DS6731: Statistical Foundations
Mini Project
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April 16, 2024

House Prices - Advanced Regression Techniques

Introduction

In this study, prompted by our client, Century 21 Ames, we were tasked with first developing a model to predict the Sale Price of houses with three Neighborhoods based on the Square Footage. Next we were tasked with trying to develop a Simple Linear Regression model, and two Multiple Regression Models using any of the variables.

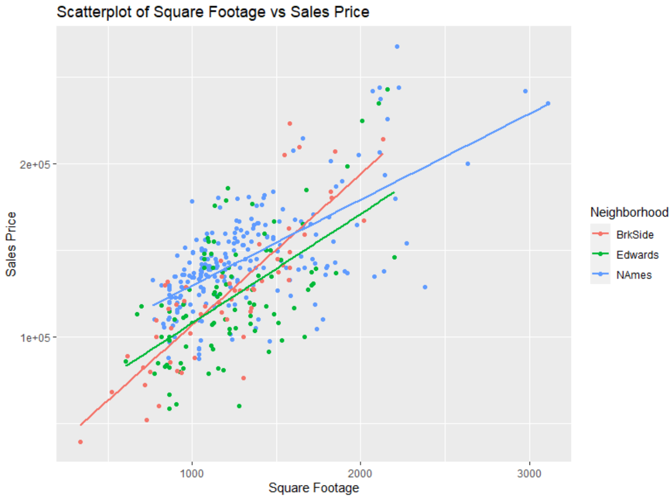
Data Description

The data that is being analyzed was obtained from the website Kaggle, they obtained it from this data from Century 21 Ames. This data contains 79 different explanatory variables to try and predict 1 dependent variable, Sale Price. There are 1460 different homes that are being observed in this data set. In our analysis of the data some of the key variables we looked at to explain the Sale price were the Square footage, Neighborhood, Full Bath, and Overall Quality.

Analysis Question 1:

Restatement of Problem

The first problem we were tasked to look at and estimate a model between Sale Price and Square footage with respect to three Neighborhoods. The three Neighborhoods in question were NAmes, Edwards and BrkSide.

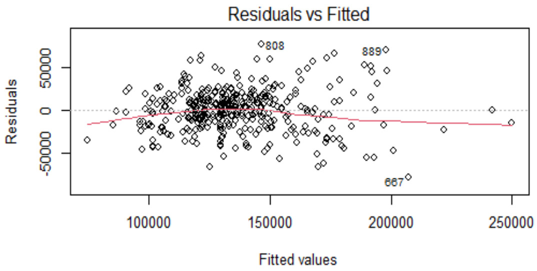


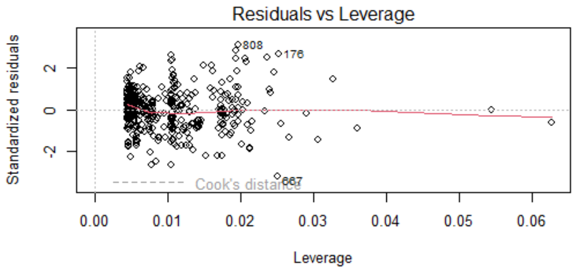
We built a model to estimate the Sale Price for each of the three Neighborhoods. Each off the neighborhoods has their own slopes:

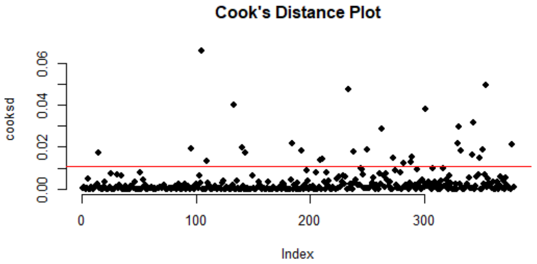
BrkSide: SalePrice = 19971.514 + 87.163*GrLIvArea

Edwards: SalePrice = 88353.1 + 29.751*GrLIvArea

NAmes: SalePrice = 74676.4 + 54.316*GrLIvArea







Assumptions

The plots bove are the Residual plot, Cook's D plot, and Leverage plot that were created after the elimination of a few outliers. The outliers were taken out of the data set because they were high priced homes with low square footage for the neighborhoods. These houses were ID # 524, 1299, 643, 725 and 1424. The residual plot shows that there is a fairly random distribution of points along with an equal amount positive and negative. For the Cook's D plot it shows that there are no outliers within the data set and that there aren't any influential points. The Leverage plot shows that there are no points with significant leverage.

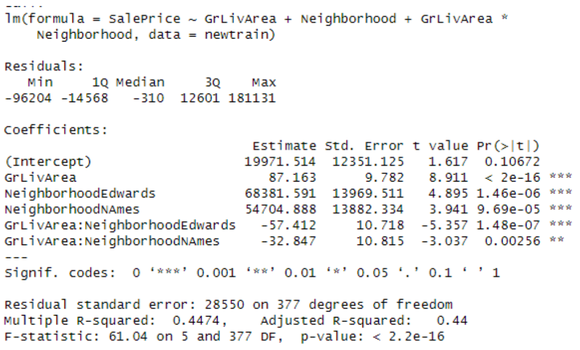
Comparing Competing Models

Adj R^2 = 0.44

Internal CV Press

- BrkSide = 0.1871246213
- Edwards = 0.2393758557
- NAmes = 0.2363974899

Parameters



```
lm(formula = SalePrice ~ GrLivArea + Neighborhood + GrLivArea *
    Neighborhood, data = newtrain)

Residuals:
   Min     1Q Median     3Q    Max
-96204 -14568   -310  12601 181131

Coefficients:
                               Estimate Std. Error t value Pr(>|t|)
(Intercept)                   19971.514  12351.125   1.617  0.10672
GrLivArea                        87.163      9.782   8.911  < 2e-16 ***
NeighborhoodEdwards           68381.591  13969.511   4.895 1.46e-06 ***
NeighborhoodNAmes             54704.888  13882.334   3.941 9.69e-05 ***
GrLivArea:NeighborhoodEdwards   -57.412     10.718  -5.357 1.48e-07 ***
GrLivArea:NeighborhoodNAmes     -32.847     10.815  -3.037  0.00256 **
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 28550 on 377 degrees of freedom
Multiple R-squared:  0.4474,    Adjusted R-squared:   0.44
F-statistic: 61.04 on 5 and 377 DF,  p-value: < 2.2e-16
```

Interpretation

Based on the BrkSide: SalePrice = 19971.514 + 87.163*GrLIvArea equation for every 100 square feet increase the Sale Price for BrkSide Neighborhood is estimated to increase $8716.3. Based on the Edwards: SalePrice = 88353.1 + 29.751*GrLIvArea equation for every 100 square feet increase the estimated Sale Price will increase by $2975.1 in the Sale Price. Based on the NAmes: SalePrice = 74676.4 + 54.316*GrLIvAre equation for every 100 square feet increase the estimated Sale Price will increase by $5431.6.

Confidence Intervals

For the BrkSide Neighborhood we are 95% confident that for every 100 square feet increase the Sale Price is estimated to increase between $6792.85 and $10639.66. For the Edwards Neighborhood we are 95% confident that for every 100 square feet increase the Sale Price is estimated to increase between $-1055.76 and $7005.82. For the NAmes Neighborhood we are 95% confident that for every 100 square feet increase the Sale Price is estimated to increase between $1381.58 and $9481.59.

Conclusion

In conclusion, based on the Models for every 100 Square feet increase the BrkSide Neighborhood Sale Price is estimated to increase by $8716.3, the Edwards Neighborhood Sale Price is estimated to increase by $2975.1, and the NAmes Neighborhood Sale Price is estimated to increase by $5431.6. Each neighborhood was determined to have their own independent slopes as depicted in the graph above, and thus their own equation.

R Shiny: Price v. Living Area Chart

https://nolandulude.shinyapps.io/StatsProject/

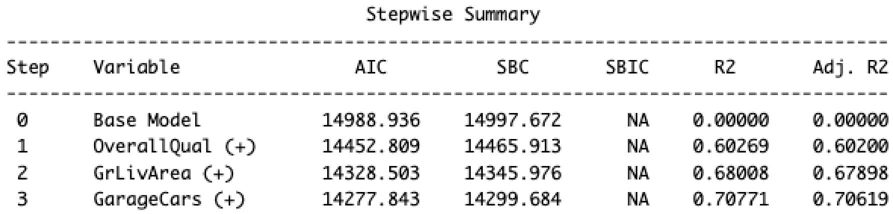
Analysis Question 2:

Restatement of Problem

In this problem, we were asked to build the most predictive models for sales prices of homes in all of Ames, Iowa: one being a simple linear regression model in which we pick the explanatory variable, a multiple linear regression model (SalePrice~GrLivArea + FullBath), and another multiple linear regression model where we select the explanatory variables. We were to generate an adjusted R2, CV Press and Kaggle Score for each of these models and clearly describe which model is the best in predicting future sale prices of homes in Ames, Iowa.

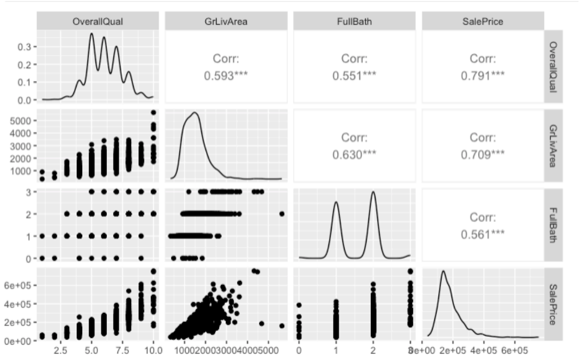
Candidate Models:

With the same data used to solve Analysis Problem 1, we sought to identify the best variables to predict sale price of Ames homes. After dropping variables not suited for Linear Regression Models, we put together our models.



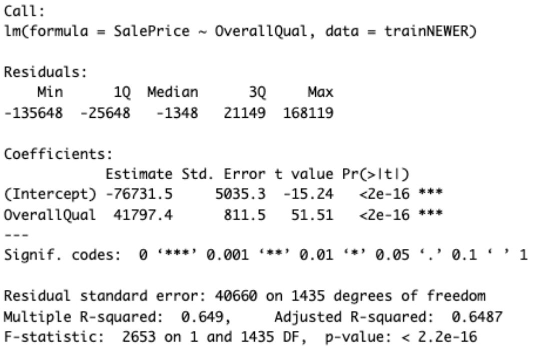
```
                              Stepwise Summary
------------------------------------------------------------------------------
Step    Variable              AIC          SBC       SBIC       R2       Adj. R2
------------------------------------------------------------------------------
 0      Base Model         14988.936    14997.672     NA     0.00000    0.00000
 1      OverallQual (+)    14452.809    14465.913     NA     0.60269    0.60200
 2      GrLivArea (+)      14328.503    14345.976     NA     0.68008    0.67898
 3      GarageCars (+)     14277.843    14299.684     NA     0.70771    0.70619
```

With the stepwise model selection, we found the two best fit variables to be OverallQual and GrLivArea. These two, along with FullBath, will be used in the Linear regression model and multiple linear regression models we intend to conduct. Before running those models, we first want to check assumptions and assess the normality of the data.



There is visual evidence of a relationship between overall qual and GrLivArea, OverallQual and FullBath, OverallQual and SalePrice, GrLivArea and FullBath, FullBath and SalePrice. There appears to be a linear relationship between GrLivArea and SalePrice with outliers (those we struck out in the first problem).

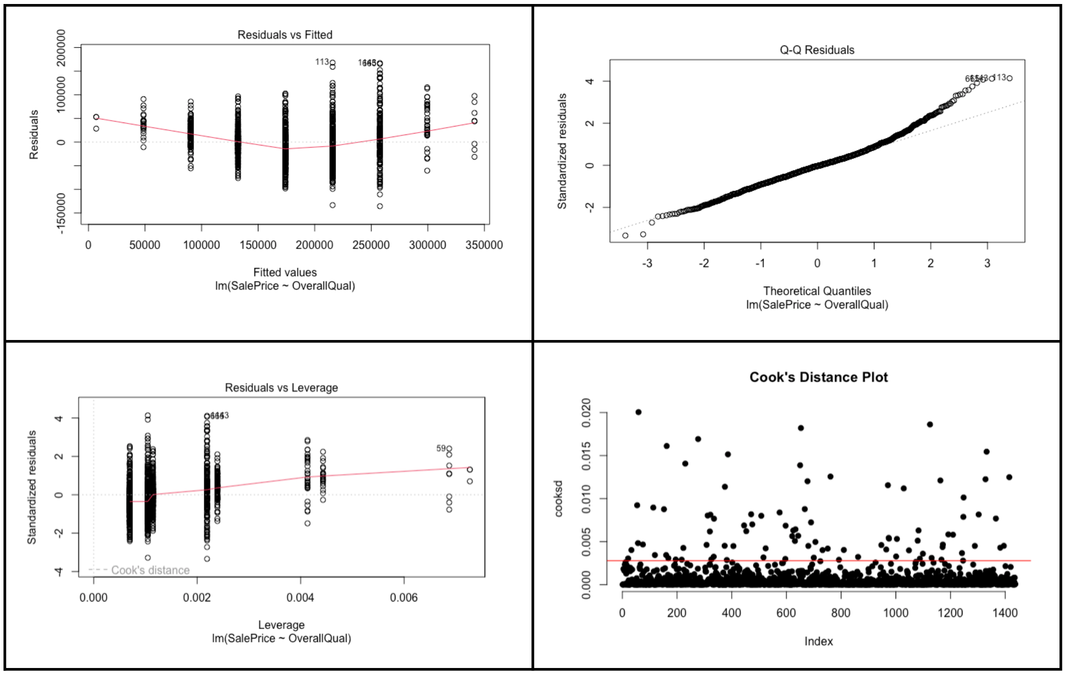
SLR (SalePrice ~ OverallQual)



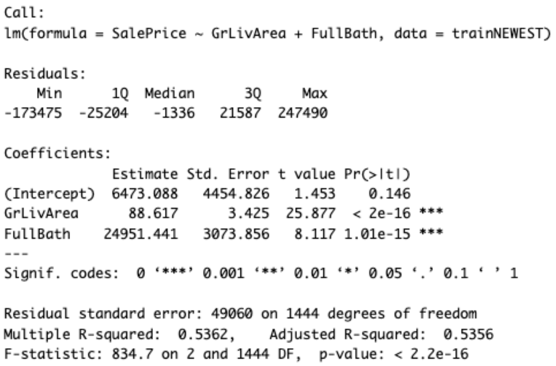
```
Call:
lm(formula = SalePrice ~ OverallQual, data = trainNEWER)

Residuals:
    Min      1Q  Median      3Q     Max 
-135648  -25648   -1348   21149  168119 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept) -76731.5     5035.3  -15.24   <2e-16 ***
OverallQual  41797.4      811.5   51.51   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 40660 on 1435 degrees of freedom
Multiple R-squared:  0.649,	Adjusted R-squared:  0.6487 
F-statistic:  2653 on 1 and 1435 DF,  p-value: < 2.2e-16
```

With the model **SalePrice = -76731.5 + 41797.4OverallQual**, there is a significant relationship between the overall quality of the home and the sale price of the homes in Ames, as evidenced by the p-value of the OverallQual variable (<0.0000000000000002) and the overall p-value of <0.00000000000000022.

Checking assumptions for this model, we found that the data was adequately scattered in the residual plot so there was little evidence of variance , the data was reasonably fitted to the line in the qq-plot, suggesting normal distribution, and through the process of deleting high leverage outliers, the Cook’s d plot showed a good distribution for us to move forward with the model.



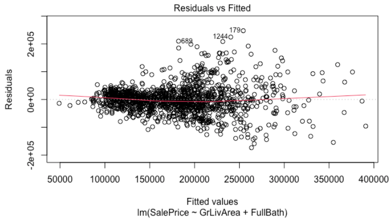
MLR 1: Model Provided by Century21 Ames (SalePrice ~ GrLivArea + FullBath)

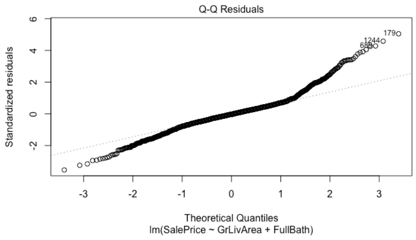


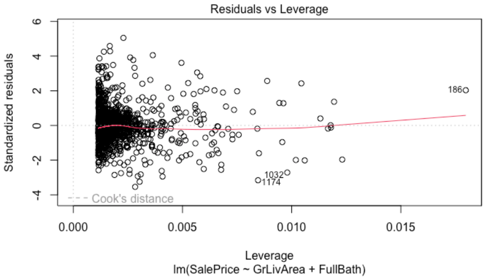
```
Call:
lm(formula = SalePrice ~ GrLivArea + FullBath, data = trainNEWEST)

Residuals:
    Min      1Q  Median      3Q     Max 
-173475  -25204   -1336   21587  247490 

Coefficients:
             Estimate Std. Error t value Pr(>|t|)    
(Intercept)  6473.088   4454.826   1.453    0.146    
GrLivArea      88.617      3.425  25.877  < 2e-16 ***
FullBath    24951.441   3073.856   8.117 1.01e-15 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 49060 on 1444 degrees of freedom
Multiple R-squared:  0.5362,	Adjusted R-squared:  0.5356 
F-statistic: 834.7 on 2 and 1444 DF,  p-value: < 2.2e-16
```

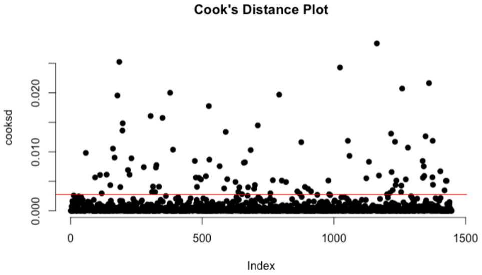
With the model **SalePrice = 6473.1 + 88.62GrLivArea + 24951.44FullBath**, there is a statistically significant relationship between the gross living area and number of full baths on the sale price of the homes in Ames, as evidenced by their respective small p-values (<0.0000000000000002, .00000000000000101) and the overall p-value of <0.00000000000000022.

Checking assumptions for this model, we found that the data was adequately scattered in the residual plot so there was little evidence of variance , the data was reasonably fitted to the line in the qq-plot, suggesting normal distribution, and through the process of deleting high leverage outliers, the Cook’s d plot showed a good distribution for us to move forward with the model

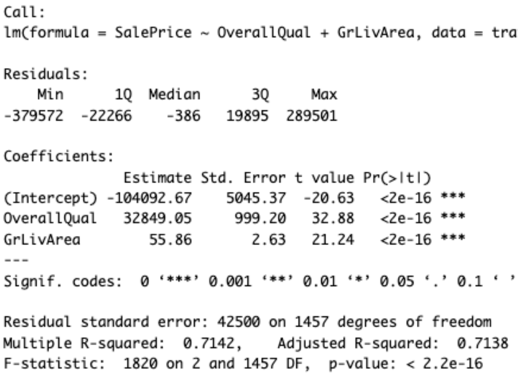








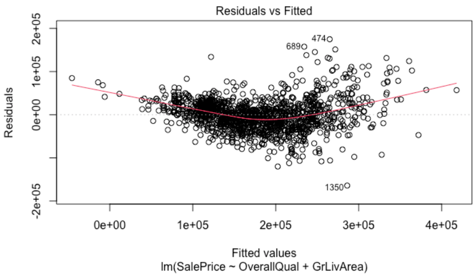
MLR 2 (SalePrice ~ OverallQual + GrLivArea)

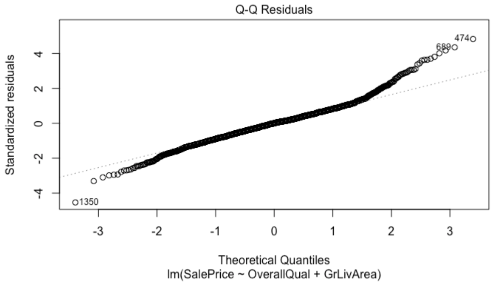


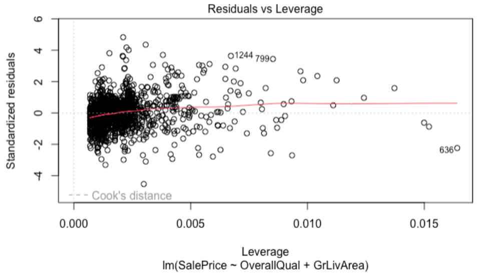
```
Call:
lm(formula = SalePrice ~ OverallQual + GrLivArea, data = trainNEW)

Residuals:
    Min      1Q  Median      3Q     Max 
-379572  -22266    -386   19895  289501 

Coefficients:
              Estimate Std. Error t value Pr(>|t|)    
(Intercept) -104092.67    5045.37  -20.63   <2e-16 ***
OverallQual   32849.05     999.20   32.88   <2e-16 ***
GrLivArea        55.86       2.63   21.24   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 42500 on 1457 degrees of freedom
Multiple R-squared:  0.7142,	Adjusted R-squared:  0.7138 
F-statistic:  1820 on 2 and 1457 DF,  p-value: < 2.2e-16
```

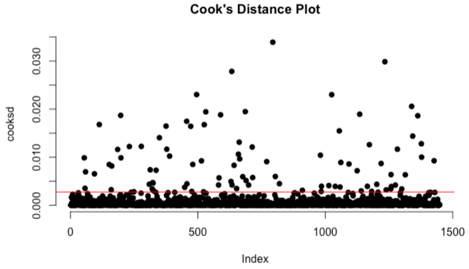
With the model **SalePrice = -104092.67 + 32849.1OverallQual + 55.86GrLivArea**, there is a statistically significant relationship between the overall quality of the homes and the gross living area of the homes in predicting the sale price of the homes in Ames, as evidenced by their respective small p-values (<0.0000000000000002, <0.0000000000000002) and the overall p-value of <0.00000000000000022.

Checking assumptions for this model, we found that the data was adequately scattered in the residual plot so there was little evidence of variance, the data was reasonably fitted to the line in the qq-plot, suggesting normal distribution, and through the process of deleting high leverage outliers, the Cook's d plot showed a good distribution for us to move forward with the model.









Comparing Competing Models

Comparing the three models using test data, our multiple linear regression model is best fit, evidenced by the higher r-squared, adjusted r-squared, and small mean CV press value. You will note that the MLR we created has a slightly higher mean CV press in comparison to Century21 Ames', suggesting a slightly better predictive performance, however, with much higher correlation of variables in our MLR, we decided that the latter was best fit in predicting the sale prices using Test data.

Predictive Models	**Adjusted R2**	**CV PRESS**	**Kaggle Score**
Simple Linear Regression	0.6487	0.002726416	0.48351
MLR_C21_2	0.5356	0.0009129459	0.61812
Multiple Linear Regression	0.7138	0.001248771	0.28542

Conclusion

Through simple and multiple linear regression analysis, we found that the explanatory variables that best predicted the sale price of homes in Ames, IA were GrLivArea and OverallQual. These variables were used in the multiple linear regression model and proved to explain the variation in sale price in homes. We suggest Century21 Ames utilize this model to predict sale prices while conducting business in the Ames, IA area.

Appendix

1. R Code

Analysis Problem # 1

```
library(tidyverse)

library(car)

train <- read.csv(choose.files())

head(train)


#Question 1

#Selecting for NAmes, Edwards, and BrkSide

match1 <- grepl("NAmes", train$Neighborhood)

match2 <- grepl("Edwards", train$Neighborhood)

match3 <- grepl("BrkSide", train$Neighborhood)


new1 <- train[match1, ]

new2 <- train[match2, ]

new3 <- train[match3, ]


#New data set

newtrain <- rbind(new1, new2, new3)


#Graphing each Neighborhood alone and together

newtrain %>% filter(Neighborhood == "NAmes") %>% ggplot(aes(x = GrLivArea, y = SalePrice,
colour = Neighborhood)) + geom_point() + labs(x = "Square Footage", y = "Sales Price") +
ggtitle("Scatterplot of Square Footage vs Sales Price for the NAmes Neighborhood")
```

```
newtrain %>% filter(Neighborhood == "Edwards") %>% ggplot(aes(x = GrLivArea, y =
SalePrice, colour = Neighborhood)) + geom_point() + labs(x = "Square Footage", y = "Sales
Price") + ggtitle("Scatterplot of Square Footage vs Sales Price for the Edwards Neighborhood")


newtrain %>% filter(Neighborhood == "BrkSide") %>% ggplot(aes(x = GrLivArea, y = SalePrice,
colour = Neighborhood)) + geom_point() + labs(x = "Square Footage", y = "Sales Price") +
ggtitle("Scatterplot of Square Footage vs Sales Price for the BrkSide Neighborhood")



newtrain %>% ggplot(aes(x = GrLivArea, y = SalePrice, colour = Neighborhood))+geom_point()
+ geom_smooth(method = "lm", se = FALSE) + labs(x = "Square Footage", y = "Sales Price") +
ggtitle("Scatterplot of Square Footage vs Sales Price")


#After looking at the residual plot and Cooks plot there appears to be a couple outliers.


which(newtrain$Id == 1299)

id1 <- newtrain[313, c("GrLivArea", "SalePrice", "Neighborhood")]

which(newtrain$Id == 524)

id2 <- newtrain[258, c("GrLivArea", "SalePrice", "Neighborhood")]

summary(newtrain$SalePrice)

summary(newtrain$GrLivArea)


fit = lm(SalePrice~GrLivArea + Neighborhood, data = newtrain)

fit_summary <- summary(fit)


#Visualize LRM
```

```
par(mfrow = c(2, 2))

plot(fit)

#Calculate Cook's distances

cooksd <- cooks.distance(fit)


#Plot Cook's distances

plot(cooksd, pch = 19, frame = FALSE, main = "Cook's Distance Plot")

abline(h = 4/length(cooksd), col = "red")  # Add a horizontal line at Cook's distance = 4/n



#Set a threshold for identifying outliers.

threshold <- 16/length(cooksd)


#Identify outliers based on Cook's distance exceeding the threshold

outliers <- which(cooksd > threshold)


#Print the indices of outliers

print(outliers)

print(train[c(524, 1299, 643, 725, 1424), ])


#Outliers were removed

newer_train<- newtrain[-c(313, 258, 99, 275, 322), ]
```

```
#After removal of Outliers

cooksd <- cooks.distance(fit)

plot(cooksd, pch = 19, frame = FALSE, main = "Cook's Distance Plot")

abline(h = 4/length(cooksd), col = "red")  # Add a horizontal line at Cook's distance = 4/n


#Graphing each Neighborhood alone and together

newer_train %>% filter(Neighborhood == "NAmes") %>% ggplot(aes(x = GrLivArea, y =
SalePrice, colour = Neighborhood)) + geom_point() + labs(x = "Square Footage", y = "Sales
Price") + ggtitle("Scatterplot of Square Footage vs Sales Price for the NAmes Neighborhood")


newer_train %>% filter(Neighborhood == "Edwards") %>% ggplot(aes(x = GrLivArea, y =
SalePrice, colour = Neighborhood)) + geom_point() + labs(x = "Square Footage", y = "Sales
Price") + ggtitle("Scatterplot of Square Footage vs Sales Price for the Edwards Neighborhood")


newer_train %>% filter(Neighborhood == "BrkSide") %>% ggplot(aes(x = GrLivArea, y =
SalePrice, colour = Neighborhood)) + geom_point() + labs(x = "Square Footage", y = "Sales
Price") + ggtitle("Scatterplot of Square Footage vs Sales Price for the BrkSide Neighborhood")


newer_train %>% ggplot(aes(x = GrLivArea, y = SalePrice, colour =
Neighborhood))+geom_point() + geom_smooth(method = "lm", se = FALSE) + labs(x = "Square
Footage", y = "Sales Price") + ggtitle("Scatterplot of Square Footage vs Sales Price")


#Here is the Model and with the ADJR^2, and internal CV Press, along with confidence
intervals.

fit1 = lm(SalePrice~GrLivArea + Neighborhood+GrLivArea*Neighborhood, data = newtrain)

fit_summary1 <- summary(fit1)

adj_r_squared <- fit_summary1$adj.r.squared
```

```
internal_cv_press <- fit_summary1$cov.unscaled
conf_intervals <- confint(fit1)
par(mfrow = c(2, 2))
plot(fit1)


#Here is the code of the R Shiny app
library(shiny)
library(ggplot2)

train <- read.csv(choose.files())

#Selecting for NAmes, Edwards, and BrkSide
match1 <- grepl("NAmes", train$Neighborhood)
match2 <- grepl("Edwards", train$Neighborhood)
match3 <- grepl("BrkSide", train$Neighborhood)

new1 <- train[match1, ]
new2 <- train[match2, ]
new3 <- train[match3, ]

#New data set
newtrain <- rbind(new1, new2, new3)
```

```
ui <- fluidPage(
  titlePanel("House Price vs. Square Footage"),
  sidebarLayout(
    sidebarPanel(
      selectInput("neighborhood",
                  "Choose a Neighborhood:",
                  choices = c("NAmes", "Edwards", "BrkSide"),
                  selected = "NAmes")
    ),
    mainPanel(
      plotOutput("scatterplot"),
      plotOutput("combined_plot")
    )
  )
)

# Server Logic
server <- function(input, output) {

  output$scatterplot <- renderPlot({
    neighborhood_data <- subset(newtrain, Neighborhood == input$neighborhood)
    ggplot(neighborhood_data, aes(x = GrLivArea, y = SalePrice)) +
      geom_point() +
      geom_smooth(method = "lm", se = FALSE) +  # Add linear trend line
      labs(title = paste("House Price vs. Square Footage in", input$neighborhood),
           x = "Square Footage",
           y = "Price")
  })

  output$combined_plot <- renderPlot({
    ggplot(newtrain, aes(x = GrLivArea, y = SalePrice, color = Neighborhood)) +
      geom_point() +
      geom_smooth(method = "lm", se = FALSE) +  # Add linear trend line
      labs(title = "House Price vs. Square Footage (Combined)",
           x = "Square Footage",
           y = "Price",
           color = "Neighborhood")
  })
}

# Run the App
shinyApp(ui = ui, server = server)
```

Code for Analysis Problem #2:

```
library(tidyverse)
library(ggplot2)
library(scales)
library(pwr)
library(agricolae)
install.packages("huxtable")
library(huxtable)
install.packages("lawstat")
library(lawstat)
```

~~~
library(lsmeans)
library(dplyr)
library(WDI)
library(investr)
library(multcomp)
library(pairwiseCI)
install.packages("DescTools")
library(DescTools)
install.packages("GGally")
library(GGally)
install.packages("olsrr")
library(olsrr)
library(tidyverse)
library(car)
```
~~~

In order to create our simple linear regression, we will use an automatic variable selection technique.

Select explanatory variable for determining sales prices of homes in Ames

~~~
```{r}
#Review data
head(train)
summary(train)

#Create tentative linear regression model to plug into Backward, Forward, and Stepwise Selection Models
# Load the necessary libraries
library(MASS)  # For stepAIC function

# Start with an empty model
best_model <- lm(SalePrice ~ 1, data = train)

# Number of predictors in the dataset
num_predictors <- ncol(train) - 1  # Excluding the target variable 'SalePrice'

# Initialize variables to store the best predictor and its associated AIC
best_predictor <- NULL
best_AIC <- Inf

# Forward selection loop
for (predictor in names(train)[-which(names(train) == "SalePrice")]) {
  # Construct formula for current predictor
  formula_str <- paste("SalePrice ~", predictor)

  # Fit a model with the current predictor
~~~

~~~
  model <- lm(formula_str, data = train)

  # Compute AIC for the current model
  model_AIC <- AIC(model)

  # Update the best predictor if current AIC is lower
  if (model_AIC < best_AIC) {
    best_AIC <- model_AIC
    best_predictor <- predictor
  }
}

# Display the best predictor found
print(best_predictor)
```
~~~

Using Forward Step Selection, we found that the best predictor variable in the 79 variable dataset is PoolQC. We will use this variable in the simple linear regression model.

#Selection for top variables

~~~
```{r}
#TRANSFORM CAT VARS TO FACTORS AND TRY STEPWISE

# Identify variables with categorical data types
categorical_vars <- sapply(train, function(x) is.factor(x) || is.character(x))

# List variables with categorical data types
cat_vars_names <- names(categorical_vars)[categorical_vars]
cat_vars_names

# Convert variables with categorical data types to factors
train[, cat_vars_names] <- lapply(train[, cat_vars_names], as.factor)

fit <- lm(SalePrice ~ ., data = train)
result <- ols_step_both_p(fit, penter = 0.01, prem = 0.05, details = FALSE)

# Filter the output of str() to only display factor variables
str(train[, sapply(train, is.factor)])

# Check levels of each factor variable
lapply(train[, cat_vars_names], function(x) levels(x))

```
~~~

#In the process of running the forward step, we found that the PoolQC, Fence, MiscFeature, Alley, and Utilities variables had a number of NA values that were not suitable to be run in a

linear regression model. We dropped those variables from the dataset and ran stepwise step again.
```{r}
trainNEW = subset(train, select=-c(PoolQC, Fence, MiscFeature, Alley, Utilities))

fit <- lm(SalePrice ~ ., data = trainNEW)
```

#Now we will try stepwise selection.
```{r}
# Stepwise

# Perform stepwise selection with different p-values for entering and exiting variables
result <- ols_step_both_p(fit, penter = 0.01, prem = 0.05, details = FALSE)
print(result)
```
With the stepwise model selection, we found the two best fit variables to be OverallQual and GrLivArea. These two, along with FullBath, will be used in the Linear regression model and multiple linear regression models we intend to conduct. Before running those models, we first want to check assumptions and assess the normality of the data.

```{r}
# Create scatterplot matrix
ggpairs(trainNEW[, c("OverallQual", "GrLivArea", "FullBath", "SalePrice")])
```
#There is visual evidence of a relationship between overall qual and GrLivArea, OverallQual and FullBath, OverallQual and SalePrice, GrLivArea and FullBath, FullBath and SalePrice. There appears to be a linear relationship between GrLivArea and SalePrice with outliers (those we struck out in the first problem).

#We will assess outliers in the models we create below.
```{r}
#Simple Linear Regression
SLR = lm(SalePrice ~ OverallQual, data = trainNEW)
summary(SLR)

#Visualize SLR
plot(SLR)

#Calculate Cook's distances
cooksd <- cooks.distance(SLR)

#Plot Cook's distances
plot(cooksd, pch = 19, frame = FALSE, main = "Cook's Distance Plot")
```

~~~~
abline(h = 4/length(cooksd), col = "red")  # Add a horizontal line at Cook's distance = 4/n
```
#The qqplot and cook's d plots show evidence of outliers. In an effort to give Century21 Ames the best results informed by a best fit model, we will remove these outliers.
```{r}
#Set a threshold for identifying outliers.
threshold <- 16/length(cooksd)

#Identify outliers based on Cook's distance exceeding the threshold
outliers <- which(cooksd > threshold)

#Print the indices of outliers
print(outliers)
```
#There are 20 outliers in the dataset with leverage that impact the our model's ability to predict saleprice. The outliers stand out as anomalies that should be selected and deleted.
```{r}
print(trainNEW[c(179,186,350,376,441,458,474,497,524,528,534,592,692,770,799,804,899,1047,1170,1183,1244,1299,1374), ])
trainNEWER<- trainNEW[-c(179,186,350,376,441,458,474,497,524,528,534,592,692,770,799,804,899,1047,1170,1183,1244,1299,1374), ]

#Simple linear regression
SLR_2 = lm(SalePrice ~ OverallQual, data = trainNEWER)
summary(SLR_2)

#Calculate Cook's distances
cooksd <- cooks.distance(SLR_2)

#Plot Cook's distances
plot(cooksd, pch = 19, frame = FALSE, main = "Cook's Distance Plot")
abline(h = 4/length(cooksd), col = "red")  # Add a horizontal line at Cook's distance = 4/n
```
#The residuals are better fit on the qqplot and the cook's d plot shows differences in residuals on a much smaller scale. Outliers have been sufficiently eliminated. Checking assumptions for this model, we found that the data was adequately scattered in the residual plot so there was little evidence of variance , the data was reasonably fitted to the line in the qq-plot, suggesting normal distribution, and through the process of deleting high leverage outliers, the Cook’s d plot showed a good distribution for us to move forward with the model.

#Now we will visualize and assess the simple linear regression.
```{r}
#Summarize Simple linear model
~~~~

~~~
summary(SLR_2)

#Visualize LRM
plot(SLR_2)

#Find Adjusted R-Squared Value
SLR_2_fit_summary <- summary(SLR_2)
SLR_2_adj_r_squared <- SLR_2_fit_summary$adj.r.squared
print(SLR_2_adj_r_squared)

#Find CV Press
SLR_2_internal_cv_press <- SLR_2_fit_summary$cov.unscaled
mean(SLR_2_internal_cv_press)
print(mean(SLR_2_internal_cv_press))

```
#Now we will run a Multiple Linear Regression with the variables you all provided wherein
GrLivArea + FullBath predict SalePrice.
```{r}
#Multiple Linear Regression
MLR_C21 = lm(SalePrice ~ GrLivArea + FullBath, data = trainNEW)
summary(MLR_C21)

#Visualize multiple linear regression
plot(MLR_C21)

#Calculate Cook's distances
cooksd <- cooks.distance(MLR_C21)

#Plot Cook's distances
plot(cooksd, pch = 19, frame = FALSE, main = "Cook's Distance Plot")
abline(h = 4/length(cooksd), col = "red")  # Add a horizontal line at Cook's distance = 4/n
```
#There are clearly some outliers in this plot.

```{r}
#Set a threshold for identifying outliers.
threshold <-32/length(cooksd)

#Identify outliers based on Cook's distance exceeding the threshold
outliers <- which(cooksd > threshold)

#Print the indices of outliers
print(outliers)
~~~

~~~
```
```{r}
print(trainNEW[c(54,441,524,636,665,692,770,804,899,1047,1170,1183,1299), ])
trainNEWEST<- trainNEW[-c(54,441,524,636,665,692,770,804,899,1047,1170,1183,1299), ]

#Simple linear regression
MLR_C21_2 = lm(SalePrice ~ GrLivArea + FullBath, data = trainNEWEST)
summary(MLR_C21_2)
plot(MLR_C21_2)

#Calculate Cook's distances
cooksd <- cooks.distance(MLR_C21_2)

#Plot Cook's distances
plot(cooksd, pch = 19, frame = FALSE, main = "Cook's Distance Plot")
abline(h = 4/length(cooksd), col = "red")  # Add a horizontal line at Cook's distance = 4/n
```
#The residuals are better fit on the qqplot and the cook's d plot shows differences in residuals
on a much smaller scale. We also got rid of the outlier with high leverage. Outliers have been
sufficiently eliminated. Checking assumptions for this model, we found that the data was
adequately scattered in the residual plot so there was little evidence of variance , the data was
reasonably fitted to the line in the qq-plot, suggesting normal distribution, and through the
process of deleting high leverage outliers, the Cook’s d plot showed a good distribution for us to
move forward with the model.

#Now we will visualize and assess the simple linear regression.
```{r}
#Summarize Simple linear model
summary(MLR_C21_2)

#Visualize LRM
plot(MLR_C21_2)

#Find Adjusted R-Squared Value
MLR_C21_2_fit_summary <- summary(MLR_C21_2)
MLR_C21_2_adj_r_squared <- MLR_C21_2_fit_summary$adj.r.squared
print(MLR_C21_2_adj_r_squared)

#Find CV Press
MLR_C21_2_internal_cv_press <- MLR_C21_2_fit_summary$cov.unscaled
mean(MLR_C21_2_internal_cv_press)
print(mean(MLR_C21_2_internal_cv_press))

```
~~~

#Judging from the parameter estimate table, there is overwhelming evidence to suggest that the combination of GrLivArea and FullBath are statistically significant in predicting SalePrice.

#Our team was able to develop a model that similarly predicts sale price.

```{r}
MLR = lm(SalePrice ~ OverallQual + GrLivArea, data = trainNEW)
summary(MLR)

#Visualize multiple linear regression
plot(MLR)

#Calculate Cook's distances
cooksd <- cooks.distance(MLR)

#Plot Cook's distances
plot(cooksd, pch = 19, frame = FALSE, main = "Cook's Distance Plot")
abline(h = 4/length(cooksd), col = "red")  # Add a horizontal line at Cook's distance = 4/n
```

#There are clearly some outliers in this plot. Let's identify and remove them if necessary.

```{r}
#Set a threshold for identifying outliers.
threshold <-32/length(cooksd)

#Identify outliers based on Cook's distance exceeding the threshold
outliers <- which(cooksd > threshold)

#Print the indices of outliers
print(outliers)
```

#The outliers were homes with unusual living area sizes which stood out from the homes in Ames, IA. Remove the outliers and reassess model fit.

```{r}
print(trainNEW[c(179,441,524,692,770,804,899,1047,1170,1183,1299), ])
trainNEW_MLR<- trainNEW[-c(179,441,524,692,770,804,899,1047,1170,1183,1299), ]

#Simple linear regression
MLR_2 = lm(SalePrice ~ OverallQual + GrLivArea, data = trainNEW_MLR)
summary(MLR_2)
plot(MLR_2)

#Calculate Cook's distances
cooksd <- cooks.distance(MLR_2)

#Plot Cook's distances
```

~~~~
plot(cooksd, pch = 19, frame = FALSE, main = "Cook's Distance Plot")
abline(h = 4/length(cooksd), col = "red")  # Add a horizontal line at Cook's distance = 4/n
```
#The residuals are better fit on the qqplot and the cook's d plot shows differences in residuals on a much smaller scale. We also got rid of an outlier with relatively high leverage. Outliers have been sufficiently eliminated. Checking assumptions for this model, we found that the data was adequately scattered in the residual plot so there was little evidence of variance , the data was reasonably fitted to the line in the qq-plot, suggesting normal distribution, and through the process of deleting high leverage outliers, the Cook’s d plot showed a good distribution for us to move forward with the model.

#Now we will visualize and assess the multiple linear regression.
```{r}
#Summarize Simple linear model
summary(MLR_2)

#Visualize LRM
plot(MLR_2)

#Find Adjusted R-Squared Value
MLR_2_fit_summary <- summary(MLR_2)
MLR_2_adj_r_squared <- MLR_2_fit_summary$adj.r.squared
print(MLR_2_adj_r_squared)

#Find CV Press
MLR_2_internal_cv_press <- MLR_2_fit_summary$cov.unscaled
mean(MLR_2_internal_cv_press)
print(mean(MLR_2_internal_cv_press))

```
#Judging from the parameter estimate table, there is overwhelming evidence to suggest that the combination of OverallQual and GrLivArea are statistically significant in predicting SalePrice.

#We decided to test the models used in this exercise using Kaggle's test data.
```{r}
#Read in data
test<- read.csv(choose.files())
#Check data
head(test)


#Test Simple Linear Regression
predictions_SLR <- predict(SLR_2, newdata = test)
head(predictions_SLR)
~~~~

```
test$SalePrice_Predicted <- predictions_SLR
SLR_test <- test[c("Id", "SalePrice_Predicted")]
write.csv(SLR_test, "SLR_predictions.csv", row.names = FALSE)

#Test Multiple Linear Regression provided by Century21 Ames
predictions_MLR_C21_2 <- predict(MLR_C21_2, newdata = test)
head(predictions_MLR_C21_2)
test$SalePrice_Predicted2 <- predictions_MLR_C21_2
MLR_test <- test[c("Id", "SalePrice_Predicted2")]
write.csv(MLR_test, "MLR_C21_2_predictions.csv", row.names = FALSE)

#Test Multiple Linear Regression
predictions_MLR_2 <- predict(MLR_2, newdata = test)
head(predictions_MLR_2)
test$SalePrice_Predicted3 <- predictions_MLR_2
MLR_2_test <- test[c("Id", "SalePrice_Predicted3")]
write.csv(MLR_2_test, "MLR_2_predictions.csv", row.names = FALSE)
```

#Comparing the three models using test data, our multiple linear regression model is best fit, evidenced by the higher r-squared, adjusted r-squared, and small mean CV press value. You will note that the MLR we created has a slightly higher mean CV press in comparison to Century21 Ames', suggesting a slightly better predictive performance, however, with much higher correlation of variables in our MLR, we decided that the latter was best fit in predicting the sale prices using Test data.

2. Further Information on the Researchers

For further information on the researchers, we invite you to visit our github pages which document our bios and previous work in the field of data science.

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