

431 Class 09

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2017-09-26

Today's Agenda

- ① Discussion of Assignment 2
- ② Silver, Chapters 2 and 3
- ③ Associations, Using Linear Models (Notes: Ch 11)
 - A study of von Hippel-Lindau disease
 - Associations, Correlation and Scatterplots
 - Fitting a Linear Model
- ④ Setting Up Project Task B Groups

Assignment 2 feedback

<https://github.com/THOMASELOVE/431homework/tree/master/HW2> has the (password-protected pdf and non-protected Rmd) answer sketch, the grades, and the grading rubric

- I'm no longer suggesting people use `gg_qq`, and I've removed it from the Course Notes and answer sketch.

Four Interesting Essays

Tell us about an example in your own field/work/experience where a “surplus” of information made (or makes) it easier for people dealing with a complex system to cherry-pick information that supports their prior positions. What were the implications of your example in terms of lessons that can be learned?

Visit <https://goo.gl/5q6Nrw> to read excerpts from four of the more interesting responses.

- 1 On Screening, Hepatitis C and Liver Cancer
- 2 On Web MD, and “a little knowledge is a dangerous thing”
- 3 Is self-control like a muscle? The problem of underpowered studies
- 4 On the polarizing impact of the free flow of “information”

The Signal and The Noise

Chapter 2: Political Predictions

When forecasting political events,

- Pundits and experts usually do no better than chance
- Pundits and experts usually do worse than crude statistical models.

What are the characteristics of experts who **are** substantially more accurate?
How can you tell a *fox* from a *hedgehog*?

Chapter 3: Baseball

When you have a whole lot of data, that's one thing. But what if you have a truly **rich** collection of data?

- How can you build a simple model to describe how the performance of a baseball player varies with age?
- Why is age such an important predictor of future performance?

The Signal and The Noise: Coming Up

Read by October 10 for in-class discussion

- Chapter 4: Weather Predictions
- Chapter 5: Earthquake Predictions

Read by October 17

- Chapter 7: Disease Outbreaks
- Chapter 8: Bayes' Theorem

R setup for Today

```
library(forcats); library(tidyverse)

## source("Love-boost.R")
## isn't needed today

VHL <- read.csv("vonHippel-Lindau.csv") %>% tbl_df
```

Von Hippel - Lindau study Codebook

- p.ne = plasma norepinephrine (pg/ml)
- tumorvol = tumor volume (ml)
- disease = 1 for patients with multiple endocrine neoplasia type 2
- disease = 0 for patients with von Hippel-Lindau disease

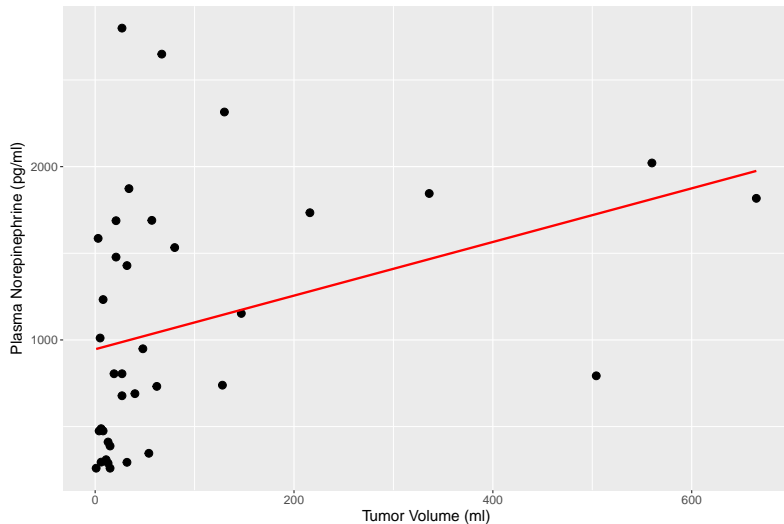
VHL

```
# A tibble: 37 x 4
```

	id	disease	p.ne	tumorvol
	<int>	<int>	<int>	<int>
1	101	0	289	13
2	102	1	294	32
3	103	0	2799	27
4	104	0	2649	67
5	105	0	346	54
6	106	0	1690	57
7	107	0	805	19

A Linear Model for the p.ne - volume relationship

Association of p.ne with tumor volume



The Linear Model

```
model1 <- lm(p.ne ~ tumorvol, data = VHL)
model1
```

Call:

```
lm(formula = p.ne ~ tumorvol, data = VHL)
```

Coefficients:

(Intercept)	tumorvol
946.185	1.547

The (simple regression / prediction / ordinary least squares) model is

- $$p.ne = 946.2 + 1.55 * tumorvol.$$

Using the model to make predictions (PI)

To predict the p.ne for a subject with tumor volume 100 ml, we have

- $p.ne = 946.2 + 1.55 * 100$

A 95% **prediction interval** for a single subject with volume 100 ml...

```
predict(model1, newdata = data_frame(tumorvol = 100),  
        interval = "prediction", level = 0.95)
```

	fit	lwr	upr
1	1100.925	-308.7478	2510.598

Using the model to make predictions (CI)

To predict the p.ne for a subject with tumor volume 100 ml, we have

- $$\text{p.ne} = 946.2 + 1.55 * 100$$

A 95% **confidence interval** for the population average of all subjects with volume 100 ml...

```
predict(model1, newdata = data_frame(tumorvol = 100),  
        interval = "confidence", level = 0.95)
```

	fit	lwr	upr
1	1100.925	872.0323	1329.818

Summary of our Linear (OLS) Model

```
> summary(model1)

Call:
lm(formula = p.ne ~ tumorvol, data = VHL)

Residuals:
    Min       1Q   Median       3Q      Max
-933.1 -555.3 -170.6  453.6 1811.0

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)  946.1846    130.4810   7.252 1.81e-08 ***
tumorvol      1.5474      0.7079   2.186  0.0356  *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 685.2 on 35 degrees of freedom
Multiple R-squared:  0.1201,    Adjusted R-squared:  0.09497
F-statistic: 4.778 on 1 and 35 DF,  p-value: 0.03561
```

Key Elements of the Summary (1)

```
Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)  946.1846   130.4810   7.252 1.81e-08 ***
tumorvol     1.5474     0.7079    2.186  0.0356  *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

- The straight line model for these data fitted by ordinary least squares is $p.ne = 946 + 1.55 \text{ tumorvol}$.
- The slope of tumorvol is positive, which indicates that as tumorvol increases, we expect that p.ne will also increase.
- Specifically, we expect that for every additional ml of tumorvol, the p.ne is increased by 1.55 pg/ml.

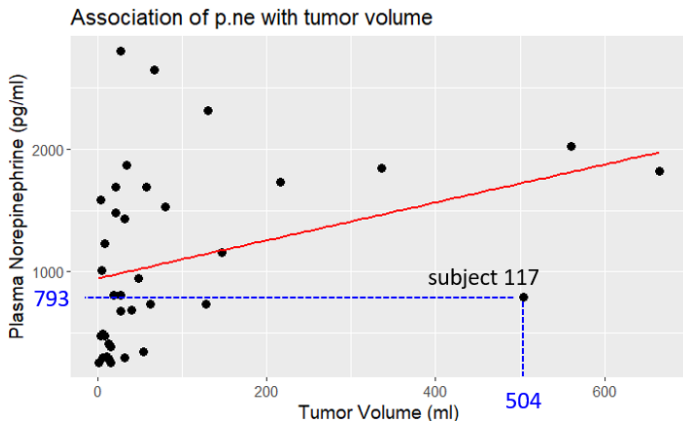
Key Elements of the Summary (2)

```
Call:
lm(formula = p.ne ~ tumorvol, data = VHL)

Residuals:
    Min       1Q   Median       3Q      Max
-933.1  -555.3  -170.6   453.6  1811.0
```

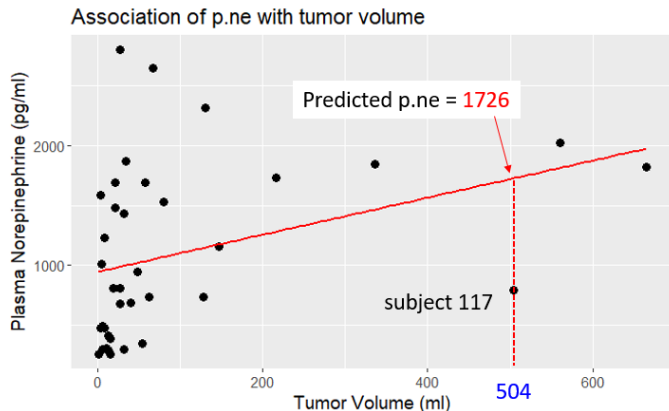
- Here, the **outcome** is p.ne, and the **predictor** is tumorvol.
- The **residuals** are the observed p.ne values minus the model's predicted p.ne. The sample residuals are the prediction errors.
- The biggest miss is for a subject whose observed p.ne was 1,811 pg/nl higher than the model predicts based on the subject's tumor volume.
- The mean residual will always be zero in an OLS model.

Understanding Regression Residuals (A)



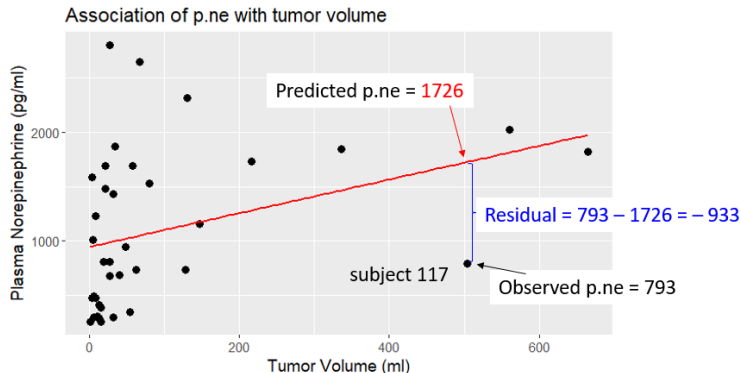
Subject 117 has tumorvol = 504, and observed p.ne = 793 pg/nl.

Understanding Regression Residuals (B)



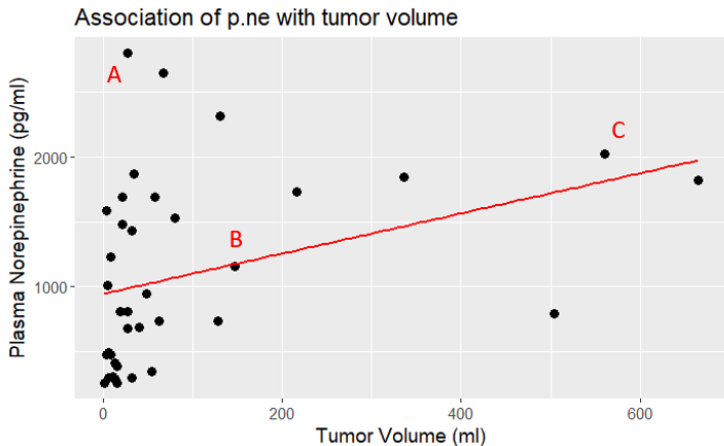
Subject 117 has tumorvol = 504, and observed p.ne = 793 pg/nl.
Model predicts p.ne is $946.2 + 1.55(504) = 1726$ pg/nl.

Understanding Regression Residuals (C)



Subject 117 has tumorvol = 504, and observed p.ne = 793 pg/ml.
Model predicts p.ne is $946.2 + 1.55(504) = 1726$. So, residual = $793 - 1726 = -933$

Understanding Regression Residuals (D)



Which point (A, B or C) has the largest positive residual?

Key Elements of the Summary (3)

```
Residual standard error: 685.2 on 35 degrees of freedom  
Multiple R-squared: 0.1201, Adjusted R-squared: 0.09497  
F-statistic: 4.778 on 1 and 35 DF, p-value: 0.03561
```

- The multiple R-squared (squared correlation coefficient) is 0.12, which implies that 12% of the variation in `p.ne` is explained using this linear model with `tumorvol`.
- It also implies that the Pearson correlation between `p.ne` and `tumorvol` is the square root of 0.12, or 0.347.

```
cor(VHL$p.ne, VHL$tumorvol)
```

```
[1] 0.3465646
```

Correlation Coefficients

Two key types of correlation coefficient to describe an association between quantities.

- The one most often used is called the *Pearson* correlation coefficient, symbolized r or sometimes ρ (ρ).
- Another is the Spearman rank correlation coefficient, also symbolized by ρ .

```
cor(VHL$p.ne, VHL$tumorvol)
```

```
[1] 0.3465646
```

```
cor(VHL$p.ne, VHL$tumorvol, method = "spearman")
```

```
[1] 0.5414319
```

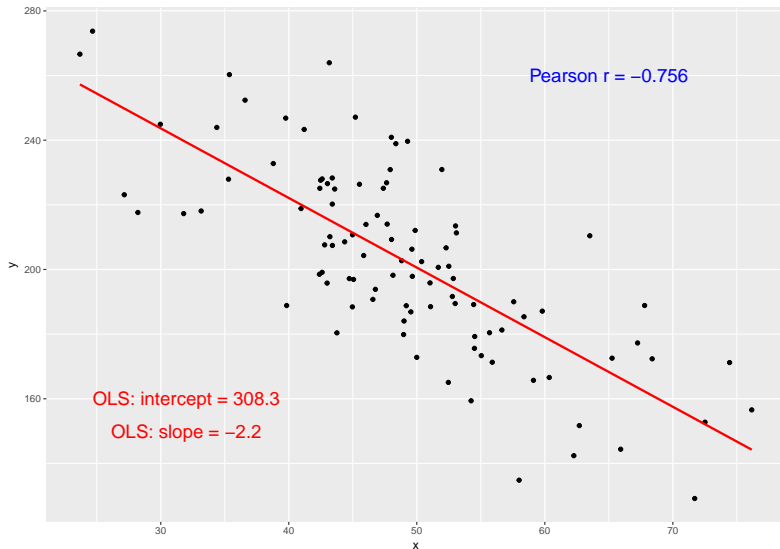
Meaning of Pearson Correlation

The Pearson correlation coefficient assesses how well the relationship between X and Y can be described using a linear function.

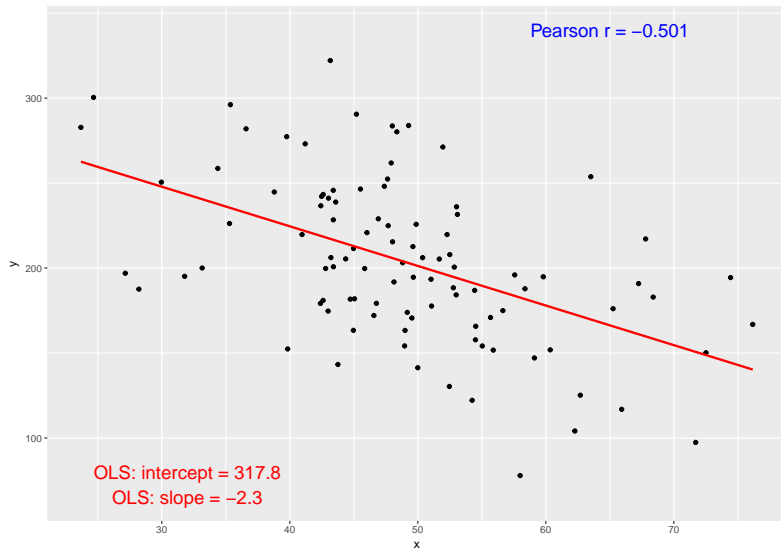
- The Pearson correlation is dimension-free.
- It falls between -1 and +1, with the extremes corresponding to situations where all the points in a scatterplot fall exactly on a straight line with negative and positive slopes, respectively.
- A Pearson correlation of zero corresponds to the situation where there is no linear association.
- Unlike the estimated slope in a regression line, the sample correlation coefficient is symmetric in x and y, so it does not depend on labeling one of them (y) the response variable, and one of them (x) the predictor.

$$r_{XY} = \frac{1}{n-1} \sum_{i=1}^n \left(\frac{x_i - \bar{x}}{s_x} \right) \left(\frac{y_i - \bar{y}}{s_y} \right)$$

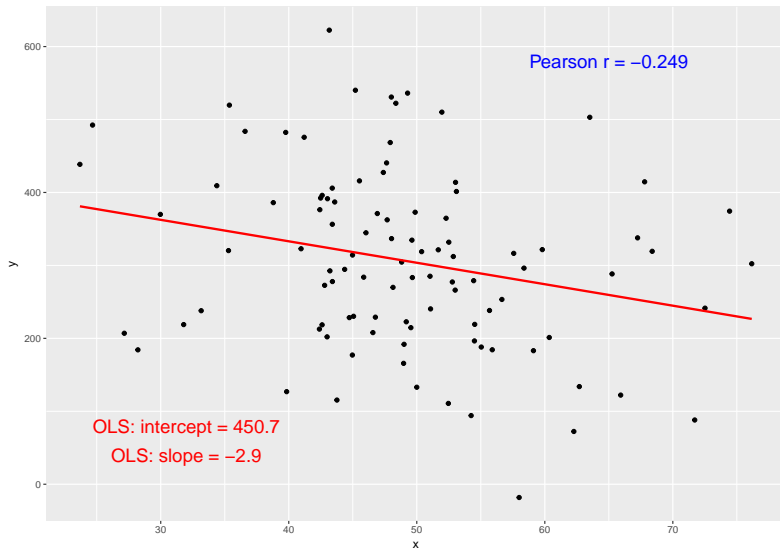
Simulated Example 1



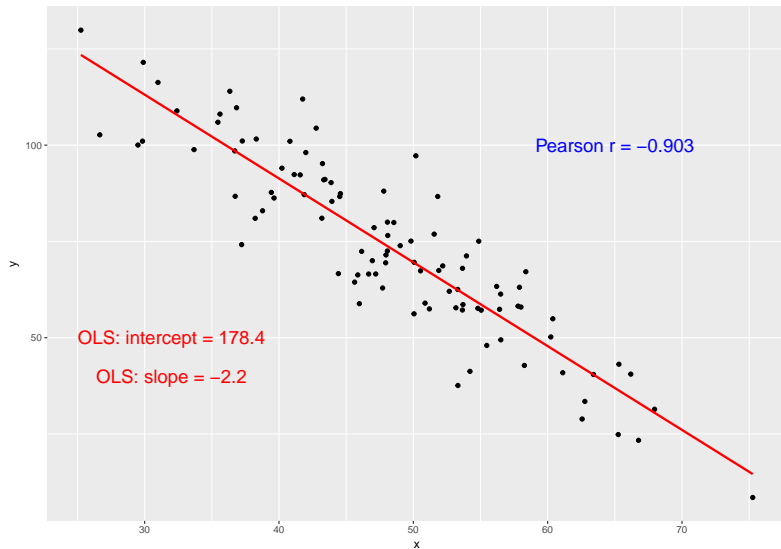
Simulated Example 2



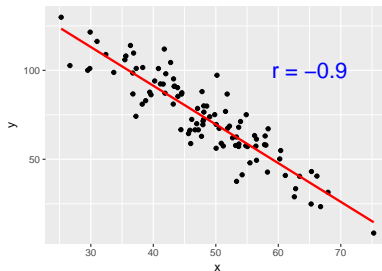
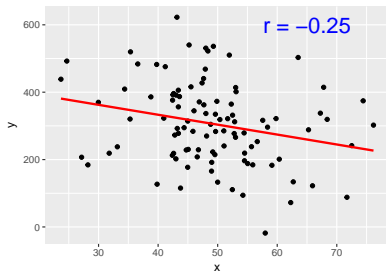
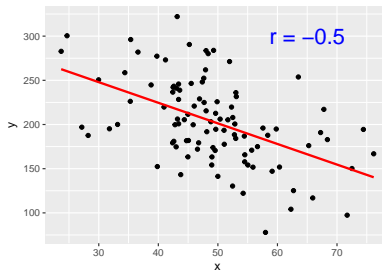
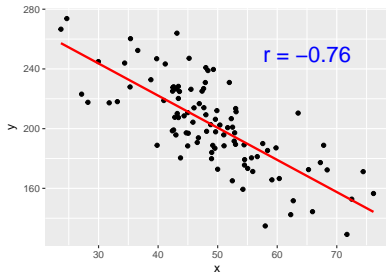
Simulated Example 3



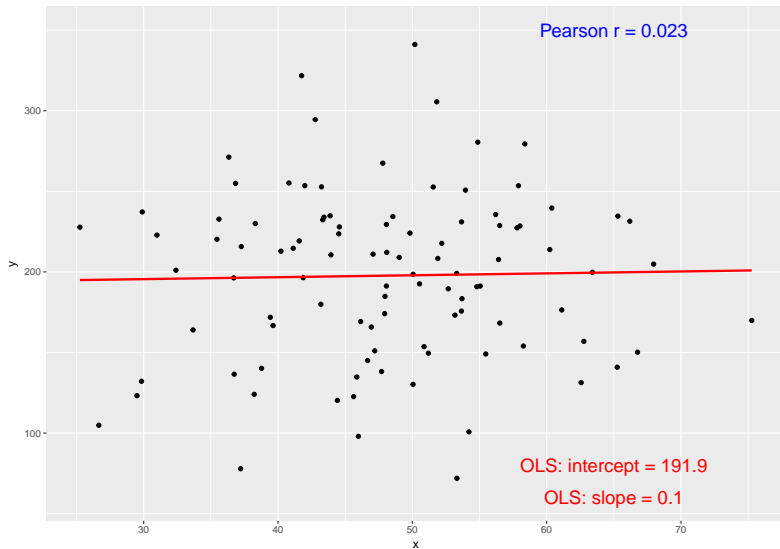
Simulated Example 4



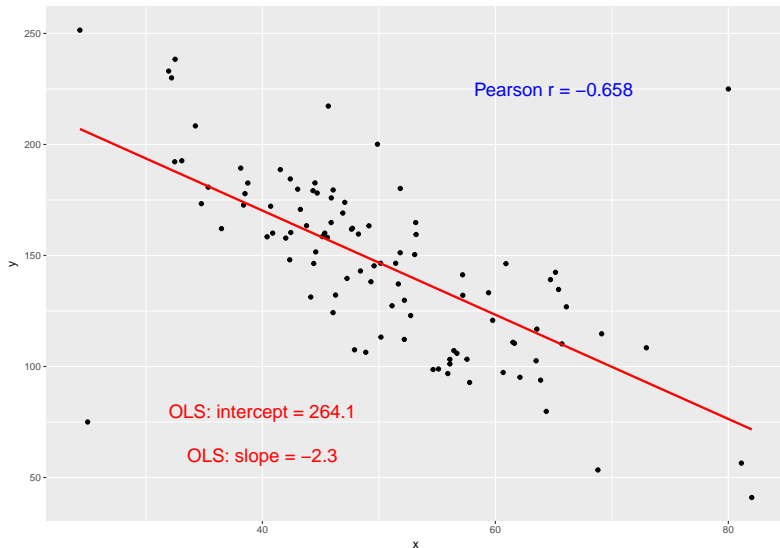
Calibrate Yourself on Correlation Coefficients



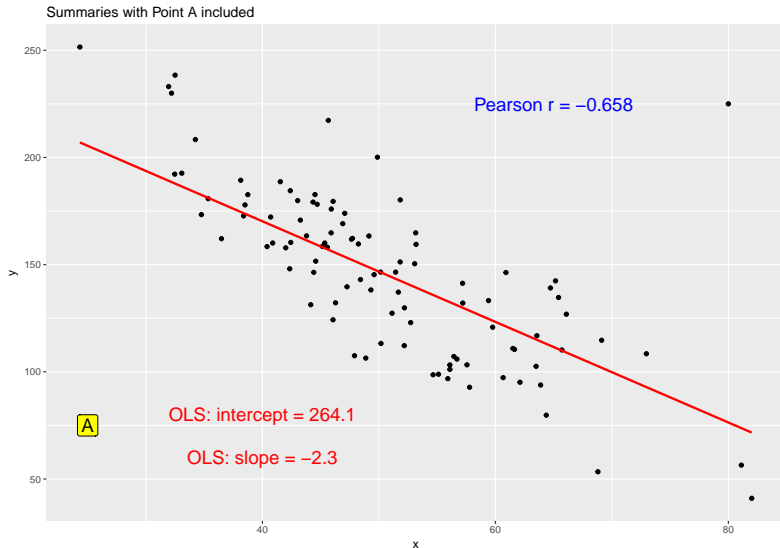
Simulated Example 5



Simulated Example 6



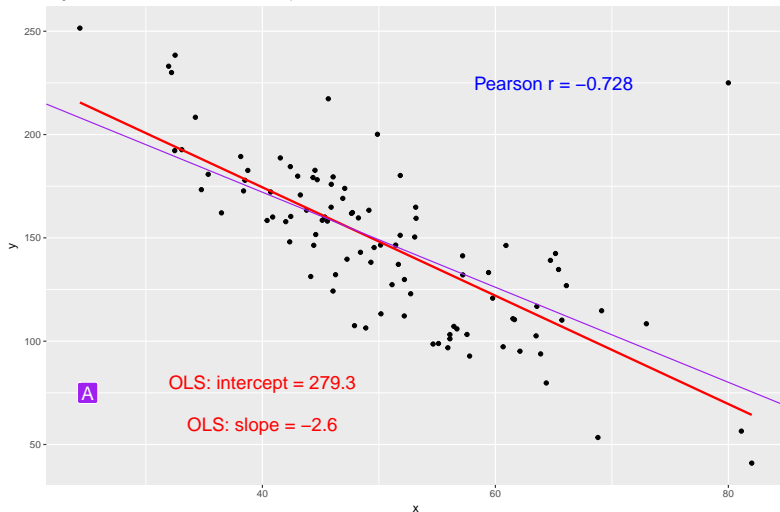
Example 6: What would happen if we omit Point A?



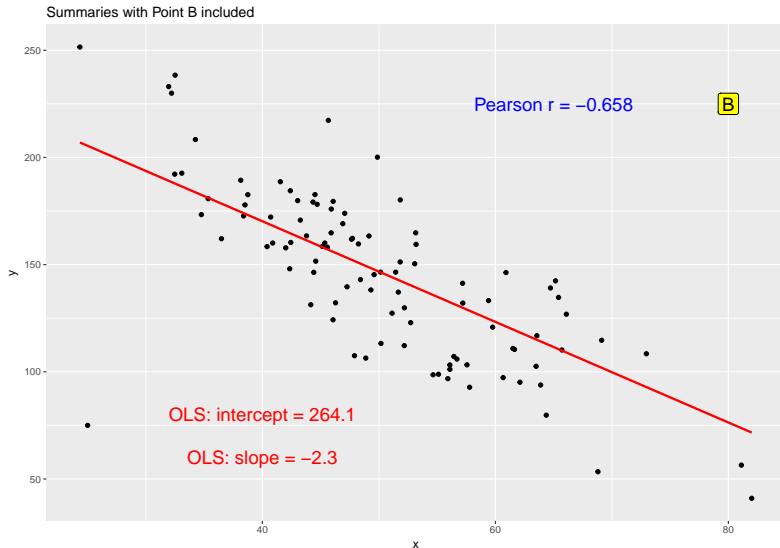
Example 6: Result if we omit Point A

Summaries, Model Results without Point A

Original Line with Point A included is shown in Purple



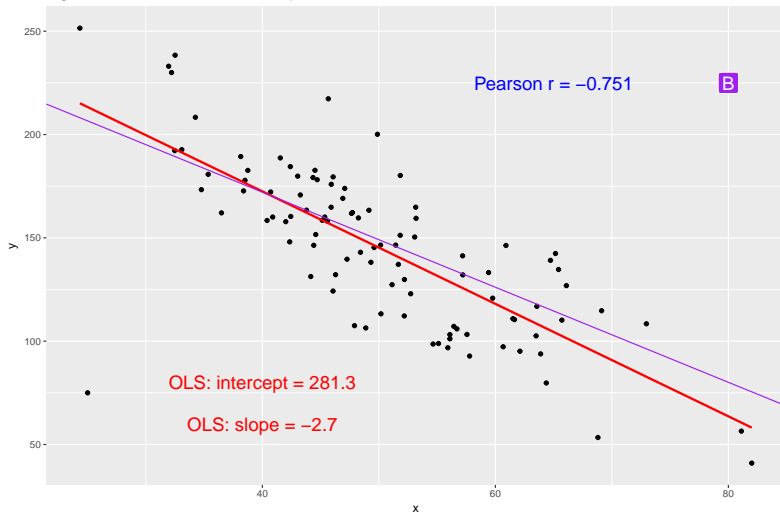
Example 6: What would happen if we omit Point B?



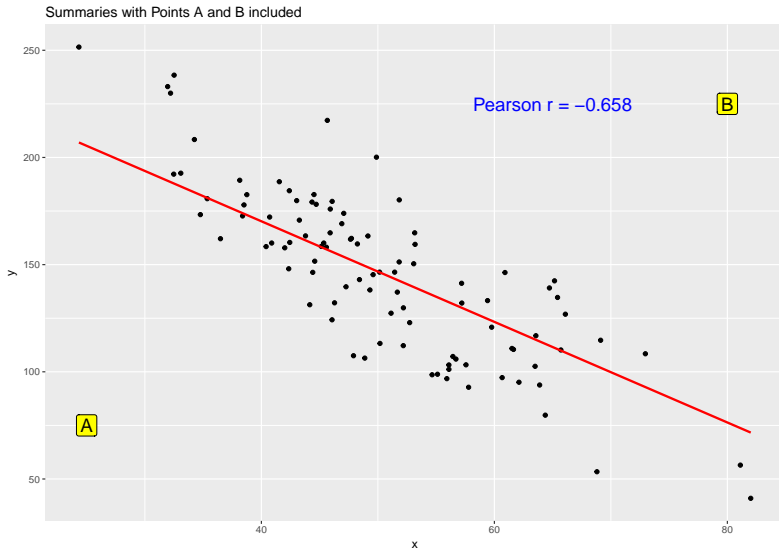
Example 6: Result if we omit Point B

Summaries, Model Results without Point B

Original Line with Point B included is shown in Purple



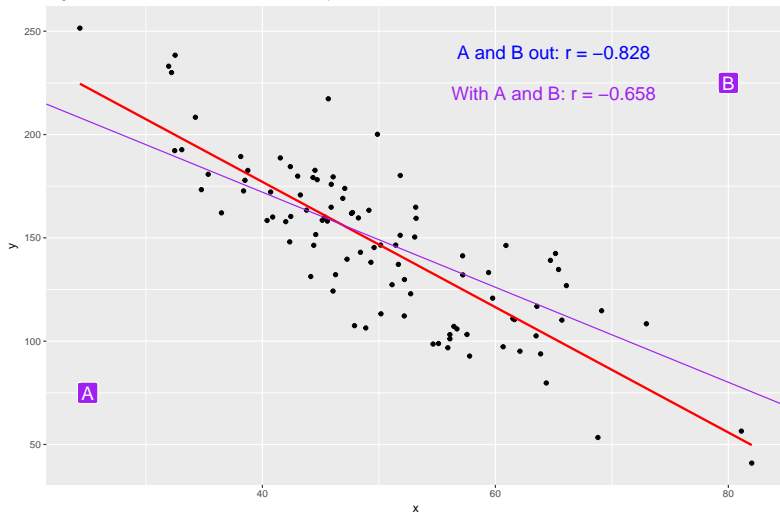
Example 6: What if we omit Point A AND Point B?



Example 6: Result if we omit Points A and B

Summaries, Model Results without A or B

Original Line with Points A and B included is shown in Purple

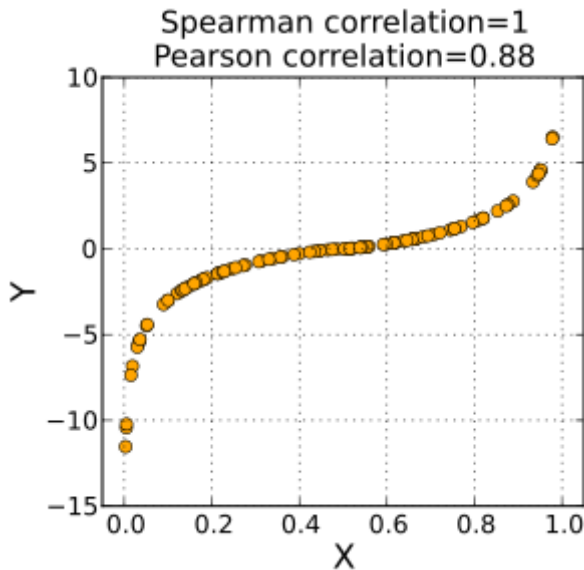


The Spearman Rank Correlation

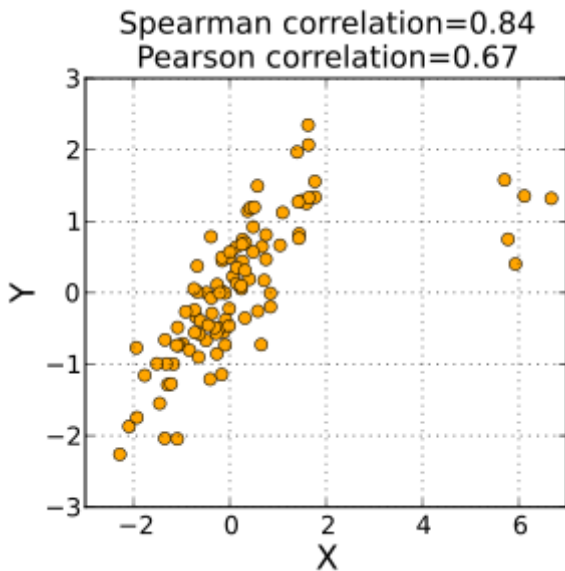
The Spearman rank correlation coefficient assesses how well the association between X and Y can be described using a **monotone function** even if that relationship is not linear.

- A monotone function preserves order - that is, Y must either be strictly increasing as X increases, or strictly decreasing as X increases.
- A Spearman correlation of 1.0 indicates simply that as X increases, Y always increases.
- Like the Pearson correlation, the Spearman correlation is dimension-free, and falls between -1 and +1.
- A positive Spearman correlation corresponds to an increasing (but not necessarily linear) association between X and Y , while a negative Spearman correlation corresponds to a decreasing (but again not necessarily linear) association.

Monotone Association (Source: Wikipedia)

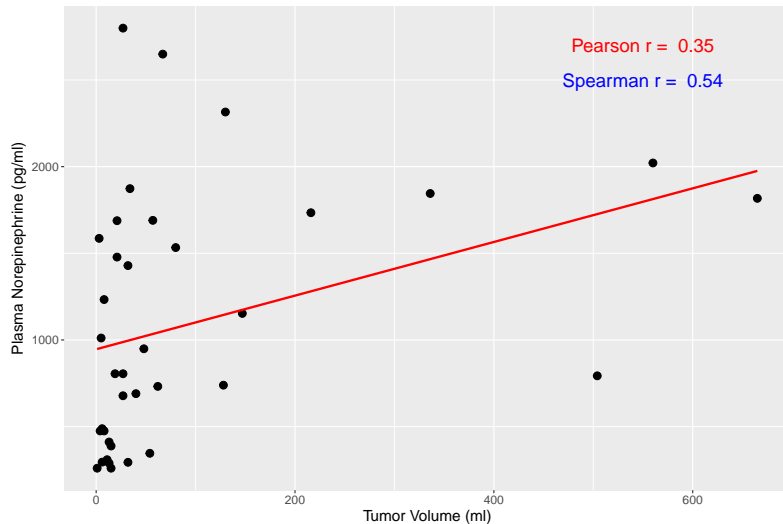


Spearman correlation reacts less to outliers



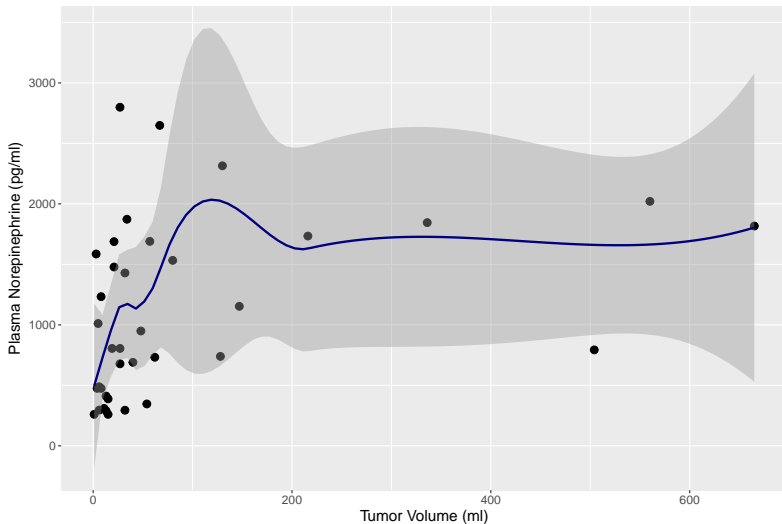
Our Key Scatterplot again

Association of p.ne with tumor volume



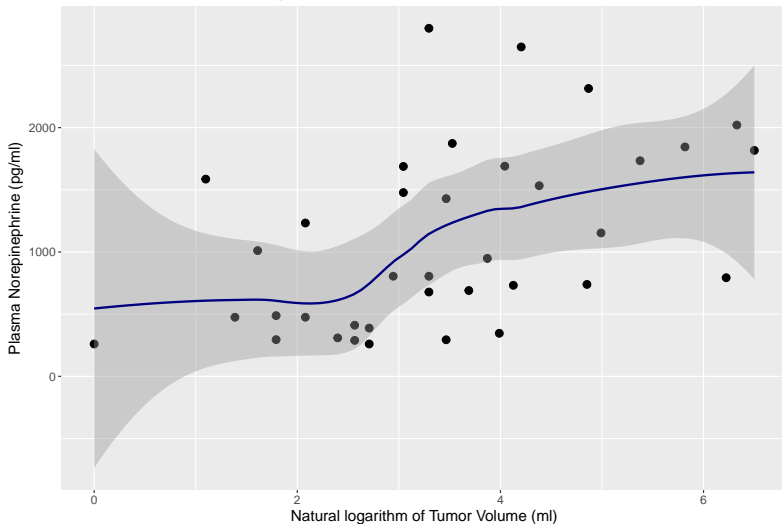
Smoothing using loess, instead

Association of p.ne with tumor volume

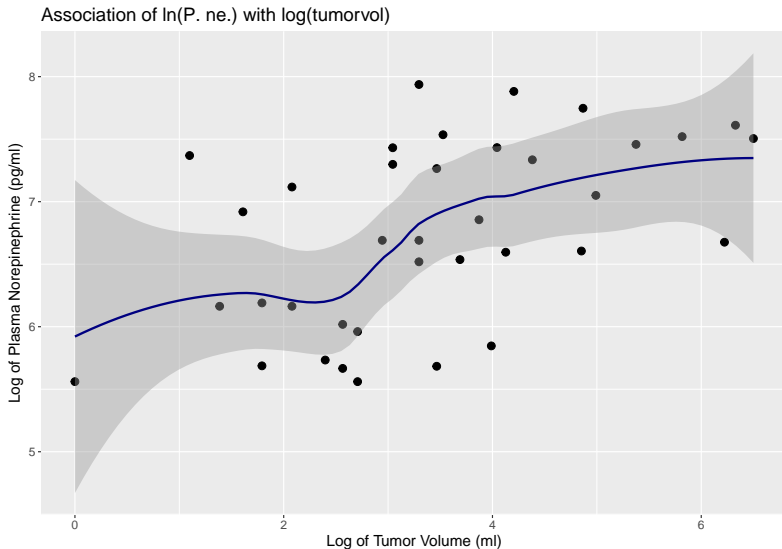


Using the Log transform to spread out the Volumes

Association of p.ne with log(tumor volume)

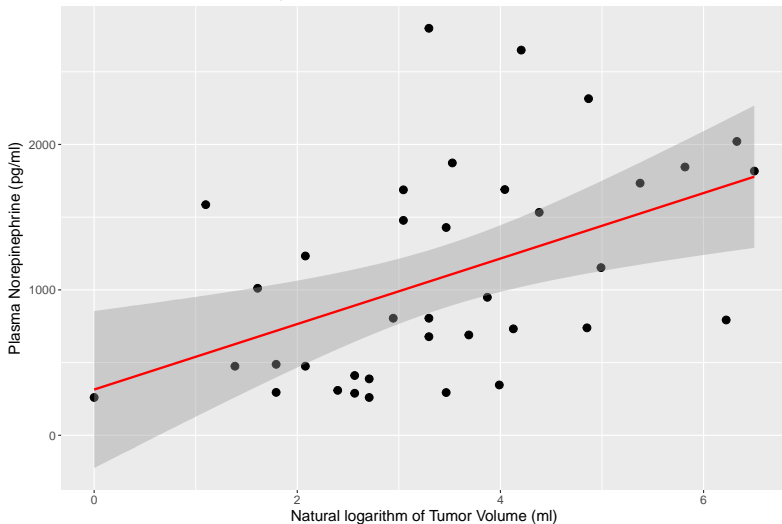


Does a Log-Log model seem like a good choice?



Linear Model for p.ne using log(tumor volume)

Association of p.ne with log(tumorvol)



Creating a Factor to represent disease diagnosis

We want to add a new variable, specifically a factor, called `diagnosis`, which will take the values `von H-L` or `neoplasia`.

- Recall `disease` is a numeric 1/0 variable (0 = `von H-L`, 1 = `neoplasia`)
- Use `fct_recode` from the `forcats` package...

```
VHL <- VHL %>%  
  mutate(diagnosis = fct_recode(factor(disease),  
                                "neoplasia" = "1",  
                                "von H-L" = "0")  
  )
```

Now, what does VHL look like?

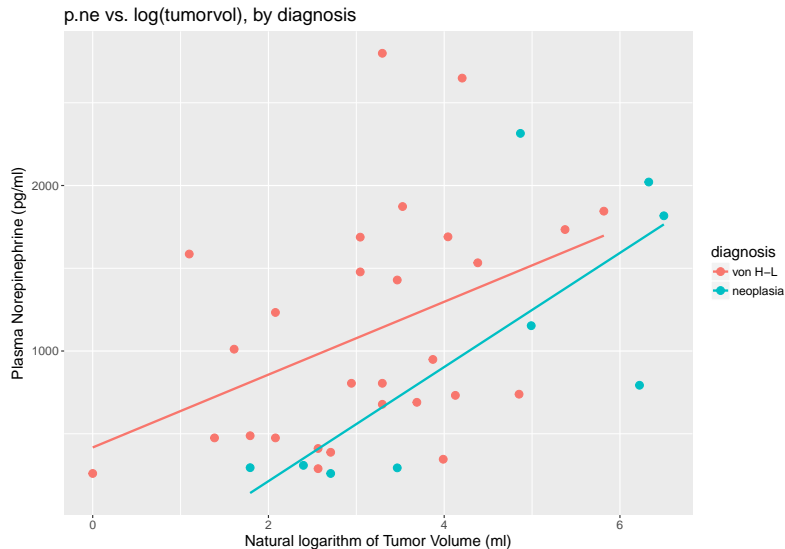
VHL

```
# A tibble: 37 x 5
```

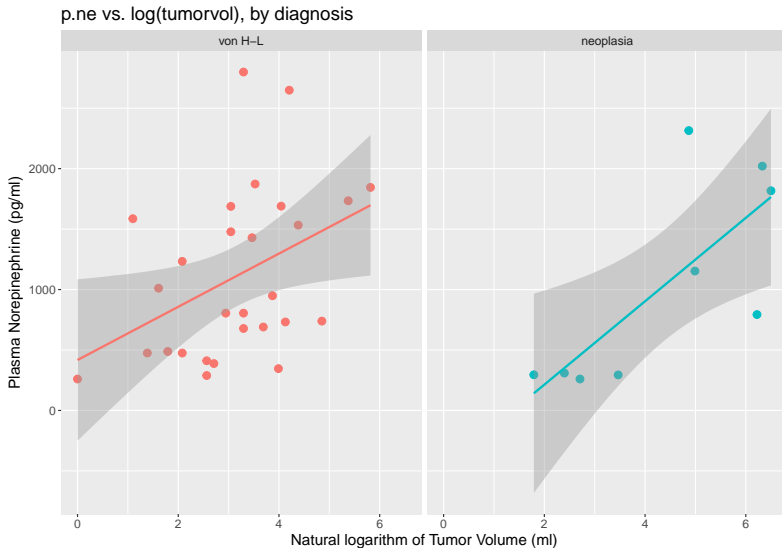
	id	disease	p.ne	tumorvol	diagnosis
	<int>	<int>	<int>	<int>	<fctr>
1	101	0	289	13	von H-L
2	102	1	294	32	neoplasia
3	103	0	2799	27	von H-L
4	104	0	2649	67	von H-L
5	105	0	346	54	von H-L
6	106	0	1690	57	von H-L
7	107	0	805	19	von H-L
8	108	1	1153	147	neoplasia
9	109	0	678	27	von H-L
10	110	1	1817	665	neoplasia

```
# ... with 27 more rows
```

Compare the patients by diagnosis



Facetted Scatterplots by diagnosis



Model accounting for different slopes and intercepts

```
model2 <- lm(p.ne ~ log(tumorvol) * diagnosis, data = VHL)
model2
```

Call:

```
lm(formula = p.ne ~ log(tumorvol) * diagnosis, data = VHL)
```

Coefficients:

```
              (Intercept)
                417.2
        log(tumorvol)
                220.0
diagnosisneoplasia
               -893.3
log(tumorvol):diagnosisneoplasia
                  124.8
```


Model 2 results

$$p.ne = 417 + 220 \log(\text{tumorvol}) - 893 (\text{diagnosis} = \text{neoplasia}) + 125 (\text{diagnosis} = \text{neoplasia}) * \log(\text{tumorvol})$$

where the indicator variable $(\text{diagnosis} = \text{neoplasia}) = 1$ for neoplasia subjects, and 0 for other subjects...

- Model for $p.ne$ in von H-L patients:
 - $417 + 220 \log(\text{tumorvol})$
- Model for $p.ne$ in neoplasia patients:
 - $(417 - 893) + (220 + 125) \log(\text{tumorvol})$
 - $-476 + 345 \log(\text{tumorvol})$

Model 2 Predictions

What is the predicted p.ne for a single new subject with tumorvol = 55 ml (so $\log(\text{tumorvol}) = 4.01$) in each diagnosis category?

```
predict(model2, newdata = data_frame(tumorvol = 55,  
  diagnosis = "neoplasia"), interval = "prediction")
```

	fit	lwr	upr
1	905.7322	-456.1596	2267.624

```
predict(model2, newdata = data_frame(tumorvol = 55,  
  diagnosis = "von H-L"), interval = "prediction")
```

	fit	lwr	upr
1	1299.003	-23.21001	2621.215

Setting up the Task B Groups

- ❶ We want ten groups, each with 4-6 people. 5 is ideal.
- ❷ You need the full names of your group members.
- ❸ And their email addresses.
- ❹ Select a group reporter and a group name.
- ❺ Have the reporter fill out the Google Form from the Project Task B instructions.

Google Form for Project Task B groups is linked at
<https://github.com/thomaseLove/431project>

The Form's Questions...

Fall 2017 Project Task B Groups

This is the form to specify the group name and membership for Task B. Only one person from your group should fill out this form. The Task B groups will be formed in class on 2017-09-26. This form needs to be submitted by noon on 2017-09-27. If you have questions, contact Dr. Love directly.

Your email address (**tel3@case.edu**) will be recorded when you submit this form. Not you? [Switch account](#)

* Required

What is the name of your Task B group? *

100 characters or less, please.

Your answer

Please select the names of the members of your group from the list below.

Your group must include 4-6 people, in total. Be sure to check the box for each group member, including yourself.

In Our Group

Albar, Zainab

☐

Asagba, Oghenerukema

☐