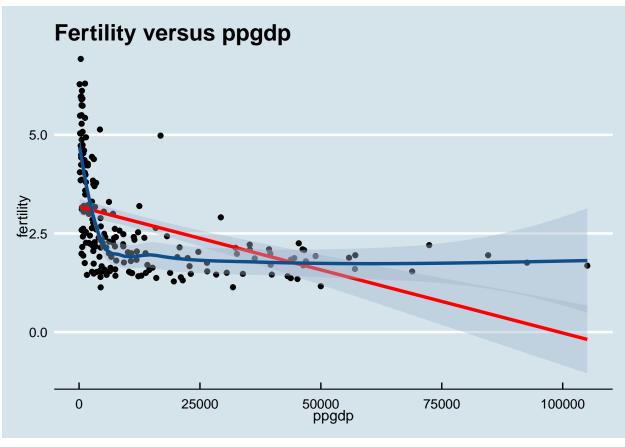
# STATS 413 Hw1

Shu Zhou

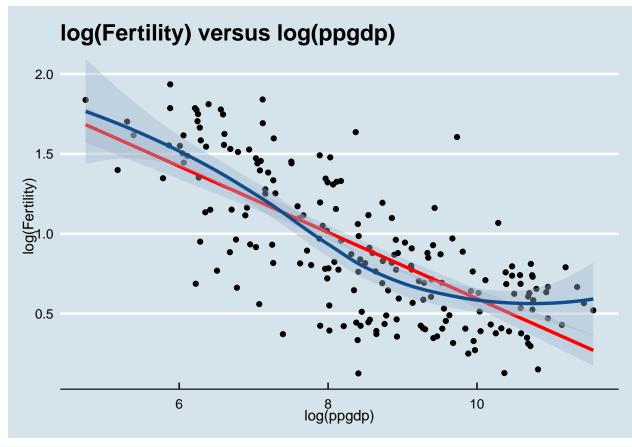
2020/9/14

```
##This is the Assignment 1 of STATS 413
##Author: Shu Zhou
##UMID: 19342932
```

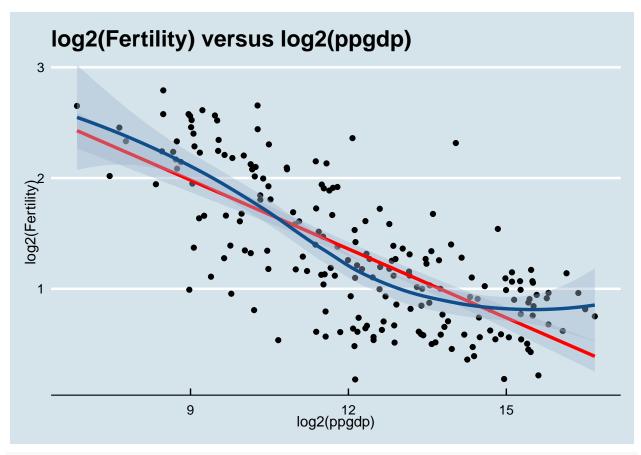
#### 1. United Nations Data



## `geom\_smooth()` using formula 'y ~ x'



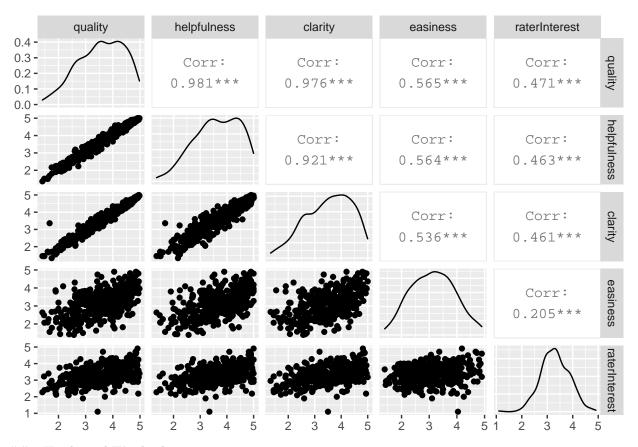
```
## `geom_smooth()` using formula 'y ~ x'
## `geom_smooth()` using formula 'y ~ x'
```



##Hence, the shape of the graph won't change, but the values on the axes will.

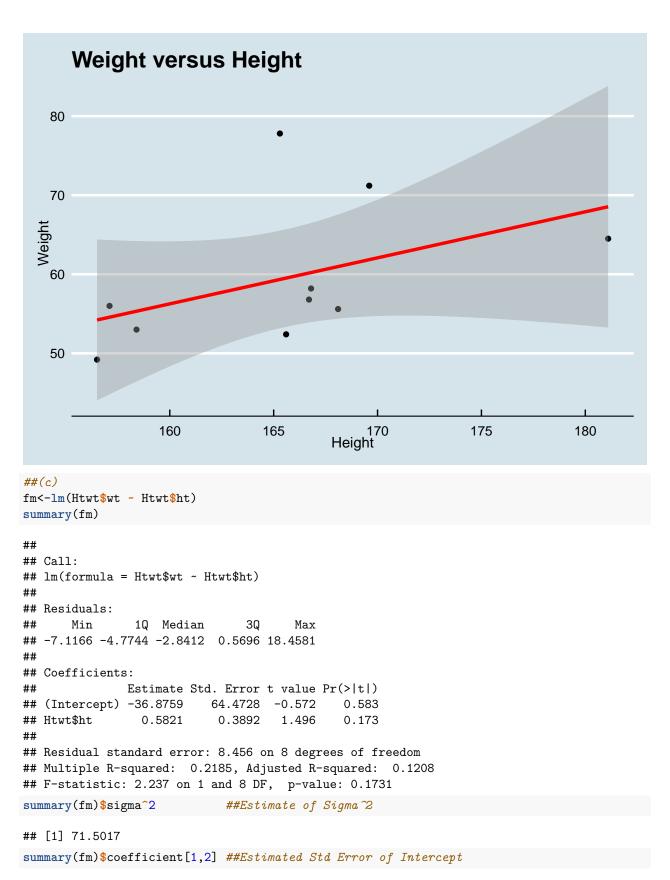
## 2.Professor ratings Data

ggpairs (Rateprof[,9: 13])



## 3.Height and Weight data

```
Weight versus Height
    70
 Weight
    60
    50
                                            170
Height
                   160
                                  165
                                                                 175
                                                                                180
##A straight line is not plausible for a summary to this relationship, since
## there is no clear linear pattern between this two variables
lm(Htwt$wt ~ Htwt$ht)
##
## Call:
## lm(formula = Htwt$wt ~ Htwt$ht)
##
## Coefficients:
                    Htwt$ht
## (Intercept)
      -36.8759
                     0.5821
ggplot(Htwt, aes (y=wt, x=ht ) )+ geom_point()+
  scale_fill_brewer(palette = "OrRd")+
  geom_smooth(method = "lm", col = "red", size = 1.2)+
  ggtitle( "Weight versus Height")+
  labs(x = "Height", y = "Weight")+
  theme_economist()+
  theme(axis.text.x = element_text(size=10),
        axis.text.y = element_text(size=10), legend.position = "right")
```



## [1] 64.4728

summary(fm)\$coefficient[2,2] ##Estimated Std Error of Slope

## [1] 0.3891815

## 4. Simple Linear Regression

According to Cramer's rule, the function we calculate  $\hat{\beta}_0$  and  $\hat{\beta}_1$ 

$$n\hat{\beta}_0 + \hat{\beta}_1 \sum x_i = \sum y_i \tag{1}$$

We divide n on both sides of the equation, hence it becomes

$$\hat{\beta}_0 + \hat{\beta}_1 \frac{\sum x_i}{n} = \frac{\sum y_i}{n} \tag{2}$$

Since  $\frac{\sum x_i}{n} = \overline{x_i}$  and  $\frac{\sum y_i}{n} = \overline{y_i}$  Hence

$$\hat{\beta}_0 + \hat{\beta}_1 \overline{x_i} = \overline{x_i} \tag{3}$$

Which shows that the least squared line always passes through the mean point

## 5. Multi-task Regression

a

We first calculate the  $\hat{\beta}$  that minimizes the RSS

$$y = X\hat{\beta} \tag{4}$$

$$(X^T X)\hat{\beta} = X^T y \tag{5}$$

$$\hat{\beta} = (X^T X)^{-1} X^T y \tag{6}$$

Hence RSS is calculated by

$$RSS = \hat{e}^T \hat{e} = (y - X\hat{\beta})^T (y - X\hat{\beta}) = y^T y - 2\hat{\beta}^T X^T y + \hat{\beta}^T X^T X\hat{\beta}$$
 (7)

Hence

$$RSS = y^{T}[1 - X(X^{T}X)^{-1}X^{T}]y$$
(8)

b

We have already calculated the  $\hat{\beta}$  in (a) eq. (4) - eq. (6).

$$\hat{\beta} = (X^T X)^{-1} X^T y \tag{9}$$

 $\mathbf{c}$ 

The regression coefficients from the m separate regressions will be different from the matrix of regression coefficients that minimizes the RSS.

When we derive a multiple regression, any element in the vector  $\hat{\beta}$  minimizes the the correlation between any dependent variable y and the regressor.

So, in this problem, when we try to calculate the regression coefficients separately, each coefficient was not significant enough.

As a result, the RSS calculated form the regression coefficients in this problem will be much larger.=