

Midterm Exam Part 2: Hands-on Coding Assignment (12 points; 14 questions)

Instructions

Type in your SUID in place of the zeros below and run the cell (click Ctrl + Enter):

```
suid <- 889489533
```

The block of code below creates a custom data set for you to analyze. Your dataset is different from every other student's dataset. The goal of this part of the exam is to write code and comments that address the research questions described below. The quality of your comments is critical to your success on this exam! You will only be submitting this file and there are several important results that require an explanation in plain language. Pay close attention to the research questions described below when writing your code and comments.

Do not modify any of the code, just run it as is:

```
if (suid == 0) {cat("Please update your SUID (above) before running this code.")} else {cat(paste("Lyft, Uber Fare Comparison Study Number: 889489533", "Sample size for this study: 115"))}
```

Your Assignment: rYdZ Analysis

The code you just ran generates a unique dataframe called **testDF**.

You can explore it by running, e.g. `head(testDF)`.

There is an upstart in the ride-sharing market: The new start-up firm **rYdZ** (pronounced rides) is driver-owned and operated. In addition to providing safe rides at competitive prices, the mission of **rYdZ** is to provide a working wage to **rYdZ** drivers. But the leadership team at **rYdZ** believes there is a problem: the two giants in the industry, **Lyft** and **Uber**, are coordinating to set prices for rides that are artificially low? The team at **rYdZ** has produced a data set of more than 100 fares offered to drivers from **Lyft** and **Uber**. Your job is to analyze this data set and infer whether there is some sort of coordination between **Lyft** and **Uber** to set prices, as well as understand if either is pricing based on miles driven, or perhaps, based on geography.

Data Set Description:

Your data set contains **seven variables**: They account for the **ride number**, the **fare** (in dollars and cents) of a ride offered to a driver from Lyft and Uber, as well as the **distance** of those rides (in miles). There is also a **The State the ride was taken in** from Uber and Lyft). There are at least 100 observations (rows) in your dataset, and possibly more. Each observation was done at roughly the same time for Uber and Lyft (the data for the ride in a row was collected at roughly the same time).

Research Questions (tasks to do):

1. Output the 5th Lift fare (0.5 pts)

```
#testDF
subset(testDF, driver==5, select = (Lyft_35))
```

```
##   Lyft_35
## 5    29.55
```

```
testDF[5,2]
```

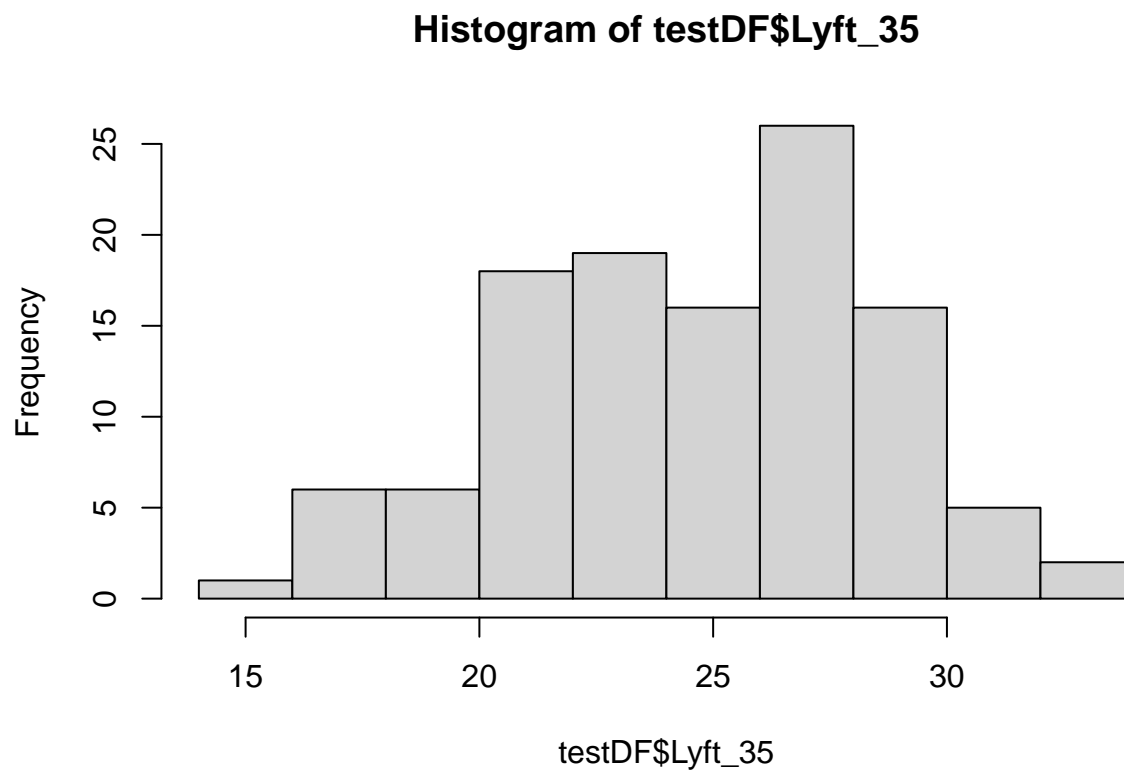
```
## [1] 29.55
```

2. Describe the fares provided by Lyft and Uber (separately) using descriptive statistics that you calculate in R (1 pts):

```
#summary(testDF) #Summary of the whole testDF dataframe
summary(testDF$Lyft_35) #Summary of the Lyft_35 column of the dataframe
```

```
##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
## 15.91   21.62   24.81   24.63   27.42   33.24
```

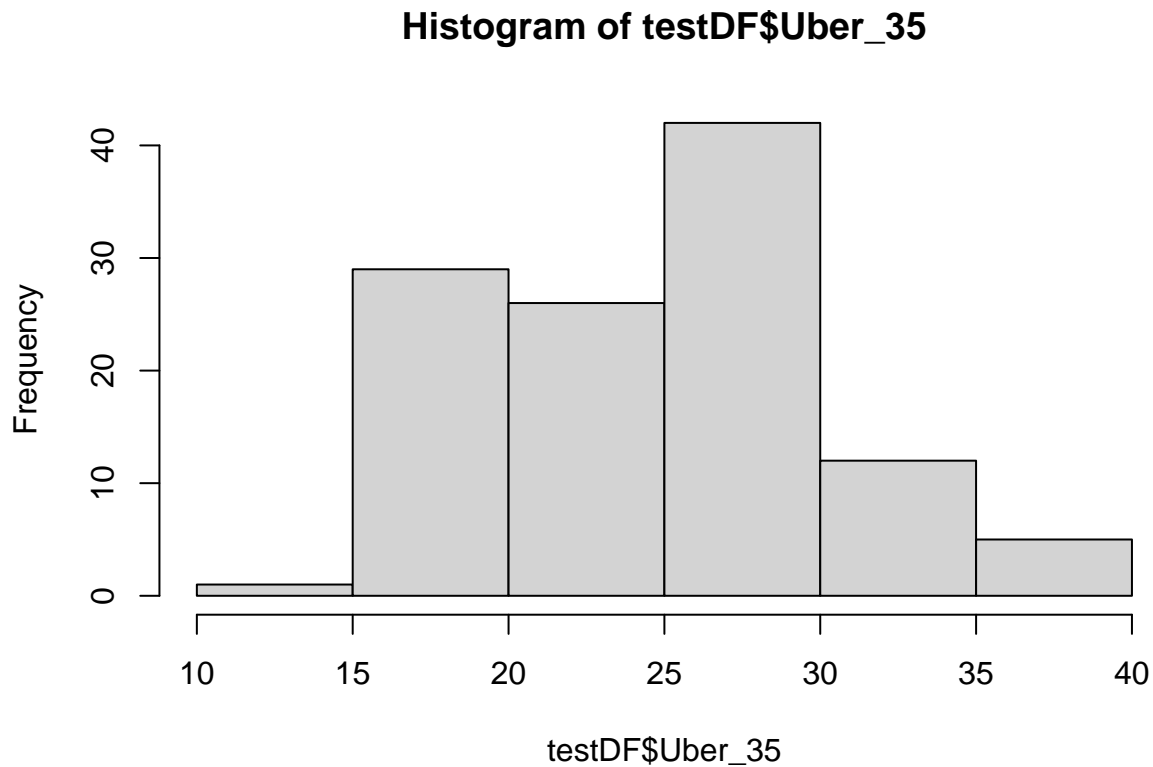
```
hist(testDF$Lyft_35) #Histogram
```



```
summary(testDF$Uber_35) #Summary of the Uber_35 column of the dataframe
```

```
##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##    14.51   19.32   25.17   24.75   29.16   37.63
```

```
hist(testDF$Uber_35) #Histogram
```



3. Describe the shape of the distribution for Lyft fares. Do the same for Uber fares (1 pt)

```
#The shape of the distribution for Lyft fares is pretty much normally distributed, with a min of 15.91,
```

```
#The shape of the distribution for Lyft fares is also normally distributed, with a min of 14.51, max of
```

4. Based on the fares offered by both companies, on average, which company is more expensive, Lyft or Uber? By how much? (0.5 pts)

```
mean_Lyft_35 <- mean(testDF$Lyft_35)
mean_Uber_35 <- mean(testDF$Uber_35)
mean_Lyft_35
```

```
## [1] 24.62817
```

```
mean_Uber_35
```

```
## [1] 24.75435
```

```
#We can observe that average Uber fares are higher than that of Lyft fares. Thus, Uber is generally mor  
difference <- mean_Uber_35 - mean_Lyft_35  
difference
```

```
## [1] 0.1261739
```

```
#Average Uber fares are higher than Lyft fares by $0.12617.
```

5. Create a new attribute, called 'diff' in testDF, that represents the difference in fares between Uber and Lyft for each observation - in other words, the difference for each row(0.5 pts):

```
testDF$diff <- testDF$Uber_35 - testDF$Lyft_35  
testDF
```

```
##      driver Lyft_35 Uber_35 Lyft_35_distance Uber_35_distance Lyft_35_state  
## 1         1  26.46  28.66      63.770791      35.15218      Florida  
## 2         2  17.86  29.88      22.701646      36.13890        Texas  
## 3         3  24.45  19.08      36.321004      23.74384      New York  
## 4         4  27.15  19.14      62.364721      26.71386      New York  
## 5         5  29.55  31.02      63.684445      37.86171        Texas  
## 6         6  20.74  25.05      32.014158      30.70382      New York  
## 7         7  27.80  27.83      60.039761      35.16039        Texas  
## 8         8  23.51  16.26      20.071887      21.18680      Florida  
## 9         9  22.30  25.17      43.342825      32.75983      New York  
## 10        10  25.74  21.67      84.490662      27.09633        Texas  
## 11        11  27.24  26.87      76.967172      32.98336      Florida  
## 12        12  28.04  29.14      47.006770      36.53638      New York  
## 13        13  21.19  27.83      43.915779      34.80935      New York  
## 14        14  24.81  21.91      29.432940      28.94104        Texas  
## 15        15  26.13  26.95      60.595981      35.43072      Florida  
## 16        16  28.44  33.38      19.200787      39.23079        Texas  
## 17        17  23.86  17.89       4.388303      22.31568      Florida  
## 18        18  22.94  29.52      53.677322      37.02667      New York  
## 19        19  24.13  14.51      52.107999      21.58759        Texas  
## 20        20  20.81  16.94      64.359109      24.28997        Texas  
## 21        21  22.84  24.60      78.398380      31.96528        Texas  
## 22        22  27.86  29.78      74.747588      35.06849        Texas  
## 23        23  16.42  22.49      54.510339      26.23378      New York  
## 24        24  30.79  23.15      27.782055      29.98007        Texas  
## 25        25  29.15  23.06      34.290939      29.93104      Florida  
## 26        26  22.18  23.13      52.217394      31.31574      New York  
## 27        27  26.54  20.93      29.416690      26.56547      New York  
## 28        28  31.02  25.79      84.547909      31.00649        Texas  
## 29        29  33.24  37.63      38.901216      43.91328      New York  
## 30        30  25.70  18.78      49.278921      23.53185      New York  
## 31        31  22.36  18.33      54.060381      28.38043      New York  
## 32        32  21.63  24.39      77.716822      31.42080      Florida
```

## 33	33	16.82	17.41	68.436793	22.90503	New York
## 34	34	21.59	19.31	58.572150	24.40327	Texas
## 35	35	23.38	25.92	37.723282	33.93535	Florida
## 36	36	26.12	31.60	50.061625	35.37445	Florida
## 37	37	28.81	17.05	69.850761	21.69321	Florida
## 38	38	29.68	35.47	46.240381	42.38979	Texas
## 39	39	25.42	26.67	54.113559	30.48443	New York
## 40	40	22.87	19.34	44.720780	25.87562	Texas
## 41	41	25.84	26.12	25.732217	35.11915	Florida
## 42	42	27.46	21.22	44.004867	26.66737	Florida
## 43	43	21.90	26.35	37.465067	33.84197	Texas
## 44	44	17.36	16.81	39.937051	22.14689	Texas
## 45	45	21.51	31.11	43.809603	37.70396	Florida
## 46	46	21.13	30.38	42.016452	38.56709	Texas
## 47	47	22.04	19.20	27.600094	28.65345	Texas
## 48	48	24.02	20.48	37.319986	26.98586	Texas
## 49	49	20.57	22.86	67.106135	27.51521	New York
## 50	50	27.57	30.39	76.550688	36.85256	Texas
## 51	51	23.12	19.18	43.966484	27.75506	New York
## 52	52	27.38	28.99	70.161971	34.92453	Texas
## 53	53	23.84	15.77	67.803279	23.12944	New York
## 54	54	29.60	33.93	75.245372	40.29426	Texas
## 55	55	22.80	28.12	55.968850	36.02117	Texas
## 56	56	20.51	27.50	8.999394	32.30784	Texas
## 57	57	27.55	33.60	43.517791	40.46107	Texas
## 58	58	26.31	28.26	51.173245	36.11737	New York
## 59	59	21.08	29.63	19.523510	35.94380	New York
## 60	60	28.41	31.54	48.113501	36.87524	New York
## 61	61	26.48	27.51	12.218052	32.89430	New York
## 62	62	19.41	26.71	101.311550	33.14916	Texas
## 63	63	21.08	18.98	39.578077	24.90000	Texas
## 64	64	19.20	16.42	74.615584	24.55165	Florida
## 65	65	23.40	21.01	59.107794	27.15312	Florida
## 66	66	26.43	25.23	50.544154	32.30993	Texas
## 67	67	22.81	22.52	29.812751	28.91299	New York
## 68	68	26.56	27.02	86.313872	33.22396	New York
## 69	69	25.16	29.26	25.038360	34.72565	Florida
## 70	70	24.34	29.68	59.490317	36.24331	Florida
## 71	71	28.81	31.54	76.298221	37.30273	Texas
## 72	72	23.38	27.50	55.325583	33.21883	Texas
## 73	73	30.50	36.73	40.495889	41.95958	Texas
## 74	74	29.64	29.39	87.101071	35.13040	New York
## 75	75	24.42	18.78	43.140847	24.73021	Texas
## 76	76	21.26	30.56	71.546722	37.36229	Florida
## 77	77	31.12	35.05	22.484211	40.47531	Texas
## 78	78	15.91	22.31	34.387315	29.97805	Florida
## 79	79	17.97	25.26	22.679629	31.53091	Florida
## 80	80	18.31	25.83	73.621583	32.06184	New York
## 81	81	26.77	29.01	51.220561	35.04548	New York
## 82	82	21.62	26.42	40.584678	33.62210	Florida
## 83	83	23.86	19.21	34.325855	25.41997	New York
## 84	84	16.82	18.63	54.937428	23.57925	New York
## 85	85	26.56	17.93	64.885562	23.81206	Florida
## 86	86	29.30	29.04	65.619232	34.51223	Florida

## 87	87	22.68	17.17	66.533183	23.95076	Florida
## 88	88	28.13	29.88	60.261951	33.01051	Florida
## 89	89	26.81	33.06	29.549442	40.51030	Texas
## 90	90	26.22	26.98	52.447600	31.60866	New York
## 91	91	25.45	20.87	53.389619	28.96279	Florida
## 92	92	27.88	30.00	52.388646	38.68978	New York
## 93	93	26.41	28.75	0.000000	33.51567	Texas
## 94	94	28.92	24.99	43.230302	29.68967	New York
## 95	95	29.94	21.23	46.790176	28.63599	Florida
## 96	96	29.50	18.36	101.306633	25.01995	Texas
## 97	97	25.43	23.10	82.002283	28.64902	New York
## 98	98	24.44	29.17	50.784485	33.16226	New York
## 99	99	20.35	20.90	52.167684	28.33590	Texas
## 100	100	18.54	20.27	47.968475	27.10845	New York
## 101	101	26.26	26.33	54.338782	34.16845	Texas
## 102	102	26.73	24.27	60.580043	28.77240	New York
## 103	103	19.49	17.79	30.458760	25.07885	Texas
## 104	104	31.38	20.81	68.847653	28.85298	Texas
## 105	105	21.30	17.80	40.691952	22.89772	Texas
## 106	106	25.17	18.90	37.787527	25.46384	Florida
## 107	107	26.78	21.47	74.264306	28.09948	New York
## 108	108	24.03	29.87	27.881436	35.82321	Texas
## 109	109	21.52	22.02	23.356135	29.04139	New York
## 110	110	18.48	16.59	84.958348	21.38529	Texas
## 111	111	32.54	35.37	72.149413	42.00545	Texas
## 112	112	23.95	17.35	95.813296	23.27680	Texas
## 113	113	26.05	29.35	40.453184	36.41615	New York
## 114	114	28.30	23.55	49.355202	28.68437	Texas
## 115	115	20.87	18.05	58.790638	25.07892	Texas
##	Uber_35_state	diff				
## 1	Florida	2.20				
## 2	Texas	12.02				
## 3	New York	-5.37				
## 4	New York	-8.01				
## 5	Texas	1.47				
## 6	New York	4.31				
## 7	Texas	0.03				
## 8	Florida	-7.25				
## 9	New York	2.87				
## 10	Texas	-4.07				
## 11	Florida	-0.37				
## 12	New York	1.10				
## 13	New York	6.64				
## 14	Texas	-2.90				
## 15	Florida	0.82				
## 16	Texas	4.94				
## 17	Florida	-5.97				
## 18	New York	6.58				
## 19	Texas	-9.62				
## 20	Texas	-3.87				
## 21	Texas	1.76				
## 22	Texas	1.92				
## 23	New York	6.07				
## 24	Texas	-7.64				

## 25	Florida	-6.09
## 26	New York	0.95
## 27	New York	-5.61
## 28	Texas	-5.23
## 29	New York	4.39
## 30	New York	-6.92
## 31	New York	-4.03
## 32	Florida	2.76
## 33	New York	0.59
## 34	Texas	-2.28
## 35	Florida	2.54
## 36	Florida	5.48
## 37	Florida	-11.76
## 38	Texas	5.79
## 39	New York	1.25
## 40	Texas	-3.53
## 41	Florida	0.28
## 42	Florida	-6.24
## 43	Texas	4.45
## 44	Texas	-0.55
## 45	Florida	9.60
## 46	Texas	9.25
## 47	Texas	-2.84
## 48	Texas	-3.54
## 49	New York	2.29
## 50	Texas	2.82
## 51	New York	-3.94
## 52	Texas	1.61
## 53	New York	-8.07
## 54	Texas	4.33
## 55	Texas	5.32
## 56	Texas	6.99
## 57	Texas	6.05
## 58	New York	1.95
## 59	New York	8.55
## 60	New York	3.13
## 61	New York	1.03
## 62	Texas	7.30
## 63	Texas	-2.10
## 64	Florida	-2.78
## 65	Florida	-2.39
## 66	Texas	-1.20
## 67	New York	-0.29
## 68	New York	0.46
## 69	Florida	4.10
## 70	Florida	5.34
## 71	Texas	2.73
## 72	Texas	4.12
## 73	Texas	6.23
## 74	New York	-0.25
## 75	Texas	-5.64
## 76	Florida	9.30
## 77	Texas	3.93
## 78	Florida	6.40

## 79	Florida	7.29
## 80	New York	7.52
## 81	New York	2.24
## 82	Florida	4.80
## 83	New York	-4.65
## 84	New York	1.81
## 85	Florida	-8.63
## 86	Florida	-0.26
## 87	Florida	-5.51
## 88	Florida	1.75
## 89	Texas	6.25
## 90	New York	0.76
## 91	Florida	-4.58
## 92	New York	2.12
## 93	Texas	2.34
## 94	New York	-3.93
## 95	Florida	-8.71
## 96	Texas	-11.14
## 97	New York	-2.33
## 98	New York	4.73
## 99	Texas	0.55
## 100	New York	1.73
## 101	Texas	0.07
## 102	New York	-2.46
## 103	Texas	-1.70
## 104	Texas	-10.57
## 105	Texas	-3.50
## 106	Florida	-6.27
## 107	New York	-5.31
## 108	Texas	5.84
## 109	New York	0.50
## 110	Texas	-1.89
## 111	Texas	2.83
## 112	Texas	-6.60
## 113	New York	3.30
## 114	Texas	-4.75
## 115	Texas	-2.82

6. Describe the shape of the distribution for this new variable(0.5 pts)

```
summary(testDF$diff)
```

##	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
##	-11.7600	-3.9000	0.7600	0.1262	4.1100	12.0200


```
hist(testDF$diff)
```



7. Sort testDF, based on the new attribute (*diff*), and store the sorted dataframe in 'sortedDF'. Show the first and last row in the sortedDF dataframe (1 pt)

```
sortedDF <- testDF[order(testDF$diff),]  
#sortedDF  
head(sortedDF, 5)
```

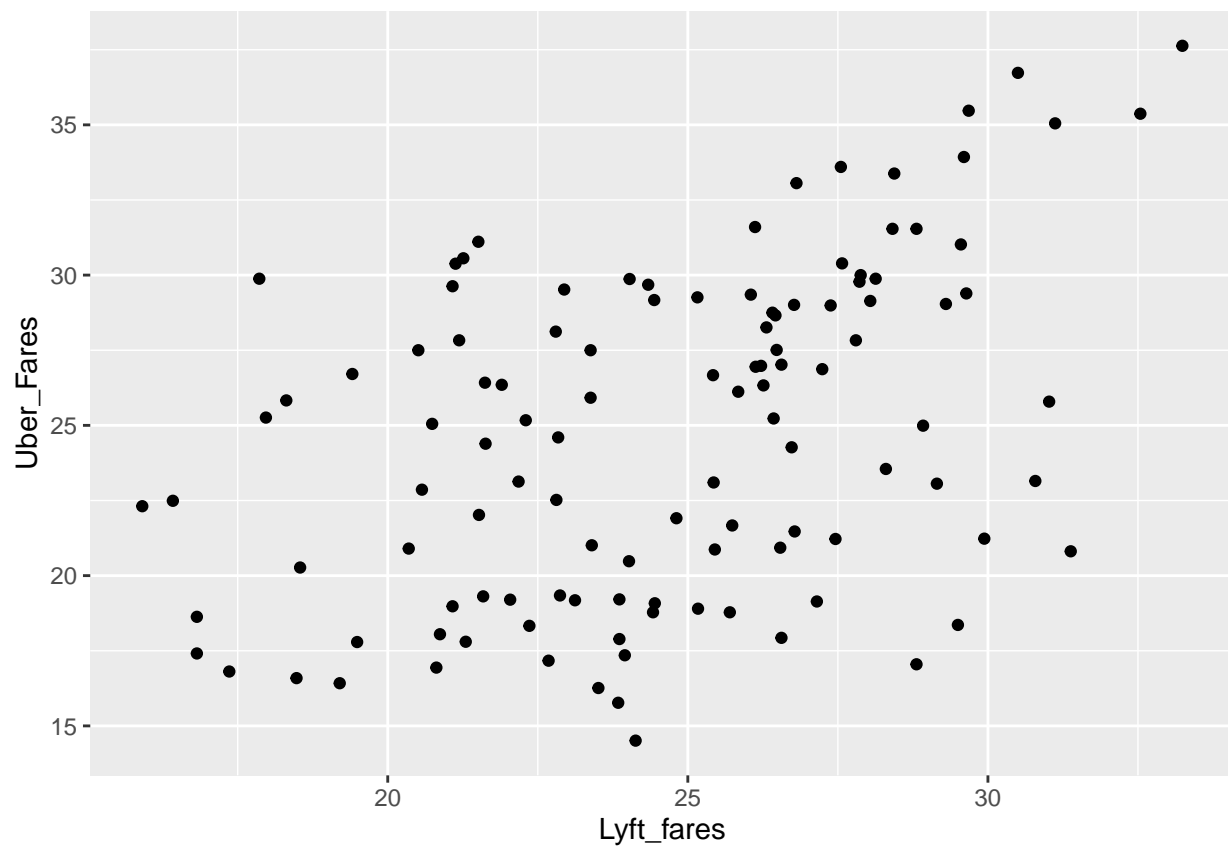
```
##      driver Lyft_35 Uber_35 Lyft_35_distance Uber_35_distance Lyft_35_state  
## 37      37   28.81  17.05         69.85076         21.69321      Florida  
## 96      96   29.50  18.36        101.30663         25.01995        Texas  
## 104     104   31.38  20.81         68.84765         28.85298        Texas  
## 19      19   24.13  14.51         52.10800         21.58759        Texas  
## 95      95   29.94  21.23         46.79018         28.63599      Florida  
##      Uber_35_state  diff  
## 37      Florida -11.76  
## 96      Texas -11.14  
## 104     Texas -10.57  
## 19      Texas  -9.62  
## 95      Florida  -8.71
```

```
tail(sortedDF, 5)
```

```
##      driver Lyft_35 Uber_35 Lyft_35_distance Uber_35_distance Lyft_35_state
## 59      59  21.08  29.63      19.52351      35.94380      New York
## 46      46  21.13  30.38      42.01645      38.56709        Texas
## 76      76  21.26  30.56      71.54672      37.36229      Florida
## 45      45  21.51  31.11      43.80960      37.70396      Florida
## 2       2  17.86  29.88      22.70165      36.13890        Texas
##      Uber_35_state diff
## 59      New York  8.55
## 46        Texas  9.25
## 76      Florida  9.30
## 45      Florida  9.60
## 2         Texas 12.02
```

8. Create an X-Y scatterplot of the Lyft and Uber fares for the unsorted dataset (make sure to provide informative labels for each axis). Does the scatterplot show an obvious pattern/relationship? (1 pt total)

```
library(ggplot2)
ggplot(testDF) + geom_point(aes(x=Lyft_35, y=Uber_35)) + xlab("Lyft_fares") + ylab("Uber_Fares")
```



#Yes, we can observe that there is indeed a relatively linear relationship of a positive slope between .

9. Generate a linear model trying to predict Lyft fares based on the distance of the trip. Interpret the coefficients of the statistically significant predictors in the model (1 pt).

```
lmOut1 <- lm(formula = Lyft_35 ~ Lyft_35_distance, data=testDF)
summary(lmOut1)
```

```
##
## Call:
## lm(formula = Lyft_35 ~ Lyft_35_distance, data = testDF)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -8.3412 -2.6270  0.2817  2.7148  8.8876
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)    23.47988    0.96200   24.407  <2e-16 ***
## Lyft_35_distance  0.02243    0.01745    1.285    0.201
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 3.821 on 113 degrees of freedom
## Multiple R-squared:  0.0144, Adjusted R-squared:  0.005681
## F-statistic: 1.651 on 1 and 113 DF, p-value: 0.2014
```

```
#Lyft_35 = 0.02243 * Lyft_35_distance + 23.47988 (y=mx+b)
# Coefficient (m) is 0.03333 and the intercept (b) is 23.38682
# Lyft_13_distance is not statistically significant as the p value(0.2014) is greater than 0.05
# Adjusted R-squared is approximately 0.005681
```

10. Generate a similar model for the Uber trips. Interpret the coefficients of the statistically significant predictors in the model (0.5 pts)

```
lmOut2 <- lm(formula = Uber_35 ~ Uber_35_distance, data=testDF)
summary(lmOut2)
```

```
##
## Call:
## lm(formula = Uber_35 ~ Uber_35_distance, data = testDF)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -3.8059 -0.8153  0.0515  0.8842  3.3022
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)    -5.0909    0.6730  -7.564 1.12e-11 ***
## Uber_35_distance  0.9594    0.0213  45.041 < 2e-16 ***
## ---
```

```
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.263 on 113 degrees of freedom
## Multiple R-squared:  0.9472, Adjusted R-squared:  0.9468
## F-statistic: 2029 on 1 and 113 DF,  p-value: < 2.2e-16
```

```
#Uber_35 = 0.9594 * Uber_35_distance - 5.0909 (y=mx+b)
# Coefficient (m) is 0.9594 and the intercept (b) is -5.0909
# Lyft_13_distance is statistically significant as the p value (2.2e-16) is lesser than 0.05
# Adjusted R-squared is approximately 0.005681
```

11. Which model is better? Please explain your answer (0.5 pts)

```
#The Uber model is significantly better as we can see that all the coefficients are highly significant
```

12. What would be your model's prediction of the Lyft fare for a 2.39 mile trip? (1 pt).

```
predDF <- data.frame(Lyft_35_distance=2.39)
predict(lmOut1, predDF)
```

```
##          1
## 23.53349
```

```
# it will cost $23.53349
```

13. Generate a map where each state is shaded according to the average fare for Uber. Make sure even states with no data are visible on your map (2 pts)

```
library(tidyverse)
```

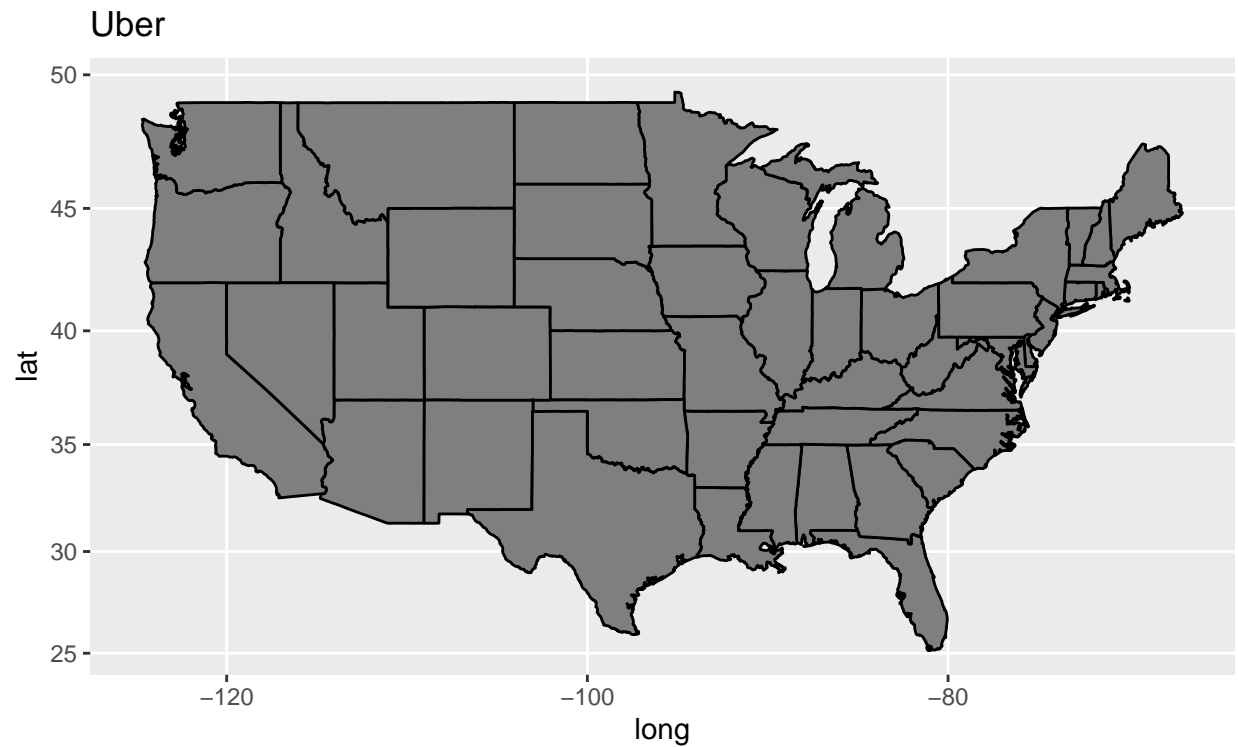
```
## -- Attaching packages ----- tidyverse 1.3.1 --
```

```
## v tibble  3.1.4      v dplyr    1.0.7
## v tidyr   1.1.3      v stringr 1.4.0
## v readr   2.0.1      v forcats 0.5.1
## v purrr   0.3.4
```

```
## -- Conflicts ----- tidyverse_conflicts() --
```

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

```
sortedDF <- sortedDF %>% group_by(Uber_35_state)
step111 <- aggregate(x=sortedDF$Uber_35, by= list(sortedDF$Uber_35_state), mean)
sortedDF$Uber_35_state <- tolower(sortedDF$Uber_35_state)
us <- map_data("state")
mergeUsData1000 <- merge(us, step111, by.x = "region", by.y = "Group.1", all.x = TRUE)
mergeUsData1000 <- mergeUsData1000 %>% arrange(order)
map40 <- ggplot(mergeUsData1000)
map40 <- map40 + geom_polygon(color="black", aes(x=long,y=lat, group=group, fill=x))
map40 <- map40 + coord_map() + ggtitle("Uber")
map40
```



14. Include a comment indicating whether or not you think Lyft and Uber fares are related based only on your data analysis. If the distributions of Lyft fares and Uber fares look similar and the distribution of the differences variable is normal and the X-Y scatterplot shows a clear pattern or relationship, then they may be related, i.e. they may be coordinating prices (1 pt).

According to me, the analysis of both of the fare distributions are normal and similar. When we analyze the data, we observed that when we are predicting fares with respect to distance, the linear model of Uber is better than Lyft.