Week 12: Logistic Regression

POP88162 Introduction to Quantitative Research Methods

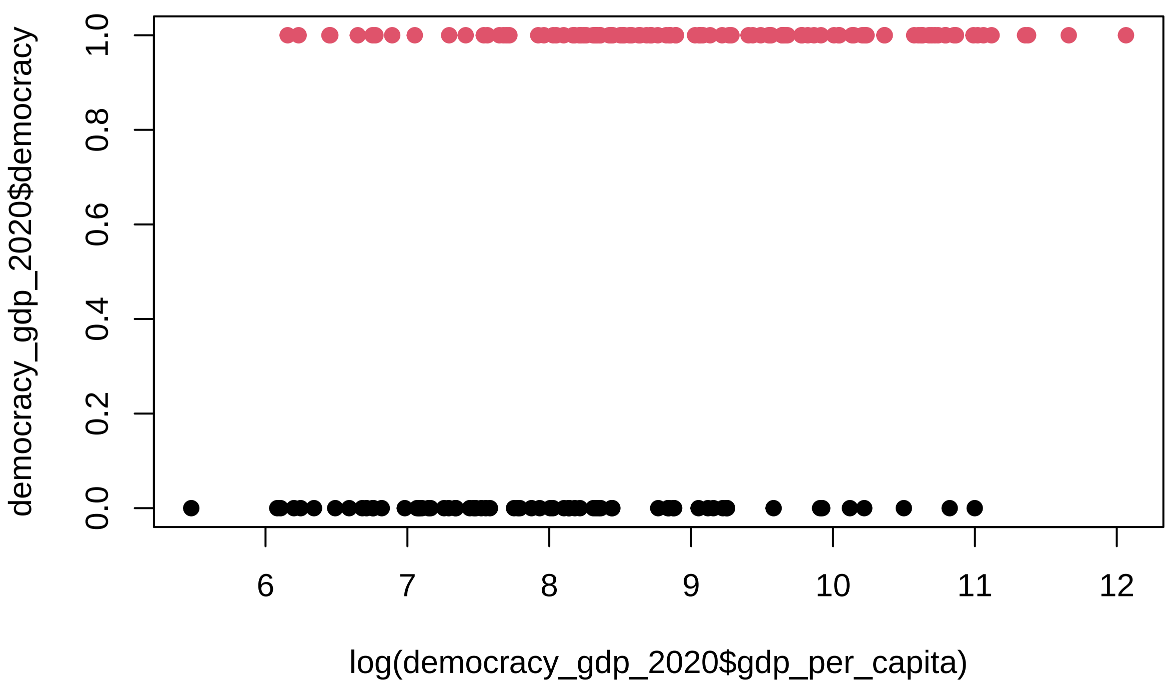
Plotting

Read in the data `democracy_gdp_2020.csv`. Use the file provided for this week as it contains additional variable representing former colonial status. You can find this dataset on Blackboard.

```
democracy_gdp_2020 <- read.csv("../data/democracy_gdp_2020.csv")
```

Let's start by replicating the plot with continuous independent and binary dependent variable.

```
plot(
  log(democracy_gdp_2020$gdp_per_capita), # X
  democracy_gdp_2020$democracy, # Y
  pch = 19, # Type of point
  col = democracy_gdp_2020$democracy + 1 # Add 1 to avoid white colour
)
```



Linear Probability Model

Start by fitting a linear probability model to the data, with binary indicator for democracy as the dependent variable and log GDP per capita as independent variable. We use `lm()` function here as this model is, essentially, just a linear regression model with a binary dependent variable.

```
lpm_fit <- lm(democracy ~ log(gdp_per_capita), data = democracy_gdp_2020)
summary(lpm_fit)
```

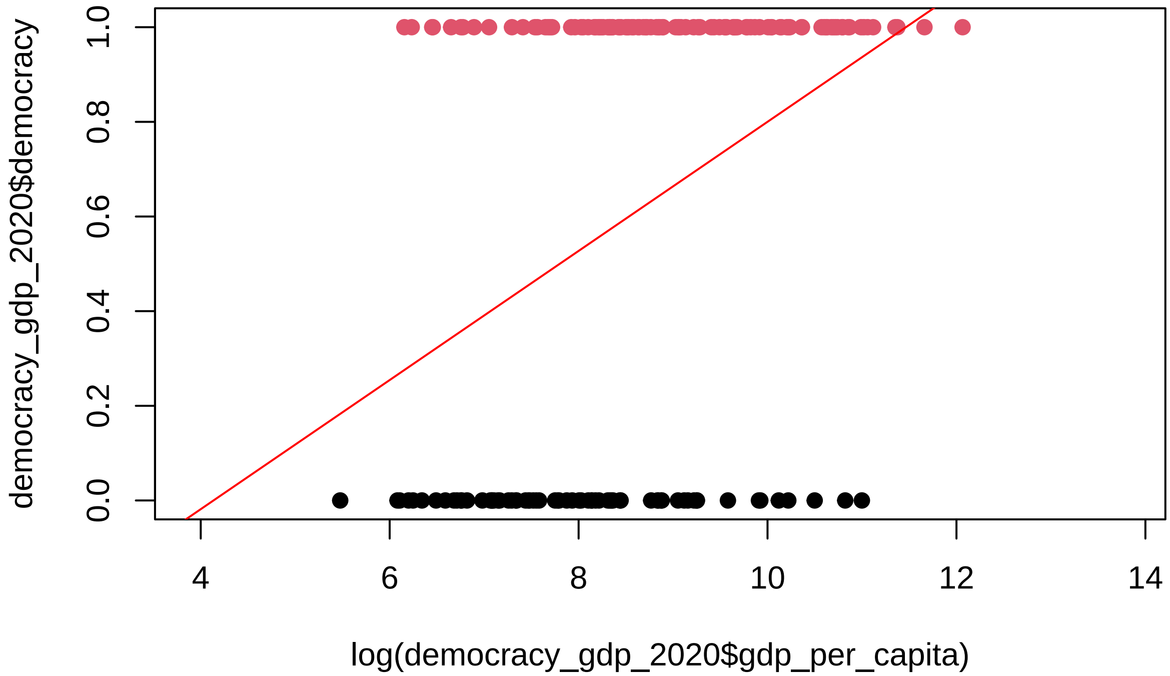
```
##
## Call:
## lm(formula = democracy ~ log(gdp_per_capita), data = democracy_gdp_2020)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -0.9363 -0.4372  0.1502  0.3861  0.7243
##
## Coefficients:
##                     Estimate Std. Error t value Pr(>|t|)
## (Intercept)         -0.56415    0.21644  -2.606  0.00995 **
## log(gdp_per_capita)  0.13642    0.02468   5.527 1.18e-07 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.4507 on 173 degrees of freedom
##   (20 observations deleted due to missingness)
## Multiple R-squared:  0.1501, Adjusted R-squared:  0.1452
## F-statistic: 30.54 on 1 and 173 DF,  p-value: 1.183e-07
```

What do these numbers tell you? What is your substantive interpertation of the estimates?

Now re-fit this model using fomer colonial status (variable `noncol`) as another independent variable. How did your estimates change?

Let's add the fitter linear regression line to our scatterplot.

```r
plot(
  log(democracy_gdp_2020$gdp_per_capita), # X
  democracy_gdp_2020$democracy, # Y
  xlim = c(log(50), log(1000000)), # Expand x-axis to better see how LPM behaves at the edges
  pch = 19,
  col = democracy_gdp_2020$democracy + 1
)
abline(lpm_fit, col = "red")
```



Logistic Regression Model

Now let's fit a logistic regression model to the same data. Instead of using `lm()` function we will be using `glm()` (for **g**eneralized **l**inear **m**odel) function. Note that in order to fit a logit model we need to specify `family` argument. The default value results in `glm()` fitting a linear model equivalent to the one that one could be fit using `lm()`.

```
glm_fit <- glm( # Note that we use glm() funtion rather than lm()
  democracy ~ log(gdp_per_capita) + noncol,
  family = binomial(link = "logit"), # tells R to use logit
  data = democracy_gdp_2020
)
```

How would you interpret the resultant coefficients? What is a null hypothesis and an alternative hypothesis for this test? What is your decision regarding a null hypothesis given the output above?