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Assignment 1

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INF 397 – Statistical Analysis and Learning w/ Prof. Varun Rai

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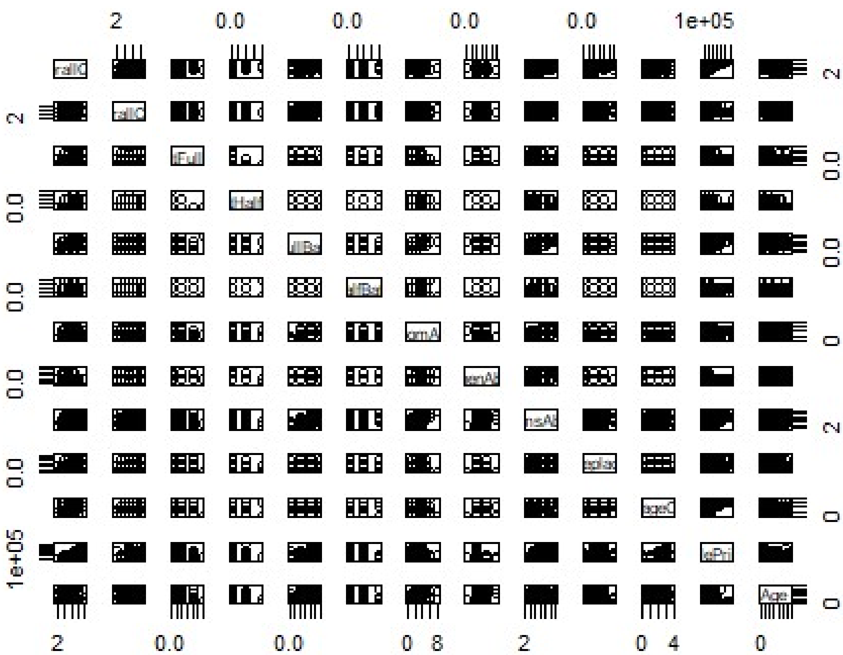
The University of Texas at Austin

```r
### Problem 2 - MLR on dataset

# Read CSV from working directory into R

MyData <- read.csv(file="austin_house_price.csv", header=TRUE, sep=",")

# a. Scatterplot matrix with all variables in dataset

pairs(MyData)
```



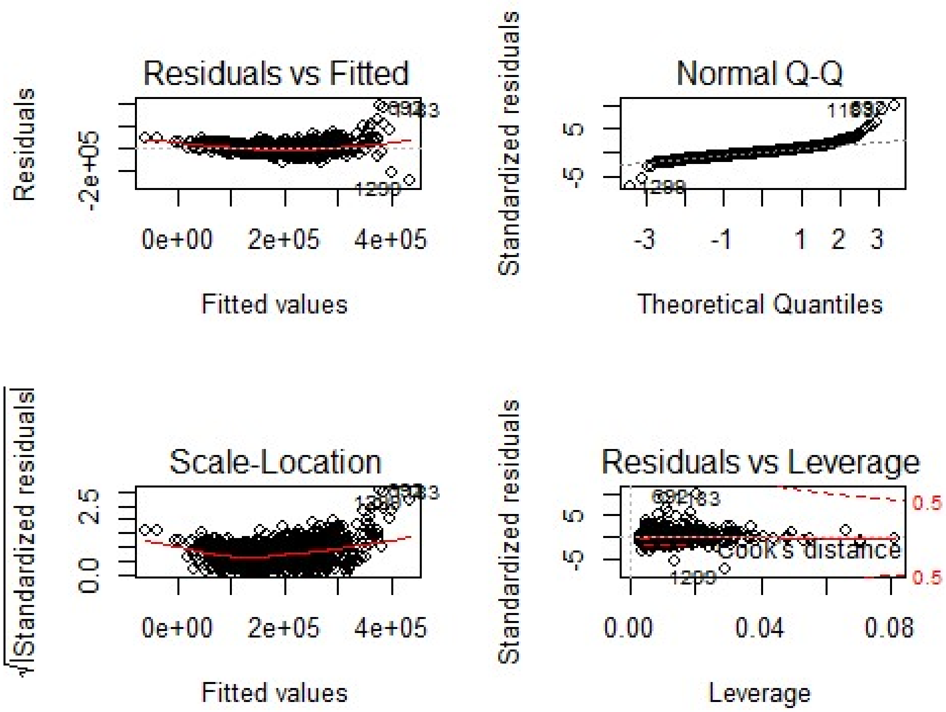
```r
# b. Matrix of correlations of all variables

cor(MyData)

##              OverallQual OverallCond BsmtFullBath BsmtHalfBath    FullBath
## OverallQual   1.00000000 -0.09193234   0.11109779  -0.04015016  0.55059971
## OverallCond  -0.09193234  1.00000000  -0.05494152   0.11782092 -0.19414949
## BsmtFullBath  0.11109779 -0.05494152   1.00000000  -0.14787096 -0.06451205
## BsmtHalfBath -0.04015016  0.11782092  -0.14787096   1.00000000 -0.05453581
## FullBath      0.55059971 -0.19414949  -0.06451205  -0.05453581  1.00000000
## HalfBath      0.27345810 -0.06076933  -0.03090496  -0.01233990  0.13638059
## BedroomAbvGr  0.10167636  0.01298006  -0.15067281   0.04651885  0.36325198
## KitchenAbvGr -0.18388223 -0.08700086  -0.04150255  -0.03794435  0.13311521
## TotRmsAbvGrd  0.42745234 -0.05758317  -0.05327524  -0.02383634  0.55478425
## Fireplaces    0.39676504 -0.02381998   0.13792771   0.02897559  0.24367050
## GarageCars    0.60067072 -0.18575751   0.13188122  -0.02089106  0.46967204
## SalePrice     0.79098160 -0.07785589   0.22712223  -0.01684415  0.56066376
## Age          -0.57262947  0.37732550  -0.18436183   0.03605963 -0.46840292
##                 HalfBath BedroomAbvGr KitchenAbvGr TotRmsAbvGrd
## OverallQual   0.27345810   0.10167636  -0.18388223   0.42745234
## OverallCond  -0.06076933   0.01298006  -0.08700086  -0.05758317
## BsmtFullBath -0.03090496  -0.15067281  -0.04150255  -0.05327524
## BsmtHalfBath -0.01233990   0.04651885  -0.03794435  -0.02383634
```

```
## FullBath      0.13638059   0.36325198   0.13311521   0.55478425
## HalfBath      1.00000000   0.22665148  -0.06826255   0.34341486
## BedroomAbvGr  0.22665148   1.00000000   0.19859676   0.67661994
## KitchenAbvGr -0.06826255   0.19859676   1.00000000   0.25604541
## TotRmsAbvGrd  0.34341486   0.67661994   0.25604541   1.00000000
## Fireplaces    0.20364851   0.10756968  -0.12393624   0.32611448
## GarageCars    0.21917815   0.08610644  -0.05063389   0.36228857
## SalePrice     0.28410768   0.16821315  -0.13590737   0.53372316
## Age          -0.24272773   0.06895972   0.17591841  -0.09695522
##               Fireplaces  GarageCars   SalePrice         Age
## OverallQual   0.39676504  0.60067072  0.79098160 -0.57262947
## OverallCond  -0.02381998 -0.18575751 -0.07785589  0.37732550
## BsmtFullBath  0.13792771  0.13188122  0.22712223 -0.18436183
## BsmtHalfBath  0.02897559 -0.02089106 -0.01684415  0.03605963
## FullBath      0.24367050  0.46967204  0.56066376 -0.46840292
## HalfBath      0.20364851  0.21917815  0.28410768 -0.24272773
## BedroomAbvGr  0.10756968  0.08610644  0.16821315  0.06895972
## KitchenAbvGr -0.12393624 -0.05063389 -0.13590737  0.17591841
## TotRmsAbvGrd  0.32611448  0.36228857  0.53372316 -0.09695522
## Fireplaces    1.00000000  0.30078877  0.46692884 -0.14854356
## GarageCars    0.30078877  1.00000000  0.64040920 -0.53872739
## SalePrice     0.46692884  0.64040920  1.00000000 -0.52335042
## Age          -0.14854356 -0.53872739 -0.52335042  1.00000000
```

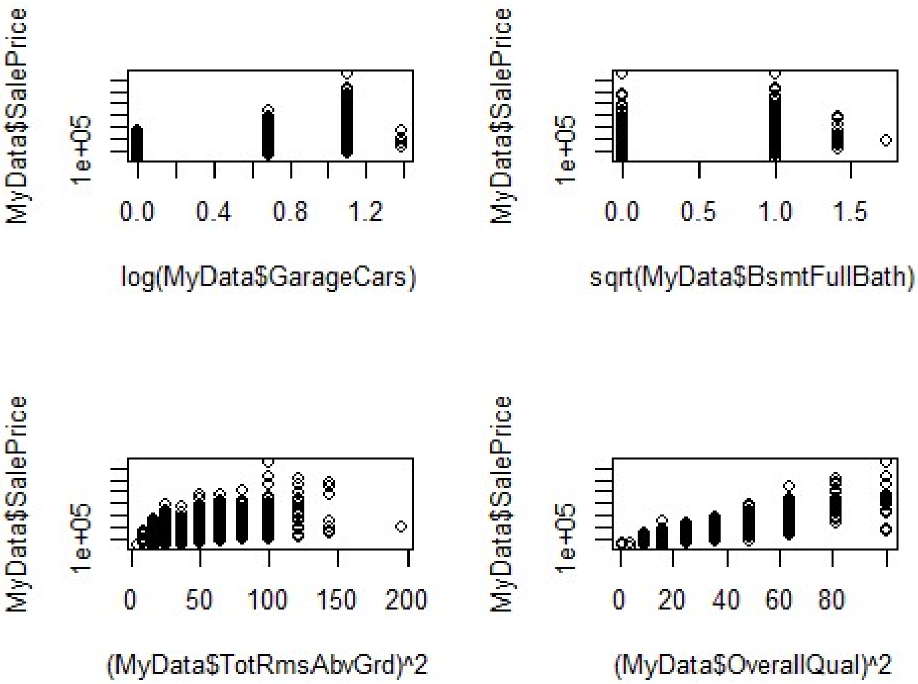
```r
# c. Multiple Linear Regression

lm.fit=lm(SalePrice~., data=MyData)
summary(lm.fit)
```

```
## 
## Call:
## lm(formula = SalePrice ~ ., data = MyData)
## 
## Residuals:
##     Min      1Q  Median      3Q     Max 
## -274626  -21629   -3288   17476  374855 
## 
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)    
## (Intercept)  -83029.36   10280.94  -8.076 1.40e-15 ***
## OverallQual   23140.58    1197.68  19.321  < 2e-16 ***
## OverallCond    4340.82    1035.88   4.190 2.95e-05 ***
## BsmtFullBath  21740.63    2130.05  10.207  < 2e-16 ***
## BsmtHalfBath  10236.97    4429.58   2.311    0.021 *  
## FullBath      13417.14    2825.20   4.749 2.25e-06 ***
## HalfBath        239.56    2329.34   0.103    0.918    
## BedroomAbvGr  -9599.12    1841.24  -5.213 2.12e-07 ***
## KitchenAbvGr -30303.01    5344.86  -5.670 1.73e-08 ***
## TotRmsAbvGrd  15129.23    1159.76  13.045  < 2e-16 ***
## Fireplaces    12668.63    1836.60   6.898 7.87e-12 ***
## GarageCars    16766.94    1873.62   8.949  < 2e-16 ***
## Age            -248.83      53.59  -4.643 3.75e-06 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## 
## Residual standard error: 39330 on 1447 degrees of freedom
```

```
## Multiple R-squared:  0.7569, Adjusted R-squared:  0.7549
## F-statistic: 375.4 on 12 and 1447 DF,  p-value: < 2.2e-16

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

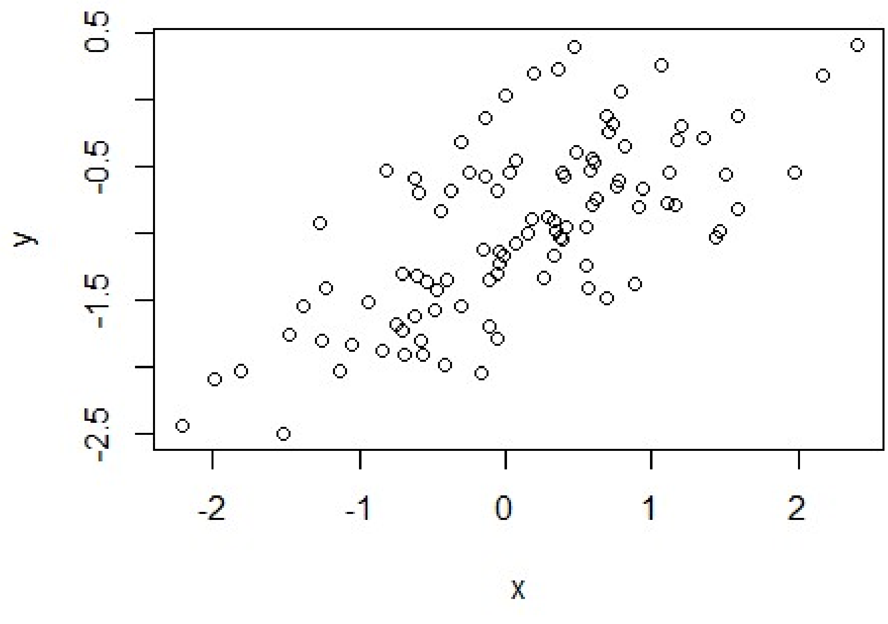



```
  # Relationship between predictors and response:

  # By testing the null hypothesis of that there is no relationship, we can
  # reject it by looking at the p-value corresponding to the F-statistic. In
  # this case, it is very small (<2.2e-16) which means there appears to be a
  # strong relationship between "SalePrice" and atleast some of the predictors.
  # Indeed, by looking at the regression coefficients it can be seen that
  # "GarageCars", "BsmtFullBath", "TotRmsAbvGrd", "OverallQual" all have small
  # p-values and are therefore statistically significant.

  # Coefficient for the age variable:

  # The regression coefficient for the age, -248.83, suggests that for every 1
  # unit in age (presumably a year), SalePrice decreases by the coefficient. In
  # other words, the price falls every year which makes sense because property is
  # usuallly more expensive the newer it is.


# d. Transformation of the variables

par(mfrow = c(2, 2))
plot(log(MyData$GarageCars), MyData$SalePrice)
plot(sqrt(MyData$BsmtFullBath), MyData$SalePrice)
plot((MyData$TotRmsAbvGrd)^2, MyData$SalePrice)
plot((MyData$OverallQual)^2, MyData$SalePrice)
```




```
  # Comment on findings:

  # I decided to transform variables that had the highest statistically
  # significance (lowest p-values) because they have the greastest impact on the
  # SalesPrice. After trying out some transformation, I believe the square of the
  # overall quality gives the most linear looking plot.


### Problem 3 - SLR on simulated data

set.seed(1)
par(mfrow = c(1, 1))

# a. Generation of Feature X

x = rnorm(100)

# b. Generation of Feature eps

eps = rnorm(100, 0, sqrt(0.25))

# c. Generation of response

y = y = -1 + 0.5*x + eps
length(y)

## [1] 100

  # Length of vector, Y:

  # The length of vector, Y, is 100 which makes sense since it a linear function
  # of 2 sets of 100 values
```

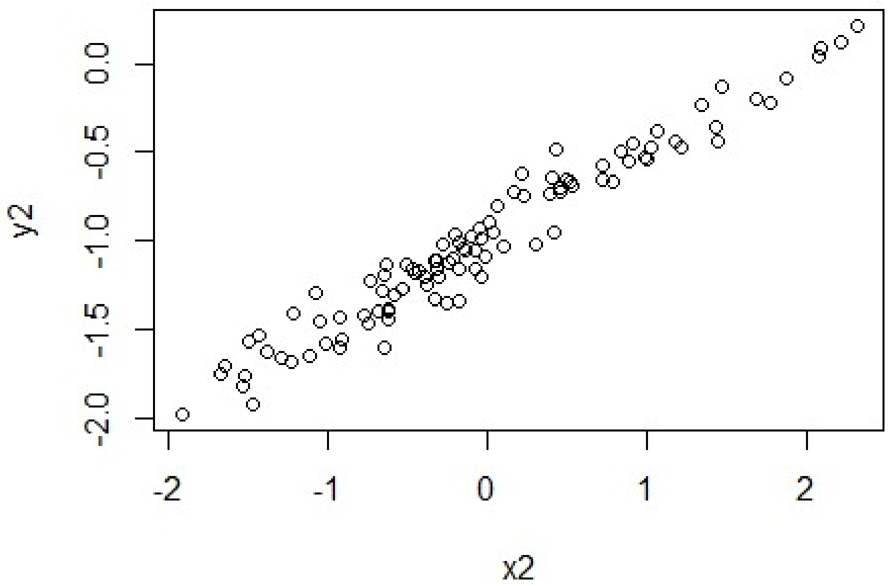
```
  # Values for B0 & B1:

  # B0 = -1, B1 = 0.5 as seen from the original equation


# d. Scatterplot

plot(x, y)
```




```
  # Comment on observations:

  # The relationship between x & y has a positive, linear slope with some
  # variance due to the noise introduced by the eps variable.

# e. Least Square Linear Model

lm.fit2 <- lm(y ~ x)
summary(lm.fit2)

##
## Call:
## lm(formula = y ~ x)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.93842 -0.30688 -0.06975  0.26970  1.17309
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) -1.01885    0.04849 -21.010  < 2e-16 ***
## x            0.49947    0.05386   9.273 4.58e-15 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
##
## Residual standard error: 0.4814 on 98 degrees of freedom
## Multiple R-squared:  0.4674, Adjusted R-squared:  0.4619
## F-statistic: 85.99 on 1 and 98 DF,  p-value: 4.583e-15

  # Comment on Model:

  # The model has a large F-statistic with a small p-value (4.583e-15) and so the null
  # hypothesis can be rejected. This makes sense to me as we know y was indeed
  # generated using x and therefore, the two definitively have a relationship.

  # How do B^0 and B^1 compare to B0 and B1:

  # The constructed values for B^0 (-1.019) and B^1 (0.499) were very close to
  # the true values of -1 and 0.5. This means the linear regression model does a
  # great job modelling the relationship between x & y.

# f. Polynomial Regression Model

lm.fit2_sq = lm(y~x+I(x^2))
summary(lm.fit2_sq)

##
## Call:
## lm(formula = y ~ x + I(x^2))
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.98252 -0.31270 -0.06441  0.29014  1.13500
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) -0.97164    0.05883 -16.517  < 2e-16 ***
## x            0.50858    0.05399   9.420  2.4e-15 ***
## I(x^2)      -0.05946    0.04238  -1.403    0.164
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.479 on 97 degrees of freedom
## Multiple R-squared:  0.4779, Adjusted R-squared:  0.4672
## F-statistic:  44.4 on 2 and 97 DF,  p-value: 2.038e-14

  # Does quadratic term improve the model fit:

  # There is evidence that the model fit has increased slightly as the RSE has
  # decreased and the R^2 is higher. However, when taking into account the large
  # p-value for the x^2 coefficient, it can be concluded that x^2 does not have
  # a relationship with y and the model is most likely overfitting the training
  # data by learning too much of the noise.

# g. Reduction of Noise

set.seed(1)
eps2 = rnorm(100, 0, 0.125)
x2 = rnorm(100)
```

```r
y2 = -1 + 0.5*x2 + eps2
plot(x2, y2)
```



```r
lm.fit3 = lm(y2~x2)
summary(lm.fit3)

##
## Call:
## lm(formula = y2 ~ x2)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.29052 -0.07545  0.00067  0.07288  0.28664
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) -0.98639    0.01129  -87.34   <2e-16 ***
## x2           0.49988    0.01184   42.22   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.1128 on 98 degrees of freedom
## Multiple R-squared:  0.9479, Adjusted R-squared:  0.9474
## F-statistic:  1782 on 1 and 98 DF,  p-value: < 2.2e-16

  # Description of Results

  # By decreasing the variance of the normal distribution that generates the
  # error term, eps, we are able to reduce noise. The coefficients for B0 and B1
  # remain very similar which tells us that the model remained the same.
  # However, the RSE has significantly decreased, and R^2 has increased which
  # means the model fits extremely well. Again, this makes sense because the
  # underlying data is near-perfect with very little error.
```