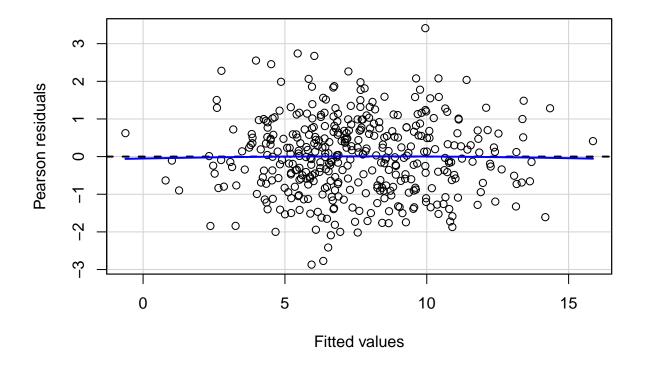
2 Q2.

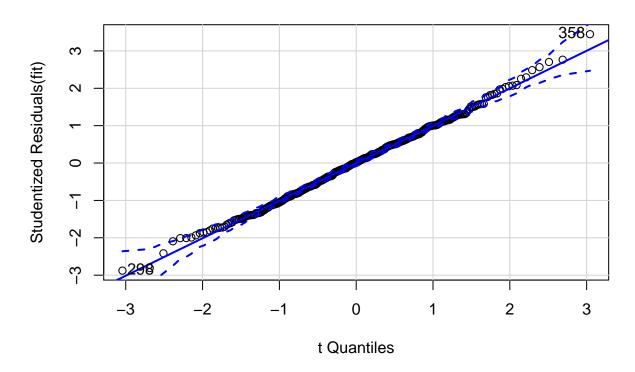
```
(a)
```

```
library(ISLR)
data("Carseats")
fit <- lm(Sales ~ CompPrice+Income+Advertising+Population+Price+ShelveLoc+Age+Education+Urban+US, data
summary(fit)
##
## Call:
## lm(formula = Sales ~ CompPrice + Income + Advertising + Population +
      Price + ShelveLoc + Age + Education + Urban + US, data = Carseats)
##
## Residuals:
      Min
               1Q Median
                              3Q
## -2.8692 -0.6908 0.0211 0.6636 3.4115
##
## Coefficients:
##
                   Estimate Std. Error t value Pr(>|t|)
## (Intercept)
                  5.6606231 0.6034487 9.380 < 2e-16 ***
                   0.0928153  0.0041477  22.378  < 2e-16 ***
## CompPrice
## Income
                   0.0158028 0.0018451
                                        8.565 2.58e-16 ***
## Advertising
                   0.1230951 0.0111237 11.066 < 2e-16 ***
## Population
                  0.0002079 0.0003705
                                         0.561
                                                  0.575
## Price
                  -0.0953579  0.0026711  -35.700  < 2e-16 ***
## ShelveLocGood
                  4.8501827 0.1531100 31.678 < 2e-16 ***
## ShelveLocMedium 1.9567148 0.1261056 15.516 < 2e-16 ***
                 -0.0460452  0.0031817  -14.472  < 2e-16 ***
## Age
                  -0.0211018 0.0197205 -1.070
## Education
                                                  0.285
## UrbanYes
                  0.1228864 0.1129761
                                         1.088
                                                  0.277
## USYes
                  0.220
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
## Residual standard error: 1.019 on 388 degrees of freedom
## Multiple R-squared: 0.8734, Adjusted R-squared: 0.8698
## F-statistic: 243.4 on 11 and 388 DF, p-value: < 2.2e-16
##The multiple R-squared value is 0.8698, which shows that this regression
##can interpret 87% of the changes of the dependent variable.
residualPlot(fit)
                        #Diagnostic residual plots
```



qqPlot(fit, main="QQ Plot") #qq plot for studentized residuals

QQ Plot



[1] 298 358

##There is no clear interaction between the predicted value and residuals

(b)

```
##We can see that CompPrice, Income, Advertising, Price,
##and ShelveLoc have significant p-values.

##For the variable "Urban", we have the P-value = 0.277 > 0.05, hence, we
##rejected the hypothesis that the variable Urban is significant.
```

(c)

```
fit1 <- lm(Sales ~ CompPrice+Income+Advertising+Price+ShelveLoc, data = Carseats)
summary(fit1)</pre>
```

```
##
## Call:
## lm(formula = Sales ~ CompPrice + Income + Advertising + Price +
       ShelveLoc, data = Carseats)
##
##
## Residuals:
       Min
                1Q Median
                                3Q
                                       Max
## -3.7962 -0.9251 0.0043 0.8457 4.4179
##
## Coefficients:
##
                    Estimate Std. Error t value Pr(>|t|)
```

```
## (Intercept)
                   2.431262
                              0.569032 4.273 2.43e-05 ***
## CompPrice
                   ## Income
                   0.016042 0.002276
                                       7.049 8.16e-12 ***
## Advertising
                   ## Price
                  -0.093241
                              0.003302 -28.236 < 2e-16 ***
## ShelveLocGood
                   4.797696
                             0.188847 25.405 < 2e-16 ***
## ShelveLocMedium 1.849895
                            0.155037 11.932 < 2e-16 ***
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.263 on 393 degrees of freedom
## Multiple R-squared: 0.8031, Adjusted R-squared: 0.8001
## F-statistic: 267.2 on 6 and 393 DF, p-value: < 2.2e-16
##The multiple R-squared value is 0.8001, which shows that this regression can
##interpret 80% of the changes of the dependent variable
\textit{##The $R$-squared value} \quad \textit{of the reduced model slightly decreased from the previous}
##value with the full model.
(d)
anova(fit,fit1)
## Analysis of Variance Table
## Model 1: Sales ~ CompPrice + Income + Advertising + Population + Price +
      ShelveLoc + Age + Education + Urban + US
## Model 2: Sales ~ CompPrice + Income + Advertising + Price + ShelveLoc
              RSS Df Sum of Sq
    Res.Df
                                    F
                                         Pr(>F)
## 1
       388 402.83
       393 626.51 -5
## 2
                      -223.68 43.088 < 2.2e-16 ***
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
#The P-value is significant, i.e. we can not reject the hypothesis that the two
# models have different variance.
#Hence, the different between the R-squared value is not significant, and the
#second model is better.
(e)
y = 2.431 + 0.096 \times CompPrice + 0.016 \times Income + 0.116 \times Advertising - 0.093 \times Price + 4.798 (If shelveLoc
= Good) + 1.850 (If ShelveLoc = Medium)
fit2 <- lm(Sales ~ CompPrice+Income+Advertising+Price+ShelveLoc + Price:ShelveLoc, data = Carseats)
summary(fit2)
##
## Call:
## lm(formula = Sales ~ CompPrice + Income + Advertising + Price +
##
      ShelveLoc + Price:ShelveLoc, data = Carseats)
##
## Residuals:
##
      Min
               1Q Median
                               3Q
                                      Max
```

```
## -3.7547 -0.9336 0.0078 0.8386 4.3561
##
## Coefficients:
                         Estimate Std. Error t value Pr(>|t|)
##
## (Intercept)
                         1.964179
                                    0.795606 2.469 0.01398 *
## CompPrice
                         0.095881
                                   0.005144 18.638 < 2e-16 ***
## Income
                         0.015969
                                   0.002290 6.974 1.32e-11 ***
                                    0.009596 12.121 < 2e-16 ***
## Advertising
                         0.116309
                                    0.005739 -15.567 < 2e-16 ***
## Price
                        -0.089335
## ShelveLocGood
                         5.353757
                                    0.920389 5.817 1.25e-08 ***
## ShelveLocMedium
                         2.473173
                                    0.774915
                                             3.192 0.00153 **
## Price:ShelveLocGood
                                    0.007752 -0.625 0.53249
                        -0.004843
## Price:ShelveLocMedium -0.005441
                                   0.006626 -0.821 0.41205
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.265 on 391 degrees of freedom
## Multiple R-squared: 0.8035, Adjusted R-squared: 0.7995
## F-statistic: 199.8 on 8 and 391 DF, p-value: < 2.2e-16
##We can see that the interaction between Price and ShelveLoc have
##non-significant p-values, hence the interaction term is not necessary.
(d)
anova(fit1,fit2)
## Analysis of Variance Table
## Model 1: Sales ~ CompPrice + Income + Advertising + Price + ShelveLoc
## Model 2: Sales ~ CompPrice + Income + Advertising + Price + ShelveLoc +
##
      Price:ShelveLoc
    Res.Df
              RSS Df Sum of Sq
##
                                    F Pr(>F)
## 1
       393 626.51
## 2
       391 625.38 2
                       1.1343 0.3546 0.7017
#The P-value is not significant, i.e. we canreject the hypothesis that the two
# models have different variance.
#Hence, the different between the R-squared value is significant, and the
#interaction term is not necessary.
```