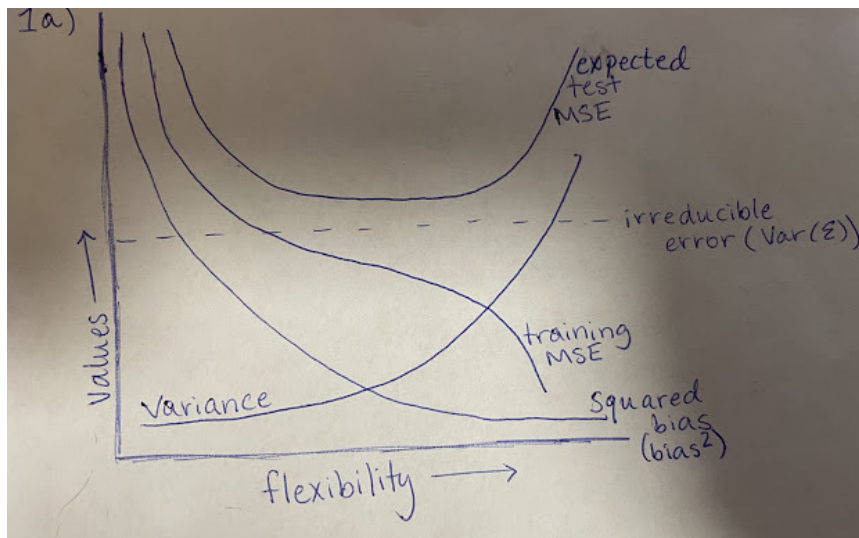


Problem 1:



- a.
- b. Expected test MSE is the expected average error if we were able to use the entire population of data. Training MSE is the average error able to be calculated using a sample of the entire population data which is basically an estimate of the expected test MSE. Bias is the tendency in which there are differences between the facts and results which is also just the difference between the actual value and the prediction from our model. Variance is how much the estimate may differ if different data was used to train the model. Irreducible error simply stated is that error can't be reduced by creating good models; it is caused by random things outside our control.
- c.
 - The irreducible error is constant and it is a parallel line. This "curve" lies below the test MSE curve since the expected test MSE will always be greater than the $\text{Var}(\epsilon)$ which is the irreducible error.
 - The training MSE decreases as flexibility increases. Because as flexibility increases, the function overfits the data and at the end, the error shows a minimum constant value.
 - The test MSE decreases until it comes to a point where flexibility starts to overfit the training data which is when the error starts to increase.
 - The squared bias decreases as the flexibility increases. Bias basically refers to the error that is introduced by approximating a real-life problem. For example, it's unlikely a real-life problem would have a simple linear relationship. So using a simple model like the linear regression line will result in some bias in the estimate of the function.
 - The variance increases as the flexibility increases. The variance is the amount of which the function hat would change if it was estimated using a different training data set. So if you were to change any point, it might cause the function hat to change which will lead to some variance.
- d. Some of the advantages of a flexible approach is that it might have a better fit for non-linear models and decrease the bias. Some of the disadvantages of a flexible approach is that it could possibly overfit the training data, have a higher variance and make it harder to interpret. A more flexible approach would probably be preferred when we are interested in prediction and not interpretability of results. Possibly also when the

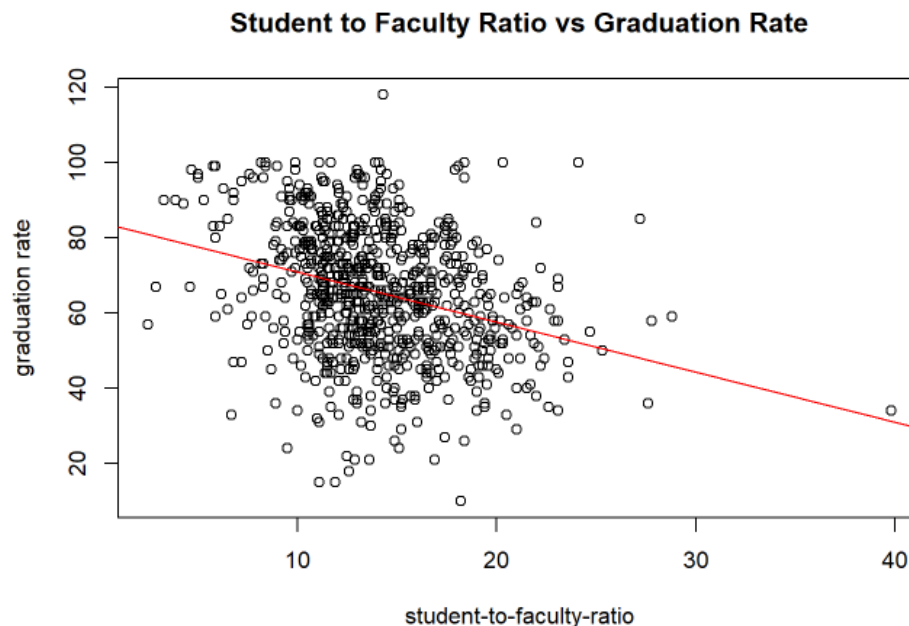
system is under fitted. A less flexible approach would probably be preferred when we are interested in the interpretability of the results.

Problem 2:

- 777 observations, 18 variables
- Statistics for a large number of US Colleges from the 1995 issue of US News and World Report.
- row 278 shows Iowa State University

	Private	Apps	Accept	Enroll	Top10perc	Top25perc	F.Undergrad	P.Undergrad		
Iowa State University	No	8427	7424	3441	26	59	18676	1715		
	Outstate	Room.	Board	Books	Personal	PhD	Terminal	S.F.Ratio	perc.alumni	Expend
Iowa State University	7550		3224	640	2055	81	88	19.2	22	8420
	Grad.Rate									
Iowa State University	65									

- Average graduation rate across all colleges: 65.46332
Iowa State University's graduation rate is 65% which is just below the average
- $\hat{B}_0 = 84.2168$, standard error = 2.1713, p value = $<2e-16$
 $\hat{B}_1 = -1.3310$, standard error = 0.1484, p value = $<2e-16$
So graduation rate is calculated by $= 84.2168 + (-1.3310)(S.F.Ratio)$
Given these statistics, $\hat{B}_1 = -1.3310$ is the average change in graduation rate as there is a one unit change in the student to faculty ratio
-



- Residuals:

Abilene Christian University	Adelphi University	Adrian College
-0.1255965	-11.9785259	-13.0468224
Agnes Scott College	Alaska Pacific University	
-14.9680482	-53.3778274	

Fitted values:

Abilene Christian University	Adelphi University	Adrian College
60.12560	67.97853	67.04682
Agnes Scott College	Alaska Pacific University	
73.96805	68.37783	

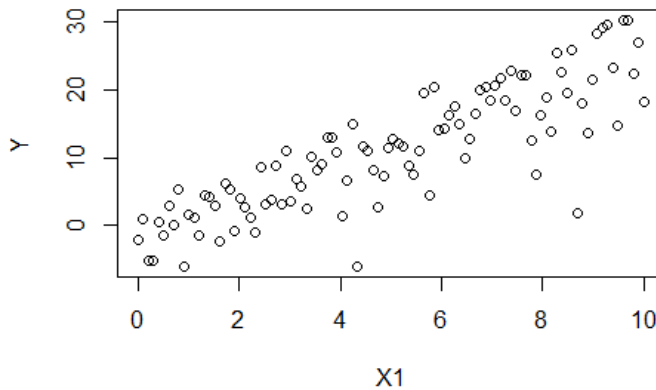
- h. predicted graduation rate when the student-to-faculty ratio is 10 = 70.90674
- i. A test MSE of the model is required to be calculated to understand the prediction accuracy of the model on data that was not included in the model developed. Like stated before, the test MSE is what we could expect the average error to be on the new data the model has not yet seen. To do this, split the data into a training and testing set. Train the model using the training data and then use this model on the test data. Then the MSE for the test data can be calculated.
 - Expected test MSE = 295.8065

Problem 3:

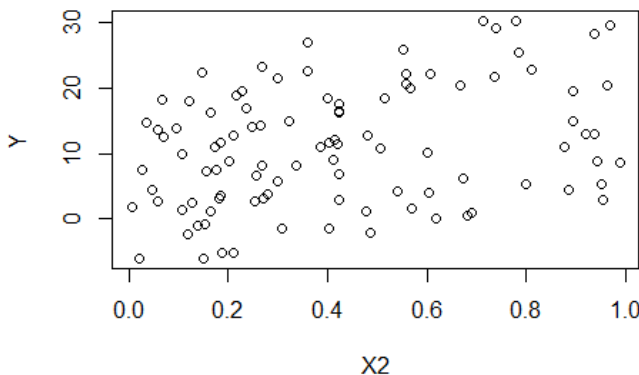
- a. $B_0 = 2, B_1 = 3, B_2 = 5$

[1]	-2.1921818	1.0513192	-5.2340411	-5.2527506	0.6130698	-1.3275483	3.0231447	0.2095631
[9]	5.3691176	-6.0070956	1.5486576	1.2272484	-1.5214411	4.5327420	4.3160611	2.9698086
[17]	-2.2023579	6.2622636	5.3479473	-0.8227962	3.9624270	2.8104741	1.1405682	-0.9413192
[25]	8.5987375	3.1469534	3.8824735	8.9387477	3.2629220	10.9802664	3.6369071	6.7871781
[33]	5.6833423	2.4277324	10.1071745	8.1188537	9.0541070	13.0552466	12.9685007	10.7307054
[41]	1.3162208	6.6933637	15.0283071	-5.9812614	11.7488068	10.9663141	8.2874999	2.6263054
[49]	7.4071819	11.4446759	12.7936996	12.0439339	11.6482617	8.8523216	7.5346995	11.0337281
[57]	19.5942452	4.5032082	20.4689567	14.0500062	14.2995218	16.3340760	17.5659908	15.0263008
[65]	9.8428349	12.8395858	16.4120028	19.9774494	20.4942753	18.5145262	20.7158312	21.7848897
[73]	18.5126209	22.7701192	16.9338435	22.2707934	22.1745199	12.6690765	7.4424298	16.3522494
[81]	18.8488076	13.8966091	25.4766260	22.5636627	19.5619779	26.0131639	1.8184290	17.9869321
[89]	13.6733143	21.5684086	28.4326513	29.1750410	29.5668087	23.2434093	14.8205705	30.2984978
[97]	30.3245585	22.4497786	26.9079566	18.1962604				

- b.
- c. Scatter plot of X_1 and Y



Scatter plot of X_2 and Y



The scatter plot of X_1 compared to Y shows a strong positive linear correlation. The scatter plot of X_2 compared to Y shows a weak positive linear correlation.

```

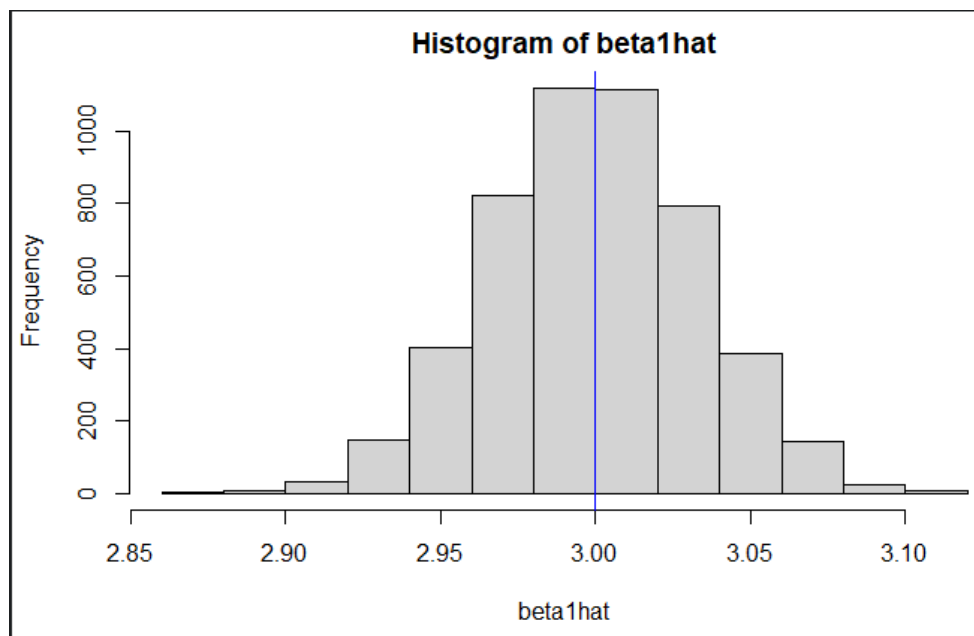
B = 5000
beta0hat = beta1hat = beta2hat = rep(NA,B)
Yhat = rep(NA,B)
for(i in 1:B){
  error = rnorm(n,0,1)
  Y = beta_0 + beta_1*x1 + beta_2*log(x2) + error
  fit = lm(Y~x1 + log(x2))
  beta1hat[i] = fit$coefficients[[2]]
}
beta1hat[i]

```

d.

Mean = 3.008005 which means B1hat is an unbiased estimator of B1

e.



```

B = 5000
beta0hat = beta1hat = beta2hat = rep(NA,B)
Yhat = rep(NA,B)
for(i in 1:B){
  error = rnorm(n,0,1)
  Y = beta_0 + beta_1*x1 + beta_2*log(x2) + error
  fit = lm(Y~x1 + log(x2))
  beta2hat[i] = fit$coefficients[[3]]
}
beta2hat[i]

```

f.

Mean = 5.009441 so B2hat is an unbiased estimator of B2

g.

