x+e
У
## [1] 119.8998 216.1285 322.8241 418.3987 530.5185
  ii. and iii.
x < c(10,20,30,40,50)
b \leftarrow rep(NA, 10000)
bweight <- rep(NA, 10000)</pre>
for(i in 1:10000){
e \leftarrow rnorm(5,mean = 0,sd = (.8*x)^{.5})
y<-20+10*x+e
unweighted.model <- lm(y~x)
enew <- residuals(unweighted.model)</pre>
s.hat <- 1/(.8*x)
weighted.ls <- lm(y-x, weights = s.hat)
b[i] <- coef(unweighted.model)[2]</pre>
bweight[i] <- coef(weighted.ls)[2]</pre>
}
mean(b)
## [1] 10.00026
var(b)
## [1] 0.0240546
mean(bweight)
## [1] 10.00163
var(bweight)
```

[1] 0.01976351

iv. Both seem to be unbiased. However, the weighted beta seems to be more precise because it is closer to 10. Also, the var of my bweight is smaller.