Lab 5

The Sound of Gunfire, Off in the Distance

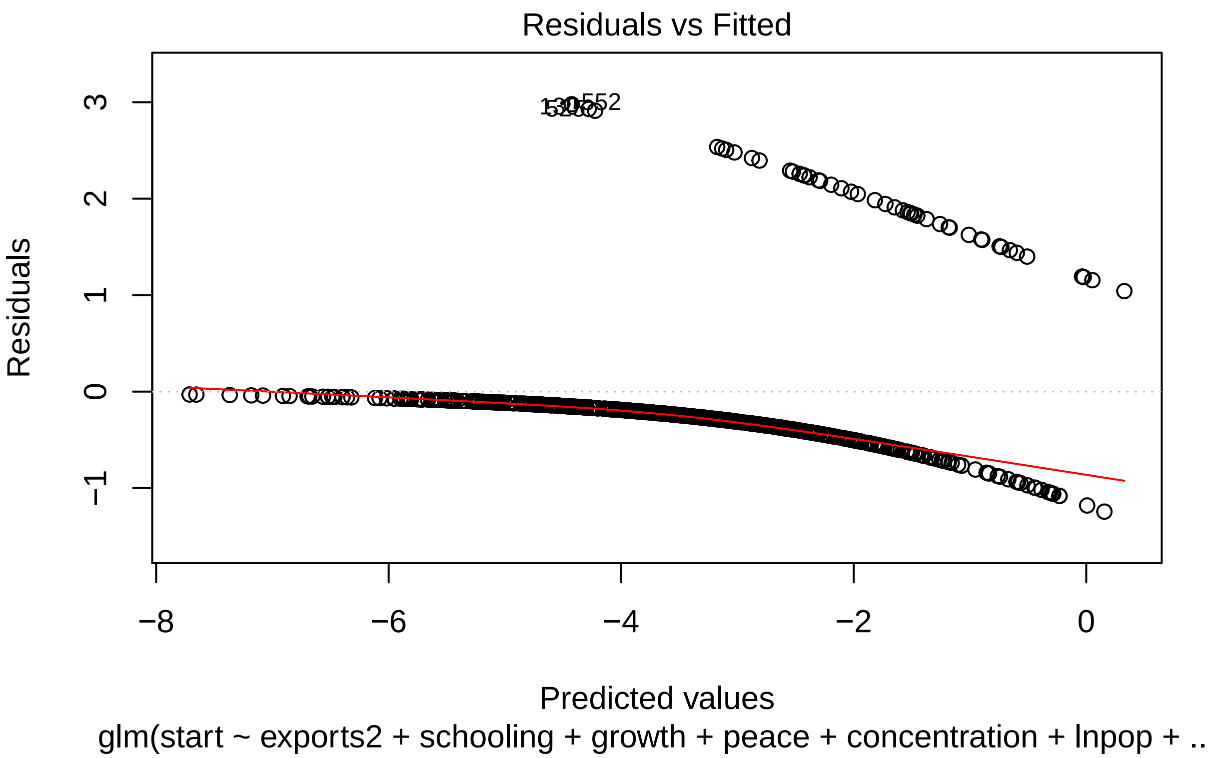
Alice Chang

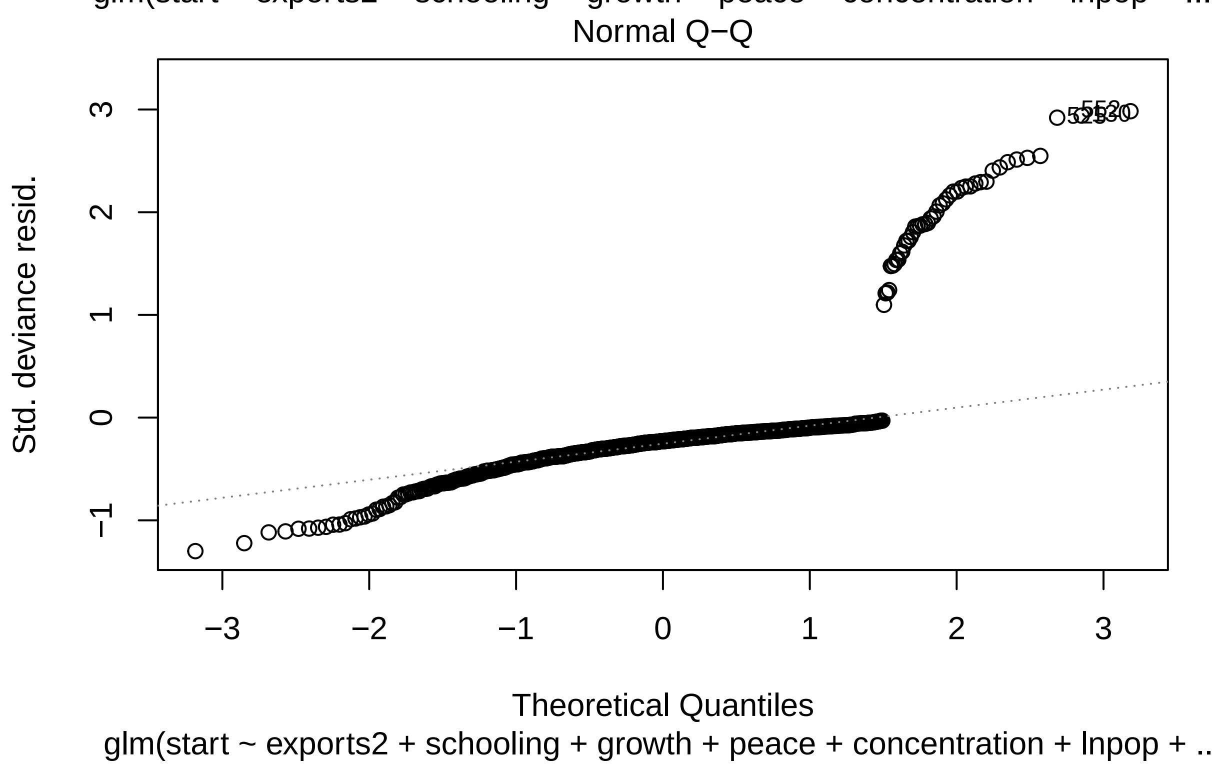
Part 1-2: Estimate

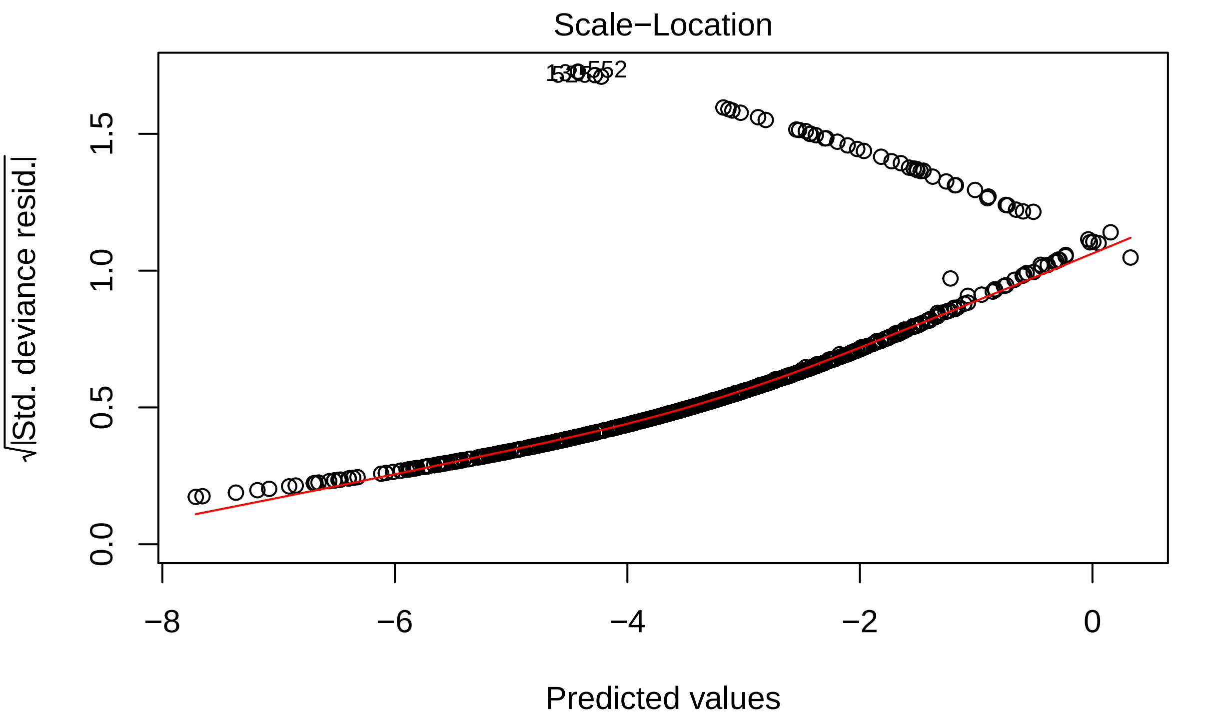
```
#load data
library(MASS)
library(dplyr)
```

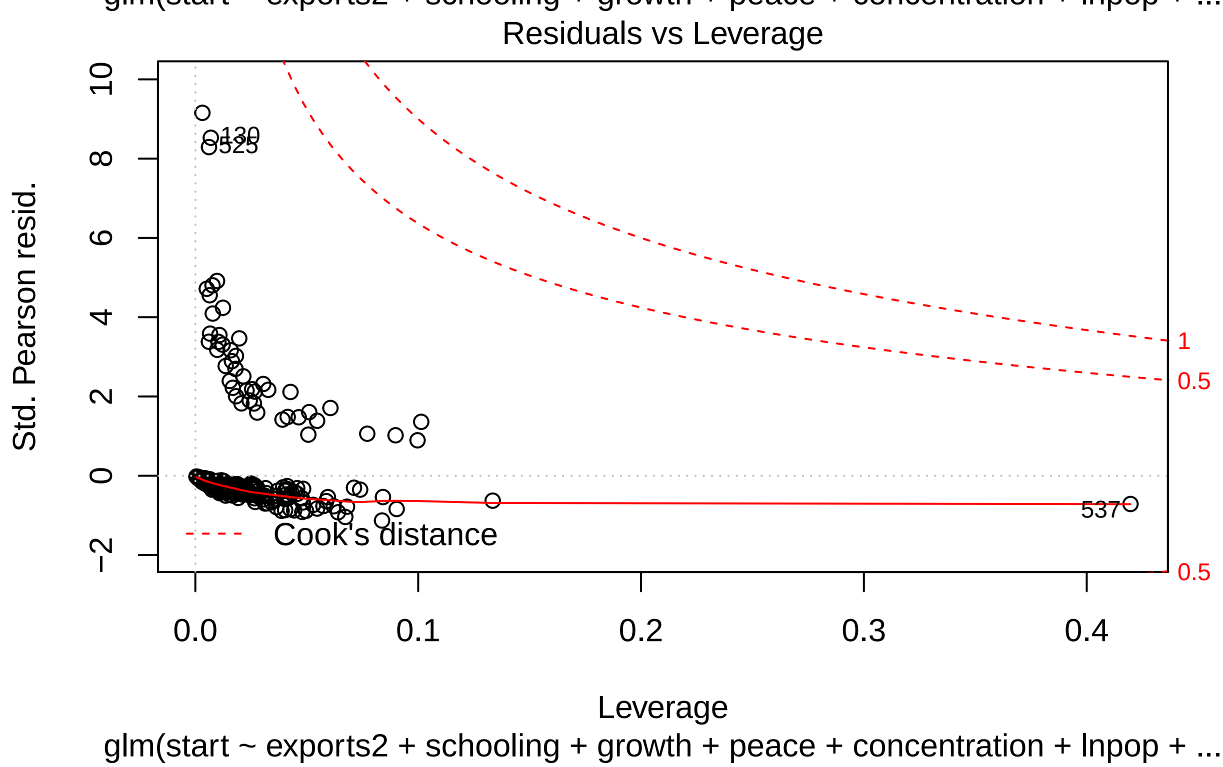
```
##
## Attaching package: 'dplyr'
## The following object is masked from 'package:MASS':
##
##     select
## The following objects are masked from 'package:stats':
##
##     filter, lag
## The following objects are masked from 'package:base':
##
##     intersect, setdiff, setequal, union
```

```
war <- read.csv("http://www.stat.cmu.edu/~cshalizi/uADA/15/hw/06/ch.csv", row.names = 1)
war_clean <- na.omit(war)
war_clean <- war_clean %>% mutate(exports2 = exports^2)
row.names(war_clean) <- (1:nrow(war_clean))
#include quadratic term



#fit logistic regression model
glm.fits <- glm(start ~ exports2 + schooling + growth + peace + concentration + lnpop + fractionalizati
plot(glm.fits)
```


Residuals vs Fitted
552
Residuals
3
2
1
0
−1
−8
−6
−4
−2
0
Predicted values
glm(start ~ exports2 + schooling + growth + peace + concentration + lnpop + ...


Normal Q−Q
552
Std. deviance resid.
3
2
1
0
−1
−3
−2
−1
0
1
2
3
Theoretical Quantiles
glm(start ~ exports2 + schooling + growth + peace + concentration + lnpop + ...






```r
summary(glm.fits)$coef
```

```
##                       Estimate   Std. Error   z value     Pr(>|z|)
## (Intercept)      -7.469538e+00 2.046470e+00 -3.649963 0.0002622786
## exports2          2.799199e+00 1.870619e+00  1.496403 0.1345487717
## schooling        -2.388170e-02 8.684965e-03 -2.749776 0.0059636089
```

```
## growth            -1.364391e-01 4.335592e-02 -3.146953 0.0016498130
## peace             -4.088964e-03 1.096575e-03 -3.728849 0.0001923564
## concentration     -1.563426e+00 9.220441e-01 -1.695609 0.0899599576
## lnpop              4.776614e-01 1.249363e-01  3.823240 0.0001317096
## fractionalization -9.910336e-05 8.230627e-05 -1.204080 0.2285585239
## dominance          5.375078e-01 3.451495e-01  1.557319 0.1193948020
```

The effect of a country's dependency on commodity exports ("exports2") (β_1 = 2.799199e+00, SE = 1.870619e+00, P = 0.1345487717), geographic concentration of the population ("concentration") (β_5 = -1.563426e+00, SE = 9.220441e-01, P = 0.0899599576), social fractionalization ("fractionalization") (β_7 = -9.910336e-05, SE = 8.230627e-05, P = 0.2285585239), and extent of ethnic dominance ("dominance") (β_8 = 5.375078e-01, SE = 3.451495e-01, P = 0.1193948020) on the likelihood of a war starting are statistically insignificant.

However, the secondary school enrollment rate for males ("schooling") (β_2 = -2.388170e-02, SE = 8.684965e-03, P = 0.00596), annual GDP growth rate ("growth"") (β_3 =-1.364391e-01, SE = 4.335592e-02, P = 0.00165), number of months since the country's last war ("peace") (β_4 = -4.088964e-03, SE = 1.096575e-03, P = 0.00019), and natural logarithm of the country's population ("lnpop") (β_6 = 4.776614e-01, SE = 1.249363e-01, P = 0.00013) are all statistically significant at the 5% level.

The negative coefficient estimates for "schooling," "growth," and "peace," suggest that as a country's school enrollment rate for males, annual GDP growth rate, and number of months since the last war increases, while holding each other and all other variables fixed, the likelihood of a war starting decreases. The positive coefficient estimate of "lnpop" suggests that, holding all other variables constant, the larger a country's population, the greater the likelihood of a war starting.

Part 2: Interpretation

```r
#India, 1975
which((war_clean$country == "India") & (war_clean$year == 1975))
```

```
## [1] 272
```

```r
war_clean[272,]
```

```
##     country year start exports schooling growth peace concentration
## 272   India 1975     0   0.026        36  0.322   112         0.537
##        lnpop fractionalization dominance exports2
## 272 20.23462              2937         0 0.000676
```

```r
#Predict for India in 1975
probs_a1 <- predict(glm.fits, newdata = data.frame(exports2 = 0.026^2, schooling = 36, growth = 0.322, p
probs_a1
```

```
##          1
## -0.2946148
```

```r
#Predict for country like India with higher schooling
probs_b1 <- predict(glm.fits, newdata = data.frame(exports2 = 0.026^2, schooling = 66, growth = 0.322, p
probs_b1
```

```
##         1
## -1.011066
```

```r
#Predict for country like India with higher export to GDP ratio
probs_c1 <- predict(glm.fits, newdata = data.frame(exports2 = (0.026 + 0.1)^2, schooling = 36, growth =
probs_c1
```

```
##         1
```

```
## -0.252067
```

```r
#Nigeria, 1965
which((war_clean$country == "Nigeria") & (war_clean$year == 1965))
```

```
## [1] 464
```

```r
war_clean[464,]
```

```
##     country year start exports schooling growth peace concentration
## 464 Nigeria 1965     1   0.123         7  1.916   232         0.539
##        lnpop fractionalization dominance exports2
## 464 17.65479              6090         0 0.015129
```

```r
#Predict for Nigeria in 1965
probs_a2 <- predict(glm.fits, newdata = data.frame(exports2 = 0.123 ^2, schooling = 7, growth = 1.916
probs_a2
```

```
##         1
## -1.817633
```

```r
#Predict for country like Nigeria, with higher schooling
probs_b2 <- predict(glm.fits, newdata = data.frame(exports2 = 0.123 ^2, schooling = 37, growth = 1.916
probs_b2
```

```
##         1
## -2.534084
```

```r
#Predict for country like Nigeria with higher export to GDP ratio
probs_c2 <- predict(glm.fits, newdata = data.frame(exports2 = (0.123 + 0.1)^2, schooling = 7, growth = 
probs_c2
```

```
##         1
## -1.720781
```

1.The model returns a very small ("negative") probablity estimate for civil war in India in 1975 of -0.2946148, indicating that it predicts the probablity that a civil war will not begin.

For a country just like India in 1975, but with a male secondary school enrollment rate 30 points higher, the model returns an extremely small probability estimate for civil war of -1.011066, indicating that it predicts the probabiltiy that a civil war will not begin.

For a country just like India in 1975, but with a ratio of commodity exports to GDP that is 0.1 higher, the model also returns a small probability estimate for civil war of -0.252067, indicating that it predicts the probablity that a civil war will not begin.

2. The model returns a very small ("negative") probablity estimate for civil war in Nigeria in 1965 of -1.817633, indicating that it predicts the probablity that a civil war will not begin under these conditions.

For a country just like Nigeria in 1965, but with a male secondary school enrollment rate 30 points higher, the model returns an extremely small probability estimate for civil war of -2.534084, indicating that it predicts the probabiltiy that a civil war will not begin under these conditions.

For a country just like Nigeria in 1965, but with a ratio of commodity exports to GDP that is 0.1 higher, the model also returns a small probability estimate for civil war of -1.720781, indicating that it still predicts the probablity that a civil war will not begin under these conditions.

3. The changes in predicted probablities of war were not equal between India and Nigeria after increasing the two predictor variables because male school enrollment rate and the ratio of community exports to GDP vary in the extent of their impact in the two countries. While increasing the rate of male school enrollment rate in India had similar effects on increasing the predicted probablity of war, the impact

was slightly higher in India due to the higher male school enrollment rate in the country. Similarly, the impact of raising the ratio of community exports to GDP in Nigeria on the predicted probablity of war was slightly higher than in India due to the orignnally higher extent of the country's dependency on its exports.

Part 3: Confusion

```
#fit logistic regression model
glm.probs = predict(glm.fits, type = "response")
#Convert to war/no war
nrow(war_clean)
```

```
## [1] 688
```

```
glm.pred = rep("No war", 688)
glm.pred[glm.probs>0.5] = "War"
#Confusion matrix
conf_log <- table(glm.pred,war_clean$start)
conf_log
```

```
##
## glm.pred   0   1
##   No war 640  44
##   War      2   2
```

```
#Cakculate misclassification rate
log_mis = (2 + 44)/688
log_mis
```

```
## [1] 0.06686047
```

```
#If always predict no war
642/688
```

```
## [1] 0.9331395
```

```
#Fracition correct where glm_fits also makes prediciton
  #glm makes only 644 no war and four war
# pundit says 688 no war
644/688
```

```
## [1] 0.9360465
```

The misclassification rate of the logistic regression model is 0.06686047.

Considering a pundit that always predicts no war, their predictions will be correct 0.9331395 of the time.

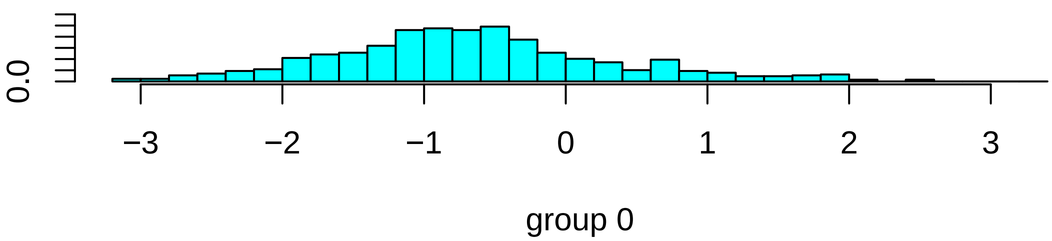
Comsidering the pundit that always predicts no war, their predictions will be correct on data points where the logistic regression model also makes a prediction0.9360465 of the time. #### Discriminant Analysis

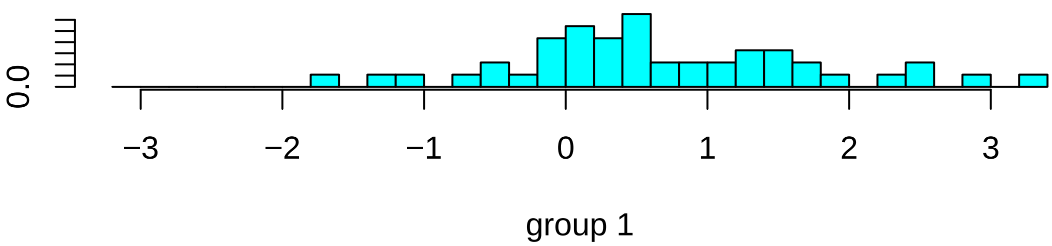
```
library(ggplot2)
#Fit LDA
lda.fit <- lda(start ~ exports2 + schooling + growth + peace + concentration + lnpop + fractionalizatio
lda.fit
```

```
## Call:
## lda(start ~ exports2 + schooling + growth + peace + concentration +
##     lnpop + fractionalization + dominance, data = war_clean)
##
## Prior probabilities of groups:
```

```
##          0          1 
## 0.93313953 0.06686047 
## 
## Group means:
##     exports2 schooling     growth    peace concentration    lnpop
## 0 0.04505594  45.64548 1.73095794 357.7850     0.6038349 15.68224
## 1 0.04127454  28.34783 0.04384783 204.2826     0.5762391 16.58465
##   fractionalization dominance
## 0          1764.882 0.4376947
## 1          2146.696 0.4565217
## 
## Coefficients of linear discriminants:
##                             LD1
## exports2           1.858921e+00
## schooling         -6.409013e-03
## growth            -1.415680e-01
## peace             -4.496371e-03
## concentration     -1.098846e+00
## lnpop              3.053406e-01
## fractionalization -6.507113e-05
## dominance          3.137136e-01
```

```r
plot(lda.fit)
```






```r
lda.pred = predict(lda.fit, war_clean)
conf_lda <- table(lda.pred$class, war_clean$start)
conf_lda
```

```
## 
##       0   1
##   0 638  41
##   1   4   5
```

```
#Find LDA misclassification rate
lda_mis = (4 + 41)/688
lda_mis
```

```
## [1] 0.06540698
```

```
#Fit QDA
qda.fit <- qda(start ~ exports2 + schooling + growth + peace + concentration + lnpop + fractionalizatio
qda.fit
```

```
## Call:
## qda(start ~ exports2 + schooling + growth + peace + concentration +
##     lnpop + fractionalization + dominance, data = war_clean)
##
## Prior probabilities of groups:
##          0          1
## 0.93313953 0.06686047
##
## Group means:
##     exports2 schooling     growth    peace concentration    lnpop
## 0 0.04505594  45.64548 1.73095794 357.7850     0.6038349 15.68224
## 1 0.04127454  28.34783 0.04384783 204.2826     0.5762391 16.58465
##   fractionalization dominance
## 0          1764.882 0.4376947
## 1          2146.696 0.4565217
```

```
qda.pred = predict(qda.fit, war_clean)
conf_qda <- table(qda.pred$class, war_clean$start)
conf_qda
```

```
##
##       0   1
##   0 623  31
##   1  19  15
```

```
#Find QDA misclassification rate
qda_mis = (19 + 31)/688
qda_mis
```

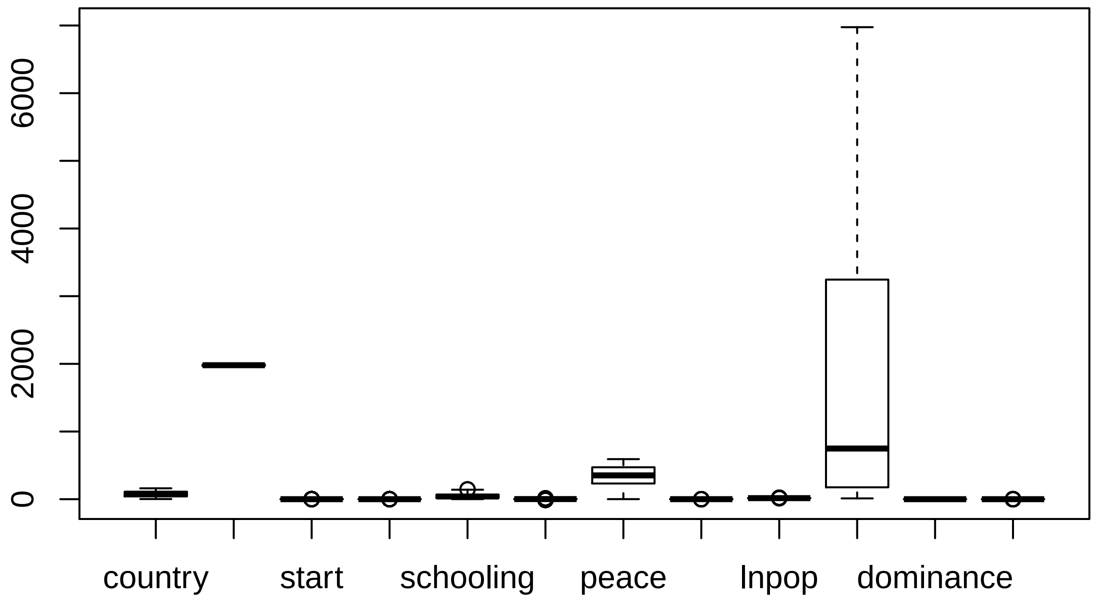
```
## [1] 0.07267442
```

```
#Why of different rates
x <- data.frame(war_clean$exports2, war_clean$schooling, war_clean$growth, war_clean$peace, war_clean$co
cor_matrix <- cor(x)
cor_matrix
```

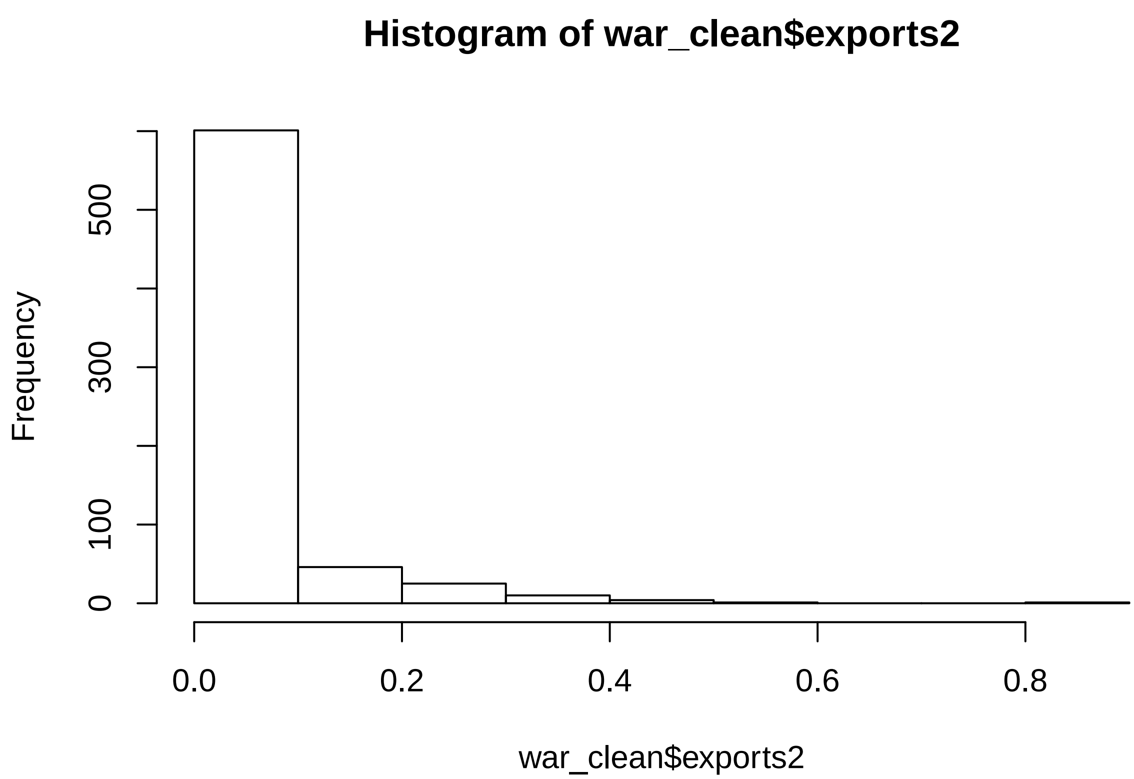
```
##                             war_clean.exports2 war_clean.schooling
## war_clean.exports2                 1.000000000         -0.08906098
## war_clean.schooling               -0.089060980          1.00000000
## war_clean.growth                   0.016181048          0.13602810
## war_clean.peace                    0.062880876          0.39800518
## war_clean.concentration            0.001536338          0.07052828
## war_clean.lnpop                   -0.303299110          0.12845771
## war_clean.fractionalization        0.181536821         -0.36567075
## war_clean.dominance                0.093155843          0.04546414
##                             war_clean.growth war_clean.peace
## war_clean.exports2               0.016181048      0.06288088
```

```
## war_clean.schooling             0.136028097     0.39800518
## war_clean.growth                1.000000000    -0.10362462
## war_clean.peace                -0.103624621     1.00000000
## war_clean.concentration         0.014257650    -0.04075917
## war_clean.lnpop                 0.049958724    -0.18824162
## war_clean.fractionalization    -0.181648026    -0.14505851
## war_clean.dominance            -0.000916039     0.09226036
##                             war_clean.concentration war_clean.lnpop
## war_clean.exports2                        0.001536338     -0.30329911
## war_clean.schooling                       0.070528281      0.12845771
## war_clean.growth                          0.014257650      0.04995872
## war_clean.peace                          -0.040759167     -0.18824162
## war_clean.concentration                   1.000000000      0.19446482
## war_clean.lnpop                           0.194464821      1.00000000
## war_clean.fractionalization              -0.136267701     -0.07710752
## war_clean.dominance                      -0.026922925     -0.14090610
##                             war_clean.fractionalization
## war_clean.exports2                            1.815368e-01
## war_clean.schooling                          -3.656707e-01
## war_clean.growth                             -1.816480e-01
## war_clean.peace                              -1.450585e-01
## war_clean.concentration                      -1.362677e-01
## war_clean.lnpop                              -7.710752e-02
## war_clean.fractionalization                   1.000000e+00
## war_clean.dominance                          -9.528842e-05
##                             war_clean.dominance
## war_clean.exports2                  9.315584e-02
## war_clean.schooling                 4.546414e-02
## war_clean.growth                   -9.160390e-04
## war_clean.peace                     9.226036e-02
## war_clean.concentration            -2.692293e-02
## war_clean.lnpop                    -1.409061e-01
## war_clean.fractionalization        -9.528842e-05
## war_clean.dominance                 1.000000e+00
```

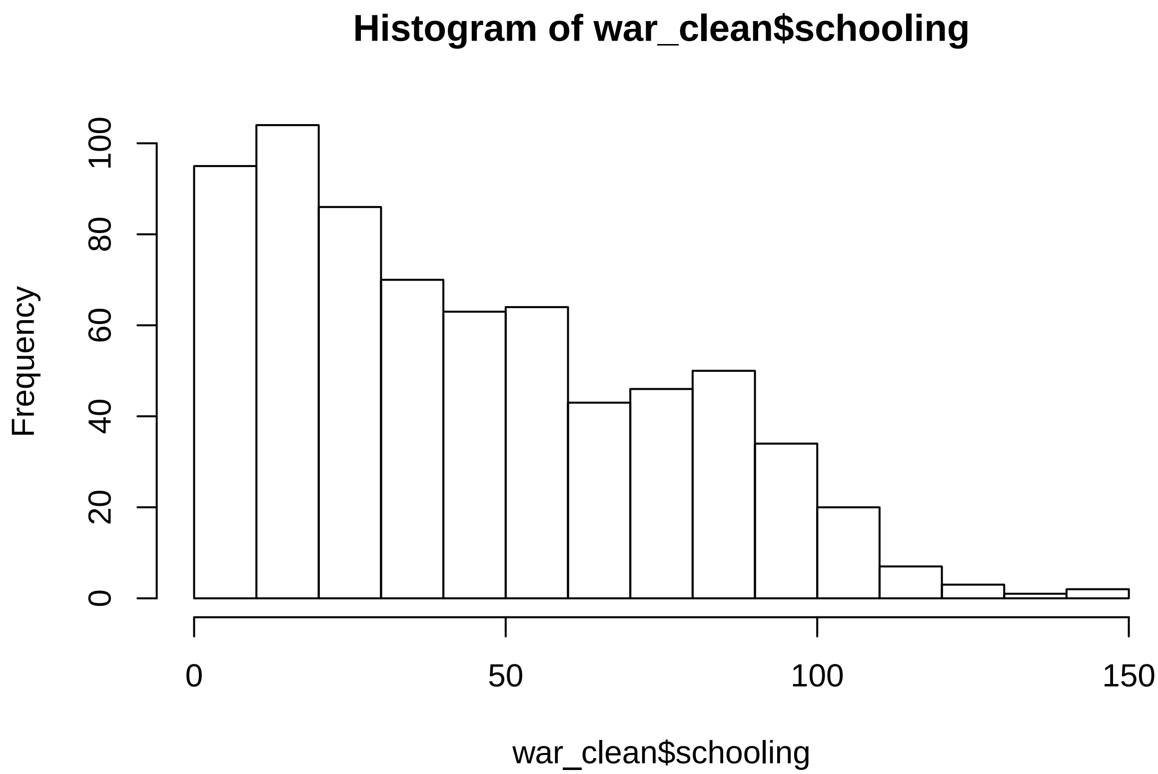
```r
#Explore data, normality etc.
boxplot(war_clean)
```



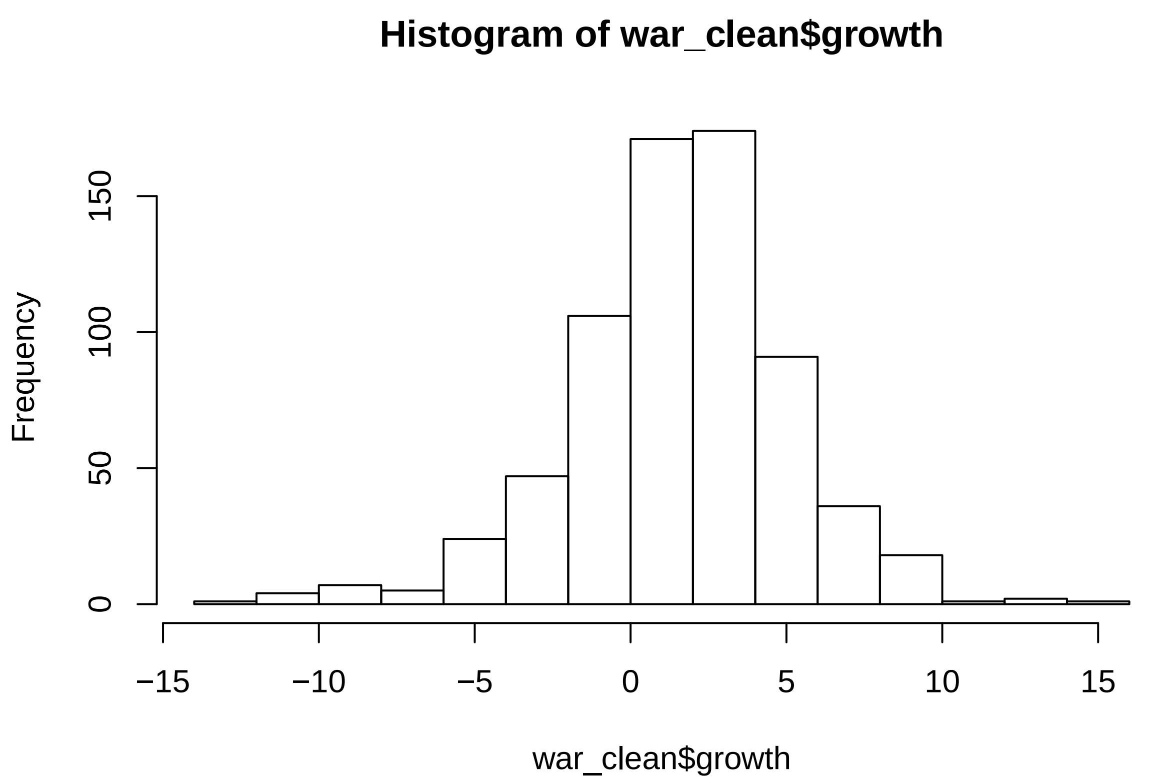

```r
hist(war_clean$exports2)
```



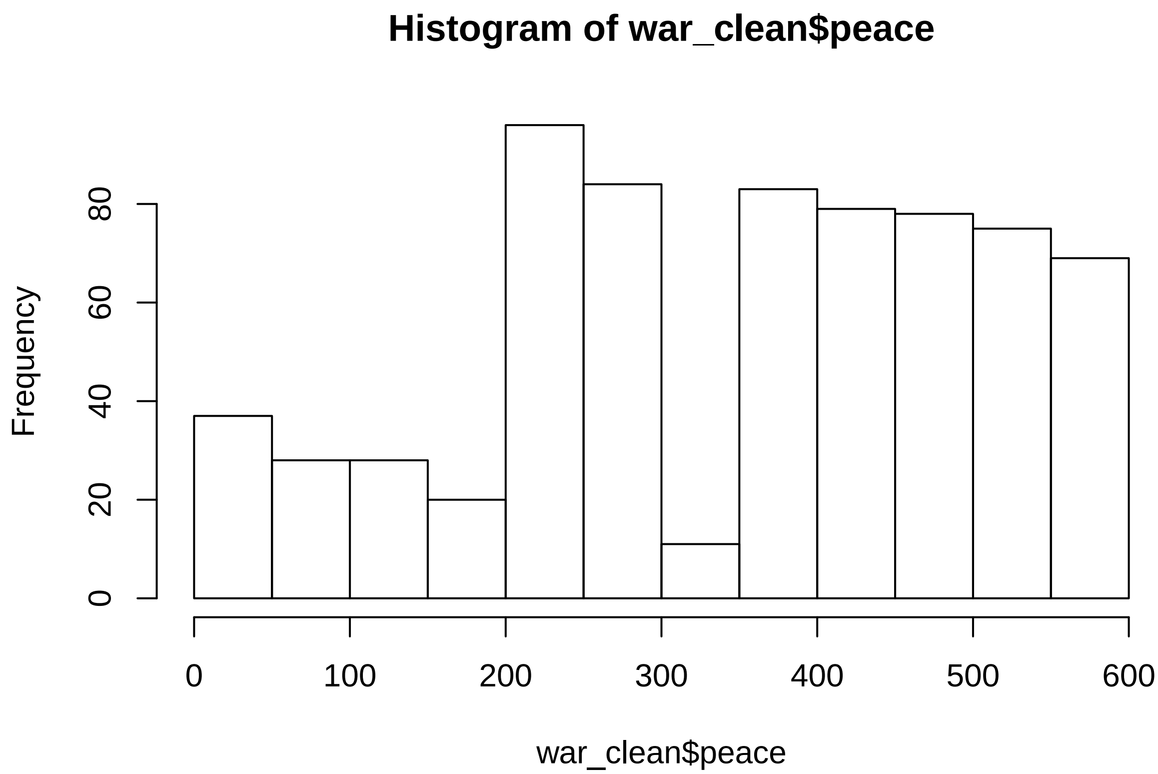

```r
hist(war_clean$schooling)
```



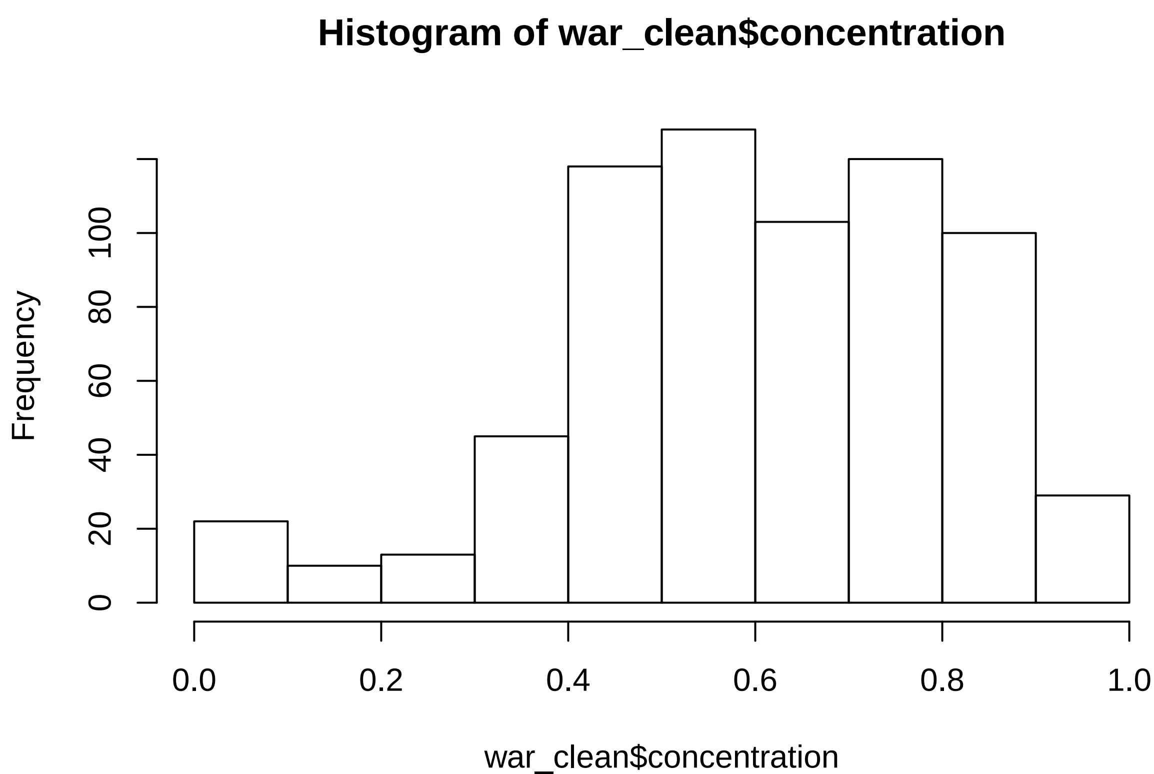

```r
hist(war_clean$growth)
```



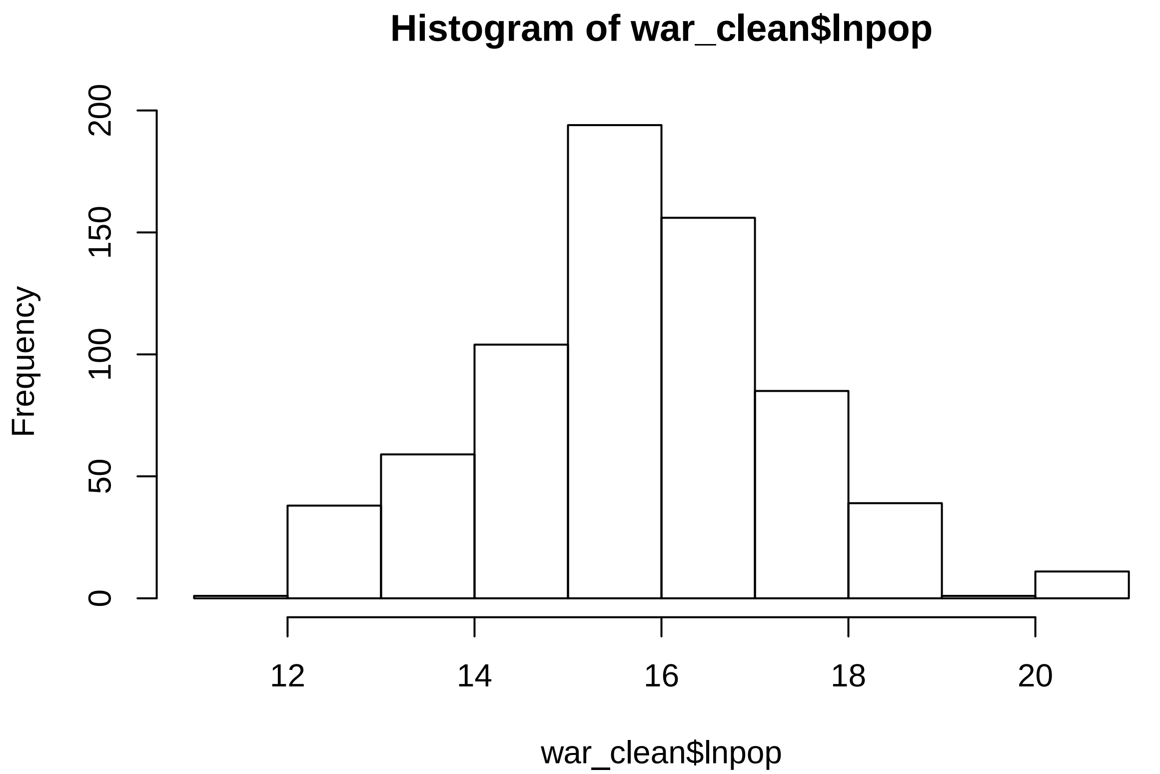

```r
hist(war_clean$peace)
```



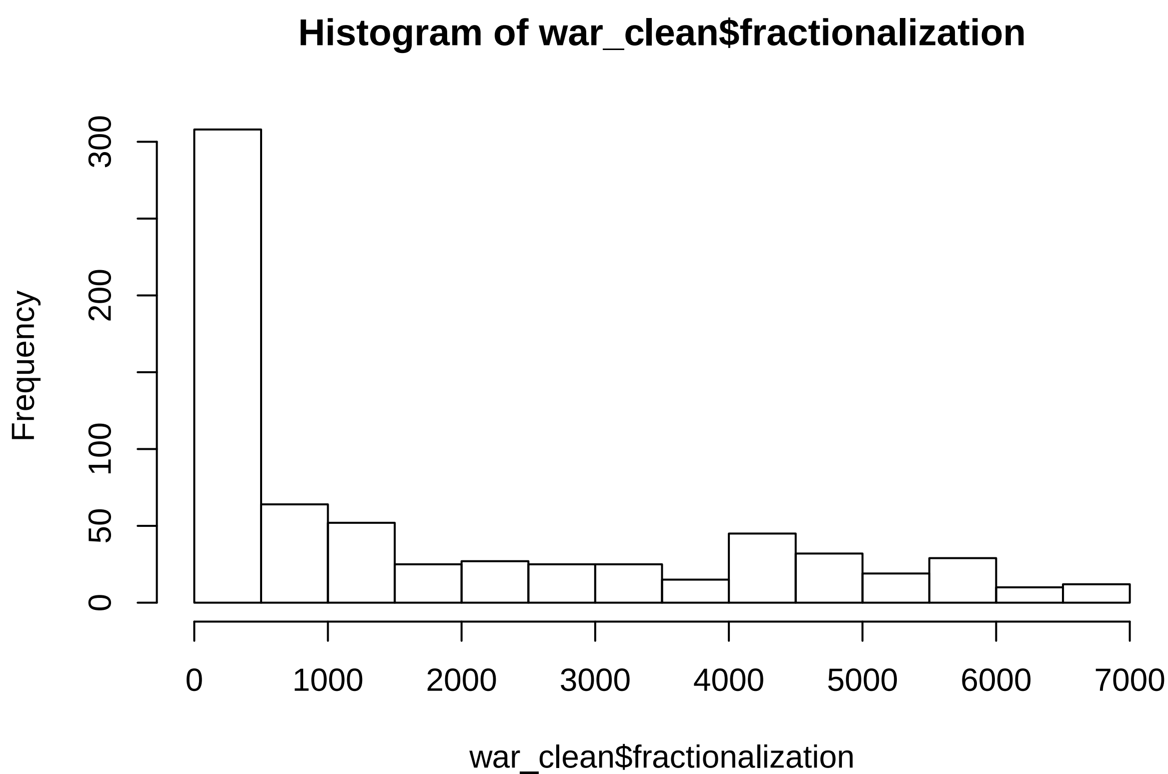

```
hist(war_clean$concentration)
```



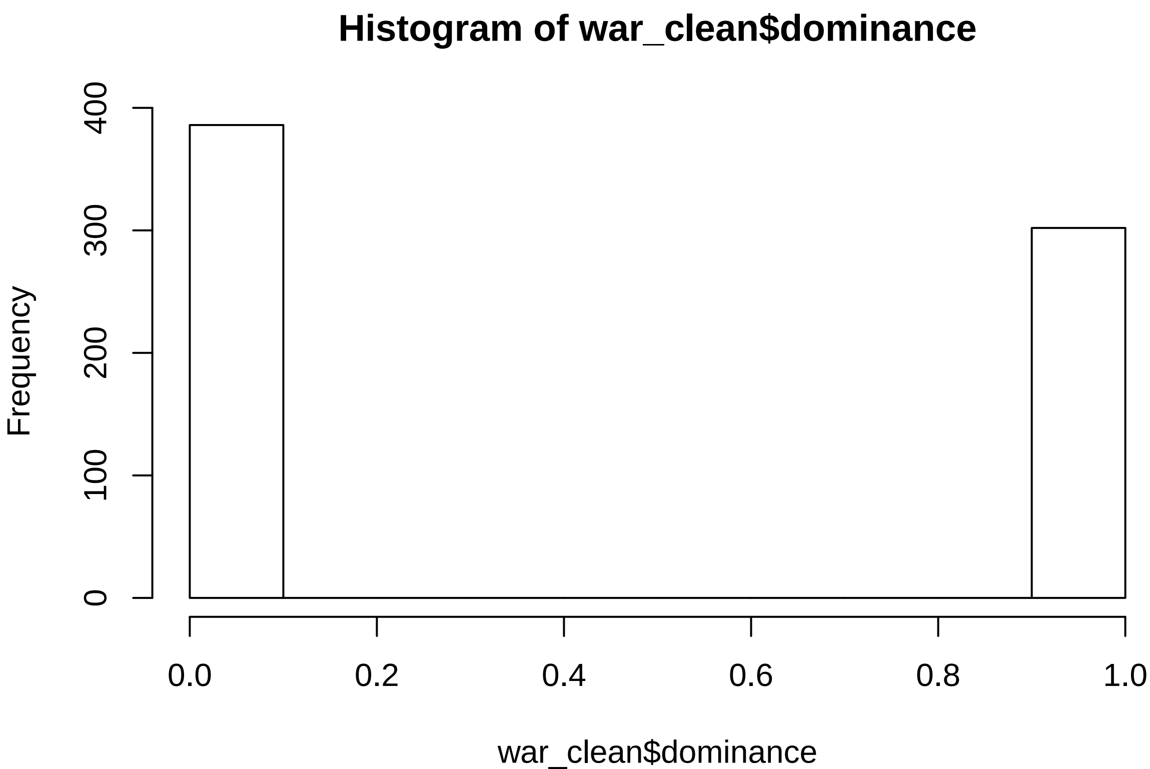

```
hist(war_clean$lnpop)
```




```
hist(war_clean$fractionalization)
```




```
hist(war_clean$dominance)
```



1. The misclassification rate for the LDA model is 0.06540698. 2. The misclassification rate for the QDA model is 0.07267442 3. While the discrepancies are not subsanstial, the misclassification rate for the QDA model is the highest and the misclassification rate for the LDA model is the lowest. The misclassification rate for the logistic regression model is slightly lower than the rate of the QDA model and higher than the LDA model (0.06686047).

The greater prediction accuracy of the LDA and logistic regression model suggest that the true decision boundaries (or set of points where both response classes do just as well) are more linear since the QDA model provides a non-linear quadratic decision boundary.

Problem Set: Chapter 4

4)

a. 10% on average (0.10^1 * 100)
b. 1% on averagse (0.10^2 * 100) (0.10^{100} * 100) d, As p increases, nearby observations decreases exponentially
c. p=1, side = 0.1 p=2, side = $\sqrt{0.1} = 0.316$ p=100, side = $0.1^{1/100} = 0.977$ As p increases, it becomes necessary to use the entire range of of each p to include 10% of the training set.

6)

a. Logistic Regression: logistic regression, $p(X) = \frac{e^{\beta_0+\beta_1 X_1+\beta_2 X_2}}{1+e^{\beta_0+\beta_1 X_1+\beta_2 X_2}}$ Plug in: $p(X) = \frac{e^{-6+0.05\times 40+1\times 3.5}}{1+e^{-6+0.05\times 40+1\times 3.5}} =$

```
exp(-6+0.05*40+1*3.5)/(1+exp(-6+0.05*40+1*3.5))
```

```
## [1] 0.3775407
```

37.75%

b.

Solve: $0.5 = \frac{e^{-6+0.05X_1+1\times 3.5}}{1+e^{-6+0.05X_1+1\times 3.5}} = log(\frac{0.5}{1-0.5}) = -6 + 0.05X_1 + 1 \times 3.5$

Which equates to solving the logit equation $log(\frac{0.5}{1-0.5}) = -6 + 0.05X_1 + 1 \times 3.5$

```
(log(0.5/(1-0.5)) + 6 - 3.5*1)/0.05
```

```
## [1] 50
```

The student needs to study for 50 hours

7.

Constant variance: $p_k(x) = \frac{\pi_k \frac{1}{\sqrt{2\pi}\sigma} \exp(-\frac{1}{2\sigma^2}(x-\mu_k)^2)}{\sum \pi_l \frac{1}{\sqrt{2\pi}\sigma} \exp(-\frac{1}{2\sigma^2}(x-\mu_l)^2)} = p_{yes}(4) = \frac{0.8 \exp(-\frac{1}{2\times 36}(4-10)^2)}{0.8 \exp(-\frac{1}{2\times 36}(4-10)^2) + (1-0.8) \exp(-\frac{1}{2\times 36}(4-0)^2)}$

```
(0.8*exp(-1/(2*36)*(4-10)^2))/(0.8*exp(-1/(2*36)*(4-10)^2)+(1-0.8)*exp(-1/(2*36)*(4-0)^2))
```

```
## [1] 0.7518525
```

The probability is 75.2%