C1M1_peer_reviewed

December 12, 2021

1 Module 1: Peer Reviewed Assignment

1.0.1 Outline:

The objectives for this assignment:

1. Learn when and how simulated data is appropriate for statistical analysis.
2. Experiment with the processes involved in simulating linear data.
3. Observe how the variance of data effects the best-fit line, even for the same underlying population.
4. Recognize the effects of standardizing predictors.
5. Interpreting the coefficients of linear models on both original and standardized data scales.

General tips:

1. Read the questions carefully to understand what is being asked.
2. This work will be reviewed by another human, so make sure that you are clear and concise in what your explanations and answers.

A Quick Note On Peer-Reviewed Assignments

Welcome to your first peer reviewed assignment! These assignments will be a more open form than the auto-graded assignments, and will focus on interpretation and visualization rather than "do you get the right numbers?" These assignments will be graded by your fellow students (except in the specific cases where the work needs to be graded by a proctor) so please make your answers as clear and concise as possible.

[4]:
```
# This cell loads the necesary libraries for this assignment
library(tidyverse)
```

```
  Attaching packages                                    tidyverse
1.3.0

  ggplot2 3.3.0      purrr   0.3.4
  tibble  3.0.1      dplyr   0.8.5
  tidyr   1.0.2      stringr 1.4.0
  readr   1.3.1      forcats 0.5.0

  Conflicts
tidyverse_conflicts()
```

```
dplyr::filter() masks stats::filter()
dplyr::lag()    masks stats::lag()
```

2 Problem 1: Simulating Data

We're going to let you in on a secret. The turtle data from the autograded assignment was simulated...fake data! Gasp! Importantly, simulating data, and applying statistical models to simulated data, are very important tools in data science.

Why do we use simulated data? Real data can be messy, noisy, and we almost never *really* know the underlying process that generated real data. Working with real data is always our ultimate end goal, so we will try to use as many real datasets in this course as possible. However, applying models to simulated data can be very instructive: such applications help us understand how models work in ideal settings, how robust they are to changes in modeling assumptions, and a whole host of other contexts.

And in this problem, you are going to learn how to simulate your own data.

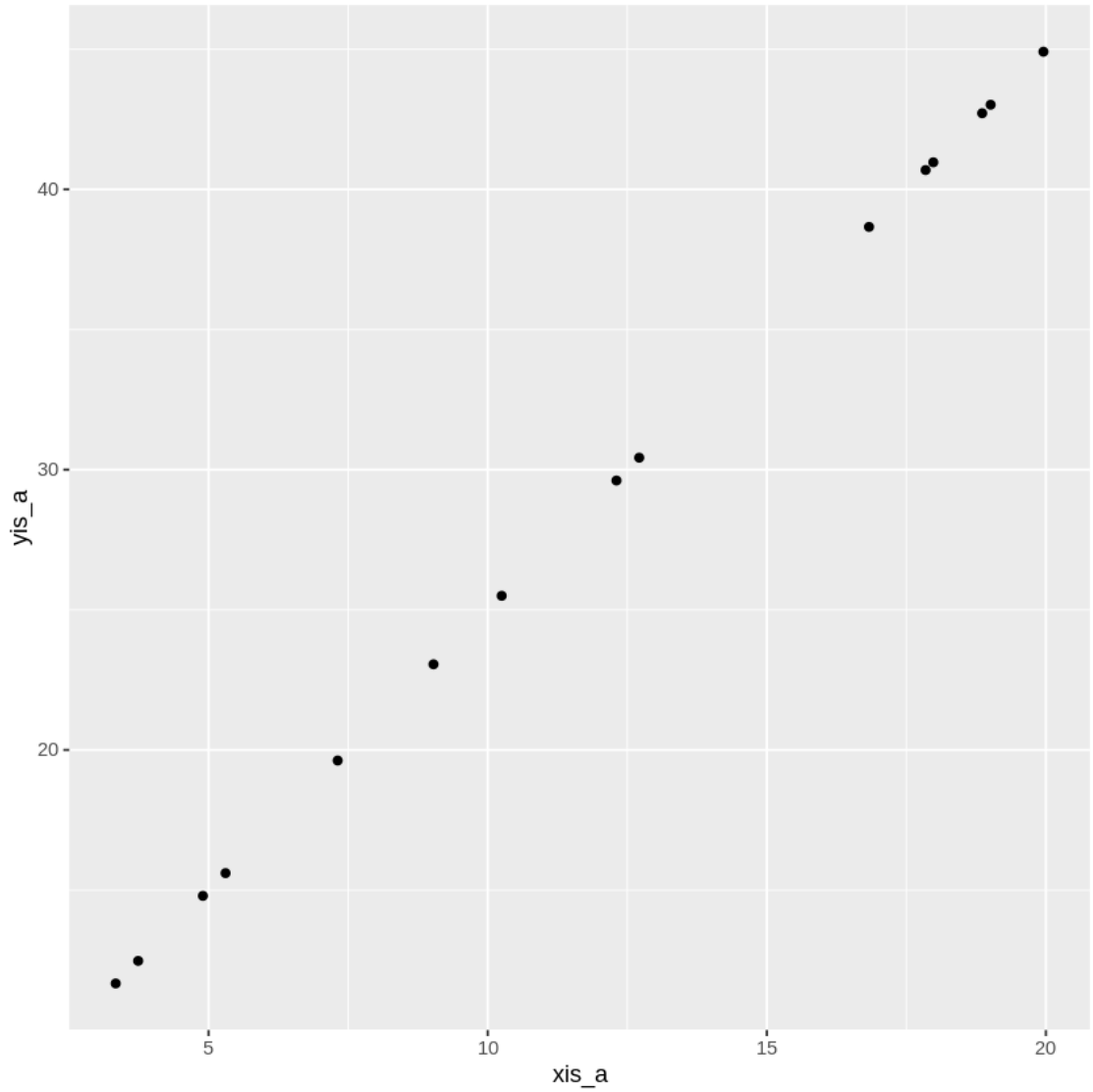
1. (a) A Simple Line Starting out, generate 10 to 20 data points for values along the x-axis. Then generate data points along the y-axis using the equation $y_i = \beta_0 + \beta_1 x_i$. Make it a straight line, nothing fancy.

Plot your data (using ggplot!) with your **x** data along the x-axis and your **y** data along the y-axis.

In the *Markdown* cell below the `R` cell, describe what you see in the plot.

Tip: You can generate your x-data *deterministically*, e.g., using either `a:b` syntax or the `seq()` function, or *randomly* using something like `runif()` or `rnorm()`. In practice, it won't matter all that much which one you choose.

[5]:
```r
# Your Code Here
set.seed(2323234)
xis_a = runif(15, min=0, max = 20)
b0_a = 5
b1_a = 2
yis_a = b0_a + (b1_a * xis_a)
p1_a= data.frame(xis_a, yis_a)
ggplot(data=p1_a, aes(x=xis_a, y=yis_a)) + geom_point()
```



The plot represents a relatively straight regression line. The line has a positive slope of 2 and begins at the y-intercept of 5 and an error variance of 0.

1. (b) The Error Component That is a perfect set of data points, but that is a problem in itself. In almost any real life situation, when we measure data, there will be some error in those measurements. Recall that our simple linear model is of the form:

$$y_i = \beta_0 + \beta_1 x_i + \epsilon_i, \qquad \epsilon_i \sim N(0, \sigma^2)$$

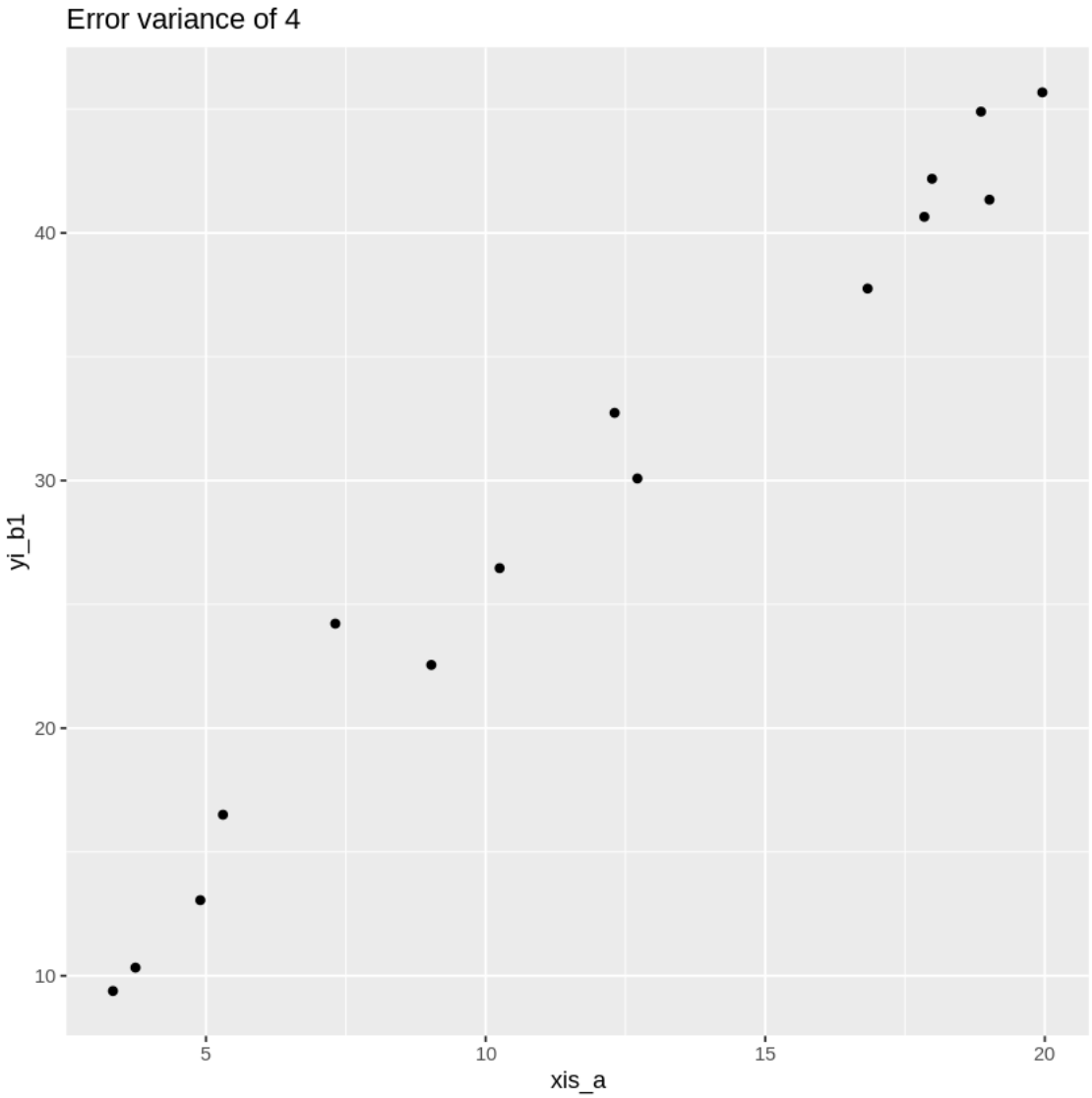
Add an error term to your y-data following the formula above. Plot at least three different plots (using ggplot!) with the different values of σ^2.

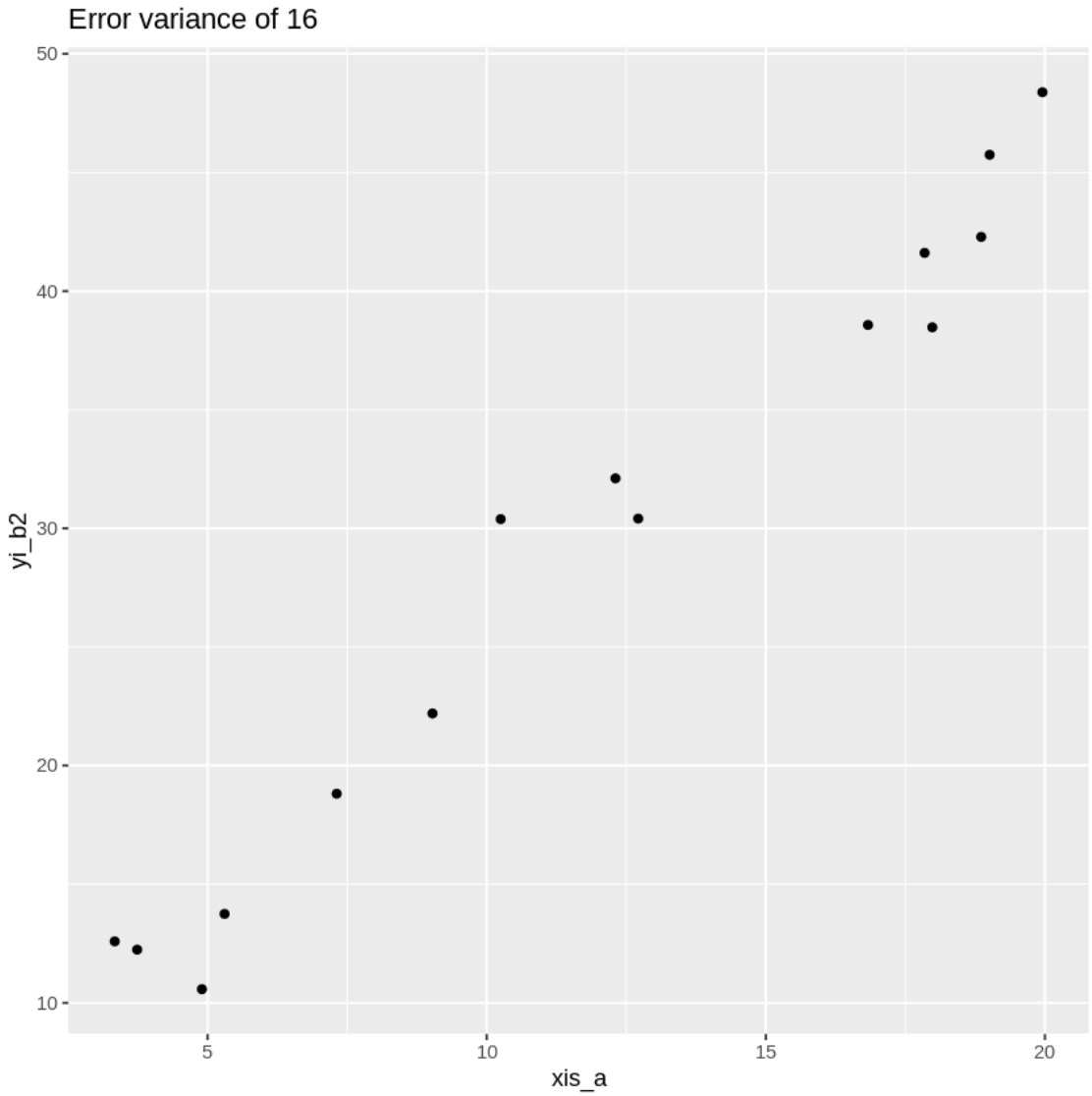
How does the value of σ^2 affect the final data points? Type your answer in the *Markdown* cell below the `R` cell.

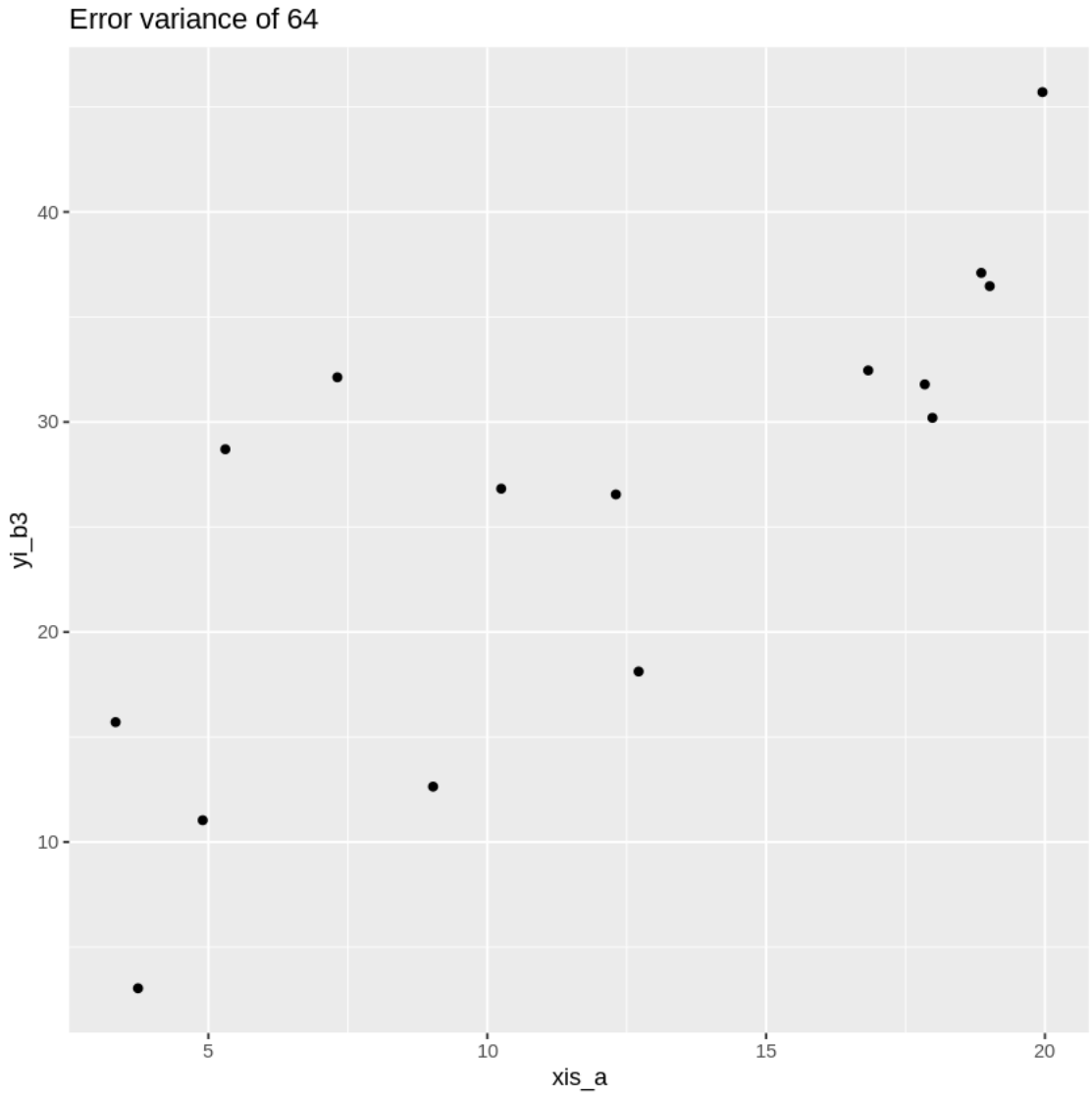
Tip: To randomly sample from a normal distribution, check out the `rnorm()` function.

[1]:
```
?rnorm
```

[6]:
```
# Your Code Here
set.seed(2324)

err1 = rnorm(15, 0, 2)
err2 = rnorm(15, 0, 4)
err3 = rnorm(15, 0, 8)

yi_b1 = (b0_a + (b1_a * xis_a)) + err1
yi_b2 = (b0_a + (b1_a * xis_a)) + err2
yi_b3 = (b0_a + (b1_a * xis_a)) + err3

p1_b1 = data.frame(xis_a, yi_b1)
p1_b2 = data.frame(xis_a, yi_b2)
p1_b3 = data.frame(xis_a, yi_b3)

ggplot(data=p1_b1, aes(x=xis_a, y=yi_b1)) + geom_point() + ggtitle("Error␣
↪variance of 4")
ggplot(data=p1_b2, aes(x=xis_a, y=yi_b2)) + geom_point() + ggtitle("Error␣
↪variance of 16")
ggplot(data=p1_b3, aes(x=xis_a, y=yi_b3)) + geom_point() + ggtitle("Error␣
↪variance of 64")
```


Error variance of 4
yi_b1
xis_a
10
20
30
40
5
10
15
20


Error variance of 16
50
40
30
20
10
yi_b2
5
10
15
20
xis_a



The larger the varaince, the less the plot looks as a straight line. The data points with a error variance of 4 are slightly scattered. However, the data points with an error variance of 16 and 64 are increasingly much more scattered and resemble less of a line.

3 Problem 2: The Effects of Variance on Linear Models

Once you've completed **Problem 1**, you should have three different "datasets" from the same underlying data function but with different variances. Let's see how those variance affect a best fit line.

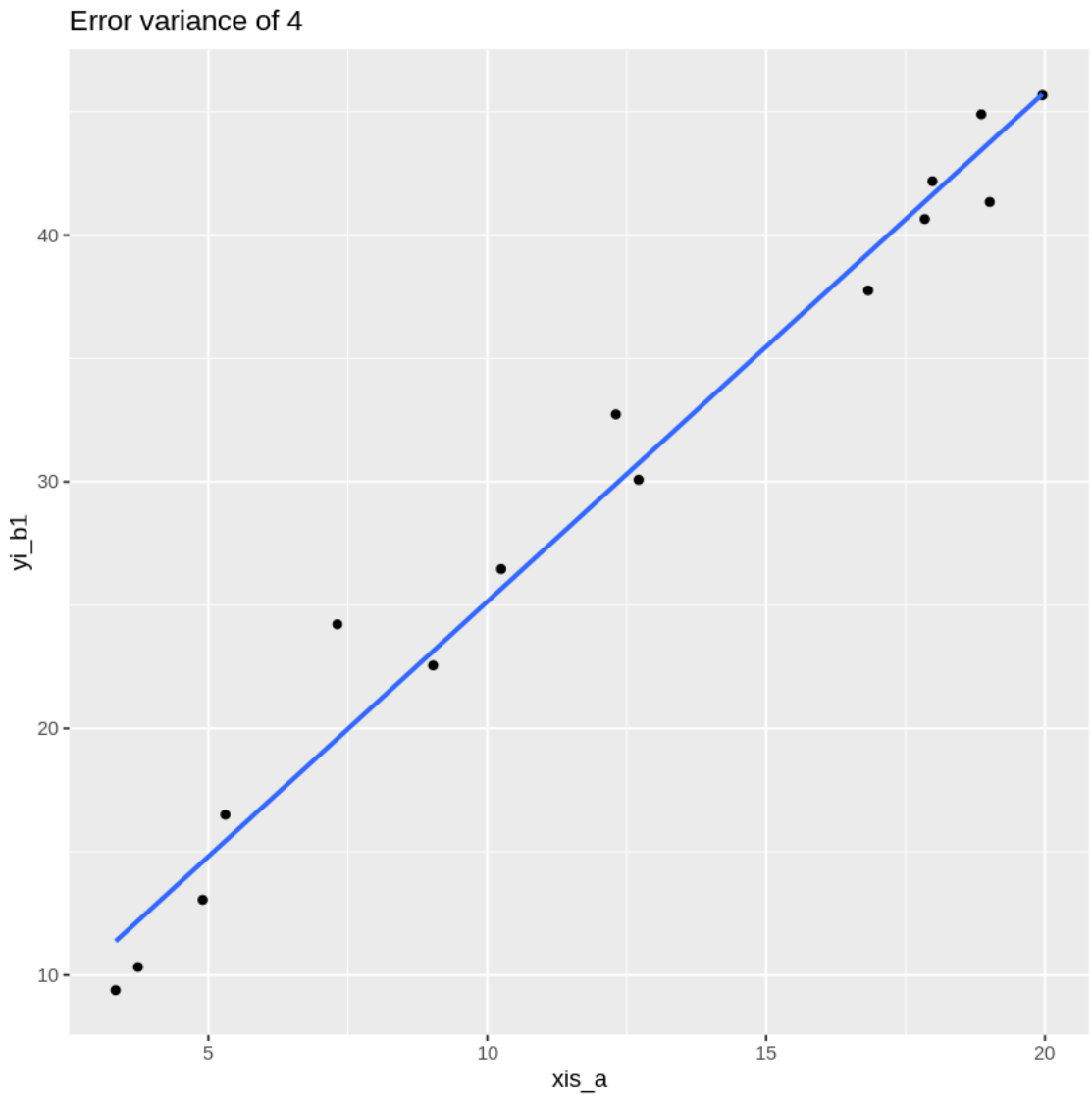
Use the `lm()` function to fit a best-fit line to each of those three datasets. Add that best fit line to each of the plots and report the slopes of each of these lines.

Do the slopes of the best-fit lines change as σ^2 changes? Type your answer in the *Markdown* cell below the `R` cell.

Tip: The `lm()` function requires the syntax `lm(y~x)`.

[16]:
```
# Your Code Here
lm(yi_b1~xis_a )
ggplot(data=p1_b1, aes(x=xis_a, y=yi_b1)) + geom_point() + ggtitle("Error␣
 ↪variance of 4") + stat_smooth(method='lm', se=FALSE)
```

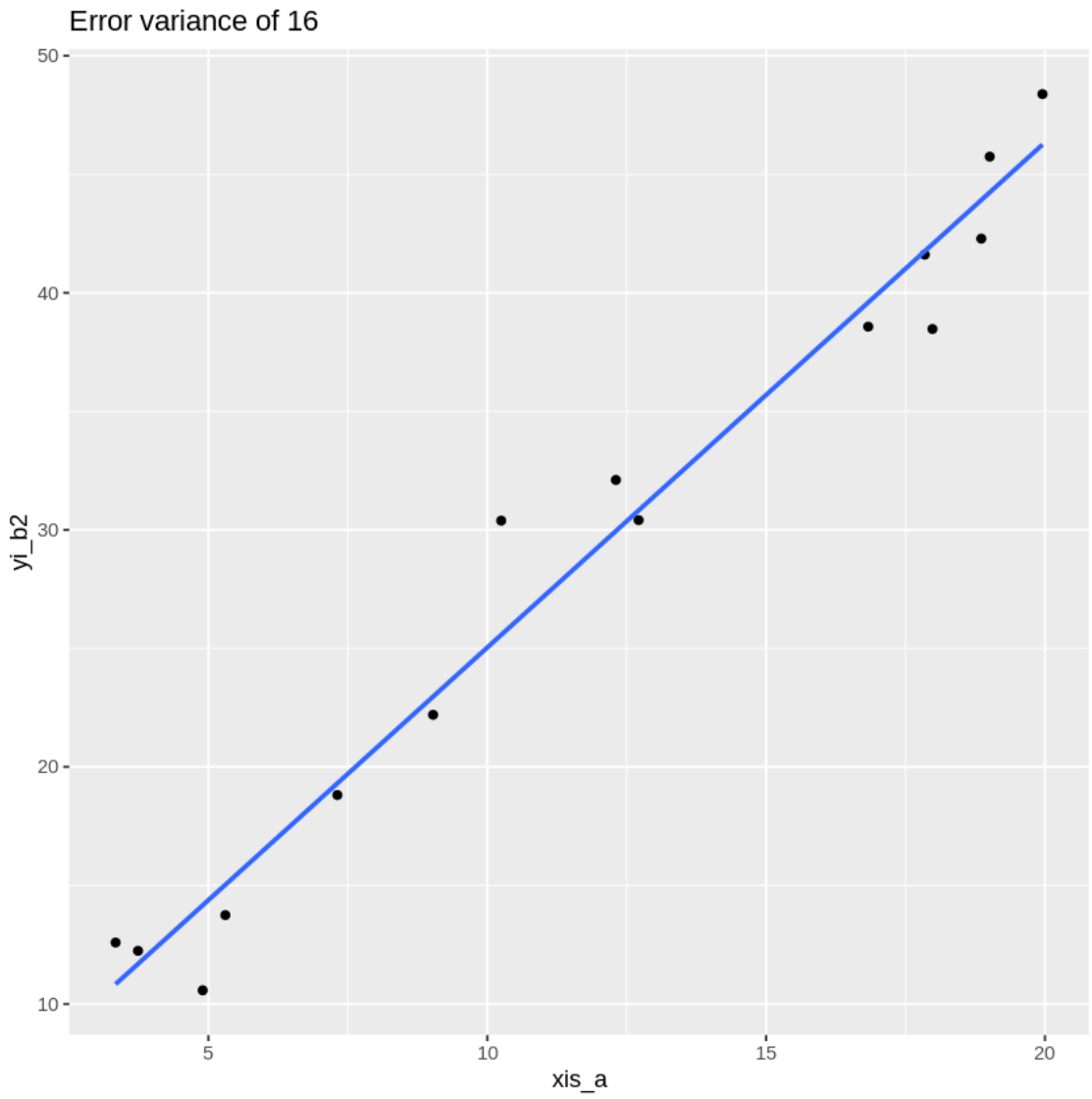
```
Call:
lm(formula = yi_b1 ~ xis_a)

Coefficients:
(Intercept)        xis_a
      4.476        2.067



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



[17]:
```
lm(yi_b2~xis_a)
ggplot(data=p1_b2, aes(x=xis_a, y=yi_b2)) + geom_point() + ggtitle("Error␣
↪variance of 16") + stat_smooth(method='lm', se=FALSE)
```

```
Call:
lm(formula = yi_b2 ~ xis_a)

Coefficients:
(Intercept)        xis_a
      3.728        2.131
```

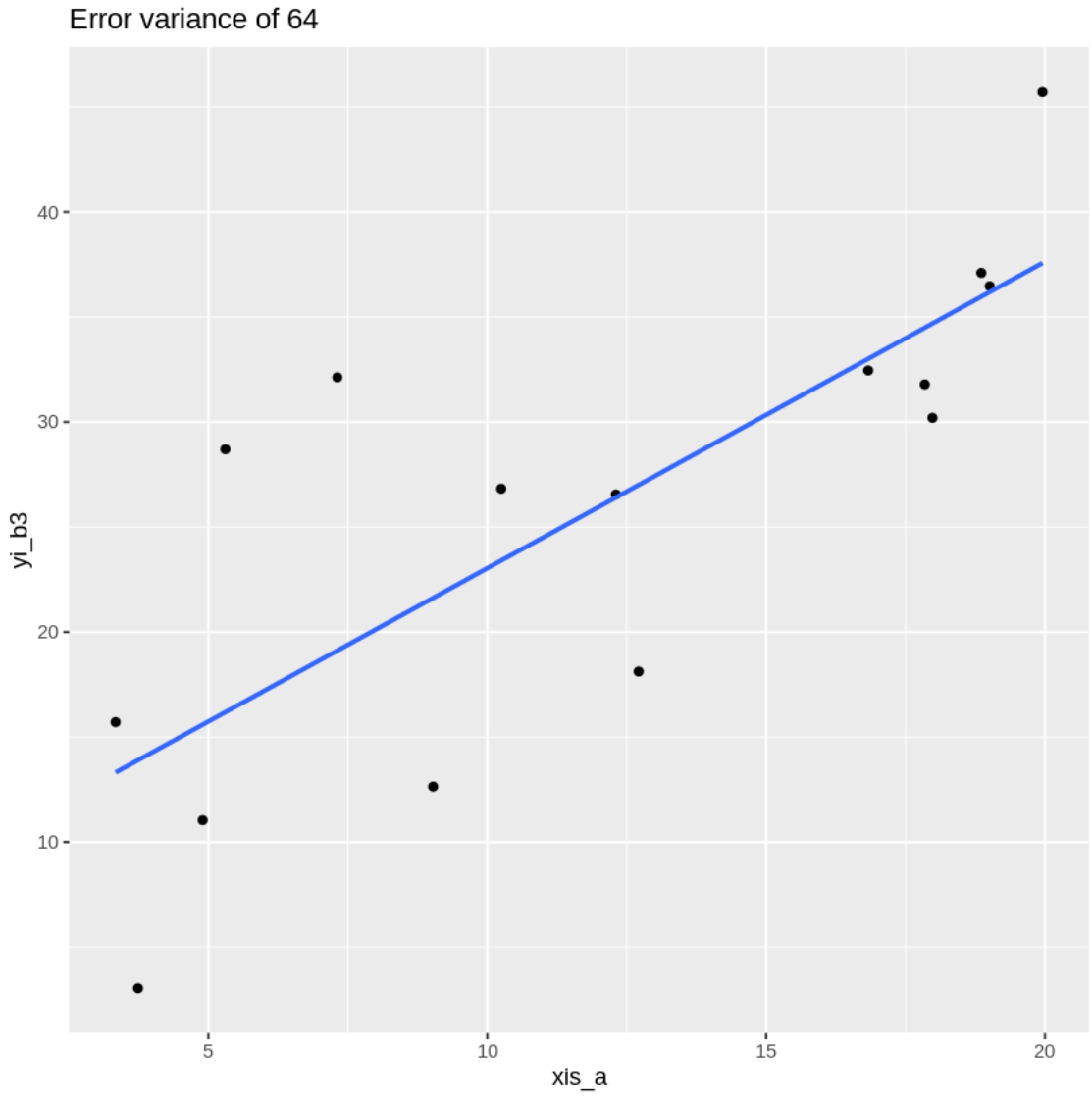
```
`geom_smooth()` using formula 'y ~ x'
```



[18]:
```
lm(yi_b3~xis_a)
ggplot(data=p1_b3, aes(x=xis_a, y=yi_b3)) + geom_point() + ggtitle("Error␣
 ↪variance of 64") + stat_smooth(method='lm', se=FALSE)
```

```
Call:
lm(formula = yi_b3 ~ xis_a)

Coefficients:
(Intercept)        xis_a
      8.444        1.459
```

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



Yes, the slope of the regression line decreases as the variance of the error terms increases. Becasuse the error terms have a larger variance, the data points are farther spread out. As a result, the regression line has a decreased slope and a more horizontal regression line.

4 Problem 3: Interpreting the Linear Model

Choose one of the above three models and write out the actual equation of that model. Then in words, in the *Markdown* cell below the `R` cell, describe how a 1 unit increase in your predictor affects your response. Does this relationship make sense?

[19]:
```
# Your Code Here
Y_3 = 8.444 + 1.459 * xis_a + err3
```

The average change in Y associated with a 1-unit increase in X is 1.459. Yes, this makes sense since the regression line, in the plot, has positive slope and far from horizontal. Looking at the regression line in plot 3 of problem 2, we see Y increases much faster than X.

5 Problem 4: The Effects of Standardizing Data

We spent some time standardizing data in the autograded assignment. Let's do that again with your simulated data.

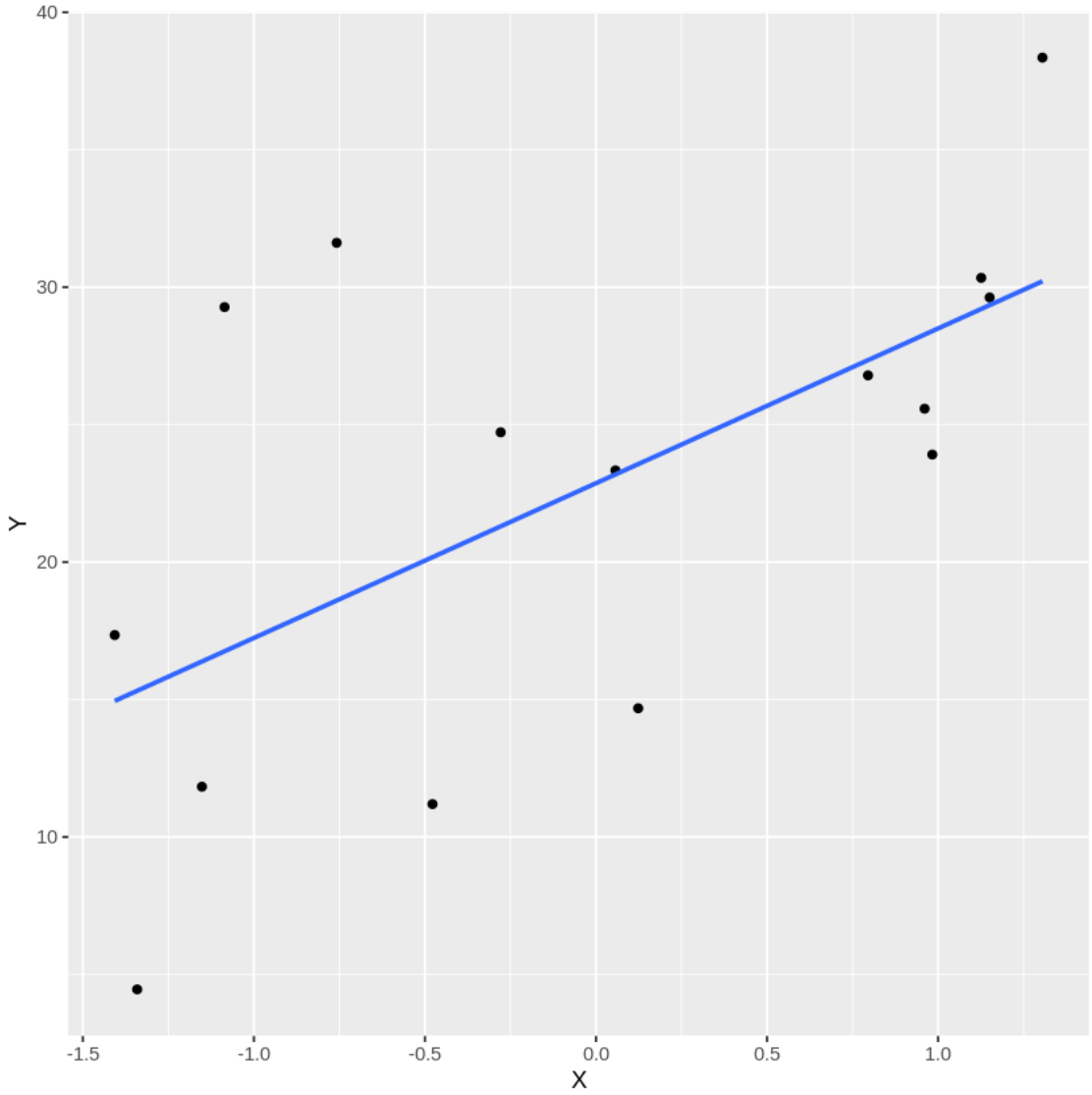
Using the same model from **Problem 3**, standardize your simulated predictor. Then, using the `lm()` function, fit a best fit line to the standardized data. Using ggplot, create a scatter plot of the standardized data and add the best fit line to that figure.

[20]:
```
# Your Code Here
x.stand = (xis_a - mean(xis_a)) / sd(xis_a)
df.stand = data.frame(X = x.stand, Y=Y_3)
lm(Y~X, data=df.stand)
```

```
Call:
lm(formula = Y ~ X, data = df.stand)

Coefficients:
(Intercept)            X
     22.872        5.629
```

[24]:
```
ggplot(df.stand, aes(x=X, y=Y)) + geom_point() + geom_smooth(method="lm",␣
↪se=FALSE)
```

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



6 Problem 5: Interpreting the Standardized Model

Write out the expression for your standardized model. In words, in the *Markdown* cell below the `R` cell, describe how a 1 unit increase in your standardized predictor affects the response. Is this value different from the original model? If yes, then what can you conclude about interpretation of standardized predictors vs. unstandardized predictors.

[25]:
```
# Your Code Here
Y_stand = 22.872 + 5.629 * xis_a
```

A 1 unit increase in our standardized predictor represents an increase of one standard deviation of X. Thus, a 1 unit increase in X would increase Y by 5.629. Yes, this value is different from the

original model; in fact, it is much larger. We can conclude that the standardized predictors would be much larger than the unstandardized predictors since it is measured in units of the standard deviation.

[ ]: