

DaigleHomework1.R

mbair

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Chris Daigle Homework 1 Exercise: 2 _____

```
#  
# 1 #####  
# Download the housing dataset from https://www.kaggle.com/harlfoxem/housesalesprediction and run a reg  
  
rm(list = ls())  
  
setwd('~/Git/MachineLearningAndBigDataWithR/Data')  
  
# dataurl = "https://www.kaggle.com/harlfoxem/housesalesprediction/downloads/kc_house_data.csv/1"  
dataName <- 'kcHouseData.csv'  
# download.file(dataurl, destfile = dataName)  
data <- read.csv(dataName, stringsAsFactors = FALSE)  
str(data)  
  
## 'data.frame': 21613 obs. of 21 variables:  
## $ id : num 7.13e+09 6.41e+09 5.63e+09 2.49e+09 1.95e+09 ...  
## $ date : chr "20141013T000000" "20141209T000000" "20150225T000000" "20141209T000000" ...  
## $ price : num 221900 538000 180000 604000 510000 ...  
## $ bedrooms : int 3 3 2 4 3 4 3 3 3 3 ...  
## $ bathrooms : num 1 2.25 1 3 2 4.5 2.25 1.5 1 2.5 ...  
## $ sqft_living : int 1180 2570 770 1960 1680 5420 1715 1060 1780 1890 ...  
## $ sqft_lot : int 5650 7242 10000 5000 8080 101930 6819 9711 7470 6560 ...  
## $ floors : num 1 2 1 1 1 1 2 1 1 2 ...  
## $ waterfront : int 0 0 0 0 0 0 0 0 0 0 ...  
## $ view : int 0 0 0 0 0 0 0 0 0 0 ...  
## $ condition : int 3 3 3 5 3 3 3 3 3 3 ...  
## $ grade : int 7 7 6 7 8 11 7 7 7 7 ...  
## $ sqft_above : int 1180 2170 770 1050 1680 3890 1715 1060 1050 1890 ...  
## $ sqft_basement: int 0 400 0 910 0 1530 0 0 730 0 ...  
## $ yr_builtin : int 1955 1951 1933 1965 1987 2001 1995 1963 1960 2003 ...  
## $ yr_renovated : int 0 1991 0 0 0 0 0 0 0 0 ...  
## $ zipcode : int 98178 98125 98028 98136 98074 98053 98003 98198 98146 98038 ...  
## $ lat : num 47.5 47.7 47.7 47.5 47.6 ...  
## $ long : num -122 -122 -122 -122 -122 ...  
## $ sqft_living15: int 1340 1690 2720 1360 1800 4760 2238 1650 1780 2390 ...  
## $ sqft_lot15 : int 5650 7639 8062 5000 7503 101930 6819 9711 8113 7570 ...  
  
# price: price of home  
# bedrooms: number of bedrooms  
# floors: number of floors  
# sqft_living: square footage of living space  
# yr_builtin  
  
lm.fit <-  
  lm(price ~ sqft_living + bedrooms + floors + yr_builtin, data = data)
```

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summary(lm.fit)

##
## Call:
## lm(formula = price ~ sqft_living + bedrooms + floors + yr_built,
##     data = data)
##
## Residuals:
##      Min       1Q   Median       3Q      Max 
## -1857482 -130242 -16610  99627 3972920 
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)    
## (Intercept) 5.810e+06 1.285e+05  45.21 <2e-16 ***
## sqft_living 3.304e+02 2.387e+00 138.42 <2e-16 ***
## bedrooms    -5.937e+04 2.211e+03 -26.86 <2e-16 ***
## floors       7.283e+04 3.672e+03 19.84 <2e-16 ***
## yr_built    -2.976e+03 6.658e+01 -44.70 <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 246700 on 21608 degrees of freedom
## Multiple R-squared:  0.5486, Adjusted R-squared:  0.5485 
## F-statistic:  6564 on 4 and 21608 DF, p-value: < 2.2e-16

names(lm.fit)

## [1] "coefficients" "residuals"      "effects"        "rank"        
## [5] "fitted.values" "assign"         "qr"            "df.residual"  
## [9] "xlevels"       "call"          "terms"         "model"      
# 2 #####
# Build a model to predict the housing price given characteristics of a house in the dataset.
# Consider the following predictors: season, sqft_living, yr_built, interaction of sqft_living yr_built
# Create a variable "season" which equals
# "Winter" if a house was sold in Jan, Feb, Mar, Dec.
# "Spring" if it was sold in Apr, May, Jun
# "Summer" if it was sold in Jul, Aug
# "Fall" if it was sold in Sep, Oct, Nov.
# Do you find any seasonality in housing price?

data <-
  transform(
    data,
    Year = substr(date, 1, 4),
    Month = substr(date, 5, 6),
    Day = substr(date, 7, 8)
  )

data$cleanDate <-
  as.Date(paste0(data$Year, '- ', data$Month, '- ', data$Day))

data$season[data$Month == '01' |
  data$Month == '02' |
  data$Month == '03' | data$Month == '12'] <- 'Winter'

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data$season[data$Month == '04' |
  data$Month == '05' | data$Month == '06'] <- 'Spring'
data$season[data$Month == '07' | data$Month == '08'] <- 'Summer'
data$season[data$Month == '09' |
  data$Month == '10' | data$Month == '11'] <- 'Fall'

lm.fit1 <-
  lm(price ~ season + sqft_living + yr_built + sqft_living * yr_built + waterfront,
  data = data)
summary(lm.fit1)

##
## Call:
## lm(formula = price ~ season + sqft_living + yr_built + sqft_living *
##       yr_built + waterfront, data = data)
##
## Residuals:
##    Min      1Q      Median      3Q      Max
## -1497733 -133514   -17225   107931   4190203
##
## Coefficients:
##                               Estimate Std. Error t value Pr(>|t|)
## (Intercept)            2.744e+06  2.686e+05 10.216 < 2e-16 ***
## seasonSpring          2.182e+04  4.519e+03  4.828 1.39e-06 ***
## seasonSummer           5.037e+03  5.102e+03  0.987  0.324
## seasonWinter          7.067e+03  4.730e+03  1.494  0.135
## sqft_living            1.055e+03  1.222e+02  8.632 < 2e-16 ***
## yr_builtin             -1.438e+03  1.364e+02 -10.543 < 2e-16 ***
## waterfront             7.828e+05  1.930e+04  40.556 < 2e-16 ***
## sqft_living:yr_builtin -3.841e-01  6.179e-02 -6.216 5.20e-10 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 243600 on 21605 degrees of freedom
## Multiple R-squared:  0.5598, Adjusted R-squared:  0.5597
## F-statistic:  3925 on 7 and 21605 DF,  p-value: < 2.2e-16

# Results
# Spring: 2.182e+04 = 2.182*(10^4) = 21820
# Summer: 5.037e+03 = 5.037*(10^3) = 5037
# Winter: 7.067e+03 = 7.067*(10^3) = 7067
# sqft_living: 1.055e+03 = 1.055*(10^3) = 1055
# yr_builtin: -1.438e+03 = -1.438*(10^3) = -1438
# waterfront: 7.828e+05 = 7.828*(10^5) = 782800
# sqft_living*yr_builtin: -3.841e-01 = -3.841*(10^(-1)) = -0.3841

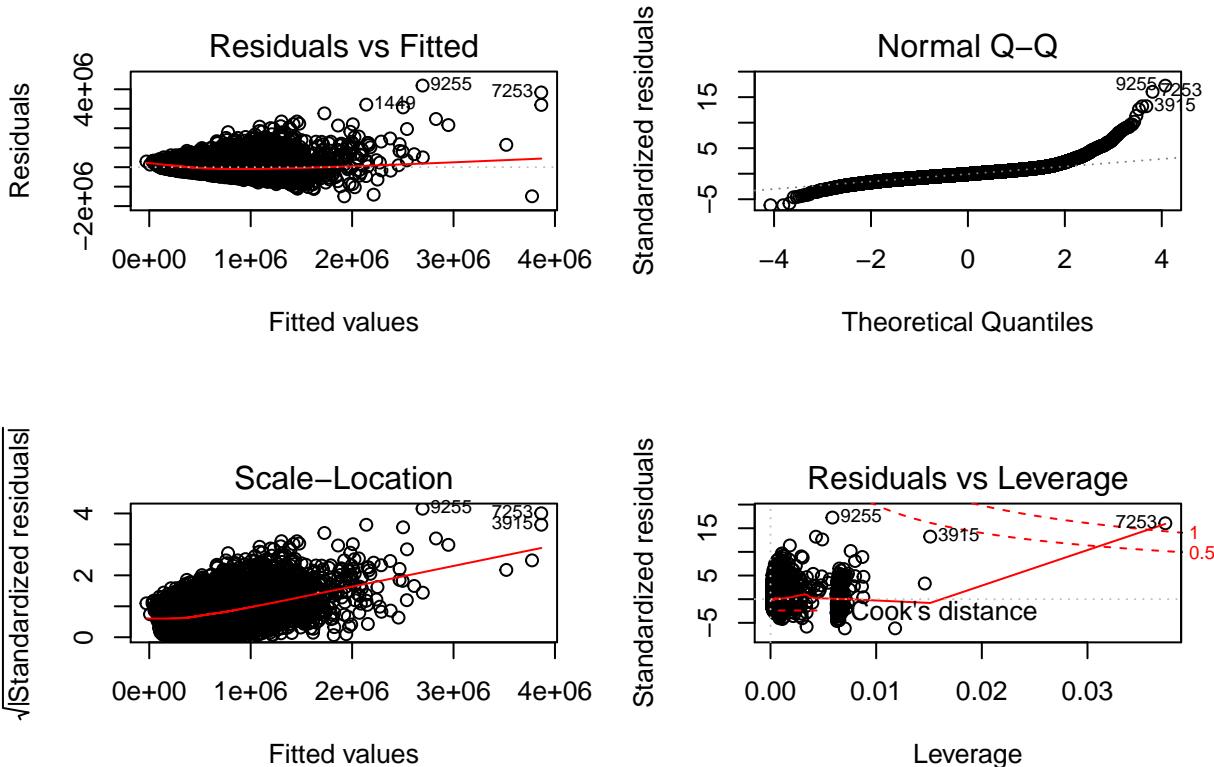
# I find seasonality in housing price - it can be seen that selling in different
# seasons contributes differently to the housing price with Spring showing
# economically significant results ($21,820) as well as statistically
# significant ones (approximately zero p-value).

# 3 ##### Do you find any nonlinearity or heteroskedasticity? YES. BREUSCH PAGAN
# TEST and NOTE FUNNEL LIKE RESIDUALS
# What is the problem if the error term is heteroskedastic? PREDICTION

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#How can you address these problems (if you have here)?
# TRANSFORM DEPENDENT/RESPONSE VARIABLE, WHITE STANDARD ERRORS

par(mfrow = c(2, 2))
plot(lm.fit1)
```



```
par(mfrow = c(1, 1))
library(lmtest)

## Loading required package: zoo

##
## Attaching package: 'zoo'

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

btptest(lm.fit1)

##
## studentized Breusch-Pagan test
##
## data: lm.fit1
## BP = 2882.7, df = 7, p-value < 2.2e-16

# The Breusch-Pagan test reveals that the null hypothesis of homoskedasticity is
# rejected, the p-value is 2.2e-16 (or incredibly near zero). We can also see the
# presence of a funnel type shape in the residuals plot and we can see the
# magnitude of the residuals tends to increase with the fitted values.
```

```

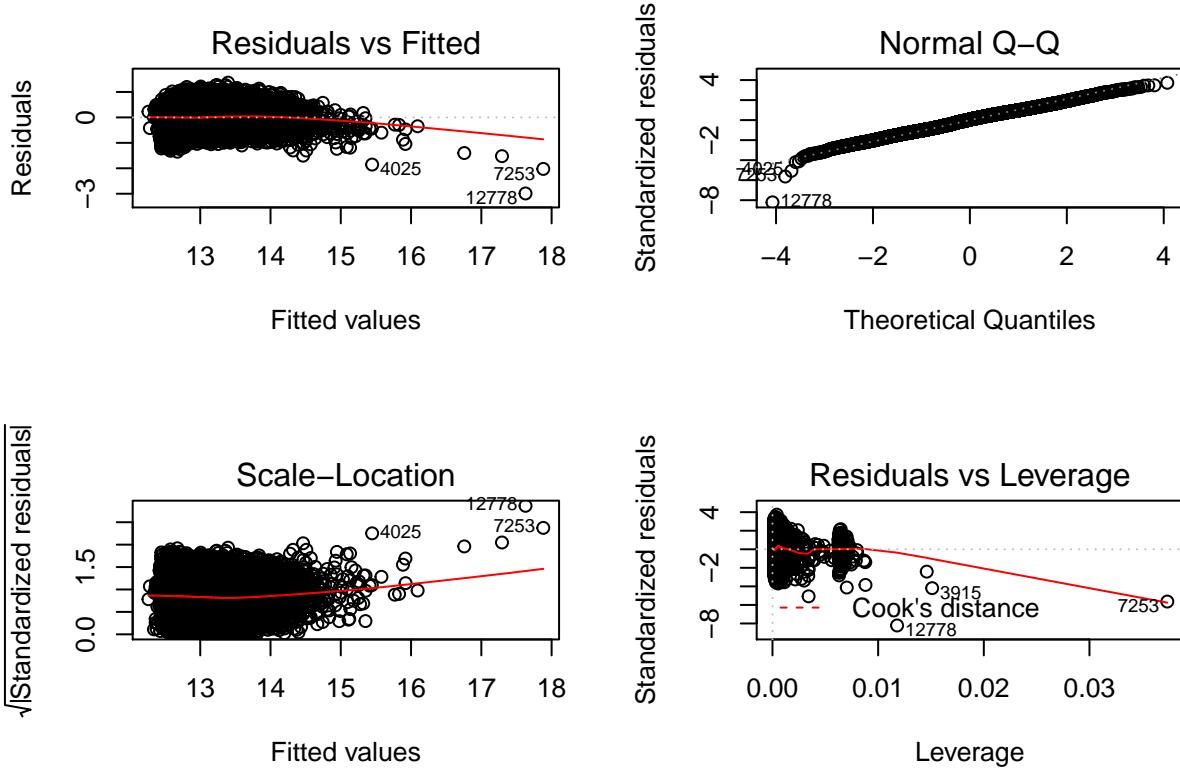
# Our ability to predict is diminished because the the variances of the error
# terms are non-constant, or put differently, the magnitude of the error terms
# changes with values of the independent variable(s).

library(sandwich)
lm.fit2 <-
  lm(log(price) ~ season + sqft_living + yr_built + sqft_living * yr_built + waterfront,
    data = data)
summary(lm.fit2)

##
## Call:
## lm(formula = log(price) ~ season + sqft_living + yr_built + sqft_living *
##       yr_built + waterfront, data = data)
##
## Residuals:
##      Min        1Q     Median        3Q       Max
## -2.98925 -0.26650  0.02222  0.25836  1.36546
##
## Coefficients:
##                               Estimate Std. Error t value Pr(>|t|)
## (Intercept)           1.457e+01  4.036e-01 36.095 < 2e-16 ***
## seasonSpring          4.374e-02  6.792e-03  6.440 1.22e-10 ***
## seasonSummer          1.388e-02  7.668e-03  1.810  0.0704 .
## seasonWinter          5.554e-03  7.110e-03  0.781  0.4347
## sqft_living           1.875e-03  1.836e-04 10.210 < 2e-16 ***
## yr_builtin            -1.228e-03  2.050e-04 -5.990 2.13e-09 ***
## waterfront            5.709e-01  2.901e-02 19.679 < 2e-16 ***
## sqft_living:yr_builtin -7.358e-07  9.287e-08 -7.923 2.44e-15 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.3662 on 21605 degrees of freedom
## Multiple R-squared:  0.5169, Adjusted R-squared:  0.5167
## F-statistic:  3302 on 7 and 21605 DF,  p-value: < 2.2e-16

par(mfrow = c(2, 2))
plot(lm.fit2)

```



```
par(mfrow = c(1, 1))
bpptest(lm.fit2)
```

```
##
## studentized Breusch-Pagan test
##
## data: lm.fit2
## BP = 405.83, df = 7, p-value < 2.2e-16
# Employing the White Standard Errors
coeftest(lm.fit2, vcov = vcovHC(lm.fit2, type = "HC1"))
```

```
##
## t test of coefficients:
##
##                               Estimate Std. Error t value Pr(>|t|)
## (Intercept)           1.4569e+01 5.8635e-01 24.8476 < 2.2e-16 ***
## seasonSpring        4.3740e-02 6.7353e-03  6.4941 8.533e-11 ***
## seasonSummer       1.3876e-02 7.4945e-03  1.8515  0.06411 .
## seasonWinter      5.5539e-03 7.1871e-03  0.7728  0.43968
## sqft_living       1.8749e-03 2.9145e-04  6.4329 1.278e-10 ***
## yr_builtin        -1.2281e-03 2.9739e-04 -4.1296 3.647e-05 ***
## waterfront         5.7092e-01 3.4235e-02 16.6764 < 2.2e-16 ***
## sqft_living:yr_builtin -7.3577e-07 1.4719e-07 -4.9988 5.815e-07 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
coeftest(lm.fit1, vcov = vcovHC(lm.fit1, type = "HC1"))
```

```
##
## t test of coefficients:
```

```

##                                     Estimate Std. Error t value Pr(>|t|) 
## (Intercept)                2.7436e+06 8.2806e+05 3.3133 0.0009234 ***
## seasonSpring               2.1817e+04 4.6100e+03 4.7325 2.231e-06 ***
## seasonSummer                5.0372e+03 5.0463e+03 0.9982 0.3181896
## seasonWinter                7.0668e+03 4.7111e+03 1.5000 0.1336213
## sqft_living                 1.0546e+03 4.5669e+02 2.3092 0.0209438 *
## yr_builtin                  -1.4382e+03 4.1915e+02 -3.4313 0.0006019 ***
## waterfront                  7.8283e+05 5.8637e+04 13.3504 < 2.2e-16 ***
## sqft_living:yr_builtin     -3.8407e-01 2.3043e-01 -1.6668 0.0955699 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

# We can transform the response variable, Y, by predicting on the square-root
# or, more commonly employed because of ease of interpretation, logarithmic which
# demonstrates an elasticity (the responsiveness of the variable to the
# independent variables). Applying the log transform diminishes the amount of
# funneling as described in the residuals, but it is not completely gone. We can
# see from the Breusch-Pagan test that the null hypothesis of homoskedasticity
# continues to be rejected. We can also use White Standard Errors.

# 4 #####
# Conduct an F test for the following hypotheses.
# H0: there is no seasonality on the housing price. H1: H0 is not true.
# THE NULL HYPOTHESIS FAILS TO HOLD

yHatU <-
  lm(price ~ season + sqft_living + yr_builtin + sqft_living * yr_builtin + waterfront,
      data = data)
yHatR <-
  lm(price ~ sqft_living + yr_builtin + sqft_living * yr_builtin + waterfront,
      data = data)
ssr_u <- sum((fitted(yHatU) - data$price)^ 2)
ssr_r <- sum((fitted(yHatR) - data$price)^ 2)
f <- ((ssr_r - ssr_u) / 3) / (ssr_u / (21613 - 5 - 1))
var.test(yHatU, yHatR, alternative = "two.sided")

##
## F test to compare two variances
##
## data: yHatU and yHatR
## F = 0.99889, num df = 21605, denom df = 21608, p-value = 0.9348
## alternative hypothesis: true ratio of variances is not equal to 1
## 95 percent confidence interval:
##  0.9726002 1.0258839
## sample estimates:
## ratio of variances
## 0.9988868

# Min's solution
# SSR <- sum((yHatU$residuals)^ 2)
# SSRR <- sum((yHatR$residuals)^ 2)
# FSTAT <- ((SSRR - SSR)/3)/(SSR/(dim(data)[1] - 7 - 1))
# qf(0.95, df1 = 3, df2 = dim(data)[1] - 7 - 1)

```

```

# 5 #####
# Predict the housing price when season = spring, sqft_living=2500, yr_built=2000, waterfront=0:
# PREDICTION RESULT: $594406.1
# 95% CONFIDENCE INTERVAL: ($589801.9, $599010.4)
lm.fit <- lm(price ~ sqft_living + yr_built + waterfront, data = data)
predict(
  object = lm.fit,
  newdata = data.frame(
    season = "Spring",
    sqft_living = 2500,
    yr_built = 2000,
    waterfront = 0
  ),
  interval = "prediction"
)

##          fit      lwr      upr
## 1 594406.1 116197.2 1072615

predict(
  object = lm.fit,
  newdata = data.frame(
    season = "Spring",
    sqft_living = 2500,
    yr_built = 2000,
    waterfront = 0
  ),
  interval = "confidence"
)

##          fit      lwr      upr
## 1 594406.1 589801.9 599010.4

predict(
  object = lm.fit,
  newdata = data.frame(
    season = "Spring",
    sqft_living = 2500,
    yr_built = 2000,
    waterfront = 0
  )
)

##          1
## 1 594406.1

```