DSC520 HousingData Exercise 8.2

Anjani Bonda

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library(readxl)  
library(dplyr)

##   
## Attaching package: 'dplyr'

## The following objects are masked from 'package:stats':  
##   
## filter, lag

## The following objects are masked from 'package:base':  
##   
## intersect, setdiff, setequal, union

library(purrr)  
library(ggplot2)  
library(lmtest)

## Loading required package: zoo

##   
## Attaching package: 'zoo'

## The following objects are masked from 'package:base':  
##   
## as.Date, as.Date.numeric

library(lm.beta)  
library(car)

## Loading required package: carData

##   
## Attaching package: 'car'

## The following object is masked from 'package:purrr':  
##   
## some

## The following object is masked from 'package:dplyr':  
##   
## recode

## Set workding directory to read source datasets.  
setwd("/Users/anjanibonda/DSC520/dsc520")  
  
## Read housing dataset  
housingdata <- read\_excel("data/week-6-housing.xlsx")  
glimpse(housingdata)

## Rows: 12,865  
## Columns: 24  
## $ `Sale Date` <dttm> 2006-01-03, 2006-01-03, 2006-01-03, 2006-01-…  
## $ `Sale Price` <dbl> 698000, 649990, 572500, 420000, 369900, 18466…  
## $ sale\_reason <dbl> 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, …  
## $ sale\_instrument <dbl> 3, 3, 3, 3, 3, 15, 3, 3, 3, 3, 3, 3, 3, 3, 3,…  
## $ sale\_warning <chr> NA, NA, NA, NA, "15", "18 51", NA, NA, NA, NA…  
## $ sitetype <chr> "R1", "R1", "R1", "R1", "R1", "R1", "R1", "R1…  
## $ addr\_full <chr> "17021 NE 113TH CT", "11927 178TH PL NE", "13…  
## $ zip5 <dbl> 98052, 98052, 98052, 98052, 98052, 98053, 980…  
## $ ctyname <chr> "REDMOND", "REDMOND", NA, "REDMOND", "REDMOND…  
## $ postalctyn <chr> "REDMOND", "REDMOND", "REDMOND", "REDMOND", "…  
## $ lon <dbl> -122.1124, -122.1022, -122.1085, -122.1037, -…  
## $ lat <dbl> 47.70139, 47.70731, 47.71986, 47.63914, 47.69…  
## $ building\_grade <dbl> 9, 9, 8, 8, 7, 7, 10, 10, 9, 8, 9, 8, 8, 9, 1…  
## $ square\_feet\_total\_living <dbl> 2810, 2880, 2770, 1620, 1440, 4160, 3960, 372…  
## $ bedrooms <dbl> 4, 4, 4, 3, 3, 4, 5, 4, 4, 4, 3, 3, 4, 3, 3, …  
## $ bath\_full\_count <dbl> 2, 2, 1, 1, 1, 2, 3, 2, 2, 1, 2, 2, 1, 2, 2, …  
## $ bath\_half\_count <dbl> 1, 0, 1, 0, 0, 1, 0, 1, 1, 0, 1, 1, 0, 0, 1, …  
## $ bath\_3qtr\_count <dbl> 0, 1, 1, 1, 1, 1, 1, 0, 1, 1, 0, 0, 1, 0, 0, …  
## $ year\_built <dbl> 2003, 2006, 1987, 1968, 1980, 2005, 1993, 198…  
## $ year\_renovated <dbl> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, …  
## $ current\_zoning <chr> "R4", "R4", "R6", "R4", "R6", "URPSO", "RA5",…  
## $ sq\_ft\_lot <dbl> 6635, 5570, 8444, 9600, 7526, 7280, 97574, 30…  
## $ prop\_type <chr> "R", "R", "R", "R", "R", "R", "R", "R", "R", …  
## $ present\_use <dbl> 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, …

## Check for nulls in all rows  
apply(housingdata, 2, function(i) any(is.na(i)))

## Sale Date Sale Price sale\_reason   
## FALSE FALSE FALSE   
## sale\_instrument sale\_warning sitetype   
## FALSE TRUE FALSE   
## addr\_full zip5 ctyname   
## FALSE FALSE TRUE   
## postalctyn lon lat   
## FALSE FALSE FALSE   
## building\_grade square\_feet\_total\_living bedrooms   
## FALSE FALSE FALSE   
## bath\_full\_count bath\_half\_count bath\_3qtr\_count   
## FALSE FALSE FALSE   
## year\_built year\_renovated current\_zoning   
## FALSE FALSE FALSE   
## sq\_ft\_lot prop\_type present\_use   
## FALSE FALSE FALSE

## Looking at the data, there is missing data for sale\_warning and ctyname

# I. Explain any transformations or modifications you made to the dataset   
colnames(housingdata)[1] <- "Sale\_Date"  
colnames(housingdata)[2] <- "Sale\_Price"  
  
## I have Changed the column names of Sale Date and Sale Price to avoid any possible issues.  
  
# II. Create two variables;  
# one that will contain the variables Sale Price and Square Foot of Lot (same variables used from previous assignment on simple regression)  
# and one that will contain Sale Price and several additional predictors of your choice.  
# Explain the basis for your additional predictor selections.  
housingdata\_lm1 <- lm(formula = Sale\_Price ~ sq\_ft\_lot, data = housingdata)  
housingdata\_lm2 <- lm(formula = Sale\_Price ~ zip5 + bedrooms + year\_built, data = housingdata)  
  
## I have inlcuded other predictors like zip5, bedroomms and year built as those are often key factors in home price predictions.  
  
# III. Execute a summary() function on two variables defined in the previous step to compare the model results.   
# What are the R2 and Adjusted R2 statistics? Explain what these results tell you about the overall model.  
# Did the inclusion of the additional predictors help explain any large variations found in Sale Price?  
summary(housingdata\_lm1)

##   
## Call:  
## lm(formula = Sale\_Price ~ sq\_ft\_lot, data = housingdata)  
##   
## Residuals:  
## Min 1Q Median 3Q Max   
## -2016064 -194842 -63293 91565 3735109   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 6.418e+05 3.800e+03 168.90 <2e-16 \*\*\*  
## sq\_ft\_lot 8.510e-01 6.217e-02 13.69 <2e-16 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 401500 on 12863 degrees of freedom  
## Multiple R-squared: 0.01435, Adjusted R-squared: 0.01428   
## F-statistic: 187.3 on 1 and 12863 DF, p-value: < 2.2e-16

summary(housingdata\_lm2)

##   
## Call:  
## lm(formula = Sale\_Price ~ zip5 + bedrooms + year\_built, data = housingdata)  
##   
## Residuals:  
## Min 1Q Median 3Q Max   
## -997873 -161449 -62624 63853 4115141   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) -1.054e+09 1.957e+08 -5.385 7.35e-08 \*\*\*  
## zip5 1.064e+04 1.996e+03 5.330 1.00e-07 \*\*\*  
## bedrooms 1.035e+05 3.842e+03 26.931 < 2e-16 \*\*\*  
## year\_built 5.527e+03 1.963e+02 28.152 < 2e-16 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 381500 on 12861 degrees of freedom  
## Multiple R-squared: 0.1103, Adjusted R-squared: 0.1101   
## F-statistic: 531.7 on 3 and 12861 DF, p-value: < 2.2e-16

## R2 for housingdata\_lm1: 0.01 adjusted: 0.01  
## R2 for housingdata\_lm2: 0.11 adjusted: 0.11  
## RSquared is a statistical measure of fit for the model.  
## These low RSquared values mean that the model is not a great fit.  
## The multiple regression seems OK, but not ideal.  
  
# IV. Considering the parameters of the multiple regression model you have created,  
# What are the standardized betas for each parameter and what do the values indicate?  
coef\_lmbeta <- lm.beta(housingdata\_lm2)  
coef\_lmbeta

##   
## Call:  
## lm(formula = Sale\_Price ~ zip5 + bedrooms + year\_built, data = housingdata)  
##   
## Standardized Coefficients::  
## (Intercept) zip5 bedrooms year\_built   
## 0.00000000 0.04458759 0.22417183 0.23537926

## zip5 (standardized β = 0.04458759) - This value indicates that as zip code increase by  
## 1 standard deviation, sales price increase by 0.04458759 standard deviation.  
## bedrooms (standardized β = 0.22417183) -This value indicates that as bedrooms  
## increase by 1 standard deviation, sales price increase by 0.22417183 standard deviation.  
## year\_built(standardized β = 0.23537926) - This value indicates that as year\_# built  
## increase by 1 standard deviation, sales price increase by 0.23537926 standard deviation.  
  
  
# V. Calculate the confidence intervals for the parameters in your model and  
# explain what the results indicate.  
confint(housingdata\_lm2)

## 2.5 % 97.5 %  
## (Intercept) -1.437177e+09 -6.701687e+08  
## zip5 6.724735e+03 1.454870e+04  
## bedrooms 9.593698e+04 1.109984e+05  
## year\_built 5.142553e+03 5.912266e+03

## In this model, the predictor (year\_built) have very tight confidence intervals,  
## indicating that the estimates for the current model are likely  
## to be representative of the true population.  
## The confidence interval for (zip5 and bedrooms) is wider but still does not cross zero,  
## indicating that the parameter for this variable is less representative, but still significant.  
  
# VI. Assess the improvement of the new model compared to your original model (simple regression model) ----  
# by testing whether this change is significant by performing an analysis of variance.  
anova(housingdata\_lm1,housingdata\_lm2)

## Analysis of Variance Table  
##   
## Model 1: Sale\_Price ~ sq\_ft\_lot  
## Model 2: Sale\_Price ~ zip5 + bedrooms + year\_built  
## Res.Df RSS Df Sum of Sq F Pr(>F)   
## 1 12863 2.0734e+15   
## 2 12861 1.8715e+15 2 2.0192e+14 693.82 < 2.2e-16 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

## The p value is very small value indeed,  
## we can say that housingdata\_lm2 significantly improved  
## the fit of the model to the data compared to housingdata\_lm1  
  
# VII. Perform casewise diagnostics to identify outliers and/or influential cases,  
# storing each function's output in a dataframe assigned to a unique variable name.  
housingdata$residuals<-resid(housingdata\_lm2)  
housingdata$standardized.residuals<- rstandard(housingdata\_lm2)  
housingdata$studentized.residuals<-rstudent(housingdata\_lm2)  
housingdata$cooks.distance<-cooks.distance(housingdata\_lm2)  
housingdata$leverage<-hatvalues(housingdata\_lm2)  
housingdata$covariance.ratios<-covratio(housingdata\_lm2)  
  
head(housingdata)

## # A tibble: 6 × 30  
## Sale\_Date Sale\_Price sale\_reason sale\_instrument sale\_warning  
## <dttm> <dbl> <dbl> <dbl> <chr>   
## 1 2006-01-03 00:00:00 698000 1 3 <NA>   
## 2 2006-01-03 00:00:00 649990 1 3 <NA>   
## 3 2006-01-03 00:00:00 572500 1 3 <NA>   
## 4 2006-01-03 00:00:00 420000 1 3 <NA>   
## 5 2006-01-03 00:00:00 369900 1 3 15   
## 6 2006-01-03 00:00:00 184667 1 15 18 51   
## # … with 25 more variables: sitetype <chr>, addr\_full <chr>, zip5 <dbl>,  
## # ctyname <chr>, postalctyn <chr>, lon <dbl>, lat <dbl>,  
## # building\_grade <dbl>, square\_feet\_total\_living <dbl>, bedrooms <dbl>,  
## # bath\_full\_count <dbl>, bath\_half\_count <dbl>, bath\_3qtr\_count <dbl>,  
## # year\_built <dbl>, year\_renovated <dbl>, current\_zoning <chr>,  
## # sq\_ft\_lot <dbl>, prop\_type <chr>, present\_use <dbl>, residuals <dbl>,  
## # standardized.residuals <dbl>, studentized.residuals <dbl>, …

# VIII. Calculate the standardized residuals using the appropriate command,  
# specifying those that are +-2, storing the results of large residuals in a variable you create.  
housingdata$large.residual <- housingdata$standardized.residuals > 2 | housingdata$standardized.residuals < -2  
head(housingdata$large.residual)

## 1 2 3 4 5 6   
## FALSE FALSE FALSE FALSE FALSE FALSE

# IX. Use the appropriate function to show the sum of large residuals.  
sum(housingdata$large.residual)

## [1] 346

# X. Which specific variables have large residuals (only cases that evaluate as TRUE)?  
housingdata[housingdata$large.residual,c("Sale\_Price", "zip5", "bedrooms", "year\_built","standardized.residuals")]

## # A tibble: 346 × 5  
## Sale\_Price zip5 bedrooms year\_built standardized.residuals  
## <dbl> <dbl> <dbl> <dbl> <dbl>  
## 1 1900000 98053 4 1990 3.14  
## 2 1520000 98052 5 1952 2.45  
## 3 1390000 98053 0 1955 3.40  
## 4 1588359 98053 2 2005 2.65  
## 5 1450000 98052 3 1972 2.52  
## 6 1450000 98052 2 1918 3.58  
## 7 2500000 98053 4 2005 4.49  
## 8 2169000 98053 4 2005 3.63  
## 9 1534000 98052 4 1963 2.60  
## 10 1968000 98053 4 1998 3.20  
## # … with 336 more rows

# XI. Investigate further by calculating the  
# leverage,  
# cooks distance,  
# and covariance ratios.  
# Comment on all cases that are problematics.  
housingdata[housingdata$large.residual , c("cooks.distance", "leverage", "covariance.ratios")]

## # A tibble: 346 × 3  
## cooks.distance leverage covariance.ratios  
## <dbl> <dbl> <dbl>  
## 1 0.000284 0.000115 0.997  
## 2 0.00114 0.000761 0.999  
## 3 0.00484 0.00167 0.998  
## 4 0.000597 0.000341 0.998  
## 5 0.000347 0.000219 0.999  
## 6 0.00563 0.00176 0.998  
## 7 0.000738 0.000146 0.994  
## 8 0.000480 0.000146 0.996  
## 9 0.000581 0.000344 0.999  
## 10 0.000300 0.000117 0.997  
## # … with 336 more rows

## None of the values has a Cook’s distance greater than 1 ,  
## The leverage values also seem miniscule.  
  
  
# XII. Perform the necessary calculations to assess the assumption of independence  
# and state if the condition is met or not.  
durbinWatsonTest(housingdata\_lm2)

## lag Autocorrelation D-W Statistic p-value  
## 1 0.6278972 0.7442029 0  
## Alternative hypothesis: rho != 0

## The test statistic is 0.7442029 and the corresponding p-value is 0.   
## Since this p-value is less than 0.05, we can reject the null hypothesis and   
## conclude that the residuals in this regression model are autocorrelated.   
## Value less than 1 suggests that the assumption might not been met.  
  
# XIII. Perform the necessary calculations to assess the assumption of no multicollinearity  
# and state if the condition is met or not.  
vif(housingdata\_lm2)

## zip5 bedrooms year\_built   
## 1.011771 1.001607 1.010570

## tolerance statistics  
1/vif(housingdata\_lm2)

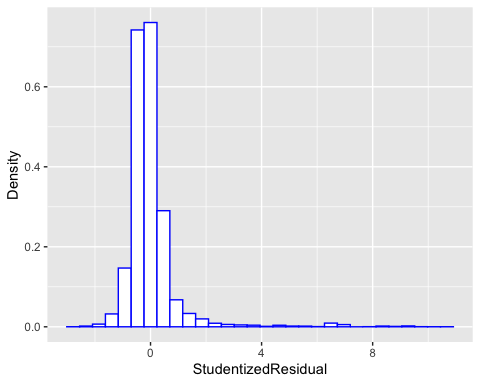
## zip5 bedrooms year\_built   
## 0.9883661 0.9983956 0.9895403

mean(vif(housingdata\_lm2))

## [1] 1.007983

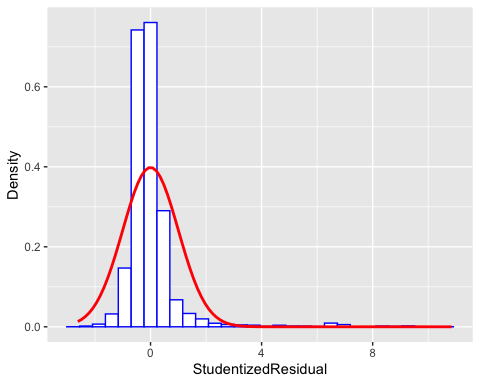
## VIF values are all below 10 and the tolerance statistics above 0.2.   
## Also, the mean VIF is ~ 1.  
## Based on these results we can conclude that there is no collinearity in data.  
  
# XIV. Visually check the assumptions related to the residuals using the plot() and hist() functions.  
# Summarize what each graph is informing you of and if any anomalies are present.  
housingdata$fitted <- housingdata\_lm2$fitted.values  
  
histogram<-ggplot(housingdata, aes(studentized.residuals)) +   
 geom\_histogram(aes(y = ..density..), colour = "blue", fill = "white") +   
 labs(x = "StudentizedResidual", y = "Density")  
histogram

## `stat\_bin()` using `bins = 30`. Pick better value with `binwidth`.



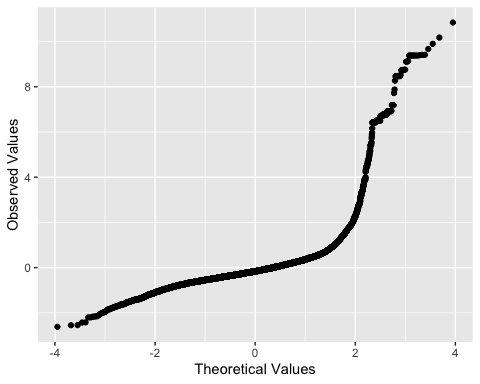
histogram + stat\_function(fun = dnorm, args = list(mean = mean(housingdata$studentized.residuals, na.rm = TRUE),   
 sd = sd(housingdata$studentized.residuals,na.rm = TRUE)), colour= "red", size = 1)

## `stat\_bin()` using `bins = 30`. Pick better value with `binwidth`.



qplot(sample = housingdata$studentized.residuals, stat="qq") + labs(x ="Theoretical Values", y = "Observed Values")

## Warning: `stat` is deprecated



## The distribution is roughly normal.  
## To summarize, the model appears to be accurate for the sample and can be generalized to the population.  
  
# XV. Overall, is this regression model unbiased?  
# If an unbiased regression model, what does this tell us about the sample vs. the entire population model?  
  
## Based on vif score/values calculated above, since the values are not close to 5, the predictors doesn't have   
## any significant multi collinearity.  
## Mean vif is also just above 1 but no where near 5.  
## Hence, Model does not appear to be biased.