## Homework 5, STAT 632

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```
hdi<-read.csv('hdi2018.csv')
# To fit multiple linear regression
lm full<-lm (hdi 2018 ~ median age + pctpop65 + pct internet + pct labour ,</pre>
data=hdi)
summary(lm_full)
##
## Call:
## lm(formula = hdi_2018 ~ median_age + pctpop65 + pct_internet +
      pct_labour, data = hdi)
##
## Residuals:
        Min
                   1Q
                         Median
                                       3Q
                                               Max
## -0.194838 -0.034699 0.003272 0.031096 0.122529
## Coefficients:
##
                 Estimate Std. Error t value Pr(>|t|)
## (Intercept)
                0.3374494 0.0319098 10.575 < 2e-16 ***
## median_age 0.0080796 0.0011337
                                      7.127 2.7e-11 ***
## pctpop65 -0.0697020 0.1022759 -0.682
                                               0.496
## pct_internet 0.0028967 0.0002451 11.817 < 2e-16 ***
## pct_labour -0.0001738 0.0003809 -0.456
                                               0.649
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.05193 on 172 degrees of freedom
## Multiple R-squared: 0.8882, Adjusted R-squared: 0.8856
## F-statistic: 341.5 on 4 and 172 DF, p-value: < 2.2e-16
```

(b) Since the p-value < 0.001, we can reject null hypothesis and we conclude that at least one predictor has a relationship between hdi\_2018.

Null hypothesis: H0 : /beta\_2 = /beta\_4 = 0. Alternative hypothesis: HA :/beta\_1 != or /beta\_2 != 0 or /beta\_3 != 0 or /beta\_4!=0

(c)For predictor variable 1 and 3, p value is < .05, so we can reject null hypothesis. Thus, we conclude that predictor variables median\_age and PCI internet are statistically significant according to individual T test.

(d)

```
lm_full1<-lm (hdi_2018 ~ median_age + pctpop65 + pct_internet + pct_labour ,
data=hdi)
lm_red<-lm(hdi_2018 ~ median_age + pct_internet , data =hdi)
anova(lm_red,lm_full)

## Analysis of Variance Table
##
## Model 1: hdi_2018 ~ median_age + pct_internet
## Model 2: hdi_2018 ~ median_age + pctpop65 + pct_internet + pct_labour
## Res.Df RSS Df Sum of Sq F Pr(>F)
## 1 174 0.46552
## 2 172 0.46380 2 0.0017236 0.3196 0.7269
```

### The p-value = 0.73 is large, so we do not reject the null hypothesis that

Null hypothesis: H0: beta\_2 = beta\_4 = 0. So we can remove both predictors, pctpop65 and pct\_labour from the model. Alternative hypothesis: HA: beta\_1!= 0, beta\_3!=0.

(e)

```
# The R2 for the full and reduced models
s1<-summary(lm_full)
s2<-summary(lm_red)
s1$r.squared

## [1] 0.8881714
s2$r.squared

## [1] 0.8877558
s1$adj.r.squared

## [1] 0.8855708
s2$adj.r.squared

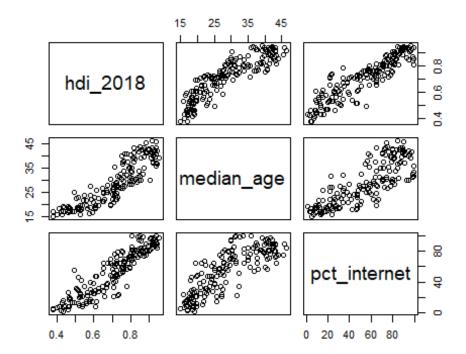
## [1] 0.8864657
```

The R2 for the full and reduced models are about the same, R2 for full model is little bit higher than reduced model and theadjusted R2 for the reduced model is a little higher.

This agrees with the conclusion of the F-test. So the adjusted-R2 also indicates that we can remove pctpop65 and pct labour.

### **Exercise 2**

```
(a)
pairs(hdi_2018 ~ median_age + pct_internet, data=hdi)
```



There is a linear relationship between variables in the scatterplot matrix. Also there seems to be some colinearity between predictor variables median\_age and pct\_internet.

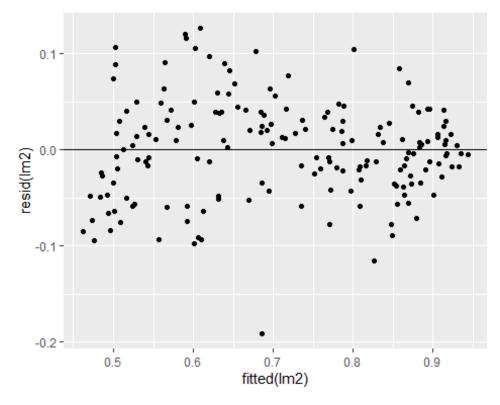
```
lm2<-lm(hdi_2018~median_age+pct_internet, data=hdi)
summary(lm2)

##
## Call:
## lm(formula = hdi_2018 ~ median_age + pct_internet, data = hdi)
##
## Residuals:</pre>
```

```
Min 10
                         Median
                                      30
                                               Max
## -0.191236 -0.034675 0.002006 0.030777
                                          0.126611
##
## Coefficients:
##
                Estimate Std. Error t value Pr(>|t|)
## (Intercept) 0.3341527 0.0142820
                                   23.397
                                             <2e-16 ***
                                     9.807
                                             <2e-16 ***
## median age
               0.0075581 0.0007706
## pct_internet 0.0029287 0.0002392 12.244
                                             <2e-16 ***
## ---
                  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## Signif. codes:
##
## Residual standard error: 0.05172 on 174 degrees of freedom
## Multiple R-squared: 0.8878, Adjusted R-squared: 0.8865
## F-statistic: 688.1 on 2 and 174 DF, p-value: < 2.2e-16
```

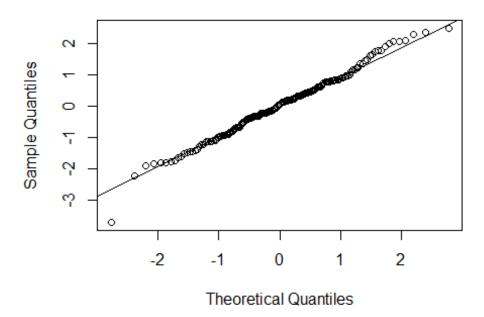
#### (b)

```
library(ggplot2)
ggplot(lm2, aes(fitted(lm2), resid(lm2) )) +
  geom_point() +
  geom_hline(yintercept=0)
```



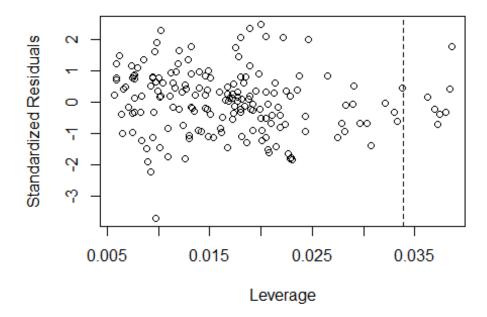
```
qqnorm(rstandard(lm2))
qqline(rstandard(lm2))
```

# Normal Q-Q Plot

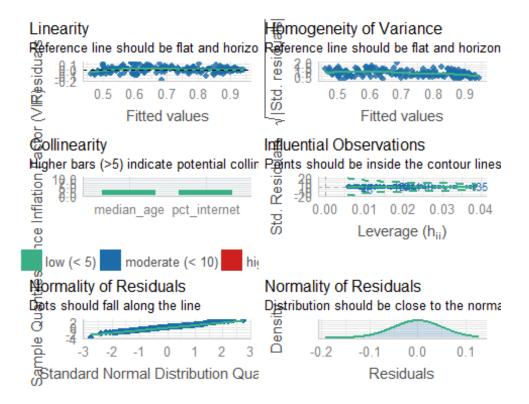


From residual vs fitted plot shows like fan pattern and qq plot indicates approximately normal with some deviation from normality near the tail.

```
(c)
plot(hatvalues(lm2), rstandard(lm2), xlab='Leverage', ylab='Standardized
Residuals')
p <- 2
n <- nrow(hdi)
abline(v = 2*(p+1)/n, lty=2)</pre>
```



```
ind <- which(hatvalues(lm2) > 0.1)
hdi[ind, ]
## [1] country
                    hdi_2018
                                                             pct_internet
                                  median_age
                                               pctpop65
## [6] pct_labour
## <0 rows> (or 0-length row.names)
Nigeria and United Kingdom countries has high leverage point.
library('performance')
## Warning: package 'performance' was built under R version 4.1.3
library('see')
## Warning: package 'see' was built under R version 4.1.3
library('patchwork')
## Warning: package 'patchwork' was built under R version 4.1.3
performance::check_model(lm2)
```



(d)

From scatter plot matrix and model diagnostic, we can say that the assumptions of multiple linear regression apparently satisfied. To better fit the model, we can remove outliers and we can do transformation to make the variance constant in the plot.