Boston Housing

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Overview

We will investigate data from the Boston Housing Market. We have data from 14 variables for individual housing units. Our goal is to investigate these variables & realationships among them, to ultimately build a Machine Learning system that could predict house prices(our response variable) with high accuracy given instances of new data containing these 13 predictor variables.

Data Investigation

The 14 variables are as listed below

crim- per capita crime rate by town.

zn- proportion of residential land zoned for lots over 25,000 sq.ft.

indus- proportion of non-retail business acres per town.

chas- Charles River dummy variable (= 1 if tract bounds river; 0 otherwise).

nox- nitrogen oxides concentration (parts per 10 million).

rm- average number of rooms per dwelling.

age- proportion of owner-occupied units built prior to 1940.

dis- weighted mean of distances to five Boston employment centres.

rad- index of accessibility to radial highways.

tax- full-value property-tax rate per $10,000.

ptratio- pupil-teacher ratio by town.

black- 1000(Bk - 0.63)^2 where Bk is the proportion of blacks by town.

lstat- lower status of the population (percent).

medv(target variable)- median value of owner-occupied homes in $1000s.

Import Data

```r
housing<-read.csv(file = 'housing.csv',sep="")
names(housing)<-c("crim","zn","indus","chas","nox","rm","age",
                  "dis","rad","tax","ptratio","black","lstat","medv")
```

Data Visualization

We will look at distributions of our given variables & their bivariate plots with respect to the the target variable (medv) to identify key variables that may act as significant features in predicting our response variable so we may build a Machine Learning system with minimal noise as input

Models that will be considering are:

1. Multiple Linear Regression

- we will look for linear relationships between variables & target variable

2. Decision Trees

- we will look for splits within the distribution of the variables that may help us identify between the 3 categories of housing prices

I have divided, the target variable (medv-housing prices), into 3 categories: low price(less than equal to $15K), medium price($15K-30K), & high price ($35K).

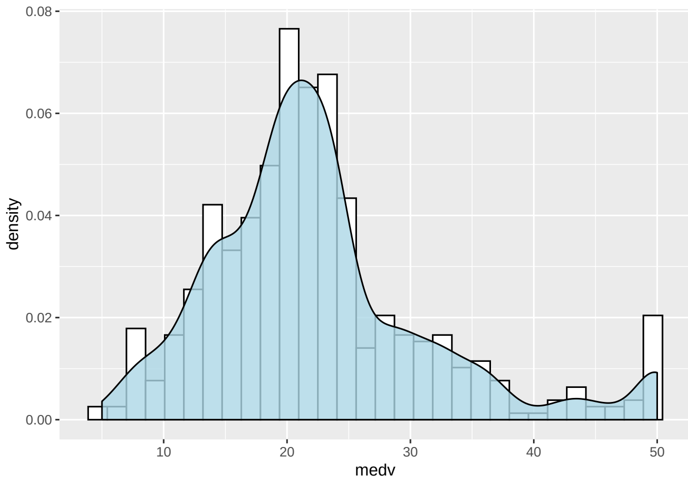
```
classifier =function(x)
{
    if(x<=15)
    {
        return ("low")
    }
    else if(x>15 & x<35)
    {
        return ("med")
    }
    else
    {
        return ("high")
    }
}

housing<-housing%>%mutate(class=sapply(medv,classifier))

attach(housing)
```

Medv (Target Variable)

Distribution for our Target Variable, & it's Distribution divided by Categorie

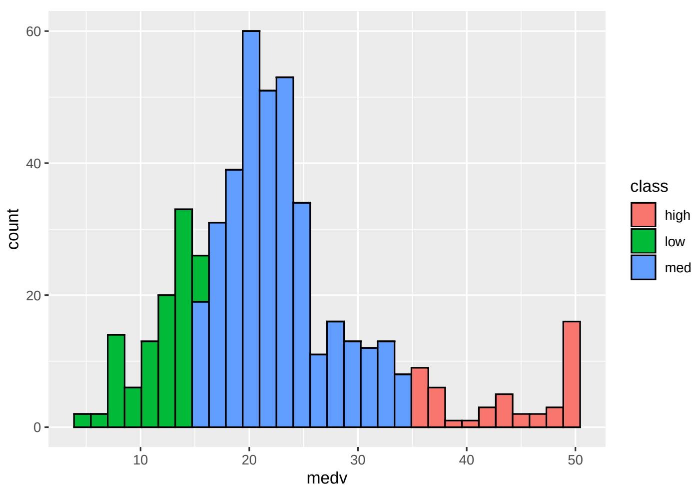
```
ggplot(housing, aes(x=medv)) +
    geom_histogram(aes(y=..density..), colour="black", fill="white")+
    geom_density(alpha=.8, fill="lightblue")
```

```
`stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```




```
ggplot(housing, aes(x=medv,fill=class)) +   geom_histogram(colour="black")
```

```
`stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```




```
count(filter(housing,class=="low"))/length(class)
```

```
          n
1 0.1920792
```

```
count(filter(housing,class=="med"))/length(class)
```

```
          n
1 0.7128713
```

```
count(filter(housing,class=="high"))/length(class)
```

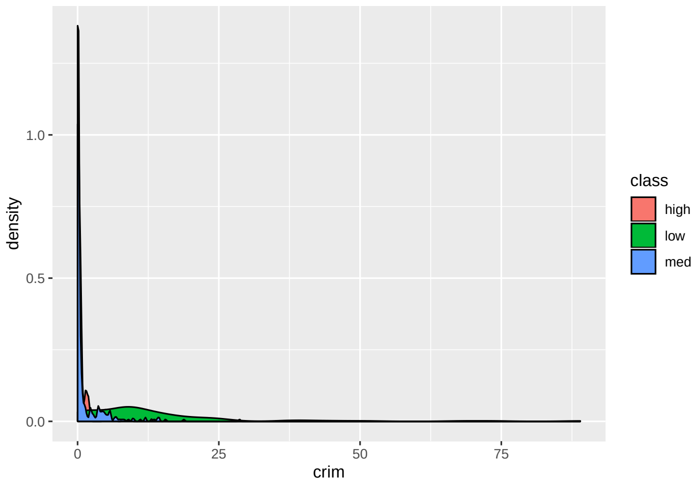
```
          n
1 0.0950495
```

Observation:

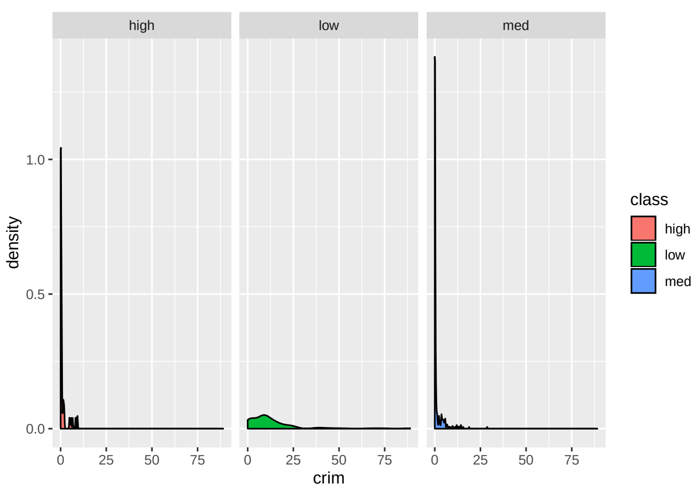
The distribution has a peak around Housing Prices of medium level($15K-$35), accounting for 71% of Prices, low level(below $15K) accounting for 19%, & high level (above $35K) accounting for 9%

Variable # 1: Crim

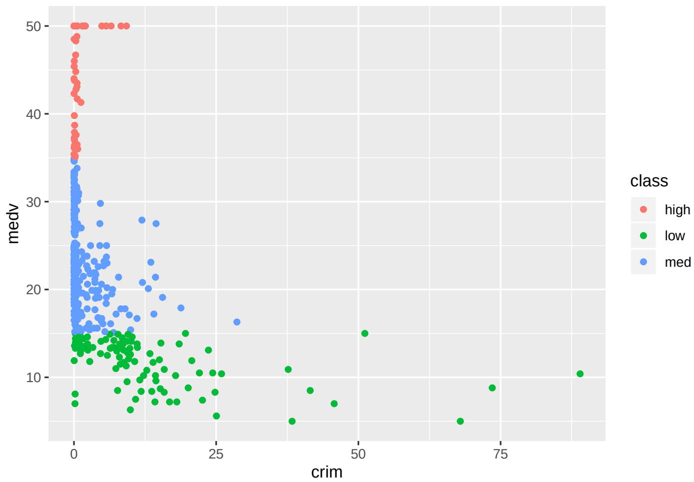
```
ggplot(housing, aes(x=crim,fill=class)) +   geom_density()
```




```
ggplot(housing, aes(x=crim,fill=class)) +   geom_density()+facet_wrap(~class)
```



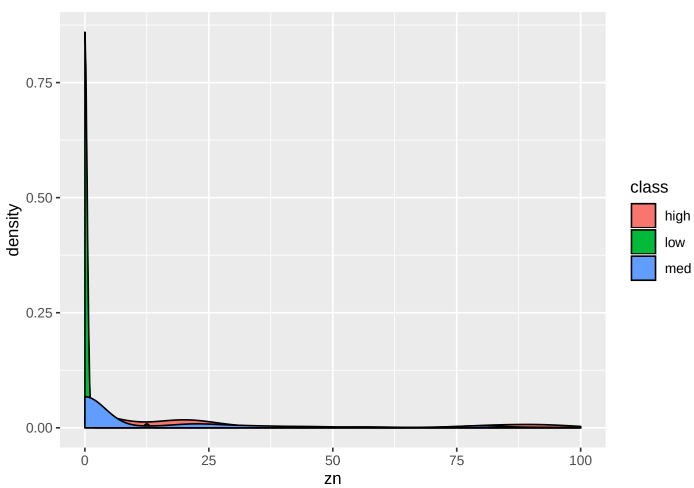

```
ggplot(housing, aes(x=crim,y=medv,color=class)) +   geom_point()
```



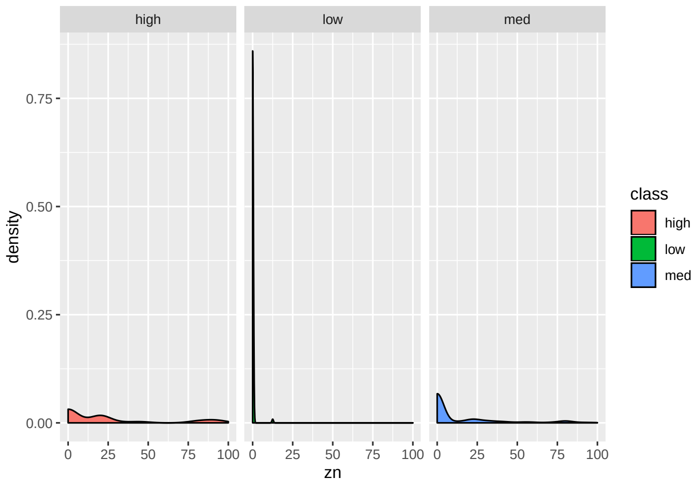
The distribution for crimes appears to have a higher spread for lower house price, and less for medium and high. Crime rates past 25% all appear to be of lower income, while those below 25% have a high concentration of all 3.

Variable # 2: Zn

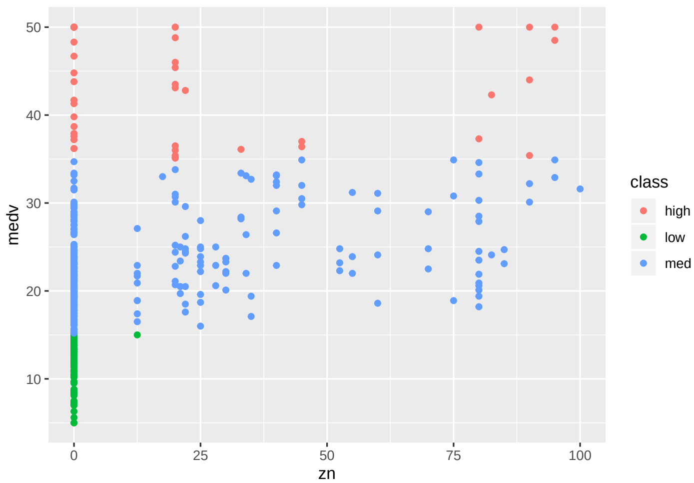
```
ggplot(housing, aes(x=zn,fill=class)) +   geom_density()
```




```
ggplot(housing, aes(x=zn,fill=class)) +   geom_density()+facet_wrap(~class)
```



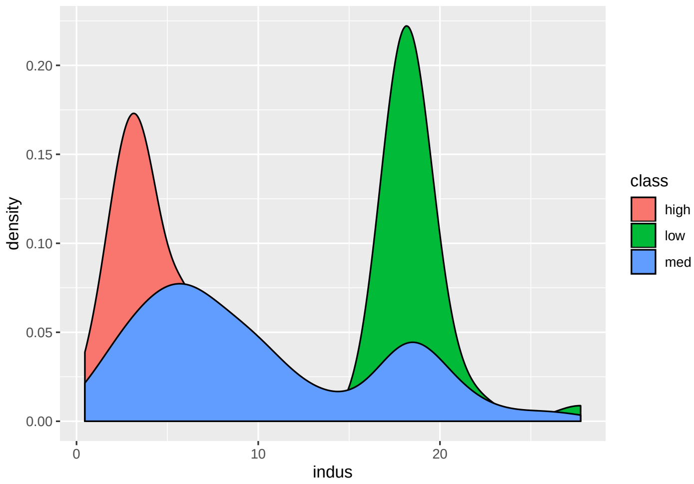

```r
ggplot(housing, aes(x=zn,y=medv,color=class)) +   geom_point()
```



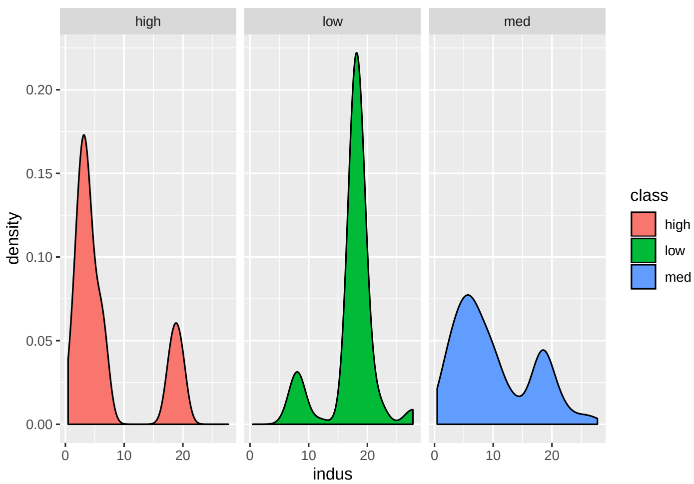
The distribution for proportion of residential land zoned for lots appears to have equal distribtion for values of 0, while greater values have a blend of med & high, no apparent relationship seems to be apparent as there is a high variance in response variable (medv)

Variable # 3: Indus

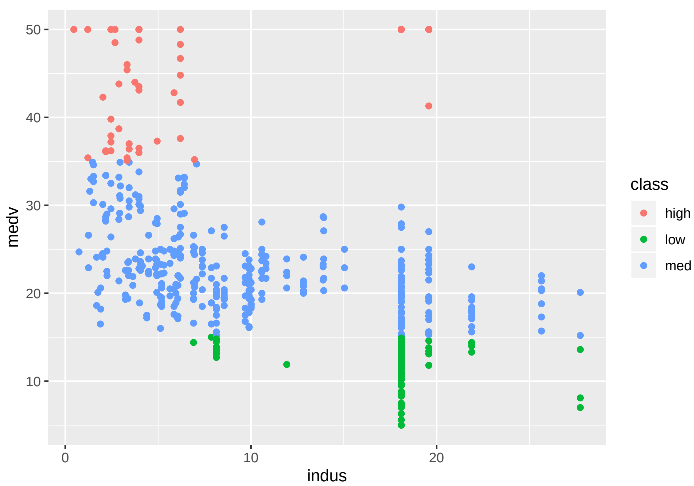
```r
ggplot(housing, aes(x=indus,fill=class)) +   geom_density()
```




```
ggplot(housing, aes(x=indus,fill=class)) +   geom_density()+facet_wrap(~class)
```



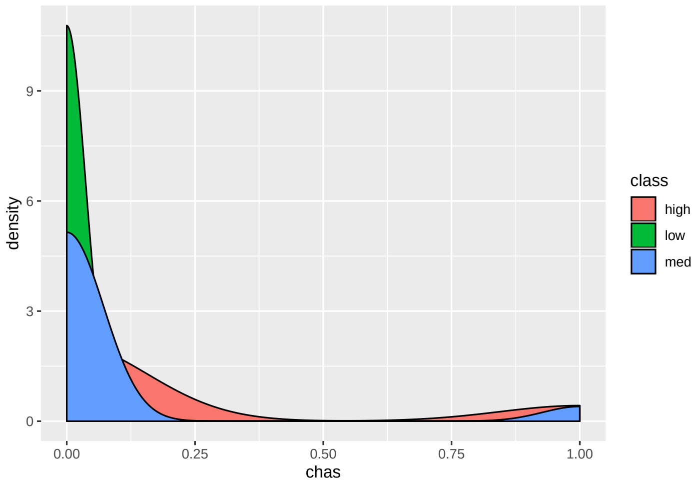

```
ggplot(housing, aes(x=indus,y=medv,color=class)) +   geom_point()
```



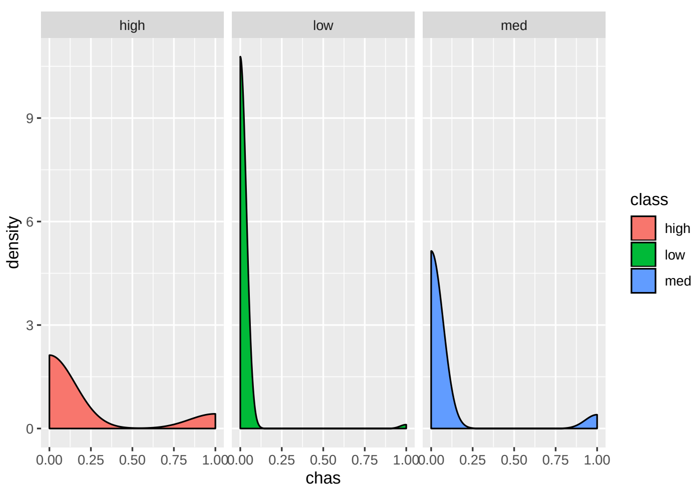
The distribution for proportion of non-retail business acres per town appears to have apparent distinctions for each categorie of house prices. There seems to be an apparent negative linear relationship, as proportion increases house prices get lower

Variable # 4: Chas

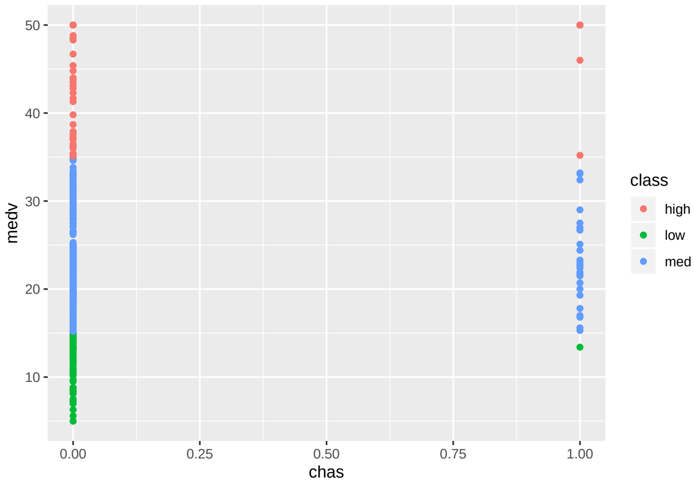
```r
ggplot(housing, aes(x=chas,fill=class)) +   geom_density()
```




```r
ggplot(housing, aes(x=chas,fill=class)) +   geom_density()+facet_wrap(~class)
```



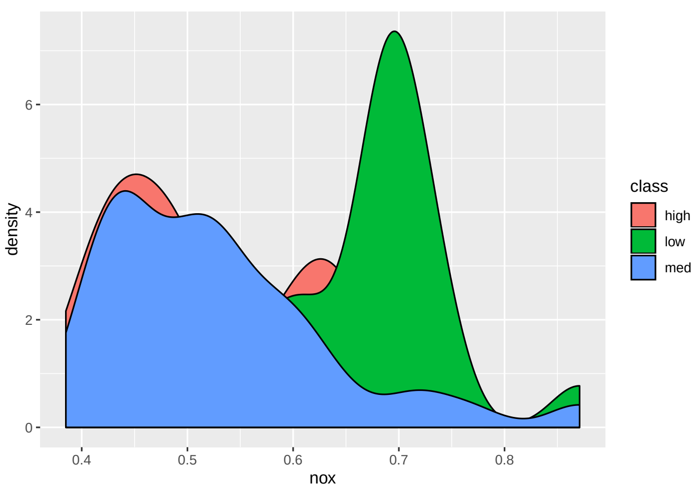

```r
ggplot(housing, aes(x=chas,y=medv,color=class)) +   geom_point()
```



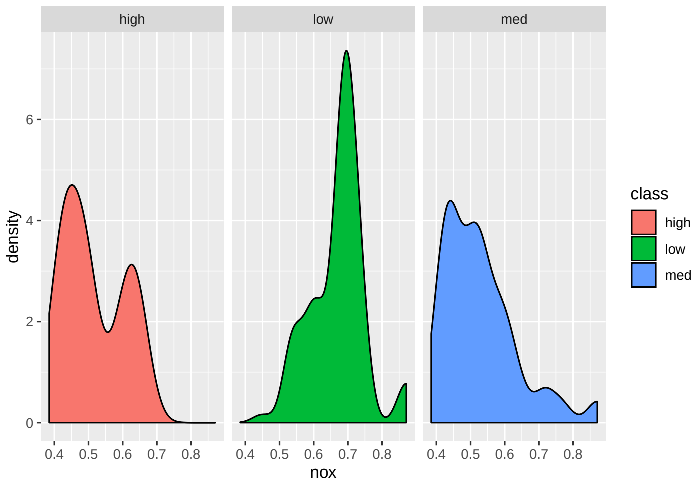
We can see that house prices are of medium range when closer to the river while those that arent are of equal distribution

Variable # 5: Nox

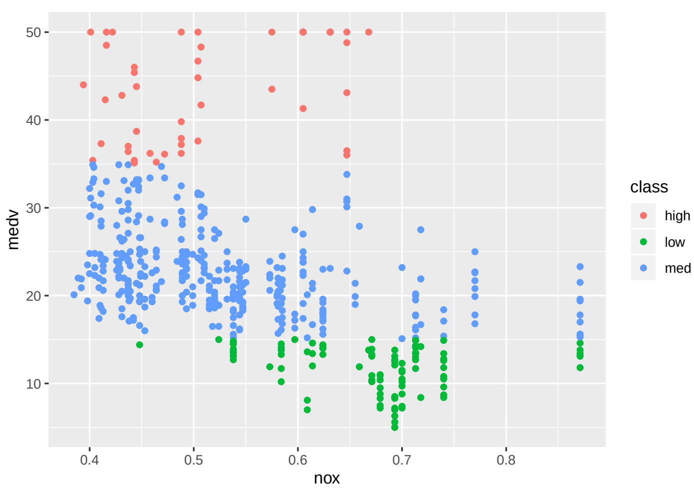
```
ggplot(housing, aes(x=nox,fill=class)) +   geom_density()
```




```
ggplot(housing, aes(x=nox,fill=class)) +   geom_density()+facet_wrap(~class)
```



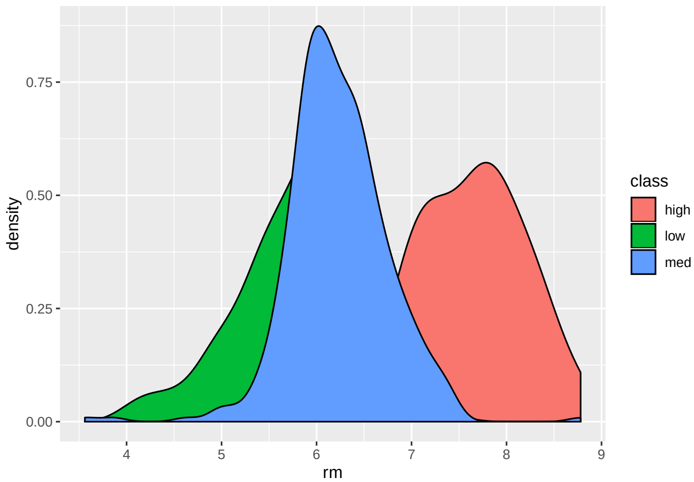

```r
ggplot(housing, aes(x=nox,y=medv,color=class)) +   geom_point()
```



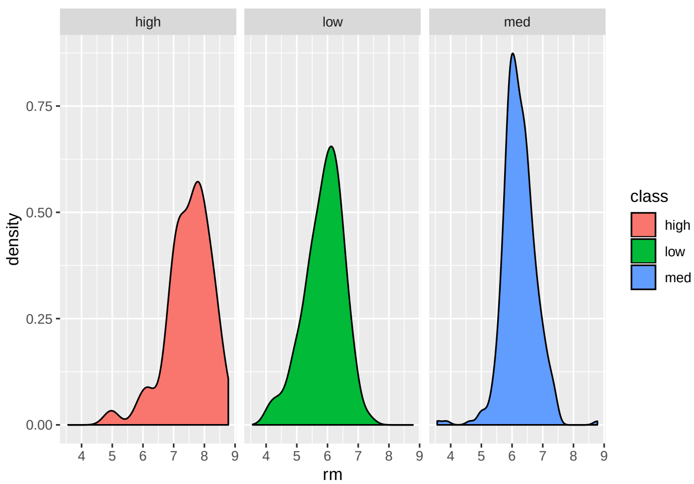
The distribution for nitrogen oxide concentration appears to have apparent distinctions for low vs med/high. There seems to be an apparent negative linear relationship, as concentration increases house prices get lower. However there seems to be high response variability for values of med and high

Variable # 6: Rm

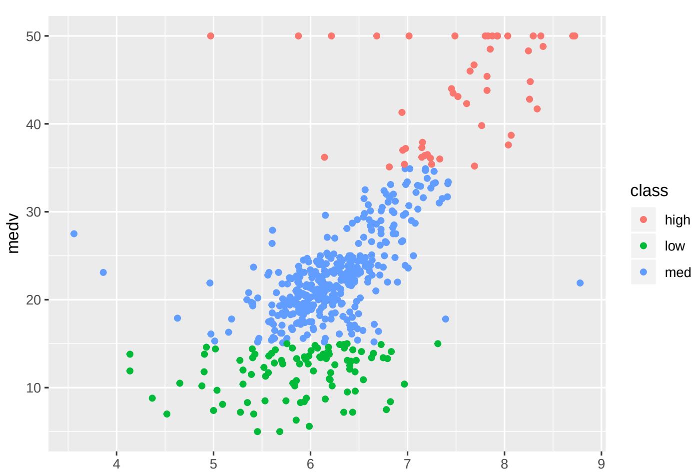
```r
ggplot(housing, aes(x=rm,fill=class)) +   geom_density()
```




```r
ggplot(housing, aes(x=rm,fill=class)) +   geom_density()+facet_wrap(~class)
```



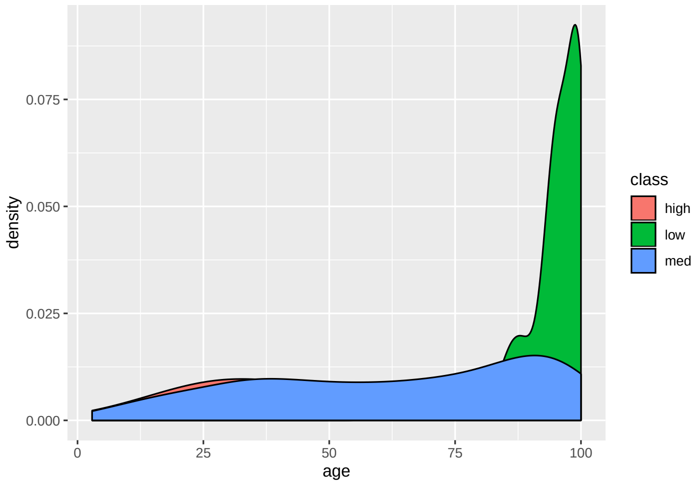

```r
ggplot(housing, aes(x=rm,y=medv,color=class)) +   geom_point()
```



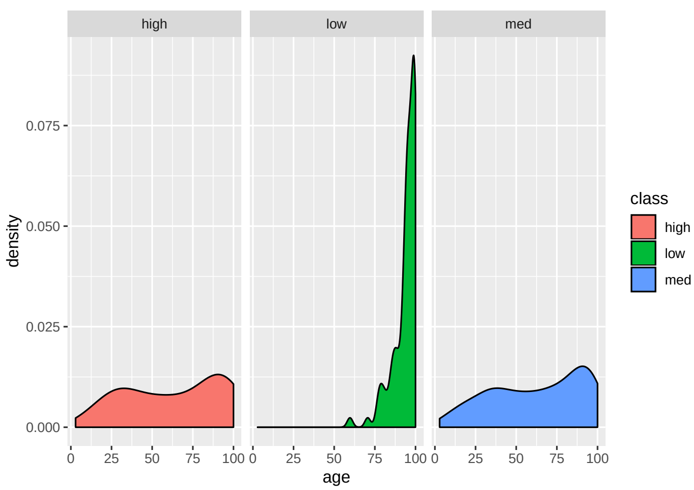
There is a high correlation between average number of rooms per dwelling & house prices, very apparent with a positive linear relationship, although there exists high variance for lower prices houses, but still follows linear relationship regardless with a few exceptions that we may be able to capture with the help of other variables

Variable # 7: Age

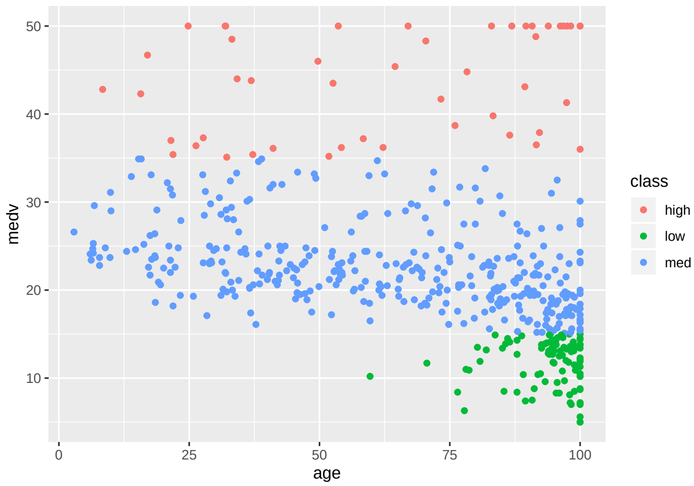
```
ggplot(housing, aes(x=age,fill=class)) +   geom_density()
```




```
ggplot(housing, aes(x=age,fill=class)) +   geom_density()+facet_wrap(~class)
```



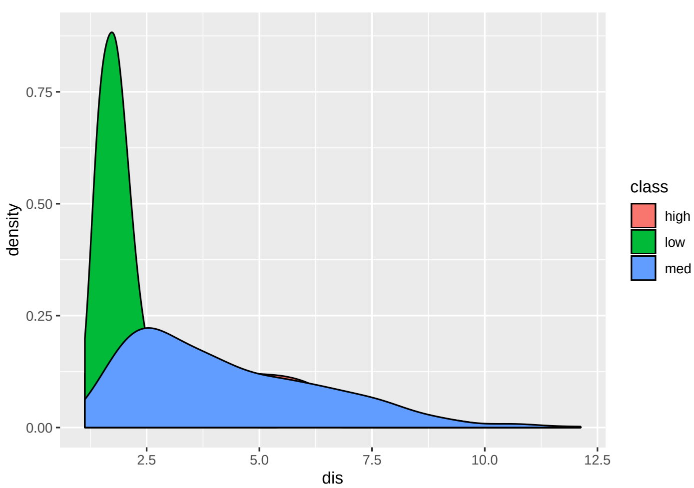

```
ggplot(housing, aes(x=age,y=medv,color=class)) +   geom_point()
```



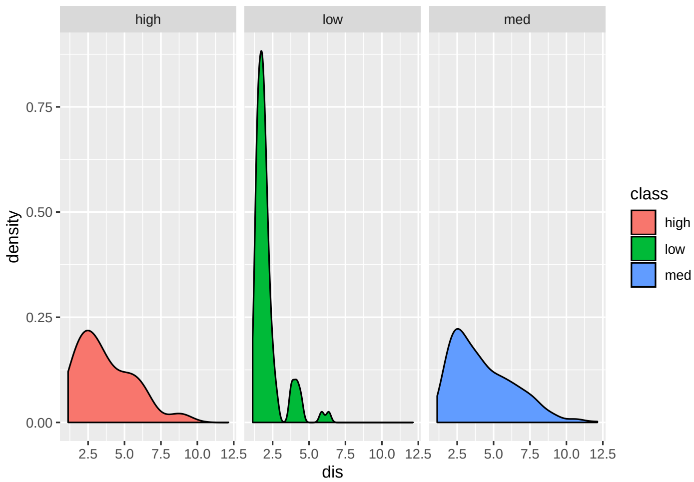
The distributions shows all low priced houses being of old age, but distributions for med & low are the same distribution with high variance in response and predictor

Variable # 8: Dis

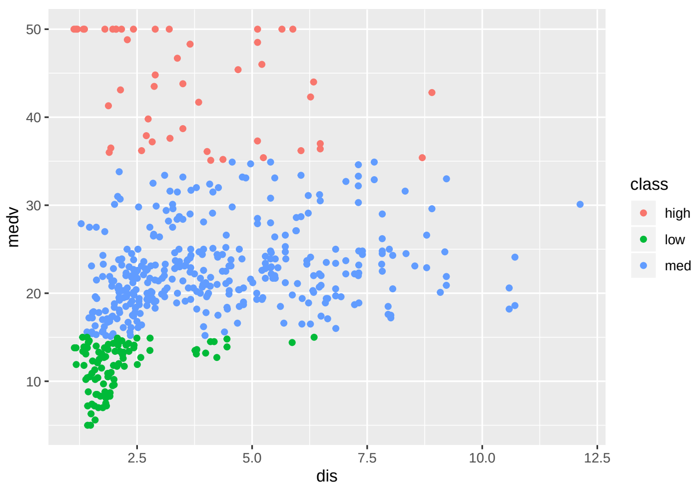
```r
ggplot(housing, aes(x=dis,fill=class)) +   geom_density()
```




```r
ggplot(housing, aes(x=dis,fill=class)) +   geom_density()+facet_wrap(~class)
```



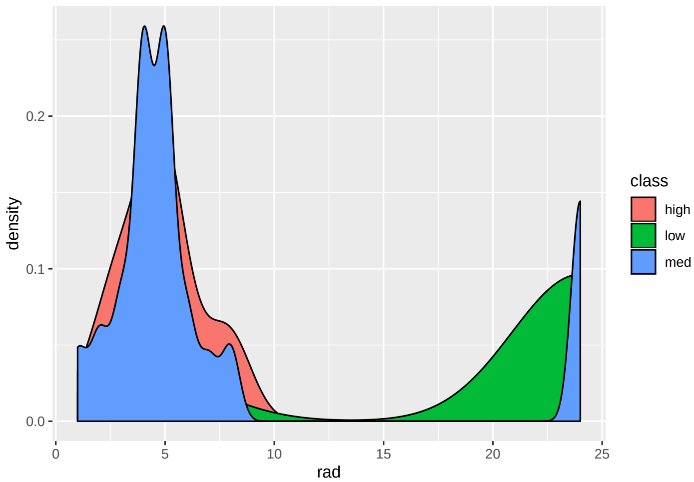

```r
ggplot(housing, aes(x=dis,y=medv,color=class)) +   geom_point()
```



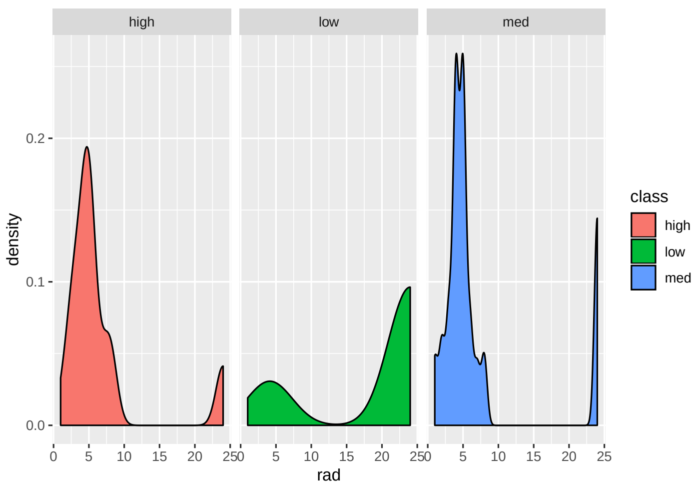
The distribution shows as weighted mean of distances to five Boston employment centres increases, the house prices are more towards the median and high side, with lower values having a mix of all 3, however the variance is quite high

Variable # 9: Rad

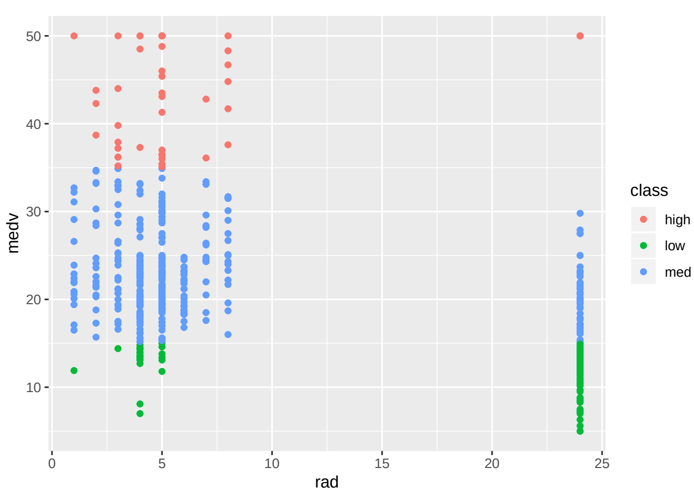
```r
ggplot(housing, aes(x=rad,fill=class)) +   geom_density()
```




```r
ggplot(housing, aes(x=rad,fill=class)) +    geom_density()+facet_wrap(~class)
```



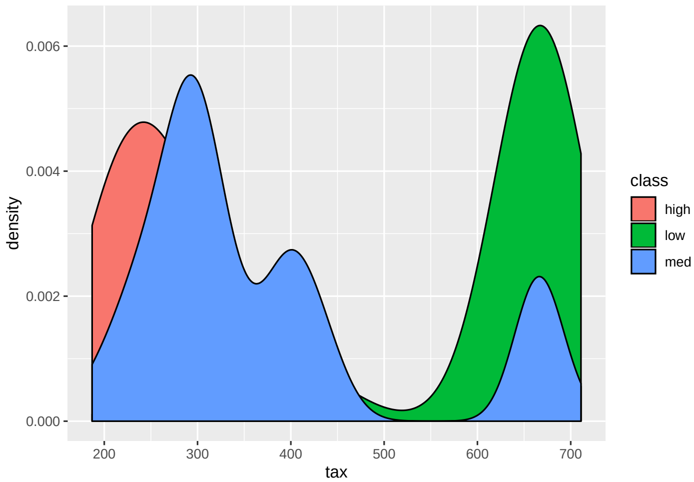

```r
ggplot(housing, aes(x=rad,y=medv,color=class)) +    geom_point()
```



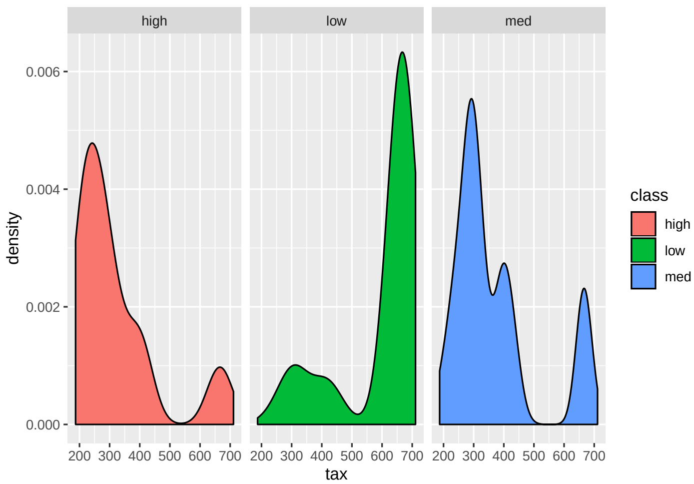
We can see that index of accessibility to radial highways, help indicate the prices of higher valued houses but fail to distinguish between low and med

Variable # 10: Tax

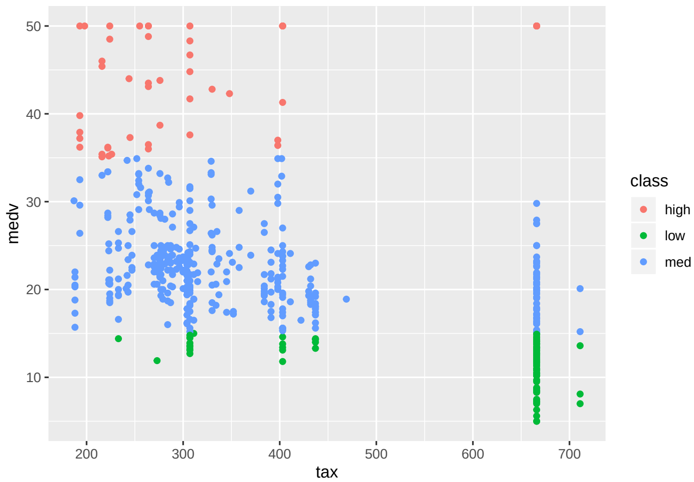
```r
ggplot(housing, aes(x=tax,fill=class)) +   geom_density()
```




```r
ggplot(housing, aes(x=tax,fill=class)) +   geom_density()+facet_wrap(~class)
```



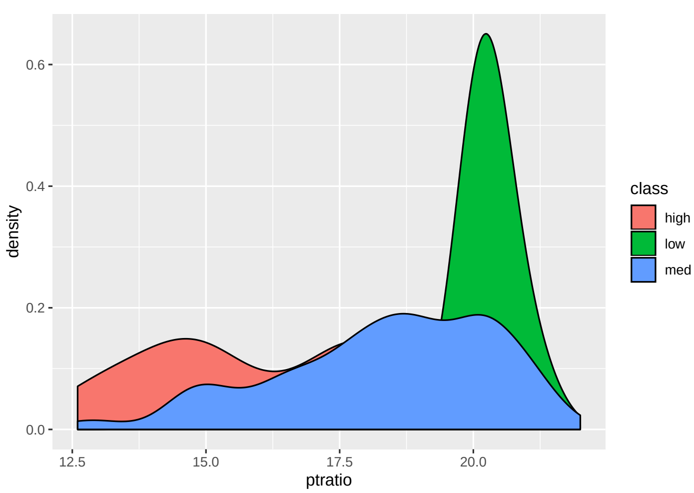

```r
ggplot(housing, aes(x=tax,y=medv,color=class)) +   geom_point()
```



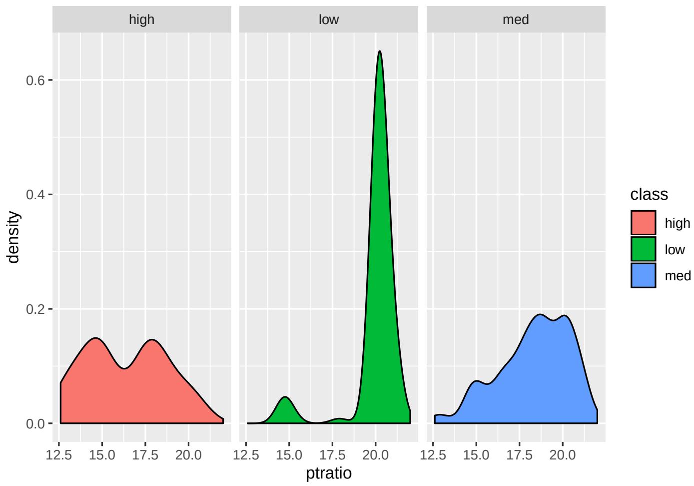
We see from the distribution that it is easy to view the distributional difference between low houses and med/high houses, and there exists large variability in med/low houses

Variable # 11: Ptratio

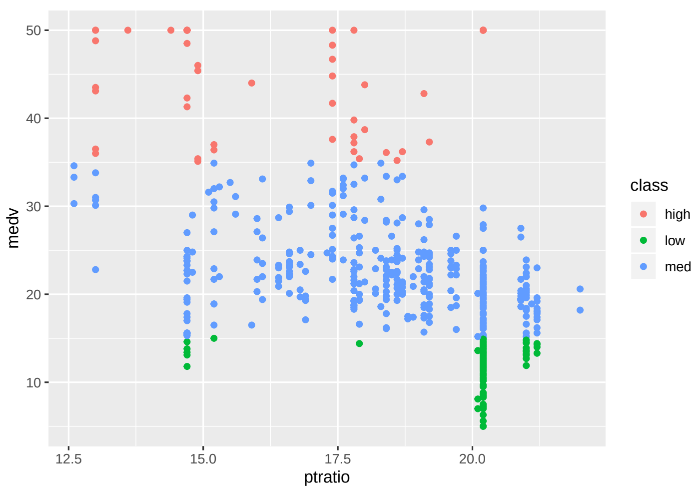
```
ggplot(housing, aes(x=ptratio,fill=class)) +   geom_density()
```




```
ggplot(housing, aes(x=ptratio,fill=class)) +   geom_density()+facet_wrap(~class)
```



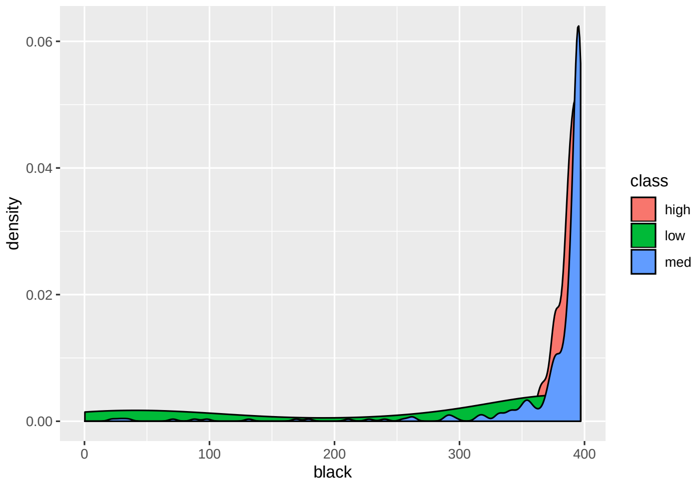

```
ggplot(housing, aes(x=ptratio,y=medv,color=class)) +   geom_point()
```



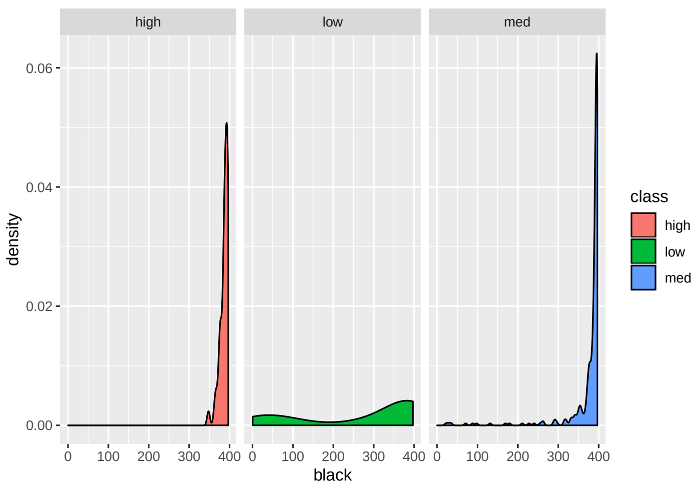
The distribution seems to have a negative liner relationship, however a very high level of variance

Variable # 12: Black

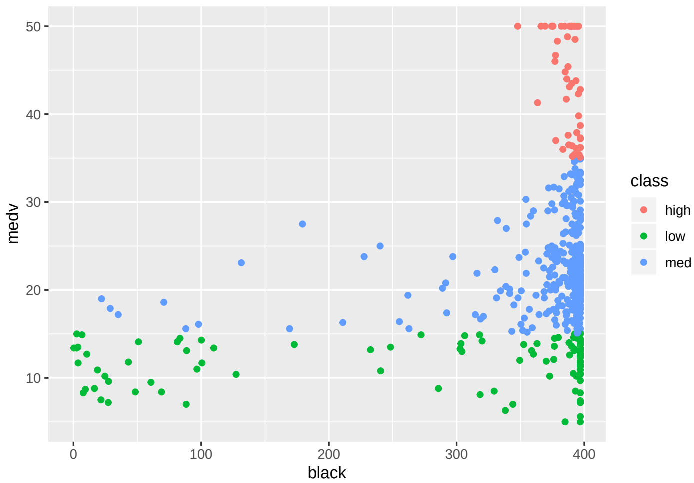
```
ggplot(housing, aes(x=black,fill=class)) +   geom_density()
```




```
ggplot(housing, aes(x=black,fill=class)) +   geom_density()+facet_wrap(~class)
```



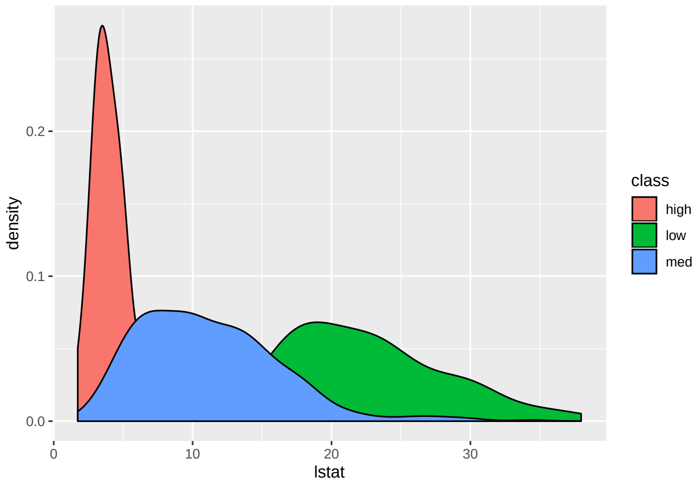

```
ggplot(housing, aes(x=black,y=medv,color=class)) +   geom_point()
```



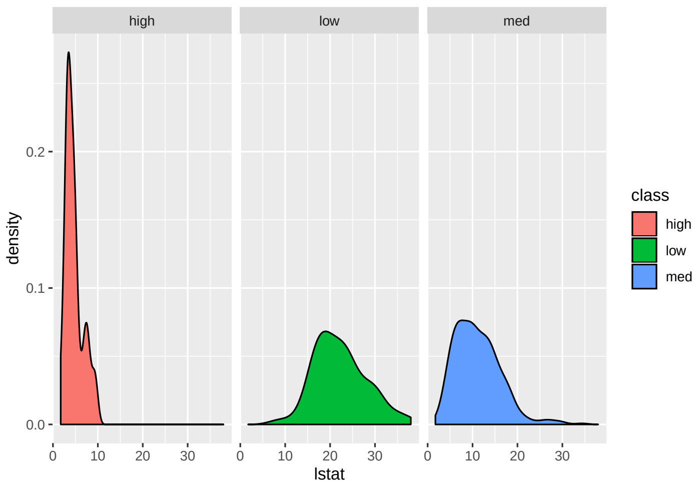
Aside from the fact that lower values tend to reflect a lower prices in houses, it seems to show no other pattern for values over 400

Variable # 13: Lstat

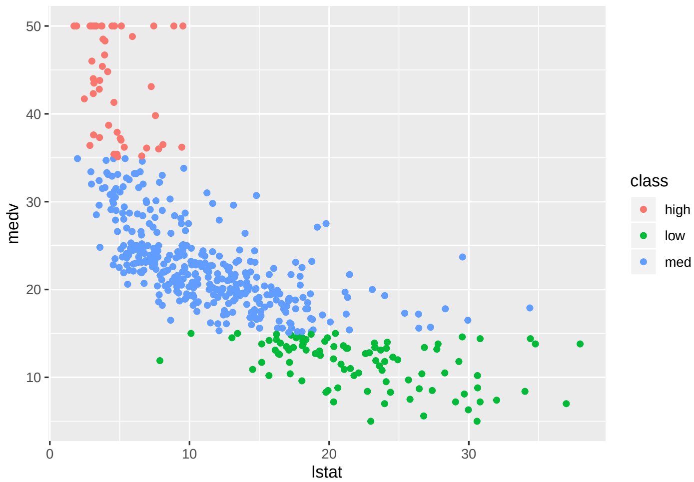
```r
ggplot(housing, aes(x=lstat,fill=class)) +   geom_density()
```




```r
ggplot(housing, aes(x=lstat,fill=class)) +   geom_density()+facet_wrap(~class)
```




```r
ggplot(housing, aes(x=lstat,y=medv,color=class)) +   geom_point()
```



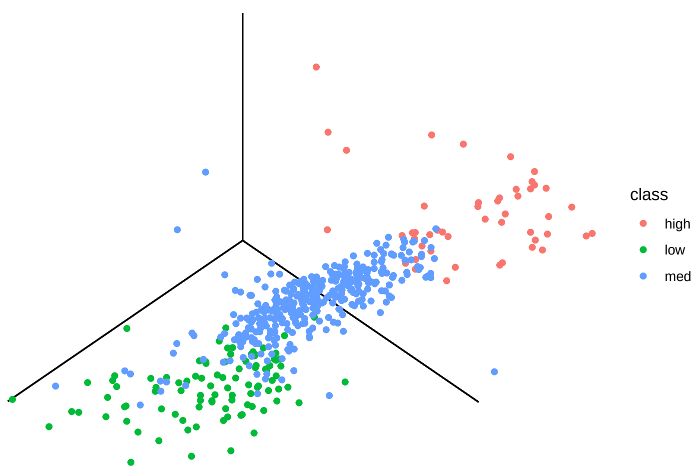
A clearly negatively linear correlation exists, with low variance comparetively as well, there seems to exist a little skew we may hope to capture

3D Plots

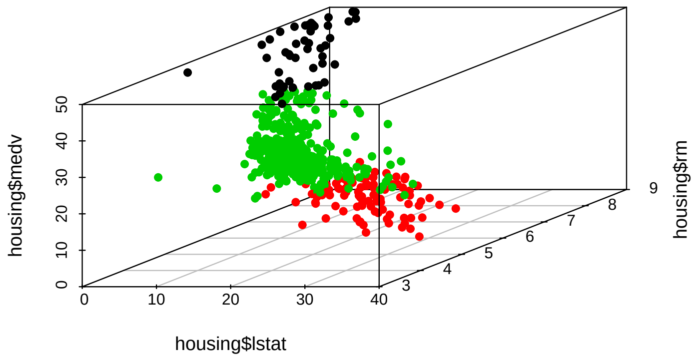
I shall plot 3 Dimensional Scatterplots of variables I believe give a strong indicator of house prices, and hypothesis on the multiple regression model to be fit

Lstat & Rm

```
ggplot(housing, aes(x=lstat, y=rm, z=medv, color=class)) +
    theme_void() +
    axes_3D() +
    stat_3D()
```

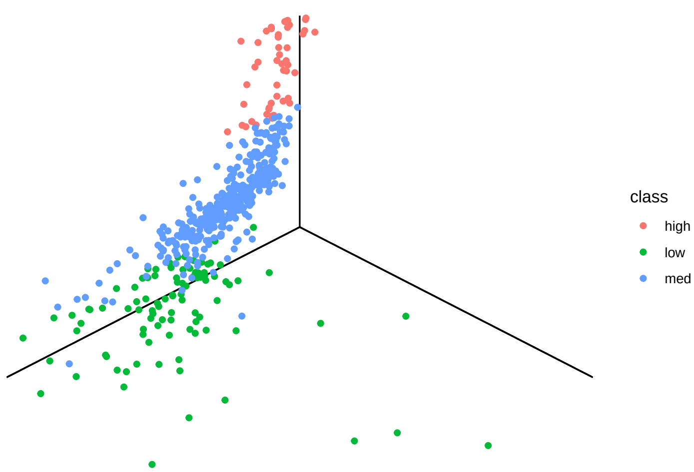



```
housing$class <- as.factor(housing$class)

scatterplot3d(x=housing$lstat, y=housing$rm, z=housing$medv,pch=16, color=as.numeric(housing$class))
```

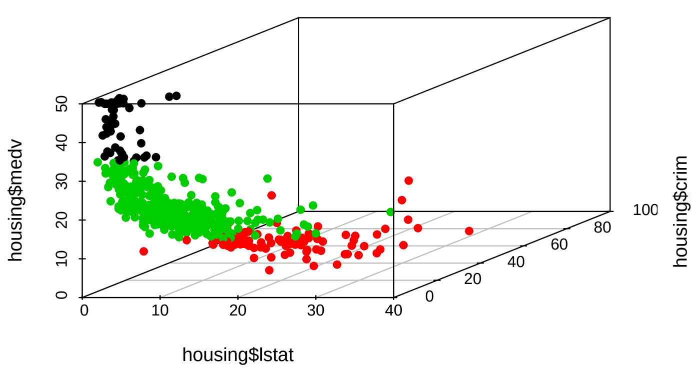


Lstat & Crim

```
ggplot(housing, aes(x=lstat, y=crim, z=medv, color=class)) +
    theme_void() +
    axes_3D() +
    stat_3D()
```

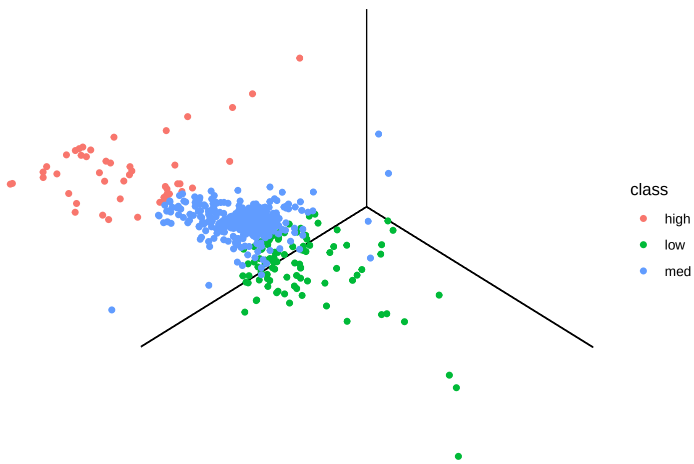



```
scatterplot3d(x=housing$lstat, y=housing$crim, z=housing$medv,pch=16, color=as.numeric(housing$class))
```

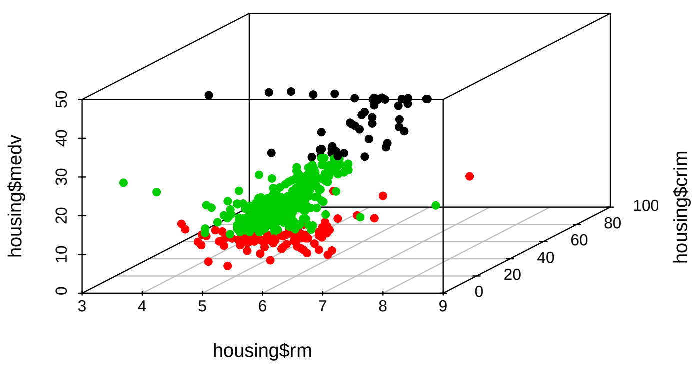


Rm & Crim

```
ggplot(housing, aes(x=rm, y=crim, z=medv, color=class)) +
    theme_void() +
    axes_3D() +
    stat_3D()
```

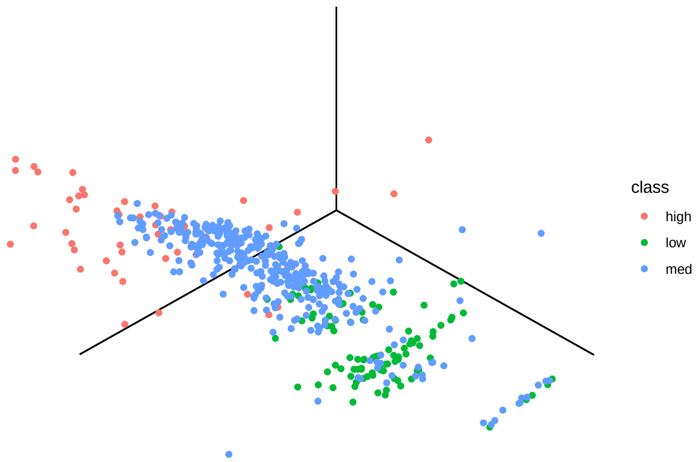



```
scatterplot3d(x=housing$rm, y=housing$crim, z=housing$medv,pch=16, color=as.numeric(housing$class))
```

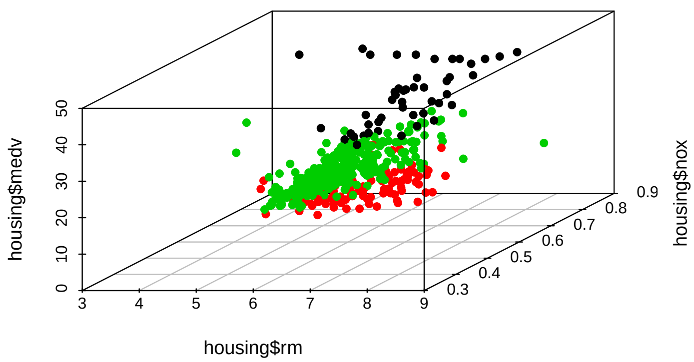


Rm & Nox

```
ggplot(housing, aes(x=rm, y=nox, z=medv, color=class)) +
    theme_void() +
    axes_3D() +
    stat_3D()
```

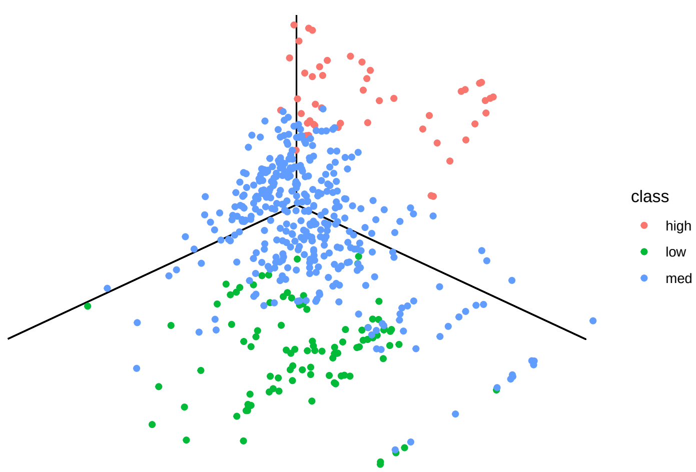



```r
scatterplot3d(x=housing$rm, y=housing$nox, z=housing$medv,pch=16, color=as.numeric(housing$class))
```

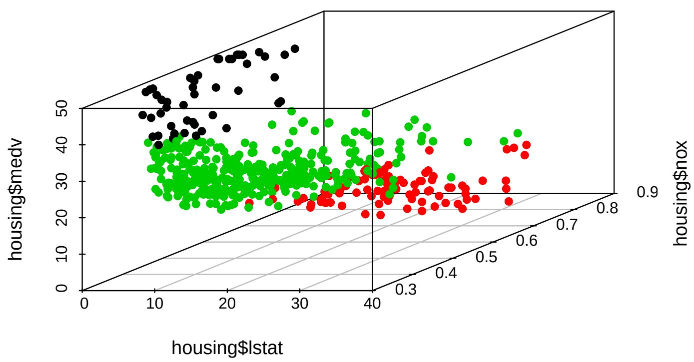


Lstat & Nox

```r
ggplot(housing, aes(x=lstat, y=nox, z=medv, color=class)) +
    theme_void() +
    axes_3D() +
    stat_3D()
```



```r
scatterplot3d(x=housing$lstat, y=housing$nox, z=housing$medv,pch=16, color=as.numeric(housing$class))
```



Observation:

These variables studied above show clear linear realationships between the predictors and the response, the variability in Medv is explained by these inputs + Noise. We shall explore Building MLR models with them, and further investigate statistically significant variable detected beyond via R commands, this allows to to view insights beyond the eye test

Multiple Linear Regression

Feature Selection

We will try out a Multiple Linear Regression Model, but first we must ensure proper features are selected for our model to reduce noise, and we shall train the model & test performance on a test set

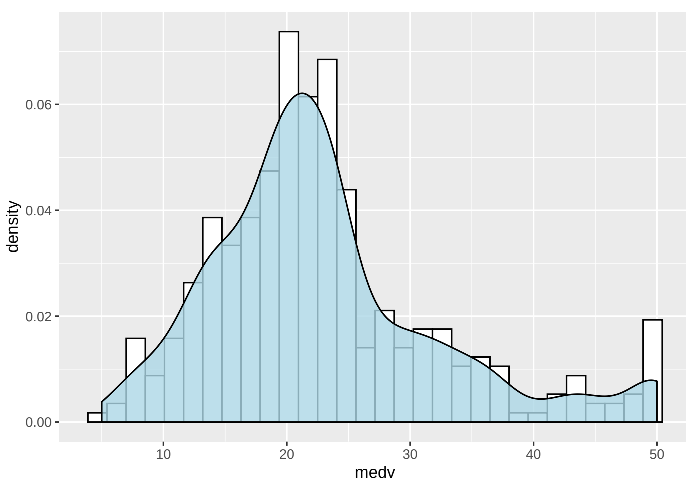
```r
housing<-housing[1:14]

model <- lm(medv ~ crim+zn+indus+chas+nox+rm+age+dis+rad+tax+ptratio+black+lstat, data = housing)

summary(model)
```

```
Call:
lm(formula = medv ~ crim + zn + indus + chas + nox + rm + age +
    dis + rad + tax + ptratio + black + lstat, data = housing)

Residuals:
     Min       1Q   Median       3Q      Max
-15.5642  -2.7248  -0.5312   1.7687  26.1511

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)  36.634941   5.102043   7.180 2.59e-12 ***
crim         -0.107417   0.032847  -3.270 0.001150 **
zn            0.046121   0.013721   3.361 0.000836 ***
indus         0.014269   0.061653   0.231 0.817071
chas          2.671108   0.861115   3.102 0.002033 **
```

```
nox         -17.633641   3.818719  -4.618 4.96e-06 ***
rm            3.794307   0.417835   9.081  < 2e-16 ***
age           0.001076   0.013205   0.081 0.935079    
dis          -1.479179   0.199347  -7.420 5.19e-13 ***
rad           0.301534   0.066398   4.541 7.04e-06 ***
tax          -0.012053   0.003765  -3.202 0.001454 ** 
ptratio      -0.958874   0.130831  -7.329 9.60e-13 ***
black         0.009305   0.002684   3.467 0.000573 ***
lstat        -0.527600   0.050732 -10.400  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 4.742 on 491 degrees of freedom
Multiple R-squared:  0.7415,    Adjusted R-squared:  0.7346 
F-statistic: 108.3 on 13 and 491 DF,  p-value: < 2.2e-16
```

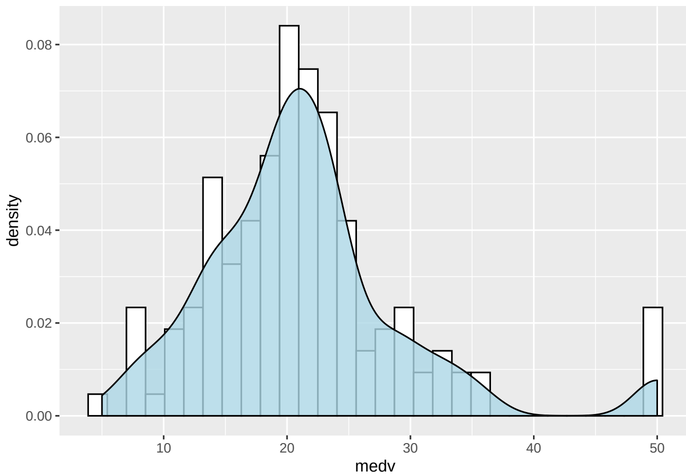
```
sample <- sample.split(medv, SplitRatio = .70)

train <- subset(housing, sample == TRUE)

test  <- subset(housing, sample == FALSE)


ggplot(train, aes(x=medv)) +
    geom_histogram(aes(y=..density..), colour="black", fill="white")+
    geom_density(alpha=.8, fill="lightblue")
```

```
`stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```




```
ggplot(test, aes(x=medv)) +
    geom_histogram(aes(y=..density..), colour="black", fill="white")+
    geom_density(alpha=.8, fill="lightblue")
```

```
`stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```




```
regfit.fwd=regsubsets(medv~.,data=train, nvmax=13,method="forward")

summary(regfit.fwd)
```

```
Subset selection object
Call: regsubsets.formula(medv ~ ., data = train, nvmax = 13, method = "forward")
13 Variables  (and intercept)
        Forced in Forced out
crim        FALSE      FALSE
zn          FALSE      FALSE
indus       FALSE      FALSE
chas        FALSE      FALSE
nox         FALSE      FALSE
rm          FALSE      FALSE
age         FALSE      FALSE
dis         FALSE      FALSE
rad         FALSE      FALSE
tax         FALSE      FALSE
ptratio     FALSE      FALSE
black       FALSE      FALSE
lstat       FALSE      FALSE
1 subsets of each size up to 13
Selection Algorithm: forward
          crim zn  indus chas nox rm  age dis rad tax ptratio black lstat
1  ( 1 )  " "  " " " "   " "  " " " " " " " " " " " " " "     " "   "*"
2  ( 1 )  " "  " " " "   " "  " " "*" " " " " " " " " " "     " "   "*"
3  ( 1 )  " "  " " " "   " "  " " "*" " " " " " " " " "*"     " "   "*"
4  ( 1 )  " "  " " " "   " "  " " "*" " " " " " " " " "*"     "*"   "*"
5  ( 1 )  " "  " " " "   " "  " " "*" " " "*" " " " " "*"     "*"   "*"
6  ( 1 )  " "  " " " "   " "  "*" "*" " " "*" " " " " "*"     "*"   "*"
7  ( 1 )  " "  "*" " "   " "  "*" "*" " " "*" " " " " "*"     "*"   "*"
8  ( 1 )  " "  "*" " "   "*"  "*" "*" " " "*" " " " " "*"     "*"   "*"
9  ( 1 )  "*"  "*" " "   "*"  "*" "*" " " "*" " " " " "*"     "*"   "*"
10  ( 1 ) "*"  "*" " "   "*"  "*" "*" " " "*" "*" " " "*"     "*"   "*"
11  ( 1 ) "*"  "*" " "   "*"  "*" "*" " " "*" "*" "*" "*"     "*"   "*"
12  ( 1 ) "*"  "*" "*"   "*"  "*" "*" " " "*" "*" "*" "*"     "*"   "*"
13  ( 1 ) "*"  "*" "*"   "*"  "*" "*" "*" "*" "*" "*" "*"     "*"   "*"
```

```r
test.mat=model.matrix(medv~.,data=test)

validation.errors=rep(NA,13)

for(i in 1:13){
  coefi=coef(regfit.fwd,id=i)
  pred=test.mat[,names(coefi)]%*%coefi
  validation.errors[i]=mean((test$medv-pred)^2)

}



validation.errors
```

```
 [1] 36.21700 29.11124 25.94498 25.39358 23.32370 24.37883 23.77584 22.52542
 [9] 22.36304 21.77664 20.65098 20.85605 20.89573
```

```r
which.min(validation.errors)
```

```
[1] 11
```

```r
coef(regfit.fwd,id=which.min(validation.errors))
```

```
  (Intercept)          crim            zn          chas           nox
 40.708506655  -0.101416843   0.038176087   1.915972649 -22.052695249
           rm           dis           rad           tax       ptratio
  3.819294696  -1.581392947   0.254704983  -0.008969070  -1.027981738
        black         lstat
  0.008315321  -0.549929286
```

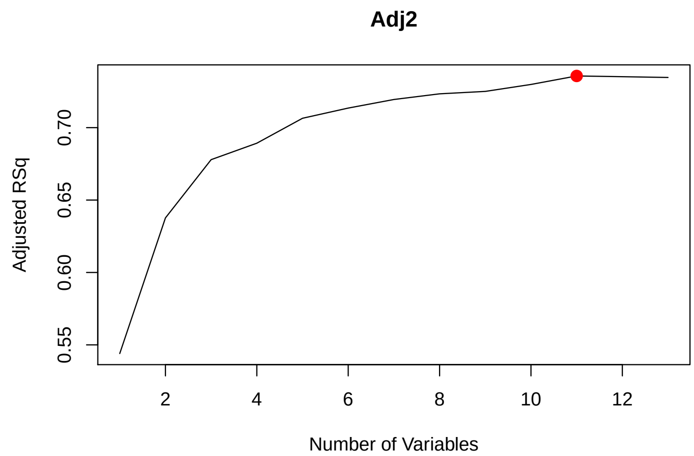
Observation:

We can see that 11 of these variables have statistical significance in the model because of there contribution in explaining the variance ifor the variable. The variables not included are indus and age. We shall test which number of variables are most optimal with more performance measures, & the test set

```r
regfit.full=regsubsets(medv~.,data=housing,nvmax=13,method="forward")
reg.summary=summary(regfit.full)

which.max(reg.summary$adjr2)
```

```
[1] 11
```

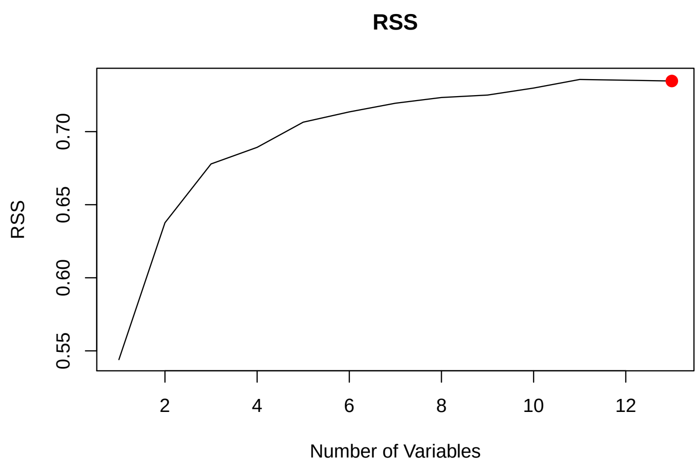
```r
plot(reg.summary$adjr2,xlab="Number of Variables",
      ylab="Adjusted RSq",type="l",main="Adj2")
points(which.max(reg.summary$adjr2),reg.summary$adjr2[which.max(reg.summary$adjr2)], col="red",cex=2,pc
```




```
which.min(reg.summary$rss)
```

```
[1] 13
```

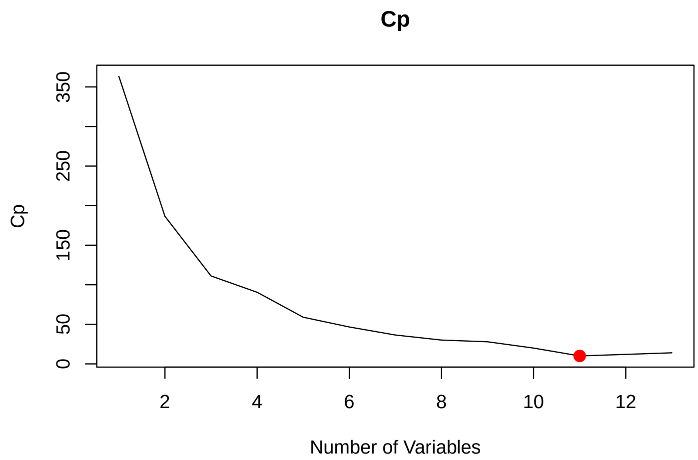
```
plot(reg.summary$adjr2,xlab="Number of Variables",
      ylab="RSS",type="l",main="RSS")
points(which.min(reg.summary$rss),reg.summary$adjr2[which.min(reg.summary$rss)], col="red",cex=2,pch=20
```




```
which.min(reg.summary$cp)
```

```
[1] 11
```

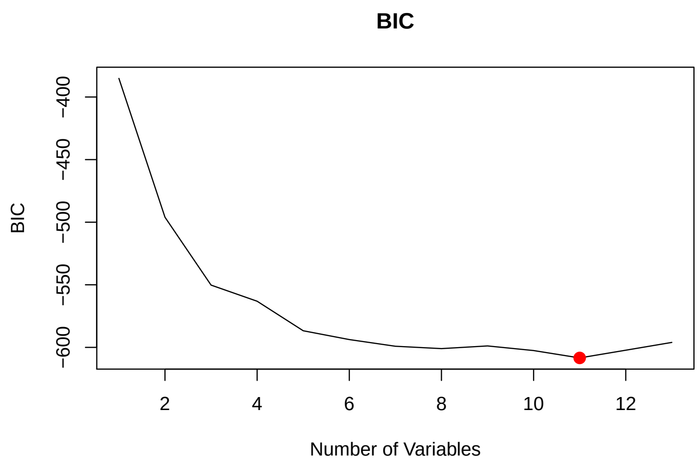
```
plot(reg.summary$cp,xlab="Number of Variables",
      ylab="Cp",type="l",main="Cp")
points(which.min(reg.summary$cp),reg.summary$cp[which.min(reg.summary$cp)], col="red",cex=2,pch=20)
```




```r
which.min(reg.summary$bic)
```

```
[1] 11
```

```r
plot(reg.summary$bic,xlab="Number of Variables",
      ylab="BIC",type="l",main="BIC")
points(which.min(reg.summary$bic),reg.summary$bic[which.min(reg.summary$bic)], col="red",cex=2,pch=20)
```



Observation:

We further confirm that 11 variables is the most optimal model to select for out Muliple Linear Regression, we shall now average error and compare predictions with the actual target. we will plot the distribution of our prediction

```r
coefficients<-as.matrix(coef(regfit.fwd,id=which.min(validation.errors)))

predictions<-function()
{
    predictions<- c()
    for(i in 1:length(medv))
    {
```

```
        input<-housing[i,][c("crim","zn","chas","nox","rm","dis","rad","tax","ptratio","black","lstat")]
        input<-as.data.frame(c(1,input))
        input<-as.matrix(input)

        prediction<-t(coefficients) %*% t(input)

        predictions<-c(predictions,prediction)
    }

    return (predictions)
}

predictions<-as.data.frame(predictions())

targetAndPrediction<-cbind(medv,predictions)
targetAndPrediction<-as.data.frame(targetAndPrediction)
names(targetAndPrediction)<-c("target","predictions")

filter(targetAndPrediction,predictions<0)
```

```
  target predictions
1   13.8 -0.09870132
2    7.0 -4.80441298
```

```
for(i in 1:length(targetAndPrediction$predictions)){

    if(targetAndPrediction$predictions[i]<0)
    {
        targetAndPrediction$predictions[i]=0
    }
}


targetAndPrediction<-targetAndPrediction%>%mutate(error=abs(target-predictions))

head(targetAndPrediction)
```

```
  target predictions     error
1   21.6    25.34659 3.7465946
2   34.7    31.04083 3.6591669
3   33.4    28.96020 4.4398007
4   36.2    28.23010 7.9699010
5   28.7    25.53852 3.1614848
6   22.9    23.10215 0.2021473
```

```
mean(targetAndPrediction$error)
```

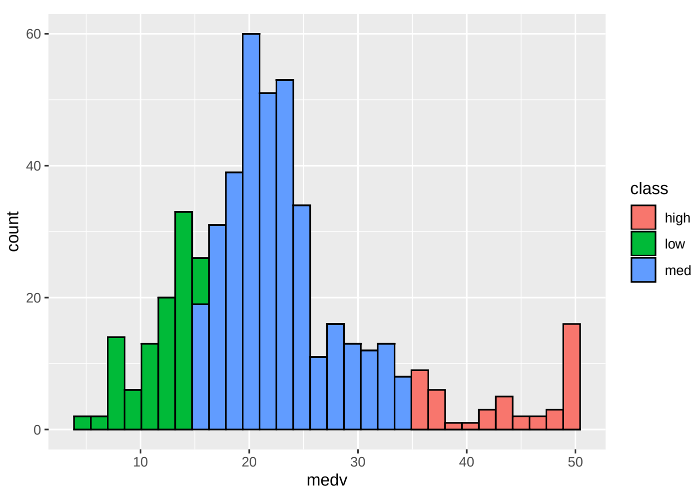
```
[1] 3.308083
```

```
filter(targetAndPrediction,error>=10)
```

```
   target predictions    error
1    14.4    3.358644 11.04136
2    50.0   37.413933 12.58607
3    50.0   37.794343 12.20566
4    50.0   36.343483 13.65652
5    23.7   10.957131 12.74287
6    46.7   35.962094 10.73791
7    48.3   37.592931 10.70707
8    42.8   30.007106 12.79289
9    21.9   36.372981 14.47298
10   27.5   13.870271 13.62973
11   23.1   10.923490 12.17651
12   50.0   23.875270 26.12473
13   50.0   31.957109 18.04289
14   50.0   33.947312 16.05269
15   50.0   24.926991 25.07301
16   50.0   25.090505 24.90949
17   13.8    0.000000 13.80000
18   15.0   25.054959 10.05496
19    7.2   17.218790 10.01879
20   17.9    1.566281 16.33372
21   11.9   22.321902 10.42190
```

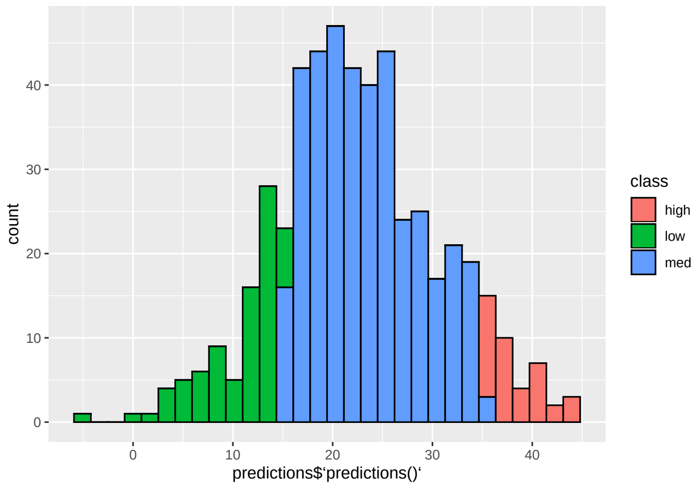
```
ggplot(housing, aes(x=medv,fill=class)) +   geom_histogram(colour="black")
```

```
`stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```




```
predictions<-predictions%>%mutate(class=sapply(predictions$`predictions()`,classifier))
ggplot(predictions, aes(x=predictions$`predictions()`,fill=class)) +   geom_histogram(colour="black")
```

```
`stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```

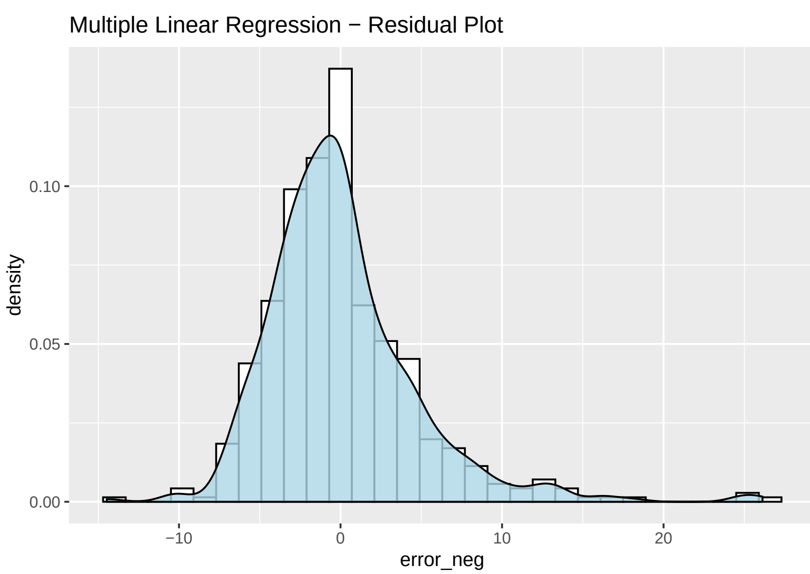



```
targetAndPrediction<-targetAndPrediction%>%mutate(error_neg=target-predictions)
```

Residual Plot-MLR

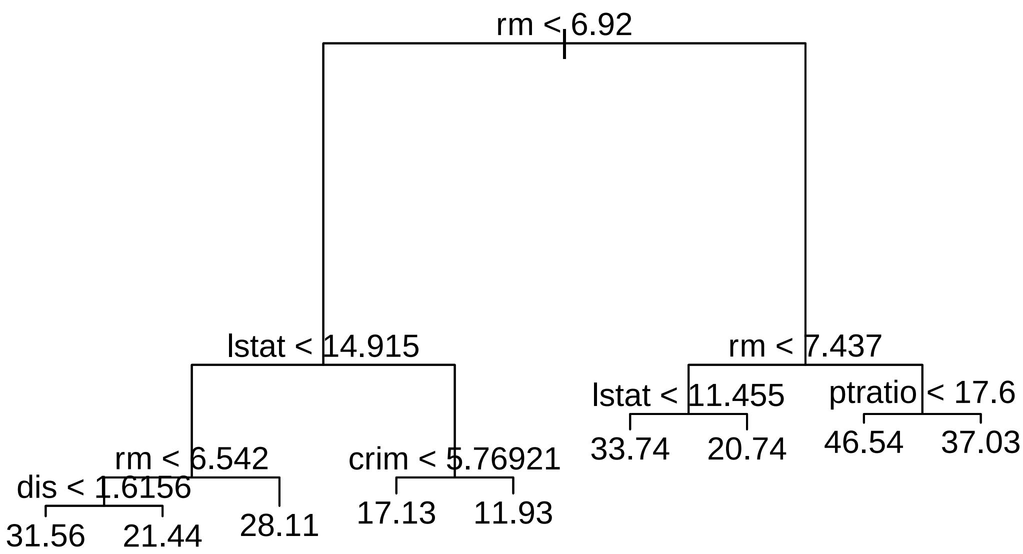
```
ggplot(targetAndPrediction, aes(x=error_neg)) +
    geom_histogram(aes(y=..density..), colour="black", fill="white")+
    geom_density(alpha=.8, fill="lightblue")+ggtitle("Multiple Linear Regression - Residual Plot")
```

```
`stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```



Decision Trees

```
tree.boston=tree(medv~.,train)
plot(tree.boston)
text(tree.boston,pretty=0)
```




```
predictions_tree=predict(tree.boston,newdata=housing)

targetAndPrediction_tree<-cbind(medv,predictions_tree)

targetAndPrediction_tree<-as.data.frame(targetAndPrediction_tree)
names(targetAndPrediction_tree)<-c("target","predictions")

filter(targetAndPrediction_tree,predictions<0)
```

```
[1] target      predictions
<0 rows> (or 0-length row.names)
```

```
for(i in 1:length(targetAndPrediction_tree$predictions)){

    if(targetAndPrediction_tree$predictions[i]<0)
    {
        targetAndPrediction_tree$predictions[i]=0
    }
}

targetAndPrediction_tree<-targetAndPrediction_tree%>%mutate(error=abs(target-predictions))
head(targetAndPrediction_tree)
```

```
  target predictions     error
1   21.6    21.44043 0.1595745
2   34.7    33.73939 0.9606061
3   33.4    33.73939 0.3393939
4   36.2    33.73939 2.4606061
5   28.7    21.44043 7.2595745
6   22.9    21.44043 1.4595745
```

```r
mean(targetAndPrediction_tree$error)
```

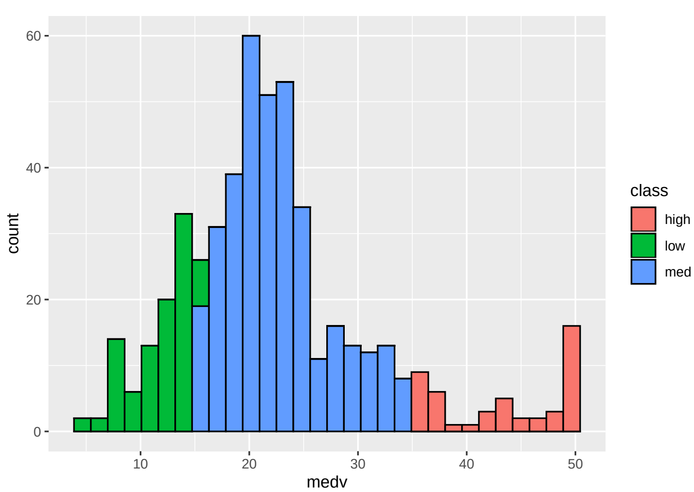
```
[1] 2.954402
```

```r
filter(targetAndPrediction_tree,error>=10)
```

```
   target predictions    error
1    23.6    33.73939 10.13939
2    19.6    31.56000 11.96000
3    15.3    31.56000 16.26000
4    36.2    21.44043 14.75957
5    50.0    37.03333 12.96667
6    21.9    37.03333 15.13333
7    50.0    31.56000 18.44000
8    50.0    28.11136 21.88864
9    50.0    33.73939 16.26061
10   50.0    31.56000 18.44000
11   50.0    31.56000 18.44000
12   10.4    20.74000 10.34000
13   27.5    11.93036 15.56964
14   15.0    31.56000 16.56000
15   10.9    21.44043 10.54043
16    7.0    17.12632 10.12632
```

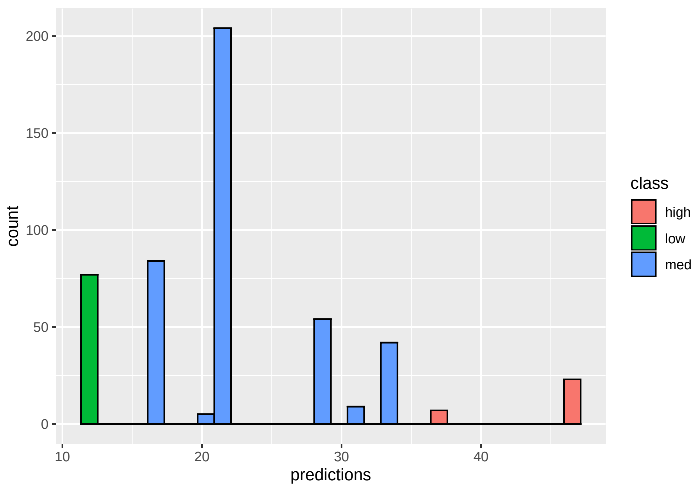
```r
targetAndPrediction_tree<-targetAndPrediction_tree%>%mutate(error_neg=target-predictions)


targetAndPrediction_tree<-targetAndPrediction_tree%>%mutate(class=sapply(predictions,classifier))

ggplot(housing, aes(x=medv,fill=class)) +   geom_histogram(colour="black")
```

```
`stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```



```r
ggplot(targetAndPrediction_tree, aes(x=predictions,fill=class)) +   geom_histogram(colour="black")
```

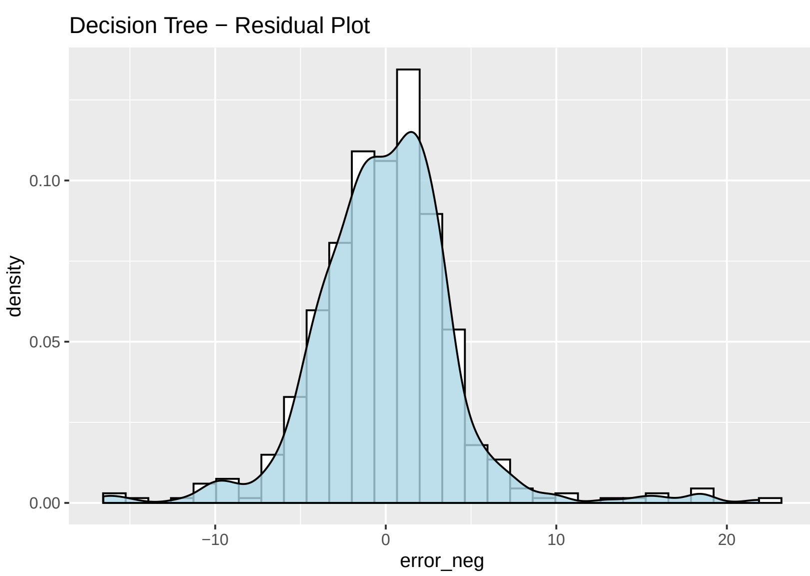
```
`stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```



Residual Plot - Decision Tree

```r
ggplot(targetAndPrediction_tree, aes(x=error_neg)) +
    geom_histogram(aes(y=..density..), colour="black", fill="white")+
    geom_density(alpha=.8, fill="lightblue")+ggtitle("Decision Tree - Residual Plot")
```

```
`stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```



Conclusions:

We have investigated our data & made visualizations for understanding key variables and their relationships, we build models for predictions that have relatively high accuracy. Multiple Linear Regression Models &

Decision Tree Models were both used, Decision trees outperformed Multiple Linear Regression slightly, by an average of 0.4 over our testing data. Errors were plotted to show a normal distribution indicating our model captures variability in our response variable