

# R Notebook

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#packages

## Housing Data Summary

House Pricing is the most intrinsic factor of economy, and they are of great interest for buyers and sellers. Moreover, nowadays housing price and property taxes is increasing rapidly and it is an important factor that needs to be considered, before purchasing a house because it is a long - term investment. From the survey of 2007 and 2008, it was found that many people bought the house on the basis of assumptions that housing price and property price will decrease in year 2007 and considering that factor, they took the loan from the bank and invested into properties, but that was not the case and this recession impacted many financial statements of individuals. Thus, the goal of the project is to build a regression model that would help to determine the factors that would lead to increase in housing price in different divisions and states. My aim is to focus on model which predict the Property Taxes on the basis of divisions, states, insurance, bathroom, kitchen and many more factors. This will give consciousness to individuals about the considerations of factors that needs to be taken before buying or selling house.

## Methodology

Moreover, from ACS housing data I have filtered some columns which includes State, Division, Acres, Tax, Agro Products sales, Bath, Kitchen, Rent of house, and other household utilities which will help me to find the prediction of house before buying. I had similarly done this project in Foundation of Modelling in which we need to analyze some research paper on the basis of some topic. So, I decided to go with the Housing data in R and apply some research methods on it. In the research paper, they had simply cleaned the data and applied linear regression model on it, but in my project I tried to do some tests on it and also performed different relation, which can help individual in buying housing property.

Therefore, I have performed different steps to identify regression model. 1st step: Loading and filtering data 2ndstep: Weighted mean of Monthly Rent and Insurance 3rd step: Labelling factors for better understanding 4th step: Performing different graphs for understanding relationship 5th step: Applied some tests on it 6th step: Checking AIC and Bic, to see which model fits better 7th step: Splitting data into train and test data 8th step: Building Linear Regression Model 9th step: Predicting model by using test data 10th step: Visualizing summary of model

```
fields <- c("RT", "DIVISION", "ADJHSG", "ST", "WGTP",
            "ACR", "AGS", "BATH", "BDSP", "HOTWAT",
            "INSP", "RMSP", "SINK", "STOV", "TEL",
            "TOIL", "VALP", "YBL", "KIT", "TAXP",
            "RNTP")

A <- data.frame(fread
("C:/Users/Janvi/Documents/R/Final Project/csv_hus/psam_husa.csv",
  header=TRUE, select = fields))

B <- data.frame(fread
("C:/Users/Janvi/Documents/R/Final Project/csv_hus/psam_husb.csv",
  header=TRUE, select = fields))

C <- data.frame(fread
("C:/Users/Janvi/Documents/R/Final Project/csv_hus/psam_husc.csv",
  header=TRUE, select = fields))

D <- data.frame(fread
("C:/Users/Janvi/Documents/R/Final Project/csv_hus/psam_husd.csv",
  header=TRUE, select = fields))

bind_data <- rbind(A,B,C,D)

bind_data <- bind_data %>%
  rename("RecordType" = RT, "DIVISION" = DIVISION,
        "Adjacent Factor" = ADJHSG, "State" = ST,
        "Housingweight" = WGTP, "HouseAcre" = ACR,
        "SaleofAgroProduct" = AGS, "Bathtub" = BATH,
        "Bedrooms" = BDSP, "HotWater" = HOTWAT,
        "Insurance" = INSP, "Stove" = STOV,
        "TelephoneService" = TEL, "Toilet" = TOIL,
        "PropertyValue" = VALP, "HouseStructureYear" = YBL,
        "Kitchen" = KIT, "Tax" = TAXP, "MonthlyRent" = RNTP)
View(bind_data)
```

# Weighted mean and labelling factors

In this section I have weighted monthly rent by adjacent factor to result it into dollars, then I have done same for the Insurance. Furthermore, I have labelled the factors of state, year built in and divisions. In the end of this chunk I have omitted the Na values and based upon that I have performed different relation of graphs.

```

#Weighted monthly rent
bind_data["RENT"]=bind_data["Adjacent Factor"]*bind_data["MonthlyRent"]/1000000

###Weighted mean of Insurance
bind_data["INSURANCE"]=bind_data["Adjacent Factor"]*bind_data["Insurance"]/1000000

#Labeling factors of DIVISION
bind_data$DIVISION <- factor(bind_data$DIVISION,
                             levels = c(1,2,3,4,5,6,7,8,9),
                             labels = c("New England", "Middle Atlantic",
                                          "East North Central",
                                          "West North Central",
                                          "South Atlantic",
                                          "East South Central",
                                          "West South Central",
                                          "Mountain","Pacific"))

bind_data$HouseStructureYear <- factor(bind_data$HouseStructureYear,
                                       levels = c(1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,
                                                  16,17,18,19,20,21),
                                       labels = c("1939 or earlier","1940 to 1949",
                                                  "1950 to 1959",
                                                  "1960 to 1969",
                                                  "1970 to 1979",
                                                  "1980 to 1989",
                                                  "1990 to 1999",
                                                  "2000 to 2004",
                                                  "2005", "2006", "2007",
                                                  "2008", "2009", "2010",
                                                  "2011", "2012", "2013",
                                                  "2014",
                                                  "2015",
                                                  "2016 ",
                                                  "2017"))

#Labeling states
bind_data$State <- factor(bind_data$State,
                          levels = c(1,2,4,5,6,8,9,
                                      10,11,12,13,15,16,17,18,
                                      19,20,21,22,23,24,25,26,27,
                                      28,29,30,31,32,33,34,35,36,
                                      37,38,39,40,41,42,44,45,
                                      46,47,48,49,50,51,53,54,
                                      55,56,72),
                          labels =
c("AL", "AK", "AZ", "AR", "CA", "CO", "CT", "DE",
  "DC", "FL", "GA", "HI", "ID", "IL", "IN", "IA",
  "KS", "KY", "LA", "ME", "MD", "MA", "MI", "MN",
  "MS", "MO", "MT", "NE", "NV", "NH", "NJ", "NM",

```

```

"NY", "NC", "ND", "OH", "OK", "OR", "PA", "RI",
"SC", "SD", "TN", "TX", "UT", "VT", "VA", "WA",
"WV", "WI", "WY", "PR"))

##Removing NA from data
Without_NA <- bind_data %>% select(State,DIVISION,Bathtub,HotWater,Bedrooms,RMSP,SINK,
Stove,Toilet,
      HouseStructureYear,Kitchen,RENT) %>% group_by(RENT) %>% na.omit()
head(Without_NA)

```

State <fctr>	DIVISION <fctr>	Bathtub <int>	HotWater <int>	Bedro... <int>	R... <int>	S... <int>	St... <int>	Toilet <int>	House <fctr>
AL	East South Central	1	9	4	6	1	1	1	1980 to
AL	East South Central	1	9	1	3	1	1	1	1970 to
AL	East South Central	1	9	1	2	1	1	1	2006
AL	East South Central	1	9	2	4	1	1	1	1990 to
AL	East South Central	1	9	2	4	1	1	1	1980 to
AL	East South Central	1	9	3	6	1	1	1	1950 to

6 rows | 1-10 of 12 columns

## Plotting Divisions by 2017 year wise

From the below graph we can see that number of houses built in South Atlantic are around 400 in year 2017 and least were built in New England, so the consumption of lands in New England is less, so we can predict that, rent in that division would be less. Moreover, when we tried that relation with omitted NA values then west south central shows highest built houses in year 2017, which is wrong prediction and thus by omitting NA can change a lot of result.

```

#Analysing Divisions Rent in 2017 year
year_division_bind <- bind_data %>%
  select(DIVISION,Bathtub,RMSP,HouseStructureYear,RENT) %>%
  filter(HouseStructureYear == 2017) %>%
  group_by(DIVISION) %>%
  summarise(Count=n())
year_division_bind

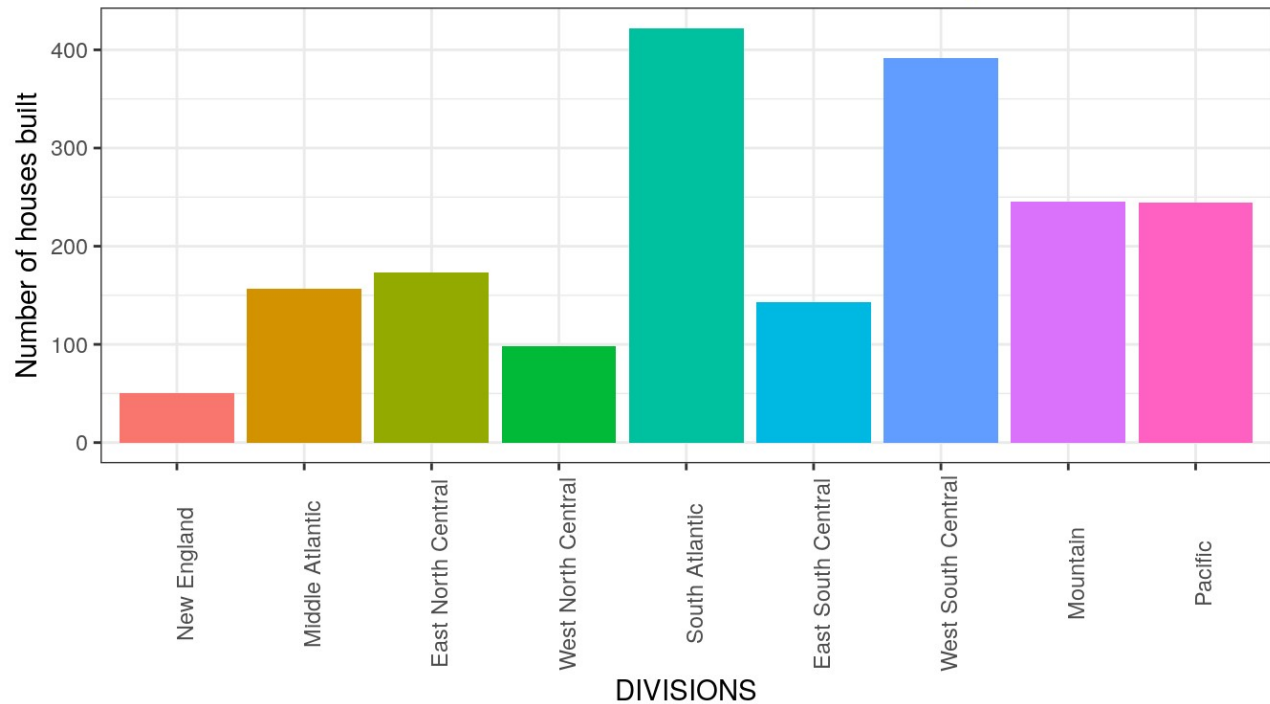
```

DIVISION <fctr>	Count <int>
New England	50
Middle Atlantic	157

<b>DIVISION</b> <fctr>	<b>Count</b> <int>
East North Central	173
West North Central	98
South Atlantic	422
East South Central	143
West South Central	392
Mountain	245
Pacific	244
9 rows	

```
#plot
ggplot(year_division_bind)+
  geom_col(mapping =aes(x= DIVISION,y= Count,fill=DIVISION))+
  ggtitle("Number of houses built in different divisions in year 2017")+
  xlab("DIVISIONS")+ylab("Number of houses built")+ theme_bw()+
  theme(plot.title= element_text(color="#0033FF",hjust = 0.5),
        axis.text.x = element_text(angle = 90),
        legend.position= "bottom")
```

## Number of houses built in different divisions in year 2017



DIVISION

<span style="color: red;">■</span> New England	<span style="color: olive;">■</span> East North Central	<span style="color: teal;">■</span> South Atlantic	<span style="color: blue;">■</span> West South Central	<span style="color: pink;">■</span> Pa
<span style="color: orange;">■</span> Middle Atlantic	<span style="color: green;">■</span> West North Central	<span style="color: cyan;">■</span> East South Central	<span style="color: purple;">■</span> Mountain	

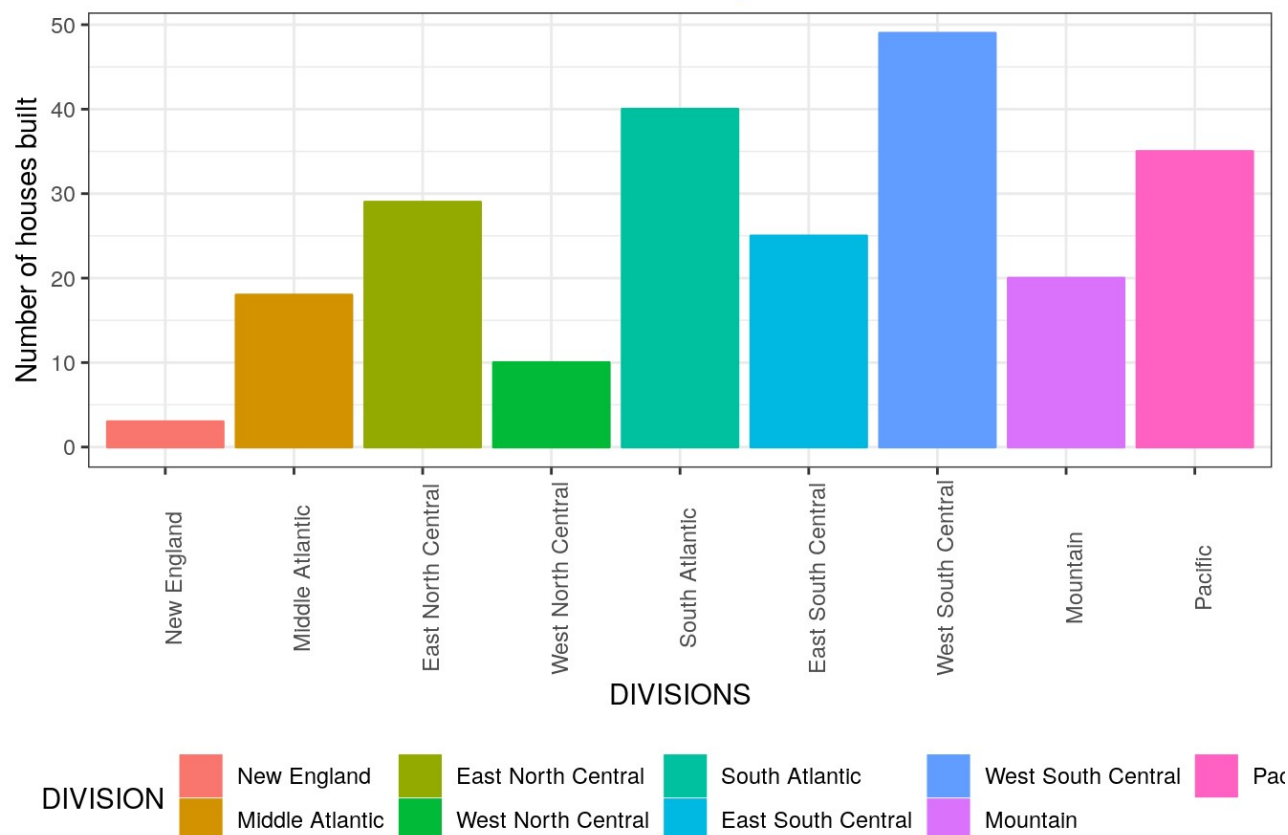
```
#Analysing Divisions Rent in 2017 year by omitting NA
year_division <- Without_NA%>%
  select(DIVISION,Bathtub,RMSP,HouseStructureYear,RENT) %>%
  filter(HouseStructureYear == 2017) %>%
  group_by(DIVISION) %>%
  summarise(Count=n())
year_division
```

DIVISION <fctr>	Count <int>
New England	3
Middle Atlantic	18
East North Central	29
West North Central	10
South Atlantic	40
East South Central	25
West South Central	49

DIVISION <fctr>	Count <int>
Mountain	20
Pacific	35
9 rows	

```
#plot
ggplot(year_division)+
  geom_col(mapping =aes(x= DIVISION,y= Count,colour =
                        DIVISION,fill=DIVISION))+
  ggtitle("Division wise House count built in year 2017 With omitted NA") +
  xlab("DIVISIONS")+ylab("Number of houses built")+ theme_bw()+
  theme(plot.title= element_text(color="#0033FF",hjust = 0.5),
        axis.text.x = element_text(angle = 90),legend.position =
        "bottom")
```

Division wise House count built in year 2017 With omitted NA





# Rent vs Division in year 2017

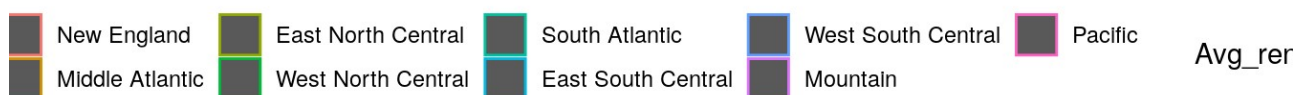
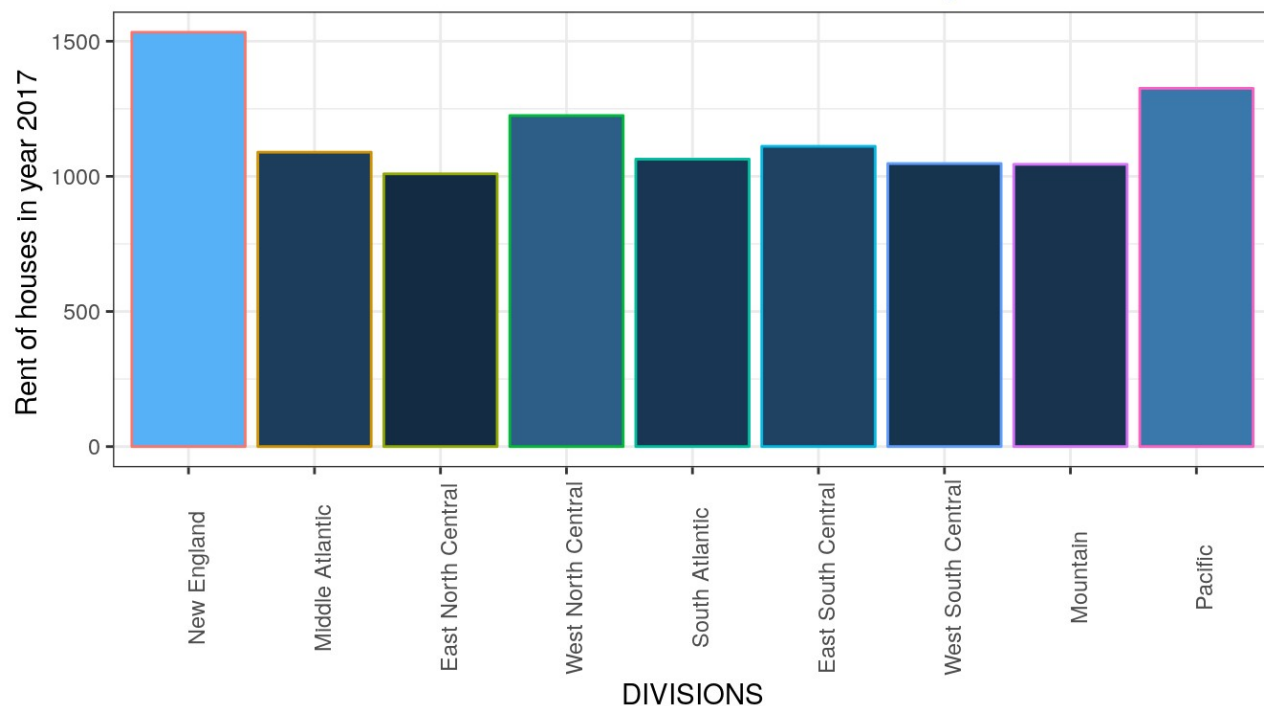
The below graph represents that average Rent of houses built in year 2017 were high in New England and least were in Mountain and East North Central, so investors can easily buy their houses on basis of rent. Moreover, in this graph when I tried with actual data without omitted NA value than I saw that there was no difference, so here I used data with omitted value to visualize data in better way.

```
#Plotting rent ,division wise in year 2017
rent_year <- Without_NA %>%
select(DIVISION,Bathtub,RMSP,HouseStructureYear,RENT) %>%
filter(HouseStructureYear == 2017 ) %>%
group_by(DIVISION) %>% summarise(Avg_rent=mean(RENT))
rent_year
```

DIVISION <fctr>	Avg_rent <dbl>
New England	1533.333
Middle Atlantic	1089.444
East North Central	1009.310
West North Central	1225.000
South Atlantic	1063.750
East South Central	1111.200
West South Central	1047.429
Mountain	1044.500
Pacific	1325.829
9 rows	

```
#Plot
ggplot(rent_year)+
  geom_col(aes(x= DIVISION,y= Avg_rent,colour = DIVISION,fill=Avg_rent))+
  ggtitle("Rent of houses built in different divisions in year 2017")+
  xlab("DIVISIONS")+ylab("Rent of houses in year 2017 ")+
  theme_bw()+
  theme(plot.title= element_text(color="#0033FF",hjust = 0.5),
        axis.text.x = element_text(angle = 90),
        legend.position = "bottom")
```

Rent of houses built in different divisions in year 2017



## ## Total Rent in different states

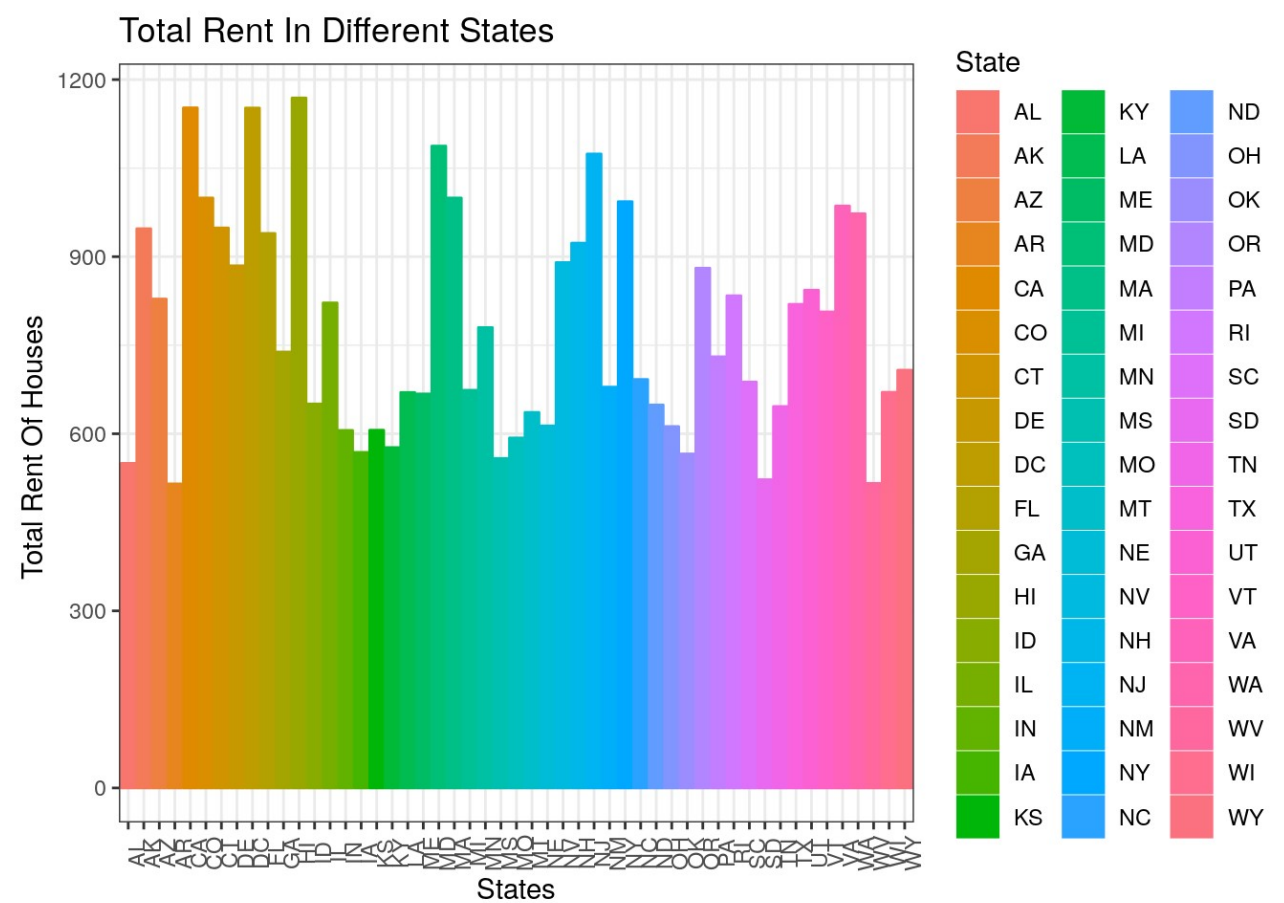
From the below graph we can see that Hawaii(HW) of United states consist highest average Rent in comaprison to other states, thus this graph helps buyers to predict that they should not invest in hawaii if their financial statement is quite low, rather than that they should invest their income in west virgina and Arkansas.

```
#Total rent in different states
rent_rooms <- Without_NA %>%
  select(State,RMSP,HouseStructureYear,RENT)%>%
  group_by(State) %>% summarise(Avg_Rent= mean(RENT))
rent_rooms
```

State <fctr>	Avg_Rent <dbl>
AL	549.8419
AK	947.3652
AZ	828.2409
AR	515.0638
CA	1152.1336

State <fctr>	Avg_Rent <dbl>
CO	999.4572
CT	948.7200
DE	884.5209
DC	1151.8638
FL	939.3696
1-10 of 51 rows	
<div> <div>Previous</div> <div>1</div> <div>2</div> <div>3</div> <div>4</div> <div>5</div> <div>6</div> <div>Next</div> </div>	

```
#Plot
ggplot(rent_rooms)+
  geom_col(mapping =aes(x= State,y=Avg_Rent,colour = State,fill=State))+
  ggtitle("Total Rent In Different States")+
  xlab("States")+ylab("Total Rent Of Houses ")+theme_bw()+
  theme(axis.text.x = element_text(angle = 90))
```



# Houses built in different years

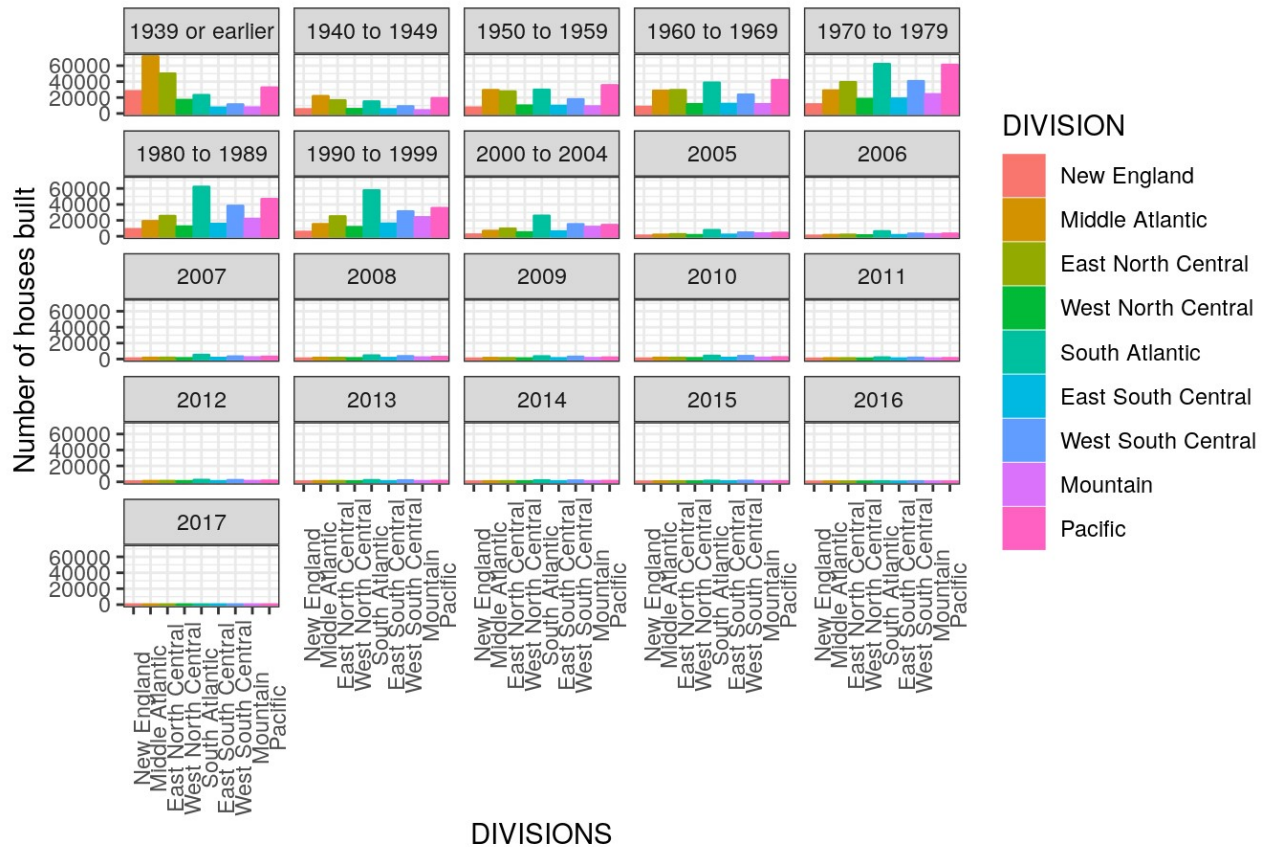
From the below graph, we can say that the ratio of houses built in early years were high compare to 2017, so we can say that houses built in recent years are less.

```
YR_division <- Without_NA%>%
  select(RENT,DIVISION,HouseStructureYear)
YR_division
```

RENT	DIVISION	HouseStructureYear
<dbl>	<fctr>	<fctr>
105.401500	East South Central	1980 to 1989
84.321200	East South Central	1970 to 1979
358.365100	East South Central	2006
1475.621000	East South Central	1990 to 1999
621.868850	East South Central	1980 to 1989
737.810500	East South Central	1950 to 1959
632.409000	East South Central	1980 to 1989
843.212000	East South Central	1980 to 1989
716.730200	East South Central	1980 to 1989
63.240900	East South Central	2000 to 2004
1-10 of 10,000 rows		Previous 1 2 3 4 5 6 ... 1000 Next

```
#plot
options(scipen = 999)
ggplot(YR_division)+geom_bar(mapping =aes(x= DIVISION ,colour =
  DIVISION,fill=DIVISION))+ facet_wrap(~HouseStructureYear)+
  ggtitle("Number of houses built in different divisions")+
  xlab("DIVISIONS")+ylab("Number of houses built")+theme_bw()+
  theme(plot.title= element_text(color="#0033FF",hjust = 0.5),
    axis.text.x = element_text(angle = 90))
```

## Number of houses built in different divisions



## Tax in different divisions Here from below graph we can see that, tax in South Atlantic is highest and lowest in New England.

So, from overall graphs we can say that it is beneficial to built or rent a house in New England, as it contains lowest price by considering taxes and rent factors.

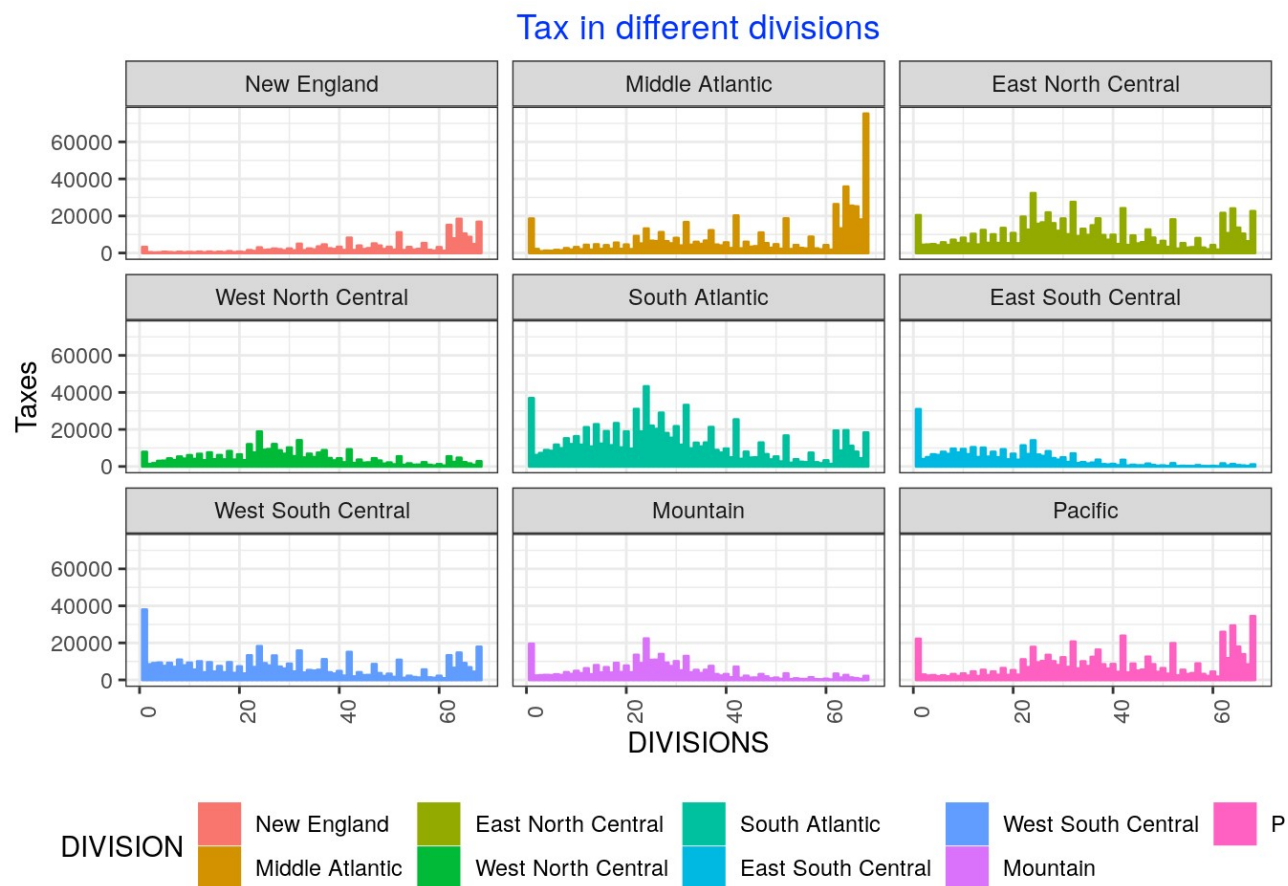
```
tax_division <- bind_data %>%
  select(RENT,DIVISION,HouseStructureYear,Tax)

tax_division
```

RENT	DIVISION	HouseStructureYear	Tax
<dbl>	<fctr>	<fctr>	<int>
NA	East South Central	NA	NA
NA	East South Central	1940 to 1949	3
NA	East South Central	1970 to 1979	6
105.40150	East South Central	1980 to 1989	NA
84.32120	East South Central	1970 to 1979	NA
NA	East South Central	1940 to 1949	3

RENT <dbl>	DIVISION <fctr>	HouseStructureYear <fctr>	Tax <int>
NA	East South Central	2000 to 2004	26
NA	East South Central	1940 to 1949	5
358.36510	East South Central	2006	NA
NA	East South Central	1960 to 1969	10
1-10 of 10,000 rows		Previous	1 2 3 4 5 6 ... 1000 Next

```
#plot
options(scipen = 999)
ggplot(tax_division)+geom_bar(mapping =aes(x= Tax ,colour =
DIVISION,fill=DIVISION))+facet_wrap(~DIVISION)+
ggtitle("Tax in different divisions")+
xlab("DIVISIONS")+ylab("Taxes")+theme_bw()+
theme(plot.title= element_text(color="#0033FF",hjust = 0.5),
axis.text.x = element_text(angle = 90),legend.position =
"bottom")
```



## Sale of Agriculture product in different division

Below graph depicts that East North Central has the highest tax on sale of agriculture products, so if any one wants to do business of agriculture products, they can easily depict from this graph information from where they can get benefit. Moreover, 300000 tax need to pay yearly by East North central which is costly for many individuals.

```
AGS_division <- bind_data %>%
  select(SaleofAgroProduct,DIVISION,Tax) %>% group_by(Tax)

AGS_division
```

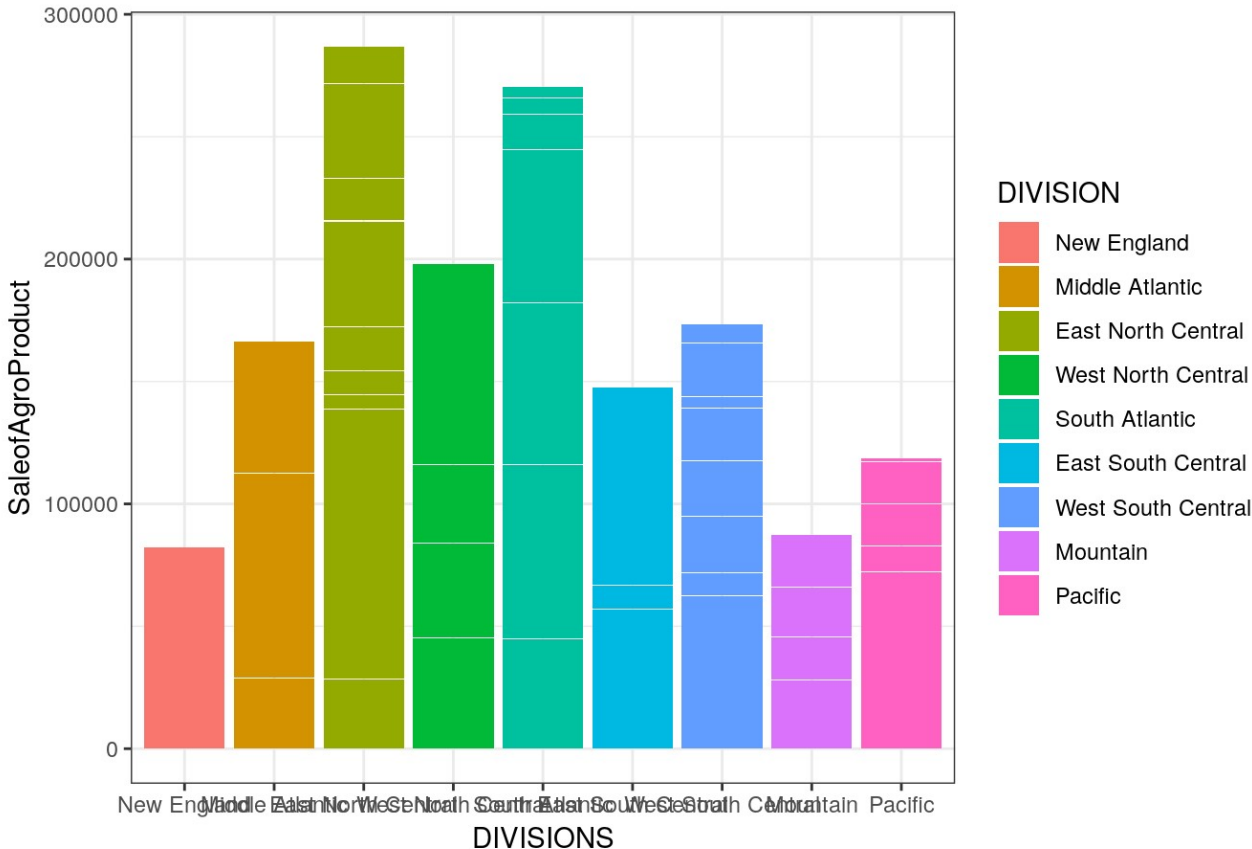
SaleofAgroProduct	DIVISION	Tax
<int>	<fctr>	<int>
NA	East South Central	NA
NA	East South Central	3
NA	East South Central	6
1	East South Central	NA
NA	East South Central	NA
NA	East South Central	3
NA	East South Central	26
1	East South Central	5
NA	East South Central	NA
1	East South Central	10

1-10 of 10,000 rows

Previous
1
2
3
4
5
6
...
1000
Next

```
#plot
ggplot(AGS_division)+
  geom_col(aes(x=DIVISION,y=SaleofAgroProduct,fill=DIVISION))+
  ggtitle("Sale of Agriculture products in different divisions")+
  xlab("DIVISIONS")+ylab("SaleofAgroProduct")+
  theme(axis.text.x = element_text(angle = 90),legend.position = "bottom")+
  theme_bw()
```

## Sale of Agriculture products in different divisions



## Performing Various test for testing P value

From the below performed test we can depict that P value will remain below 0.05, which states that there is significance difference between them, thus it rejects null hypothesis and states that difference of mean of Sale of agro products and tax is not equal to 0 and thus we accept alternative hypothesis.

```
(Variance_test <- var.test(bind_data$SaleofAgroProduct,bind_data$Tax))
```

```
##  
## F test to compare two variances  
##  
## data: bind_data$SaleofAgroProduct and bind_data$Tax  
## F = 0.002636, num df = 1199657, denom df = 4284627, p-value <  
## 0.000000000000000022  
## alternative hypothesis: true ratio of variances is not equal to 1  
## 95 percent confidence interval:  
## 0.002629336 0.002642677  
## sample estimates:  
## ratio of variances  
## 0.002635994
```



```
(Variance_test <- var.test(bind_data$HouseAcre,bind_data$Tax))
```

```
##  
## F test to compare two variances  
##  
## data: bind_data$HouseAcre and bind_data$Tax  
## F = 0.00082329, num df = 5317320, denom df = 4284627, p-value <  
## 0.000000000000000022  
## alternative hypothesis: true ratio of variances is not equal to 1  
## 95 percent confidence interval:  
## 0.0008221860 0.0008243909  
## sample estimates:  
## ratio of variances  
## 0.0008232881
```

```
(t.test(bind_data$SaleofAgroProduct,bind_data$Tax,data=bind_data))
```

```
##  
## Welch Two Sample t-test  
##  
## data: bind_data$SaleofAgroProduct and bind_data$Tax  
## t = -3366.7, df = 4364301, p-value < 0.000000000000000022  
## alternative hypothesis: true difference in means is not equal to 0  
## 95 percent confidence interval:  
## -32.63092 -32.59295  
## sample estimates:  
## mean of x mean of y  
## 1.275661 33.887593
```

#Initial model of linear regression for checking AIC and BIC

By checking AIC and BIC we can say that int\_model fits best as it has lowest AIC value. From the below image we can say that, the black colour in image means it has not included few variables in that area and the coloured area represents that they are related to log probability. The log posterior probability are scaled so 0 represents to lowest probability from other models.

```
#Initial model of linear regression  
int_model <- lm(Tax ~ State+DIVISION+ HouseAcre+ SaleofAgroProduct+  
                Bathtub+ HotWater+ Bedrooms+ RMSP+ SINK+ Stove+ Toilet+  
                HouseStructureYear+ Kitchen, data = bind_data)  
summary(int_model)
```

```
##
## Call:
## lm(formula = Tax ~ State + DIVISION + HouseAcre + SaleofAgroProduct +
##      Bathtub + HotWater + Bedrooms + RMSP + SINK + Stove + Toilet +
##      HouseStructureYear + Kitchen, data = bind_data)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -85.051  -9.225  -0.782   8.735  75.005
##
## Coefficients: (9 not defined because of singularities)
##              Estimate Std. Error t value
## (Intercept)    -11.978632    0.379278  -31.583
## StateAK         18.871273    0.322099   58.588
## StateAZ         16.630868    0.158068  105.213
## StateAR          5.818015    0.137528   42.304
## StateCA         30.540127    0.113192  269.808
## StateCO         15.790298    0.152607  103.470
## StateCT         47.127950    0.143027  329.504
## StateDE         10.332911    0.318478   32.445
## StateDC         20.907547    1.167119   17.914
## StateFL         18.281802    0.116580  156.818
## StateGA         13.209778    0.108751  121.468
## StateHI         16.465641    0.394057   41.785
## StateID         12.692697    0.193388   65.633
## StateIL         30.728808    0.122727  250.383
## StateIN         13.116626    0.124381  105.456
## StateIA         21.676571    0.159162  136.192
## StateKS         19.855180    0.167534  118.514
## StateKY          8.979579    0.127559   70.395
## StateLA          0.944223    0.139470    6.770
## StateME         24.142636    0.151454  159.406
## StateMD         31.233741    0.144384  216.324
## StateMA         42.071630    0.132679  317.093
## StateMI         20.482386    0.105622  193.922
## StateMN         19.033727    0.113131  168.245
## StateMS          4.828923    0.135862   35.543
## StateMO         12.753821    0.121243  105.192
## StateMT         17.648650    0.198275   89.011
## StateNE         23.154042    0.213143  108.632
## StateNV         16.530729    0.265788   62.195
## StateNH         45.060684    0.159561  282.405
## StateNJ         48.632161    0.146157  332.739
## StateNM          9.494139    0.189757   50.033
## StateNY         34.938775    0.106024  329.537
## StateNC         13.709460    0.108465  126.396
## StateND          8.127721    0.248994   32.642
## StateOH         24.089539    0.111405  216.233
```

## StateOK	8.427966	0.135393	62.248
## StateOR	24.318865	0.156491	155.401
## StatePA	26.995960	0.104242	258.974
## StateRI	44.161726	0.304737	144.917
## StateSC	5.897253	0.126294	46.695
## StateSD	17.018325	0.249335	68.255
## StateTN	9.615002	0.112887	85.174
## StateTX	22.133082	0.102664	215.588
## StateUT	13.537420	0.225218	60.108
## StateVT	39.553941	0.195003	202.837
## StateVA	16.754747	0.117946	142.054
## StateWA	28.891947	0.132081	218.745
## StateWV	5.338476	0.170191	31.368
## StateWI	30.288909	0.109925	275.542
## StateWY	13.949802	0.298105	46.795
## DIVISIONMiddle Atlantic	NA	NA	NA
## DIVISIONEast North Central	NA	NA	NA
## DIVISIONWest North Central	NA	NA	NA
## DIVISIONSouth Atlantic	NA	NA	NA
## DIVISIONEast South Central	NA	NA	NA
## DIVISIONWest South Central	NA	NA	NA
## DIVISIONMountain	NA	NA	NA
## DIVISIONPacific	NA	NA	NA
## HouseAcre	0.259257	0.037336	6.944
## SaleofAgroProduct	0.439793	0.015068	29.187
## Bathtub	-3.311064	0.387065	-8.554
## HotWater	NA	NA	NA
## Bedrooms	2.145049	0.018499	115.954
## RMSP	1.763974	0.007283	242.213
## SINK	3.099082	0.466792	6.639
## Stove	5.086451	0.389413	13.062
## Toilet	0.176973	0.003599	49.177
## HouseStructureYear1940 to 1949	0.915040	0.084415	10.840
## HouseStructureYear1950 to 1959	3.114449	0.067330	46.256
## HouseStructureYear1960 to 1969	3.415948	0.063914	53.446
## HouseStructureYear1970 to 1979	3.425114	0.054510	62.835
## HouseStructureYear1980 to 1989	5.104416	0.055662	91.704
## HouseStructureYear1990 to 1999	6.215056	0.053168	116.895
## HouseStructureYear2000 to 2004	8.684713	0.061854	140.406
## HouseStructureYear2005	9.855163	0.109661	89.870
## HouseStructureYear2006	10.196022	0.112380	90.728
## HouseStructureYear2007	10.493042	0.119794	87.592
## HouseStructureYear2008	10.375215	0.134688	77.031
## HouseStructureYear2009	10.071803	0.160769	62.648
## HouseStructureYear2010	9.775719	0.167285	58.437
## HouseStructureYear2011	10.165844	0.205380	49.498
## HouseStructureYear2012	9.864334	0.199505	49.444
## HouseStructureYear2013	10.777305	0.219550	49.088
## HouseStructureYear2014	10.649474	0.246261	43.245

## HouseStructureYear2015	10.357083	0.288970	35.841
## HouseStructureYear2016	8.878885	0.414538	21.419
## HouseStructureYear2017	7.995912	0.879378	9.093
## Kitchen	-7.904206	0.362184	-21.824
##		Pr(> t )	
## (Intercept)	< 0.0000000000000002	***	
## StateAK	< 0.0000000000000002	***	
## StateAZ	< 0.0000000000000002	***	
## StateAR	< 0.0000000000000002	***	
## StateCA	< 0.0000000000000002	***	
## StateCO	< 0.0000000000000002	***	
## StateCT	< 0.0000000000000002	***	
## StateDE	< 0.0000000000000002	***	
## StateDC	< 0.0000000000000002	***	
## StateFL	< 0.0000000000000002	***	
## StateGA	< 0.0000000000000002	***	
## StateHI	< 0.0000000000000002	***	
## StateID	< 0.0000000000000002	***	
## StateIL	< 0.0000000000000002	***	
## StateIN	< 0.0000000000000002	***	
## StateIA	< 0.0000000000000002	***	
## StateKS	< 0.0000000000000002	***	
## StateKY	< 0.0000000000000002	***	
## StateLA	0.0000000001288	***	
## StateME	< 0.0000000000000002	***	
## StateMD	< 0.0000000000000002	***	
## StateMA	< 0.0000000000000002	***	
## StateMI	< 0.0000000000000002	***	
## StateMN	< 0.0000000000000002	***	
## StateMS	< 0.0000000000000002	***	
## StateMO	< 0.0000000000000002	***	
## StateMT	< 0.0000000000000002	***	
## StateNE	< 0.0000000000000002	***	
## StateNV	< 0.0000000000000002	***	
## StateNH	< 0.0000000000000002	***	
## StateNJ	< 0.0000000000000002	***	
## StateNM	< 0.0000000000000002	***	
## StateNY	< 0.0000000000000002	***	
## StateNC	< 0.0000000000000002	***	
## StateND	< 0.0000000000000002	***	
## StateOH	< 0.0000000000000002	***	
## StateOK	< 0.0000000000000002	***	
## StateOR	< 0.0000000000000002	***	
## StatePA	< 0.0000000000000002	***	
## StateRI	< 0.0000000000000002	***	
## StateSC	< 0.0000000000000002	***	
## StateSD	< 0.0000000000000002	***	
## StateTN	< 0.0000000000000002	***	
## StateTX	< 0.0000000000000002	***	

```

## StateUT < 0.0000000000000002 ***
## StateVT < 0.0000000000000002 ***
## StateVA < 0.0000000000000002 ***
## StateWA < 0.0000000000000002 ***
## StateWV < 0.0000000000000002 ***
## StateWI < 0.0000000000000002 ***
## StateWY < 0.0000000000000002 ***
## DIVISIONMiddle Atlantic NA
## DIVISIONEast North Central NA
## DIVISIONWest North Central NA
## DIVISIONSouth Atlantic NA
## DIVISIONEast South Central NA
## DIVISIONWest South Central NA
## DIVISIONMountain NA
## DIVISIONPacific NA
## HouseAcre 0.000000000000382 ***
## SaleofAgroProduct < 0.0000000000000002 ***
## Bathtub < 0.0000000000000002 ***
## HotWater NA
## Bedrooms < 0.0000000000000002 ***
## RMSP < 0.0000000000000002 ***
## SINK 0.0000000000003157 ***
## Stove < 0.0000000000000002 ***
## Toilet < 0.0000000000000002 ***
## HouseStructureYear1940 to 1949 < 0.0000000000000002 ***
## HouseStructureYear1950 to 1959 < 0.0000000000000002 ***
## HouseStructureYear1960 to 1969 < 0.0000000000000002 ***
## HouseStructureYear1970 to 1979 < 0.0000000000000002 ***
## HouseStructureYear1980 to 1989 < 0.0000000000000002 ***
## HouseStructureYear1990 to 1999 < 0.0000000000000002 ***
## HouseStructureYear2000 to 2004 < 0.0000000000000002 ***
## HouseStructureYear2005 < 0.0000000000000002 ***
## HouseStructureYear2006 < 0.0000000000000002 ***
## HouseStructureYear2007 < 0.0000000000000002 ***
## HouseStructureYear2008 < 0.0000000000000002 ***
## HouseStructureYear2009 < 0.0000000000000002 ***
## HouseStructureYear2010 < 0.0000000000000002 ***
## HouseStructureYear2011 < 0.0000000000000002 ***
## HouseStructureYear2012 < 0.0000000000000002 ***
## HouseStructureYear2013 < 0.0000000000000002 ***
## HouseStructureYear2014 < 0.0000000000000002 ***
## HouseStructureYear2015 < 0.0000000000000002 ***
## HouseStructureYear2016 < 0.0000000000000002 ***
## HouseStructureYear2017 < 0.0000000000000002 ***
## Kitchen < 0.0000000000000002 ***
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 14.54 on 1073351 degrees of freedom

```

```
## (6413930 observations deleted due to missingness)
## Multiple R-squared: 0.4489, Adjusted R-squared: 0.4489
## F-statistic: 1.107e+04 on 79 and 1073351 DF, p-value: < 0.00000000000000022
```

```
int_model1 <- lm(Tax ~ Bathtub+HotWater+Bedrooms+RMSP+
                  SINK+Stove+Toilet+HouseStructureYear+
                  Kitchen,data = bind_data)
```

```
# Checking which one is better AIC or BIC, Lower the value,
#better the model fits
```

```
(aic_model <- AIC(int_model,k=2))
```

```
## [1] 8792634
```

```
(aic_model <- AIC(int_model1,k=2))
```

```
## [1] 37260276
```

```
(bic_model <- BIC(int_model))
```

```
## [1] 8793596
```

```
(bic_model <- BIC(int_model1))
```

```
## [1] 8793596
```

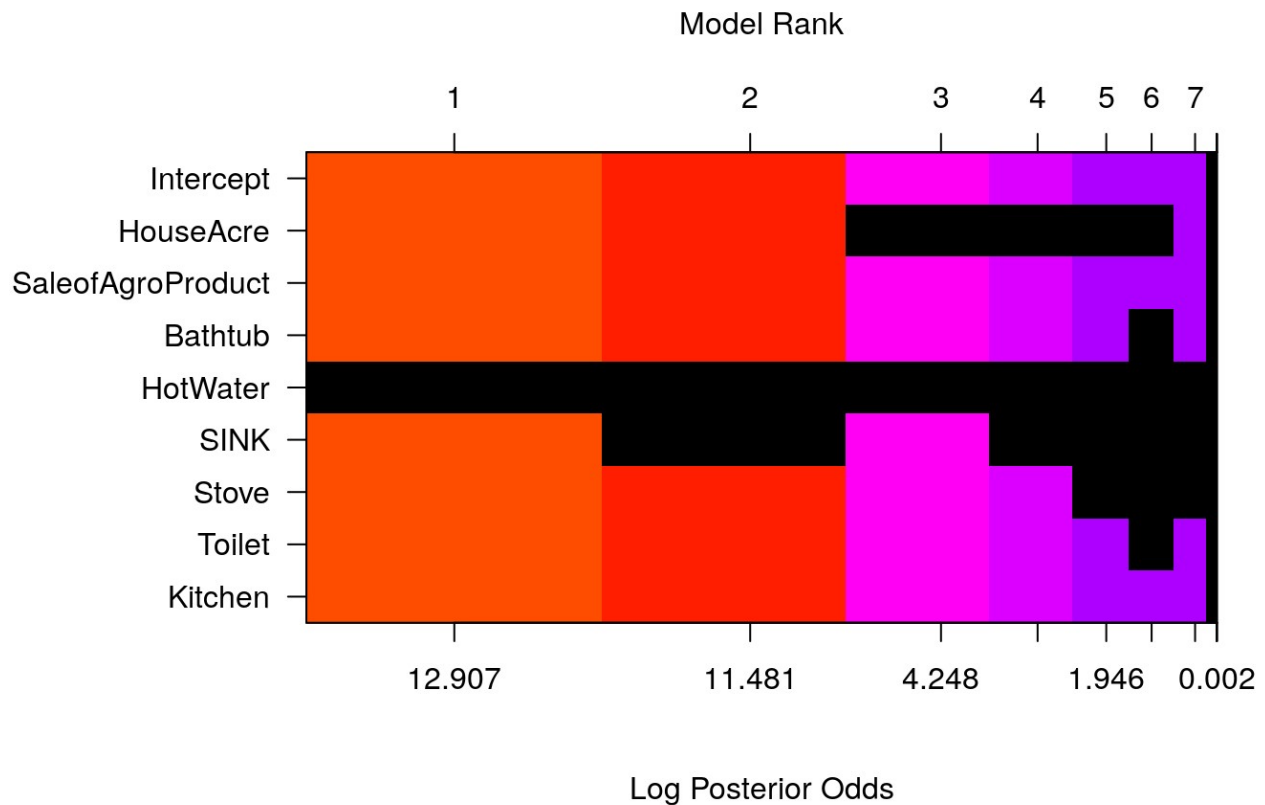
```
#value of AIC model is less so AIC is considered optimal for int_model
model_BAS <- bas.lm(log(Tax) ~ HouseAcre+SaleofAgroProduct
                    +Bathtub+HotWater+SINK+Stove+Toilet+Kitchen,
                    data = bind_data, prior = "AIC", modelprior=uniform(),
                    method = "MCMC", MCMC.iterations=500000)
summary(model_BAS)
```

```

##                P(B != 0 | Y)      model 1      model 2
## Intercept          1.000000      1.0000      1.00000000
## HouseAcre          0.999748      1.0000      1.00000000
## SaleofAgroProduct  0.999998      1.0000      1.00000000
## Bathtub            0.999986      1.0000      1.00000000
## HotWater           0.000000      0.0000      0.00000000
## SINK               0.806194      1.0000      0.00000000
## Stove              0.999958      1.0000      1.00000000
## Toilet            0.999984      1.0000      1.00000000
## Kitchen            1.000000      1.0000      1.00000000
## BF                 NA           1.0000      0.2482373
## PostProbs          NA           0.8061      0.1937000
## R2                 NA           0.0047      0.0047000
## dim               NA           8.0000      7.00000000
## logmarg            NA -7438376.5647 -7438377.9580651
##                model 3      model 4
## Intercept          1.00000000000      1.00000000000
## HouseAcre          0.00000000000      0.00000000000
## SaleofAgroProduct  1.00000000000      1.00000000000
## Bathtub            1.00000000000      1.00000000000
## HotWater           0.00000000000      0.00000000000
## SINK               1.00000000000      0.00000000000
## Stove              1.00000000000      1.00000000000
## Toilet            1.00000000000      1.00000000000
## Kitchen            1.00000000000      1.00000000000
## BF                 0.0003073404      0.00007148497
## PostProbs          0.0001000000      0.00010000000
## R2                 0.0047000000      0.00470000000
## dim               7.00000000000      6.00000000000
## logmarg            -7438384.6522496780 -7438386.11071831919
##                model 5
## Intercept          1.000000000000000000000
## HouseAcre          0.000000000000000000000
## SaleofAgroProduct  1.000000000000000000000
## Bathtub            1.000000000000000000000
## HotWater           0.000000000000000000000
## SINK               0.000000000000000000000
## Stove              0.000000000000000000000
## Toilet            1.000000000000000000000
## Kitchen            1.000000000000000000000
## BF                 0.00000000000000002643981
## PostProbs          0.000000000000000000000
## R2                 0.004599999999999999999992
## dim               5.000000000000000000000
## logmarg            -7438407.82860064785927534103

```

```
image(model_BAS, rotate = F)
```



## Splitting Train and Test data

I am making train data with 75% of train data and rest 25% are test data.

```
set.seed(99)
split <- sample(seq_len(nrow(bind_data)), size = floor(0.75 * nrow(bind_data)))
train <- bind_data[split, ]
test <- bind_data[-split, ]
```

## Building Linear Regression Model

I am predicting tax by considering different factors such as state, division, bathtub, sale of agro product and etc, by taking train data. The summary description is explained after result of summary model.

```
model2 <- lm(Tax ~ State+DIVISION+HouseAcre+SaleofAgroProduct+
              Bedrooms+RMSP+HouseStructureYear+SINK+Bathtub+
              Kitchen+INSURANCE, data=train)

(summary(model2))
```



```
##
## Call:
## lm(formula = Tax ~ State + DIVISION + HouseAcre + SaleofAgroProduct +
##      Bedrooms + RMSP + HouseStructureYear + SINK + Bathtub + Kitchen +
##      INSURANCE, data = train)
##
## Residuals:
##      Min        1Q    Median        3Q        Max
## -71.138  -8.379  -0.863   7.662  69.059
##
## Coefficients: (8 not defined because of singularities)
##
##              Estimate Std. Error t value
## (Intercept)   -12.20285590   0.35251582  -34.616
## StateAK        17.69582778   0.35623286   49.675
## StateAZ        17.18290632   0.17311286   99.258
## StateAR         5.82044765   0.14997625   38.809
## StateCA        28.01200988   0.12695324  220.648
## StateCO        13.74604994   0.17356931   79.196
## StateCT        45.52747842   0.16602066  274.228
## StateDE        11.70148306   0.34629368   33.791
## StateDC        19.89317605   1.27809000   15.565
## StateFL        14.95310148   0.13316932  112.286
## StateGA        13.16824537   0.11899211  110.665
## StateHI        14.08507248   0.45394278   31.028
## StateID        14.19249331   0.20932087   67.803
## StateIL        30.31831190   0.13395611  226.330
## StateIN        12.76131462   0.13546385   94.205
## StateIA        21.88632363   0.17362596  126.054
## StateKS        18.10230146   0.18915859   95.699
## StateKY         8.85557620   0.13947921   63.490
## StateLA       -0.22691249   0.15644730   -1.450
## StateME        25.16245457   0.16303181  154.341
## StateMD        31.39316073   0.15967069  196.612
## StateMA        40.91579165   0.14866974  275.213
## StateMI        21.15973149   0.11516788  183.729
## StateMN        17.68805415   0.12521623  141.260
## StateMS         3.99551931   0.15021201   26.599
## StateMO        11.81095063   0.13359312   88.410
## StateMT        17.18363440   0.21975790   78.193
## StateNE        22.19599338   0.23814842   93.202
## StateNV        16.99405118   0.29192128   58.214
## StateNH        45.28557594   0.17287739  261.952
## StateNJ        48.73236205   0.16476433  295.770
## StateNM        10.27962047   0.20741884   49.560
## StateNY        35.05288069   0.11656630  300.712
## StateNC        14.04629067   0.11845496  118.579
## StateND         8.50272460   0.27661432   30.739
## StateOH        24.36428559   0.12160695  200.353
```

## StateOK	6.64013387	0.15198470	43.689
## StateOR	25.10135562	0.17147528	146.385
## StatePA	27.77722368	0.11391152	243.849
## StateRI	42.78573215	0.34929794	122.491
## StateSC	6.45313242	0.13772622	46.855
## StateSD	17.40864093	0.27378557	63.585
## StateTN	9.12465574	0.12352173	73.871
## StateTX	19.37322916	0.11446258	169.254
## StateUT	15.58028438	0.24407321	63.834
## StateVT	39.82245044	0.21145812	188.323
## StateVA	17.05781070	0.12901229	132.218
## StateWA	29.05154584	0.14463226	200.865
## StateWV	7.10160304	0.18373240	38.652
## StateWI	31.47504954	0.11974143	262.858
## StateWY	13.10191289	0.33020265	39.678
## DIVISIONMiddle Atlantic	NA	NA	NA
## DIVISIONEast North Central	NA	NA	NA
## DIVISIONWest North Central	NA	NA	NA
## DIVISIONSouth Atlantic	NA	NA	NA
## DIVISIONEast South Central	NA	NA	NA
## DIVISIONWest South Central	NA	NA	NA
## DIVISIONMountain	NA	NA	NA
## DIVISIONPacific	NA	NA	NA
## HouseAcre	0.05660256	0.04121198	1.373
## SaleofAgroProduct	0.32641510	0.01715274	19.030
## Bedrooms	1.43002866	0.02099427	68.115
## RMSP	1.25823651	0.00848897	148.220
## HouseStructureYear1940 to 1949	1.33113790	0.09201083	14.467
## HouseStructureYear1950 to 1959	3.25372416	0.07376821	44.107
## HouseStructureYear1960 to 1969	3.46099137	0.07010690	49.367
## HouseStructureYear1970 to 1979	3.47062261	0.05983415	58.004
## HouseStructureYear1980 to 1989	4.78196106	0.06136985	77.920
## HouseStructureYear1990 to 1999	5.63575289	0.05873099	95.959
## HouseStructureYear2000 to 2004	7.62648117	0.06871434	110.988
## HouseStructureYear2005	8.86172914	0.12278548	72.172
## HouseStructureYear2006	9.18070061	0.12615696	72.772
## HouseStructureYear2007	9.23974146	0.13471073	68.589
## HouseStructureYear2008	9.12946545	0.15132020	60.332
## HouseStructureYear2009	9.05333219	0.17900000	50.577
## HouseStructureYear2010	9.04870387	0.18662216	48.487
## HouseStructureYear2011	9.41093483	0.22761454	41.346
## HouseStructureYear2012	9.33552999	0.22246062	41.965
## HouseStructureYear2013	10.60784753	0.24356779	43.552
## HouseStructureYear2014	10.84192760	0.27293924	39.723
## HouseStructureYear2015	10.69277643	0.31901977	33.518
## HouseStructureYear2016	8.89603288	0.46102680	19.296
## HouseStructureYear2017	7.10709750	0.99109999	7.171
## SINK	-0.06339028	0.49832837	-0.127
## Bathtub	-1.58510938	0.41452801	-3.824

## Kitchen	-1.43115857	0.28369996	-5.045
## INSURANCE	0.00833118	0.00002843	293.064
##	Pr(> t )		
## (Intercept)	< 0.0000000000000002	***	
## StateAK	< 0.0000000000000002	***	
## StateAZ	< 0.0000000000000002	***	
## StateAR	< 0.0000000000000002	***	
## StateCA	< 0.0000000000000002	***	
## StateCO	< 0.0000000000000002	***	
## StateCT	< 0.0000000000000002	***	
## StateDE	< 0.0000000000000002	***	
## StateDC	< 0.0000000000000002	***	
## StateFL	< 0.0000000000000002	***	
## StateGA	< 0.0000000000000002	***	
## StateHI	< 0.0000000000000002	***	
## StateID	< 0.0000000000000002	***	
## StateIL	< 0.0000000000000002	***	
## StateIN	< 0.0000000000000002	***	
## StateIA	< 0.0000000000000002	***	
## StateKS	< 0.0000000000000002	***	
## StateKY	< 0.0000000000000002	***	
## StateLA	0.146945		
## StateME	< 0.0000000000000002	***	
## StateMD	< 0.0000000000000002	***	
## StateMA	< 0.0000000000000002	***	
## StateMI	< 0.0000000000000002	***	
## StateMN	< 0.0000000000000002	***	
## StateMS	< 0.0000000000000002	***	
## StateMO	< 0.0000000000000002	***	
## StateMT	< 0.0000000000000002	***	
## StateNE	< 0.0000000000000002	***	
## StateNV	< 0.0000000000000002	***	
## StateNH	< 0.0000000000000002	***	
## StateNJ	< 0.0000000000000002	***	
## StateNM	< 0.0000000000000002	***	
## StateNY	< 0.0000000000000002	***	
## StateNC	< 0.0000000000000002	***	
## StateND	< 0.0000000000000002	***	
## StateOH	< 0.0000000000000002	***	
## StateOK	< 0.0000000000000002	***	
## StateOR	< 0.0000000000000002	***	
## StatePA	< 0.0000000000000002	***	
## StateRI	< 0.0000000000000002	***	
## StateSC	< 0.0000000000000002	***	
## StateSD	< 0.0000000000000002	***	
## StateTN	< 0.0000000000000002	***	
## StateTX	< 0.0000000000000002	***	
## StateUT	< 0.0000000000000002	***	
## StateVT	< 0.0000000000000002	***	

```

## StateVA < 0.0000000000000002 ***
## StateWA < 0.0000000000000002 ***
## StateWV < 0.0000000000000002 ***
## StateWI < 0.0000000000000002 ***
## StateWY < 0.0000000000000002 ***
## DIVISIONMiddle Atlantic NA
## DIVISIONEast North Central NA
## DIVISIONWest North Central NA
## DIVISIONSouth Atlantic NA
## DIVISIONEast South Central NA
## DIVISIONWest South Central NA
## DIVISIONMountain NA
## DIVISIONPacific NA
## HouseAcre 0.169613
## SaleofAgroProduct < 0.0000000000000002 ***
## Bedrooms < 0.0000000000000002 ***
## RMSP < 0.0000000000000002 ***
## HouseStructureYear1940 to 1949 < 0.0000000000000002 ***
## HouseStructureYear1950 to 1959 < 0.0000000000000002 ***
## HouseStructureYear1960 to 1969 < 0.0000000000000002 ***
## HouseStructureYear1970 to 1979 < 0.0000000000000002 ***
## HouseStructureYear1980 to 1989 < 0.0000000000000002 ***
## HouseStructureYear1990 to 1999 < 0.0000000000000002 ***
## HouseStructureYear2000 to 2004 < 0.0000000000000002 ***
## HouseStructureYear2005 < 0.0000000000000002 ***
## HouseStructureYear2006 < 0.0000000000000002 ***
## HouseStructureYear2007 < 0.0000000000000002 ***
## HouseStructureYear2008 < 0.0000000000000002 ***
## HouseStructureYear2009 < 0.0000000000000002 ***
## HouseStructureYear2010 < 0.0000000000000002 ***
## HouseStructureYear2011 < 0.0000000000000002 ***
## HouseStructureYear2012 < 0.0000000000000002 ***
## HouseStructureYear2013 < 0.0000000000000002 ***
## HouseStructureYear2014 < 0.0000000000000002 ***
## HouseStructureYear2015 < 0.0000000000000002 ***
## HouseStructureYear2016 < 0.0000000000000002 ***
## HouseStructureYear2017 0.0000000000000746 ***
## SINK 0.898778
## Bathtub 0.000131 ***
## Kitchen 0.000000454531502 ***
## INSURANCE < 0.0000000000000002 ***
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 13.24 on 731544 degrees of freedom
## (4883897 observations deleted due to missingness)
## Multiple R-squared: 0.5073, Adjusted R-squared: 0.5072
## F-statistic: 9656 on 78 and 731544 DF, p-value: < 0.00000000000000022

```

By using train data we can see that accuracy of our model got increased. Moreover, below are some descriptions of summary of model.

**Residual Standard Error :** It is the average amount that response will deviate from true regression line. In our case actual tax can deviate from true regression line by approximately 13.24. The tax is -12.98 and residual error is 13.24, so our percentage error is 0.26%.

**Multiple R-squared :** R - squared represents how our model fits the actual data. In our case, the variance is 50% so we can say that some data points will fall near regression and other 50% of data points will be away from regression line. Though we cannot predict exactly that our model will fit our data, however in our case we consider that with 50% of variance we can get predicted model with better accuracy.

**Adjusted R- squared :** It represents that, as we add on variables into the model, the model gets better and better.

**F - statistic :** In our case F - statistic value is 9656 is higher than 78, so it suggests that there is a relation between predictor and response variable.

```
##Predicting on test data

pred <- predict(model2, newdata=test)

(combine<-data.frame(cbind(test$Tax, pred)))
```

	V1 <dbl>	pred <dbl>
3	6	NA
4	NA	NA
5	NA	NA
8	5	11.99752642
11	NA	NA
14	NA	NA
20	9	NA
24	64	NA
28	1	NA
29	3	2.63236400
1-10 of 10,000 rows		
Previous 1 2 3 4 5 6 ... 1000 Next		

```
colnames(combine)<-c("Actual", "Pred")  # giving column names
```

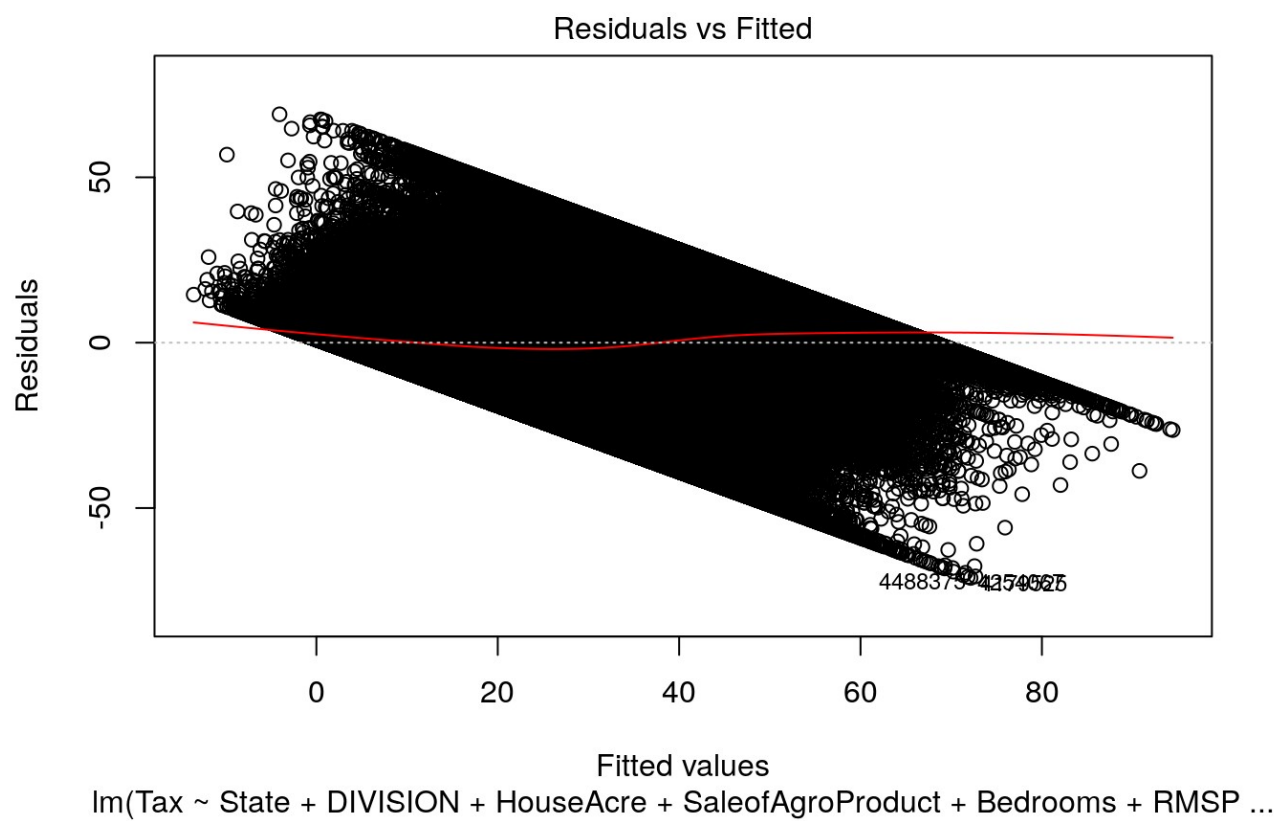
```
(correlation<-cor.test(combine$Actual,combine$Pred))  #correlation
```

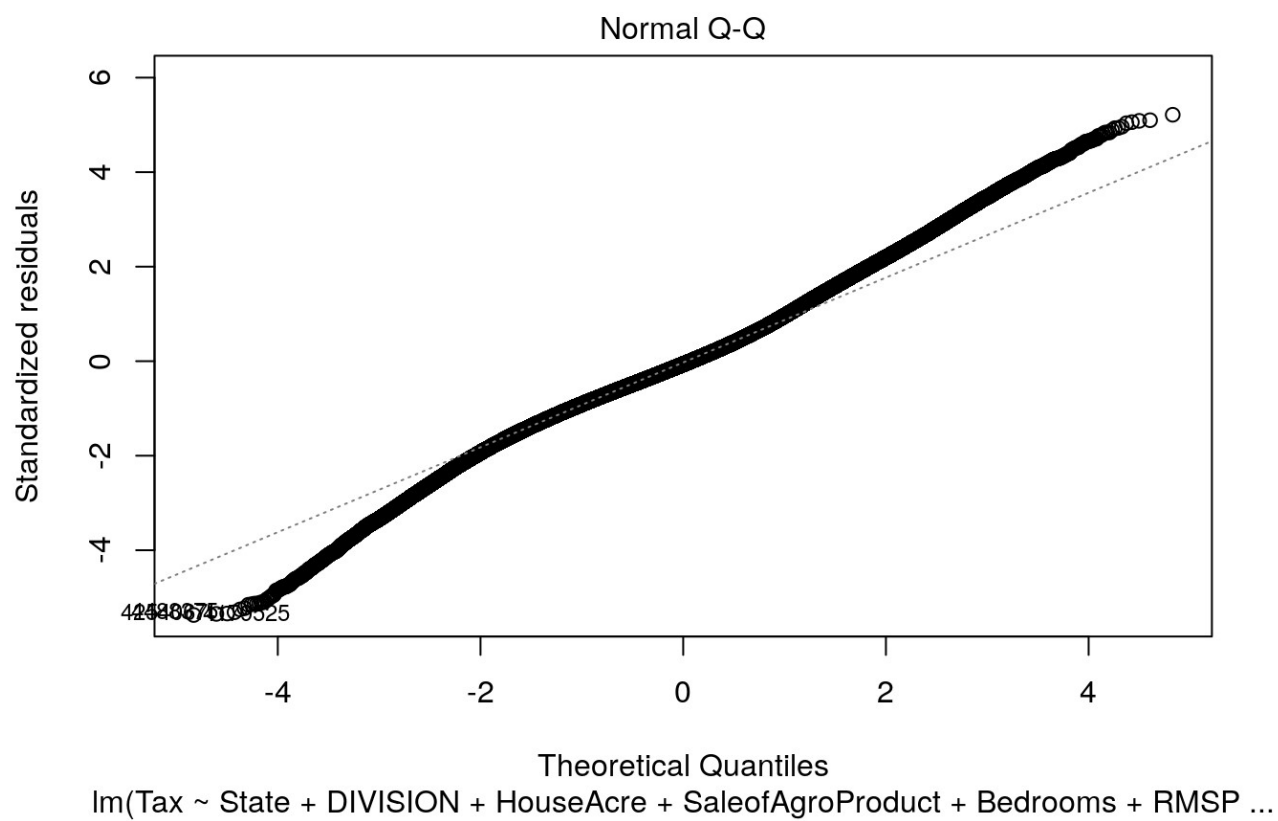
```
##  
## Pearson's product-moment correlation  
##  
## data: combine$Actual and combine$Pred  
## t = 501.2, df = 244206, p-value < 0.00000000000000022  
## alternative hypothesis: true correlation is not equal to 0  
## 95 percent confidence interval:  
## 0.7101197 0.7140298  
## sample estimates:  
## cor  
## 0.7120803
```

The correlation between Actual and predicted variable is 71%, so it depicts that there is a good relationship between response and predicted variable. Moreover, P - value is less than 0.05 so we reject the Null hypothesis and we reject that there is relation between tax and other factors. Moreover, For instance, from the combined data frame we can say that on value of actual tax is 5 and predicted tax we got is 11.99.

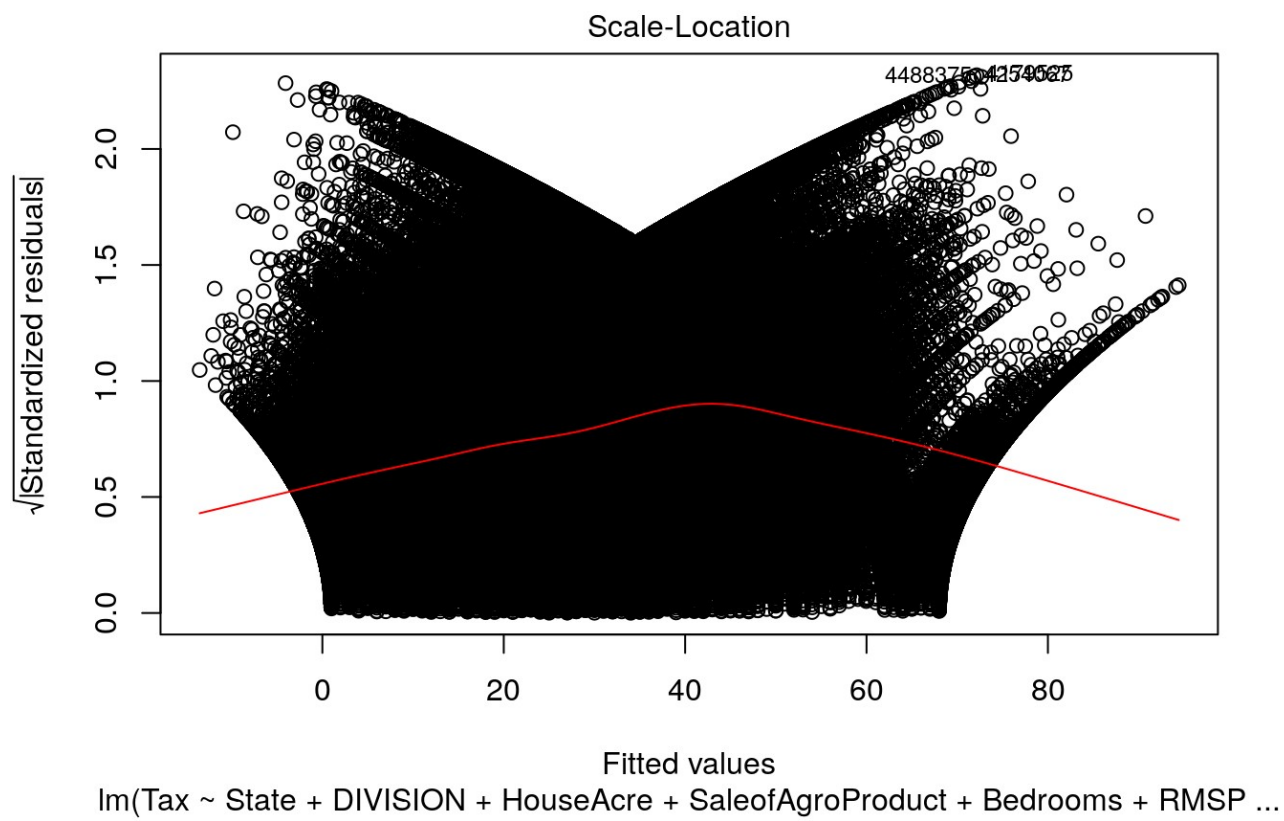
## Plot linear model

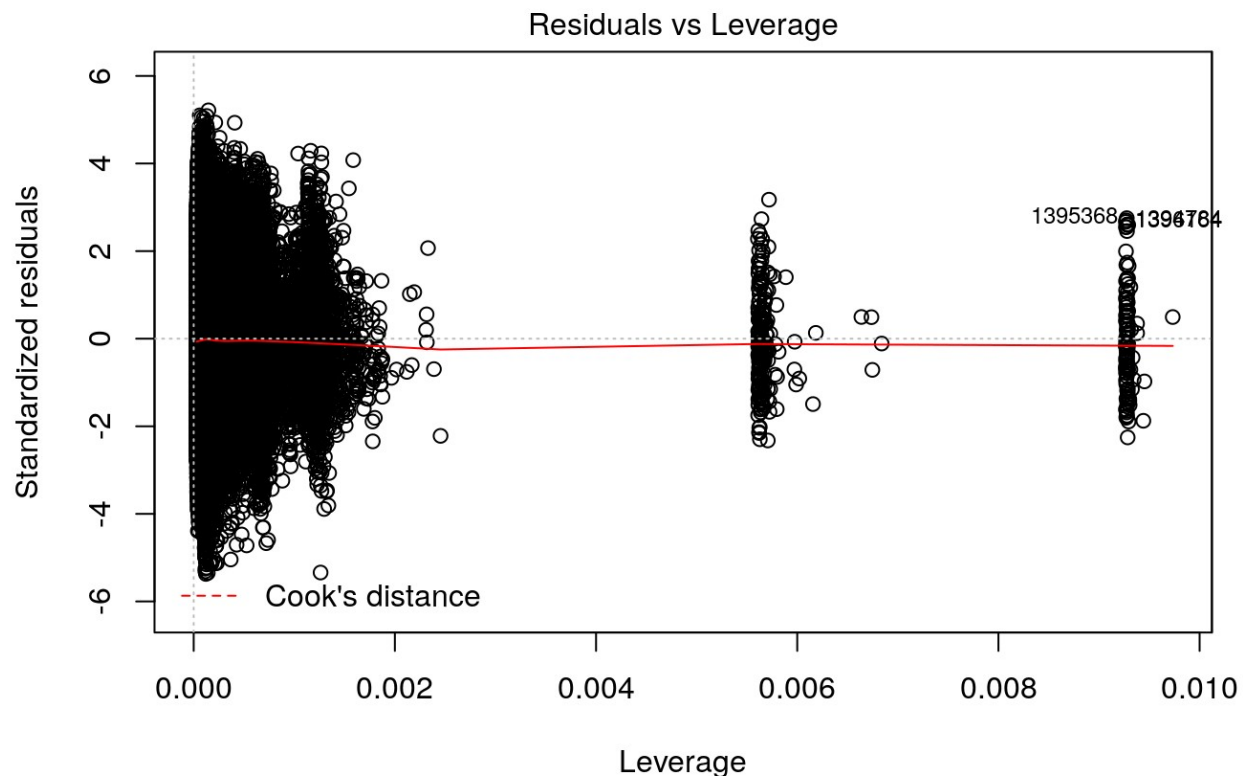
```
plot(model2)
```











$\text{lm}(\text{Tax} \sim \text{State} + \text{DIVISION} + \text{HouseAcre} + \text{SaleofAgroProduct} + \text{Bedrooms} + \text{RMSP} \dots)$   
 Explanation: Residual vs Fitted graph : From the graph we can see that, as red line shows close relation with dashed line in graph, that means it holds reasonably linearity and also there are some outliers which can affect the model.

Normal Q-Q plot : In this graph, we can see that points fits the centre line well and also there are less outliers which depicts that Q-Q plot is normally distributed.

Scale location: This graph is used to indicate whether spread of points falls near predicted range or not. So, in our case the residuals shows relation in V shape which means that as red line increases residuals comes near it and as it starts decreasing the points go away from red line.

Residuals vs Leverage: This plot helps us to find influential cases. If the point exceeds from Cook's distance that is, from dotted line then it shows that there is high leverage or potential for influencing our model if we exclude that point. In our graph, that is not the case, so we can say that there will be no high influence if we exclude outliers point.

## Conclusion:

My main aim was to identify price of house on the basis different utilities, but by performing and analysing some codes I realized that accuracy for that model is so less, in which we cannot predict the actual result. So, to overcome this problem I took linear regression model of tax and other factors and measured the tax on different products. By performing that model I came up with 50% accuracy which was not quite enough for me but as by considering other model with less accuracy, I am quite satisfied

with tax linear model. Thus, by analysing model I am somewhat confident with my tax prediction model with 50% accuracy. I don't know why I am getting less accuracy but this is what I tried and what I got by performing different modelling analysis. I also tried to generate maps on basis of states and division but I could not approach to that level, so I mainly focused on ggplots and plots of linear models.

## Appendix

### Extra code for variable importance and RMSE check

```
install.packages("Metrics")
library(Metrics)
varImp(model2, scale=FALSE)
```

	Overall <dbl>
StateAK	49.6748889
StateAZ	99.2584037
StateAR	38.8091279
StateCA	220.6482504
StateCO	79.1963161
StateCT	274.2277954
StateDE	33.7906337
StateDC	15.5647693
StateFL	112.2863853
StateGA	110.6648583
1-10 of 78 rows	Previous 1 2 3 4 5 6 ... 8 Next

```
rmse(combine$Actual, combine$Pred)
```

```
## [1] NA
```

I was trying to do linear regression of rent and other factors which can affect the overall price of house but because of less accuracy, I tried to make regression of tax and other factors, from which individuals can predict house on basis of tax in different divisions, states and other utilities. Below are some code which I tried in making linear regression of Rent including other utilities factors.

```
rent_model <- lm(RENT ~ State+DIVISION+ HouseAcre+ SaleofAgroProduct+  
                Bathtub+ HotWater+ Bedrooms+ RMSP+ SINK+ Stove+ Toilet+  
                HouseStructureYear+ Kitchen, data = bind_data)  
summary(rent_model)
```

```
##
## Call:
## lm(formula = RENT ~ State + DIVISION + HouseAcre + SaleofAgroProduct +
##       Bathtub + HotWater + Bedrooms + RMSP + SINK + Stove + Toilet +
##       HouseStructureYear + Kitchen, data = bind_data)
##
## Residuals:
```

	Min	1Q	Median	3Q	Max
	-1461.56	-220.62	-44.87	169.15	1679.20

```
##
## Coefficients: (9 not defined because of singularities)
##
```

	Estimate	Std. Error	t value
(Intercept)	460.2188	29.7227	15.484
StateAK	456.4607	22.5039	20.284
StateAZ	277.5047	12.8022	21.676
StateAR	-21.3679	11.2923	-1.892
StateCA	568.0293	8.3560	67.978
StateCO	406.1858	12.4908	32.519
StateCT	659.9316	14.5749	45.279
StateDE	322.5243	25.5864	12.605
StateDC	746.6084	86.9272	8.589
StateFL	305.9144	9.2477	33.080
StateGA	132.0896	8.4571	15.619
StateHI	620.6235	22.3202	27.805
StateID	151.9215	15.5571	9.765
StateIL	197.4104	10.5437	18.723
StateIN	93.5840	10.7059	8.741
StateIA	-6.4183	13.9916	-0.459
StateKS	34.5243	14.1019	2.448
StateKY	15.9891	10.5962	1.509
StateLA	86.5254	11.9707	7.228
StateME	195.9468	13.8302	14.168
StateMD	503.2904	12.6861	39.673
StateMA	574.0597	13.4204	42.775
StateMI	136.0332	9.3690	14.519
StateMN	143.4390	10.8887	13.173
StateMS	22.9586	11.5369	1.990
StateMO	35.8728	10.1059	3.550
StateMT	210.4411	15.9646	13.182
StateNE	1.4889	16.9086	0.088
StateNV	326.2173	17.3829	18.767
StateNH	521.6014	15.3580	33.963
StateNJ	676.9757	13.7059	49.393
StateNM	184.1733	16.4651	11.186
StateNY	309.6346	9.2682	33.408
StateNC	103.5172	8.5782	12.067
StateND	41.4986	27.3215	1.519
StateOH	110.4375	9.2568	11.930

## StateOK	29.9802	11.2535	2.664
## StateOR	324.4913	11.5787	28.025
## StatePA	168.6597	8.9594	18.825
## StateRI	570.5102	29.9481	19.050
## StateSC	62.9577	10.1903	6.178
## StateSD	-52.5596	22.5691	-2.329
## StateTN	75.9968	9.2880	8.182
## StateTX	213.0187	8.6059	24.753
## StateUT	280.0813	18.9938	14.746
## StateVT	380.8253	17.5987	21.639
## StateVA	265.7977	9.5149	27.935
## StateWA	403.6500	10.2859	39.243
## StateWV	26.5392	16.0326	1.655
## StateWI	121.5722	9.9197	12.256
## StateWY	239.0280	26.6035	8.985
## DIVISIONMiddle Atlantic	NA	NA	NA
## DIVISIONEast North Central	NA	NA	NA
## DIVISIONWest North Central	NA	NA	NA
## DIVISIONSouth Atlantic	NA	NA	NA
## DIVISIONEast South Central	NA	NA	NA
## DIVISIONWest South Central	NA	NA	NA
## DIVISIONMountain	NA	NA	NA
## DIVISIONPacific	NA	NA	NA
## HouseAcre	-74.4863	3.2002	-23.276
## SaleofAgroProduct	-10.5516	1.4556	-7.249
## Bathtub	-135.6574	27.6296	-4.910
## HotWater	NA	NA	NA
## Bedrooms	52.3548	1.6277	32.165
## RMSP	25.9464	0.7963	32.585
## SINK	75.0425	33.2013	2.260
## Stove	7.2099	26.5461	0.272
## Toilet	1.8393	0.2988	6.155
## HouseStructureYear1940 to 1949	14.3280	5.4111	2.648
## HouseStructureYear1950 to 1959	61.7424	4.6436	13.296
## HouseStructureYear1960 to 1969	73.5644	4.6455	15.836
## HouseStructureYear1970 to 1979	72.3659	4.1849	17.292
## HouseStructureYear1980 to 1989	81.6534	4.4012	18.552
## HouseStructureYear1990 to 1999	92.0277	4.3701	21.059
## HouseStructureYear2000 to 2004	128.6929	5.9223	21.730
## HouseStructureYear2005	188.1542	11.2695	16.696
## HouseStructureYear2006	224.8361	11.7077	19.204
## HouseStructureYear2007	199.1017	12.8633	15.478
## HouseStructureYear2008	202.3871	14.2476	14.205
## HouseStructureYear2009	206.7902	17.2536	11.985
## HouseStructureYear2010	194.6655	16.0304	12.144
## HouseStructureYear2011	121.9762	22.8231	5.344
## HouseStructureYear2012	202.4161	22.2270	9.107
## HouseStructureYear2013	195.7962	26.9244	7.272
## HouseStructureYear2014	184.1997	32.4892	5.670

## HouseStructureYear2015	215.4776	37.7444	5.709
## HouseStructureYear2016	188.4295	52.9710	3.557
## HouseStructureYear2017	-15.3768	173.4248	-0.089
## Kitchen	-109.1227	24.3165	-4.488
##	Pr(> t )		
## (Intercept)	< 0.0000000000000002	***	
## StateAK	< 0.0000000000000002	***	
## StateAZ	< 0.0000000000000002	***	
## StateAR	0.058461	.	
## StateCA	< 0.0000000000000002	***	
## StateCO	< 0.0000000000000002	***	
## StateCT	< 0.0000000000000002	***	
## StateDE	< 0.0000000000000002	***	
## StateDC	< 0.0000000000000002	***	
## StateFL	< 0.0000000000000002	***	
## StateGA	< 0.0000000000000002	***	
## StateHI	< 0.0000000000000002	***	
## StateID	< 0.0000000000000002	***	
## StateIL	< 0.0000000000000002	***	
## StateIN	< 0.0000000000000002	***	
## StateIA	0.646434		
## StateKS	0.014359	*	
## StateKY	0.131317		
## StateLA	0.000000000000493802	***	
## StateME	< 0.0000000000000002	***	
## StateMD	< 0.0000000000000002	***	
## StateMA	< 0.0000000000000002	***	
## StateMI	< 0.0000000000000002	***	
## StateMN	< 0.0000000000000002	***	
## StateMS	0.046592	*	
## StateMO	0.000386	***	
## StateMT	< 0.0000000000000002	***	
## StateNE	0.929835		
## StateNV	< 0.0000000000000002	***	
## StateNH	< 0.0000000000000002	***	
## StateNJ	< 0.0000000000000002	***	
## StateNM	< 0.0000000000000002	***	
## StateNY	< 0.0000000000000002	***	
## StateNC	< 0.0000000000000002	***	
## StateND	0.128791		
## StateOH	< 0.0000000000000002	***	
## StateOK	0.007722	**	
## StateOR	< 0.0000000000000002	***	
## StatePA	< 0.0000000000000002	***	
## StateRI	< 0.0000000000000002	***	
## StateSC	0.000000000651281176	***	
## StateSD	0.019871	*	
## StateTN	0.000000000000000282	***	
## StateTX	< 0.0000000000000002	***	

```

## StateUT < 0.0000000000000002 ***
## StateVT < 0.0000000000000002 ***
## StateVA < 0.0000000000000002 ***
## StateWA < 0.0000000000000002 ***
## StateWV 0.097863 .
## StateWI < 0.0000000000000002 ***
## StateWY < 0.0000000000000002 ***
## DIVISIONMiddle Atlantic NA
## DIVISIONEast North Central NA
## DIVISIONWest North Central NA
## DIVISIONSouth Atlantic NA
## DIVISIONEast South Central NA
## DIVISIONWest South Central NA
## DIVISIONMountain NA
## DIVISIONPacific NA
## HouseAcre < 0.0000000000000002 ***
## SaleofAgroProduct 0.000000000000423541 ***
## Bathtub 0.000000913056005648 ***
## HotWater NA
## Bedrooms < 0.0000000000000002 ***
## RMSP < 0.0000000000000002 ***
## SINK 0.023809 *
## Stove 0.785930
## Toilet 0.000000000752101470 ***
## HouseStructureYear1940 to 1949 0.008101 **
## HouseStructureYear1950 to 1959 < 0.0000000000000002 ***
## HouseStructureYear1960 to 1969 < 0.0000000000000002 ***
## HouseStructureYear1970 to 1979 < 0.0000000000000002 ***
## HouseStructureYear1980 to 1989 < 0.0000000000000002 ***
## HouseStructureYear1990 to 1999 < 0.0000000000000002 ***
## HouseStructureYear2000 to 2004 < 0.0000000000000002 ***
## HouseStructureYear2005 < 0.0000000000000002 ***
## HouseStructureYear2006 < 0.0000000000000002 ***
## HouseStructureYear2007 < 0.0000000000000002 ***
## HouseStructureYear2008 < 0.0000000000000002 ***
## HouseStructureYear2009 < 0.0000000000000002 ***
## HouseStructureYear2010 < 0.0000000000000002 ***
## HouseStructureYear2011 0.000000090935580362 ***
## HouseStructureYear2012 < 0.0000000000000002 ***
## HouseStructureYear2013 0.000000000000356943 ***
## HouseStructureYear2014 0.000000014359983419 ***
## HouseStructureYear2015 0.000000011409434055 ***
## HouseStructureYear2016 0.000375 ***
## HouseStructureYear2017 0.929348
## Kitchen 0.000007212301045274 ***
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 346.5 on 88829 degrees of freedom

```



```
## (7398452 observations deleted due to missingness)
## Multiple R-squared: 0.2485, Adjusted R-squared: 0.2478
## F-statistic: 371.8 on 79 and 88829 DF, p-value: < 0.00000000000000022
```

```
p2 <- predict(rent_model, newdata=test)

(combine<-data.frame(cbind(test$RENT, p2)))
```

	V1 <dbl>	p2 <dbl>
3	NA	NA
4	105.40150	512.2706
5	84.32120	NA
8	NA	441.1304
11	NA	NA
14	621.86885	NA
20	NA	NA
24	NA	934.8959
28	NA	NA
29	NA	544.7764
1-10 of 10,000 rows	Previous 1 2 3 4 5 6 ... 1000 Next	

```
colnames(combine)<-c("Actual", "Pred") # giving column names

(correlation<-cor.test(combine$Actual,combine$Pred))
```

```
##
## Pearson's product-moment correlation
##
## data: combine$Actual and combine$Pred
## t = 86.086, df = 22222, p-value < 0.00000000000000022
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
## 0.4901643 0.5098840
## sample estimates:
## cor
## 0.500089
```

The accuracy of Rent model is only 24% and from prediction we can say that by including other utilities such as Bathtub, kitchen, agro products, acres, the rent would be 105.40 whilst our predicted rent is 512, which shows a great difference between actual and predicted value. Thus, lower the accuracy, more worst our prediction would be.