Logistic Regression

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From the UN website, a country is classified as low human development when HDI is less than 0.550. So, I will create a logisitic regression for this using our choosen variables over the countries in 2021.

```r
# Load Libraries
library(dplyr)
```

```
##
## Attaching package: 'dplyr'

## The following objects are masked from 'package:stats':
##
##     filter, lag

## The following objects are masked from 'package:base':
##
##     intersect, setdiff, setequal, union
```

```r
library(ggplot2)
library(ggpubr)
library(knitr)
library(car)
```

```
## Loading required package: carData

##
## Attaching package: 'car'

## The following object is masked from 'package:dplyr':
##
##     recode
```

```r
data = read.csv("./data/data_clean.csv")
```

```r
selected_columns = data[, c("country","year", "region", "hdi", "x1.6","x3.2", "x5.1", "x6.4", "x7.3")]
selected_columns_2021 = selected_columns[selected_columns$year == "2021",]
selected_columns_2021$low_HD = as.numeric(selected_columns_2021$hdi <= 0.550)

# Fit logisitic regression
logreg = glm(low_HD~x1.6+x3.2+x5.1+x6.4+x7.3+region,data=selected_columns_2021,family="binomial")
```

```
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
```

```r
summary(logreg)
```

```
##
## Call:
## glm(formula = low_HD ~ x1.6 + x3.2 + x5.1 + x6.4 + x7.3 + region,
##     family = "binomial", data = selected_columns_2021)
##
## Deviance Residuals:
##      Min        1Q    Median        3Q       Max
## -2.69800  -0.06671  -0.00005  -0.00001   2.22328
##
## Coefficients:
##                                      Estimate Std. Error z value Pr(>|z|)
## (Intercept)                          -16.4894  3438.9872  -0.005   0.9962
## x1.6                                   8.8816     4.5466   1.953   0.0508 .
## x3.2                                  -3.8248     6.4076  -0.597   0.5506
## x5.1                                  -1.0829     4.3682  -0.248   0.8042
## x6.4                                  -7.2821     5.2367  -1.391   0.1644
## x7.3                                  -9.2245     4.4534  -2.071   0.0383 *
## regionEastern Europe & Central Asia    0.6260  5778.0978   0.000   0.9999
## regionEU + EFTA + North America        2.9538  4440.9708   0.001   0.9995
## regionLatin America & Caribbean       16.5993  3438.9861   0.005   0.9961
## regionMiddle East & North Africa       0.7979  6464.6016   0.000   0.9999
## regionSouth Asia                      19.8033  3438.9859   0.006   0.9954
## regionSub-Saharan Africa              21.7462  3438.9859   0.006   0.9950
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 127.522  on 137  degrees of freedom
## Residual deviance:  43.444  on 126  degrees of freedom
## AIC: 67.444
##
## Number of Fisher Scoring iterations: 19
```

```r
kable(summary(logreg)$coefficients)
```

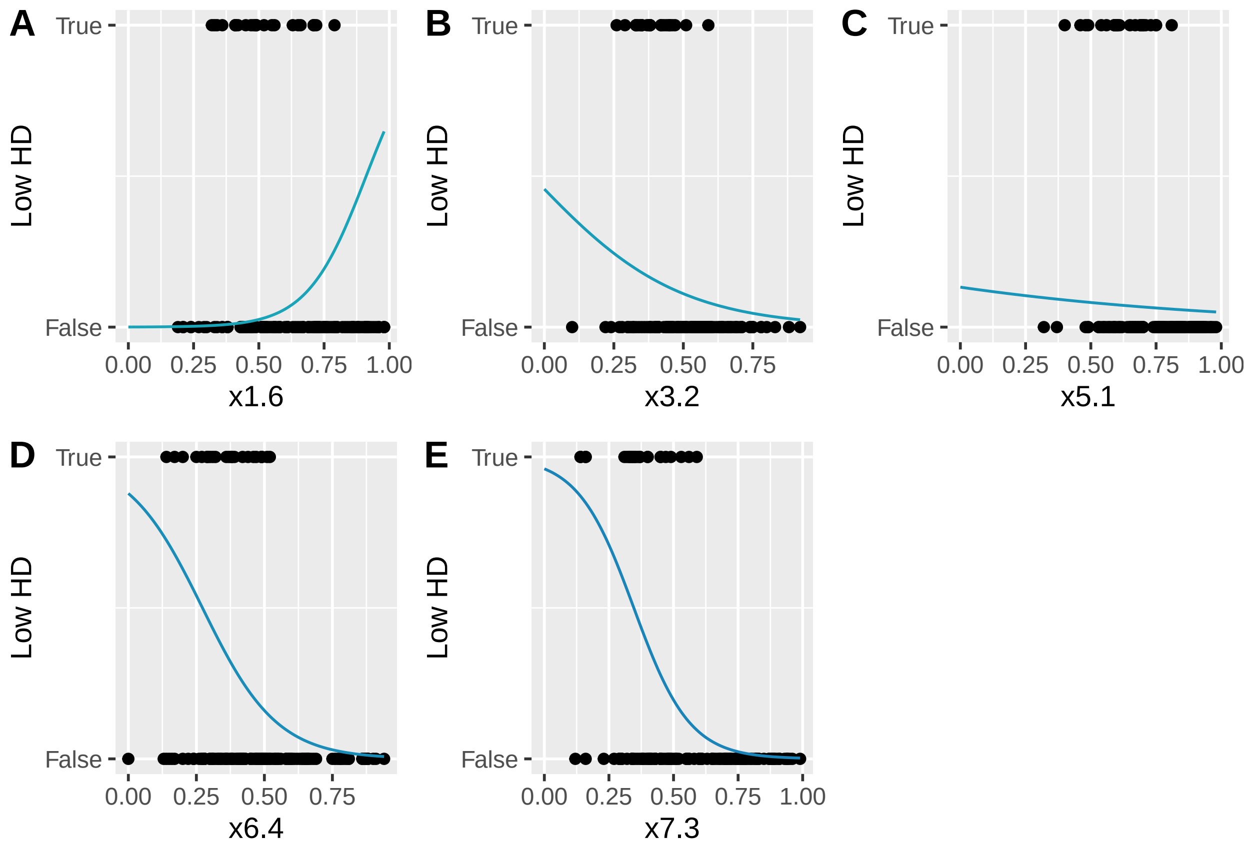
	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	-16.4894055	3438.987249	-0.0047948	0.9961743
x1.6	8.8815832	4.546560	1.9534733	0.0507635
x3.2	-3.8247623	6.407582	-0.5969119	0.5505662
x5.1	-1.0829325	4.368209	-0.2479123	0.8042023
x6.4	-7.2820756	5.236693	-1.3905867	0.1643508
x7.3	-9.2244655	4.453396	-2.0713330	0.0383277
regionEastern Europe & Central Asia	0.6259511	5778.097818	0.0001083	0.9999136
regionEU + EFTA + North America	2.9537822	4440.970799	0.0006651	0.9994693
regionLatin America & Caribbean	16.5993435	3438.986100	0.0048268	0.9961488
regionMiddle East & North Africa	0.7978667	6464.601585	0.0001234	0.9999015

	Estimate	Std. Error	z value	Pr(>|z|)
regionSouth Asia	19.8032694	3438.985864	0.0057585	0.9954054
regionSub-Saharan Africa	21.7461763	3438.985874	0.0063234	0.9949547

```
logreg_noRegion = glm(low_HD~x1.6+x3.2+x5.1+x6.4+x7.3,data=selected_columns_2021,family="binomial")

anova(logreg_noRegion, logreg, test = "LRT")
```

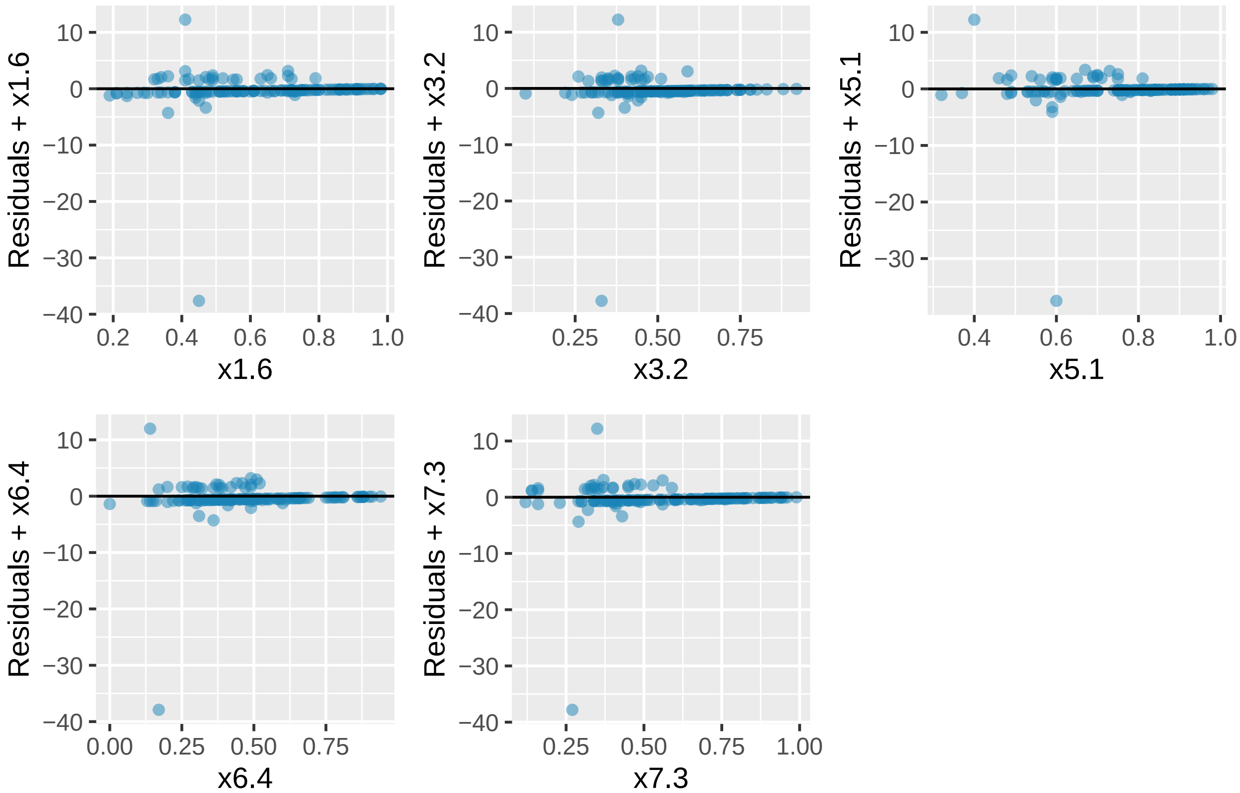
```
## Analysis of Deviance Table
##
## Model 1: low_HD ~ x1.6 + x3.2 + x5.1 + x6.4 + x7.3
## Model 2: low_HD ~ x1.6 + x3.2 + x5.1 + x6.4 + x7.3 + region
##   Resid. Df Resid. Dev Df Deviance  Pr(>Chi)
## 1       132     79.457
## 2       126     43.444  6   36.012 2.742e-06 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
# Plot regression
dummy_x1.6 = seq(0,max(selected_columns_2021$x1.6,na.rm=T),0.01)
dummy_x3.2 = seq(0,max(selected_columns_2021$x3.2,na.rm=T),0.01)
dummy_x5.1 = seq(0,max(selected_columns_2021$x5.1,na.rm=T),0.01)
dummy_x6.4 = seq(0,max(selected_columns_2021$x6.4,na.rm=T),0.01)
dummy_x7.3 = seq(0,max(selected_columns_2021$x7.3,na.rm=T),0.01)

average_x1.6 = mean(selected_columns_2021$x1.6,na.rm=T)
average_x3.2 = mean(selected_columns_2021$x1.6,na.rm=T)
average_x5.1 = mean(selected_columns_2021$x1.6,na.rm=T)
average_x6.4 = mean(selected_columns_2021$x1.6,na.rm=T)
average_x7.3 = mean(selected_columns_2021$x1.6,na.rm=T)

yhat_x1.6 = predict(logreg,new=data.frame(x1.6=dummy_x1.6, x3.2 = rep(average_x3.2, length(dummy_x1.6))
yhat_x3.2 = predict(logreg,new=data.frame(x1.6=rep(average_x1.6, length(dummy_x3.2)), x3.2 = dummy_x3.2
yhat_x5.1 = predict(logreg,new=data.frame(x1.6=rep(average_x1.6, length(dummy_x5.1)), x3.2 = rep(average
yhat_x6.4 = predict(logreg,new=data.frame(x1.6=rep(average_x1.6, length(dummy_x6.4)), x3.2 = rep(average
yhat_x7.3 = predict(logreg,new=data.frame(x1.6=rep(average_x1.6, length(dummy_x7.3)), x3.2 = rep(average

phat_x1.6 = exp(yhat_x1.6)/(1+exp(yhat_x1.6))
phat_x3.2 = exp(yhat_x3.2)/(1+exp(yhat_x3.2))
phat_x5.1 = exp(yhat_x5.1)/(1+exp(yhat_x5.1))
phat_x6.4 = exp(yhat_x6.4)/(1+exp(yhat_x6.4))
phat_x7.3 = exp(yhat_x7.3)/(1+exp(yhat_x7.3))

p1 = ggplot() + geom_point(data = selected_columns_2021, aes(x=x1.6, y=low_HD)) + geom_line(aes(x=dummy_
p2 = ggplot() + geom_point(data = selected_columns_2021, aes(x=x3.2, y=low_HD)) + geom_line(aes(x=dummy_
p3 = ggplot() + geom_point(data = selected_columns_2021, aes(x=x5.1, y=low_HD)) + geom_line(aes(x=dummy_
p4 = ggplot() + geom_point(data = selected_columns_2021, aes(x=x6.4, y=low_HD)) + geom_line(aes(x=dummy_
p5 = ggplot() + geom_point(data = selected_columns_2021, aes(x=x7.3, y=low_HD)) + geom_line(aes(x=dummy_

ggarrange(p1,p2,p3,p4,p5, nrow = 2, ncol=3, labels = c("A","B","C","D","E"))
```

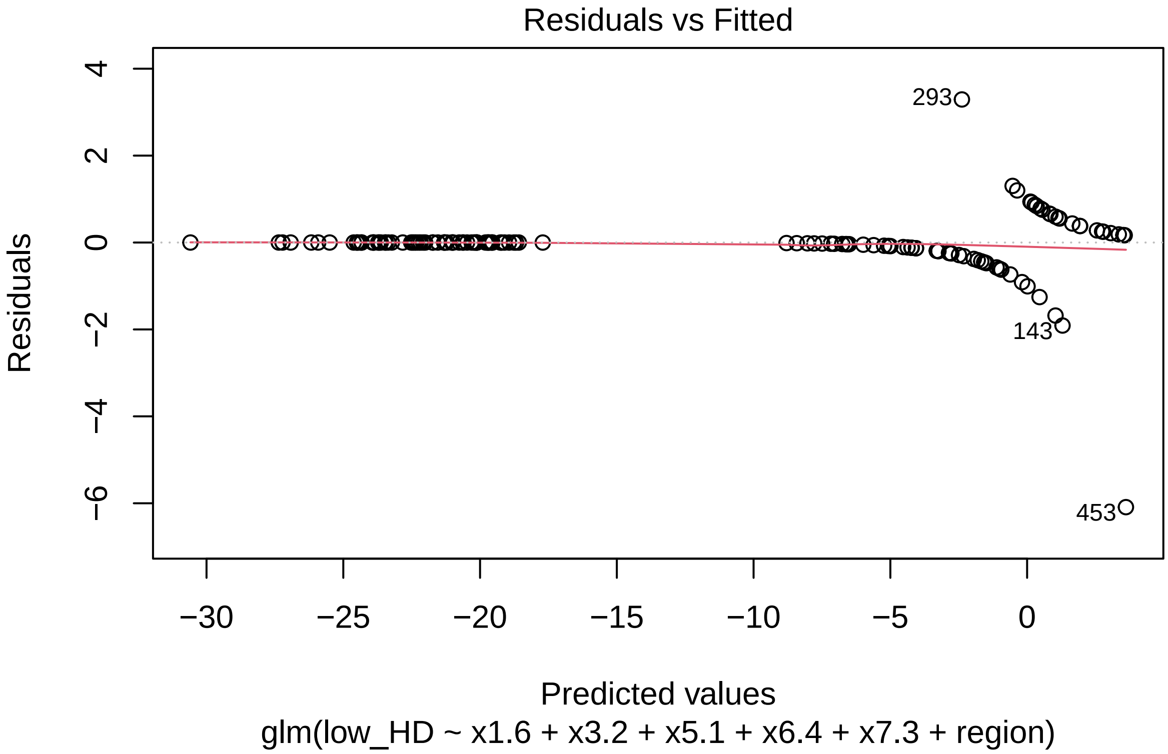


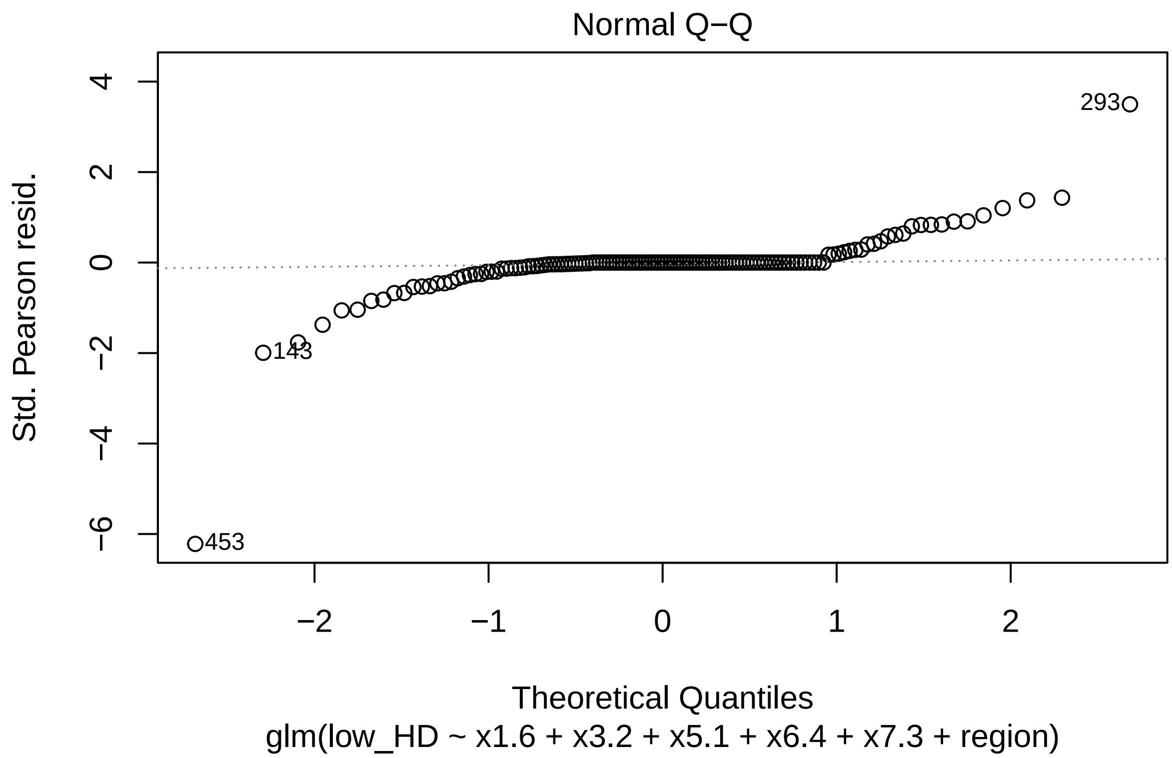

```r
# Logistic Regression Assumptions

# Check for linearity between explanatory variables and residuals, as well as with residuals and fitted
residuals = as.data.frame(cbind(selected_columns_2021, logreg$fitted.values, logreg$residuals))
p2 = ggplot() + geom_point(data = residuals, aes(x=x1.6, y=(logreg$residuals+x1.6)), color = "#1a84b8",
p3 = ggplot() + geom_point(data = logreg, aes(x=x3.2, y=(logreg$residuals+x3.2)), color = "#1a84b8", al
p4 = ggplot() + geom_point(data = logreg, aes(x=x5.1, y=(logreg$residuals+x5.1)), color = "#1a84b8", al
p5 = ggplot() + geom_point(data = logreg, aes(x=x6.4, y=(logreg$residuals+x6.4)), color = "#1a84b8", al
p6 = ggplot() + geom_point(data = logreg, aes(x=x7.3, y=(logreg$residuals+x7.3)), color = "#1a84b8", al

p7 = ggarrange(p2,p3,p4,p5,p6)
annotate_figure(p7, fig.lab = "Partial Residual Plots", top = text_grob(" ", color = "red", face = "bol
```

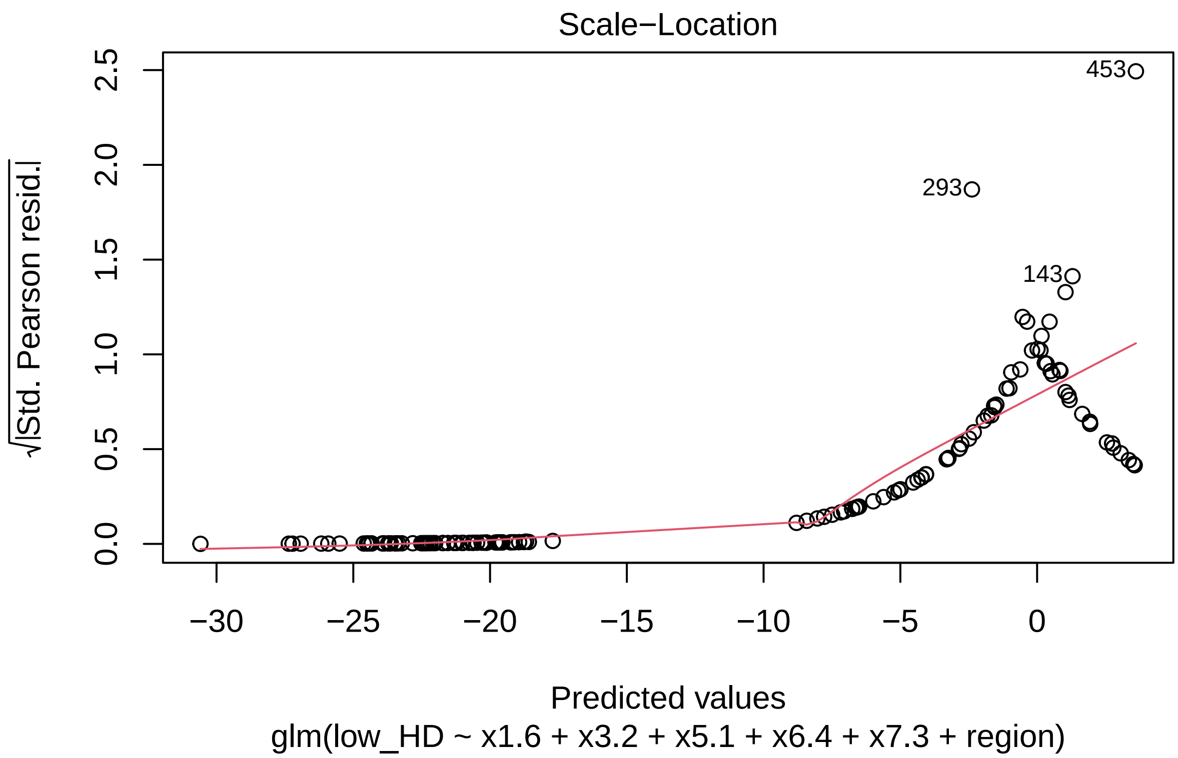
Partial Residual Plots



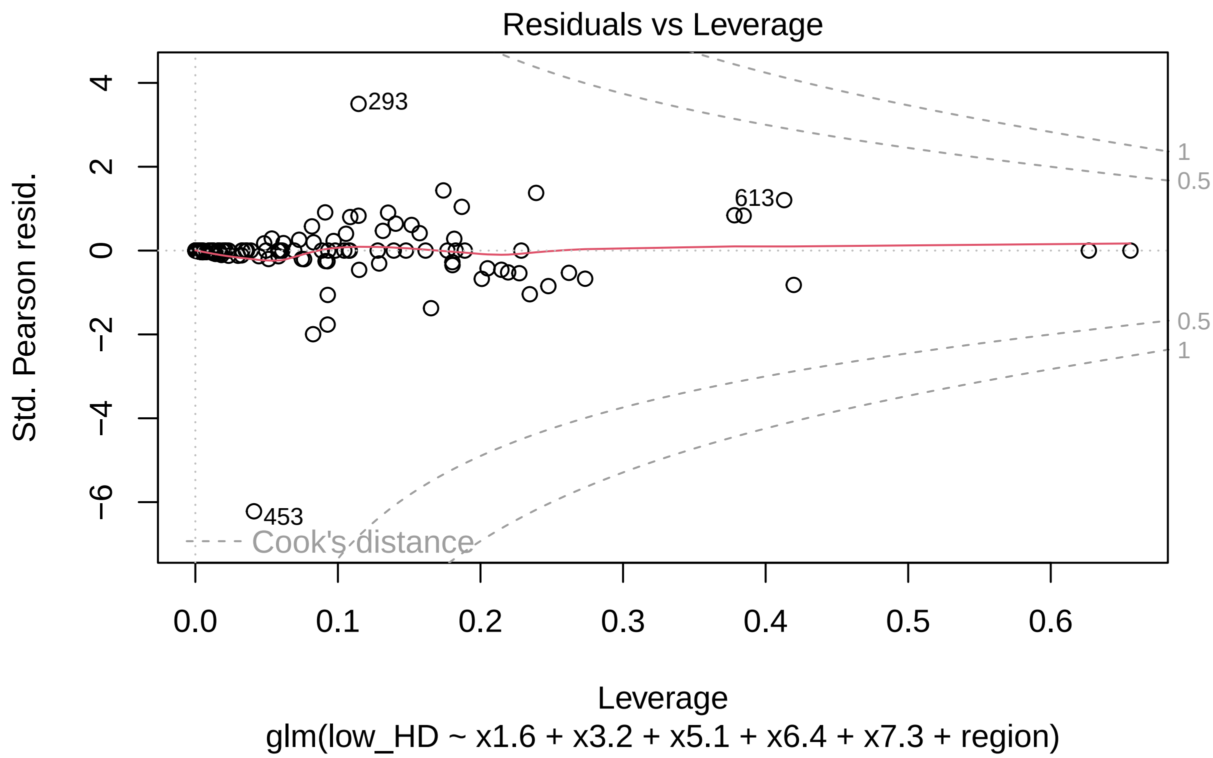

```r
# Check for multicollinearity of explanatory variables
plot(logreg)
```


Residuals vs Fitted
293
143
453
Residuals
Predicted values
glm(low_HD ~ x1.6 + x3.2 + x5.1 + x6.4 + x7.3 + region)
4
2
0
−2
−4
−6
−30
−25
−20
−15
−10
−5
0


Normal Q−Q
Std. Pearson resid.
4
2
0
−2
−4
−6
293
143
453
−2
−1
0
1
2
Theoretical Quantiles
glm(low_HD ~ x1.6 + x3.2 + x5.1 + x6.4 + x7.3 + region)



Scale−Location
√|Std. Pearson resid.|
0.0
0.5
1.0
1.5
2.0
2.5
−30
−25
−20
−15
−10
−5
0
453
293
143
Predicted values
glm(low_HD ~ x1.6 + x3.2 + x5.1 + x6.4 + x7.3 + region)




```r
kable(t(vif(logreg)[,1]))
```

x1.6	x3.2	x5.1	x6.4	x7.3	region
3.598187	2.107906	1.739619	3.392325	2.485649	2.334165

```r
kable(data.frame("Category" = c("Constraints on Government Powers","Open Government","Order and Securit
```

Category	Representative_Variable	Name
Constraints on Government Powers	Transition of power is subject to the law	x1.6
Open Government	Right to information	x3.2
Order and Security	Crime is effectively controlled	x5.1
Regulatory Enforcement	Due process is respected in administrative proceedings	x6.4
Civil Justice	Civil justice is free of corruption	x7.3