STAT 6021: Project Two

Medical Insurnace Costs

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1 Executive Summary :

The growing issue of higher medical costs per family has become a big concern to Americans. Increasing healthcare costs stop people from getting the needed care or fill prescriptions. Many families have difficulty in affording healthcare costs and this difficulty in paying bills has significant consequences for US families.

We selected a personal medical costs dataset. We want to explore what demographic characteristics affect the medical charges each family potentially pays in a year. So, we have considered Medical Cost Personal Dataset.

Dataset: datasets_13720_18513_insurance.csv

- The variables are as follows
  - **Predictors**
    - **x1**: **age**: age of primary beneficiary.
    - **x2**: **sex**: insurance contractor gender, female, male.
    - **x3**: **bmi**: Body mass index, providing an understanding of body, weights that are relatively high or low relative to height, objective index of body weight (kg / m ˆ 2) using the ratio of height to weight, ideally 18.5 to 24.9.
    - **x4**: **children**: Number of children covered by health insurance / Number of dependents.
    - **x5**: **smoker**: Smoking
    - **x6**: **region**: the beneficiary's residential area in the US, northeast, southeast, southwest, northwest.
  - **Response Variable**
    - **Y**: **charges**: Individual medical costs billed by health insurance.
- **The main objectives for this project are –**
  1. Explore relationship between response variable **charges** & the six other predictor variables (x1–x6).
  2. Analyze the correlation and directionality of the dataset.
  3. Create a model a best fit model to predict the insurance **charges** based the demographic predictor variables and evaluate the validity and usefulness of this model.

  Additionally, we plan to utilize model selection tools to give us a deeper understanding of how different potential models compare. We want to recommend a best fit model and end our section by exploring the pros and cons of our models under consideration.

2 Exploratory Data Analysis :

We start our exploratory data analysis by taking a look at the dataset.

```
data <- read.csv("datasets_13720_18513_insurance.csv", header = TRUE, sep =",",
                 stringsAsFactors = TRUE)
head(data)
```

```
  age    sex    bmi children smoker    region   charges
1  19 female 27.900        0    yes southwest 16884.924
2  18   male 33.770        1     no southeast  1725.552
3  28   male 33.000        3     no southeast  4449.462
4  33   male 22.705        0     no northwest 21984.471
5  32   male 28.880        0     no northwest  3866.855
6  31 female 25.740        0     no southeast  3756.622
```

Our dataset looks clean and has no missing values.

At a glance, we have six predictors and a response variable **charges**. The dataset has 1338 rows, and non of the columns are missing values.

```
'data.frame':   1338 obs. of  7 variables:
 $ age     : int  19 18 28 33 32 31 46 37 37 60 ...
 $ sex     : Factor w/ 2 levels "female","male": 1 2 2 2 2 1 1 1 2 1 ...
```

```
 $ bmi     : num  27.9 33.8 33 22.7 28.9 ...
 $ children: int  0 1 3 0 0 0 1 3 2 0 ...
 $ smoker  : Factor w/ 2 levels "no","yes": 2 1 1 1 1 1 1 1 1 1 ...
 $ region  : Factor w/ 4 levels "northeast","northwest",..: 4 3 3 2 2 3 3 2 1 2 ...
 $ charges : num  16885 1726 4449 21984 3867 ...
```

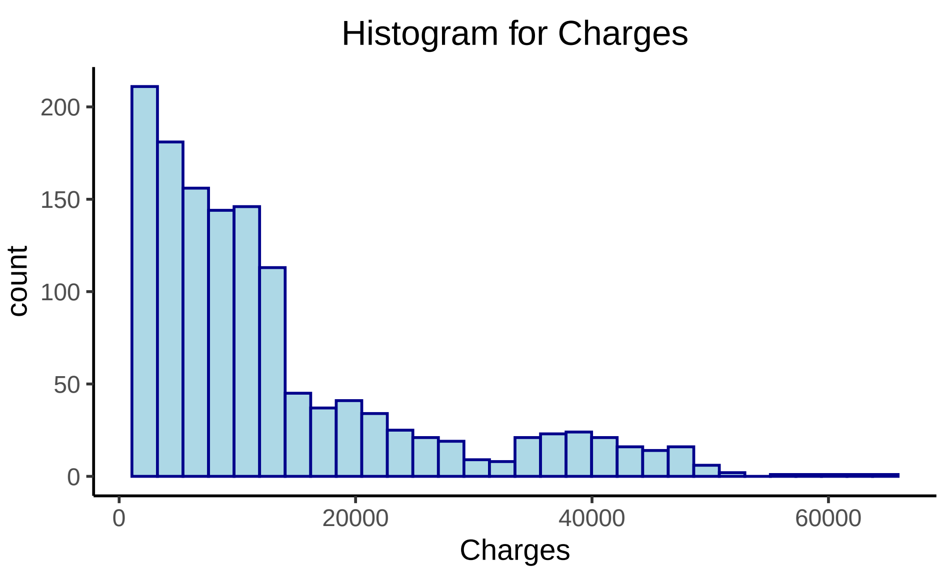
The predictor variables **sex**, **smoker**, and **region** are categorical variables. They are automatically converted as a factor by R when loading the dataset, if you use the option **stringsAsFactors = TRUE** while reading the CSV file.

```
      age            sex           bmi            children      smoker
 Min.   :18.00   female:662   Min.   :15.96   Min.   :0.000   no :1064
 1st Qu.:27.00   male  :676   1st Qu.:26.30   1st Qu.:0.000   yes: 274
 Median :39.00                Median :30.40   Median :1.000
 Mean   :39.21                Mean   :30.66   Mean   :1.095
 3rd Qu.:51.00                3rd Qu.:34.69   3rd Qu.:2.000
 Max.   :64.00                Max.   :53.13   Max.   :5.000
       region       charges
 northeast:324   Min.   : 1122
 northwest:325   1st Qu.: 4740
 southeast:364   Median : 9382
 southwest:325   Mean   :13270
                 3rd Qu.:16640
                 Max.   :63770
```

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
   1122    4740    9382   13270   16640   63770
```

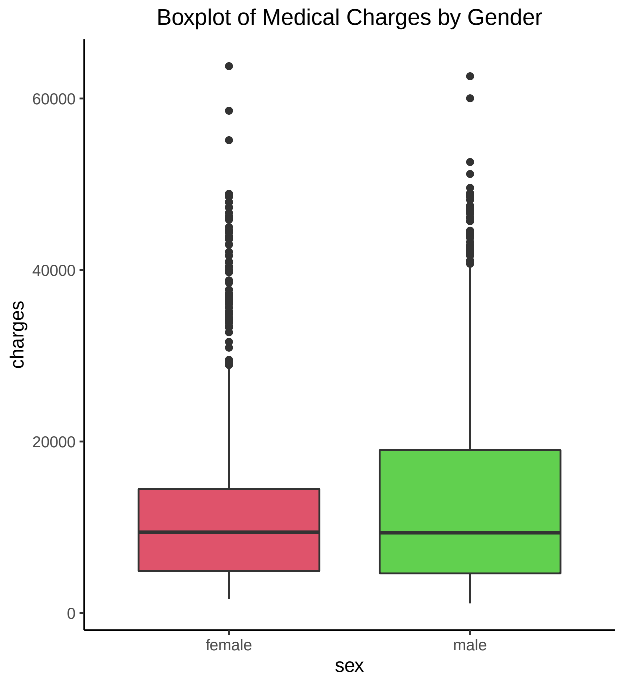
- From the summary, we can make the following observations :
  - The observations are evenly distributed across all four regions and sex.
  - The age varies between a low of 18 and a max of 64.
  - The dataset has almost 4:1 non-smoker to smoker ratio or only 20.5% of people smoke.
  - The bmi varies between a min of 15.96 and a max of 53.13.

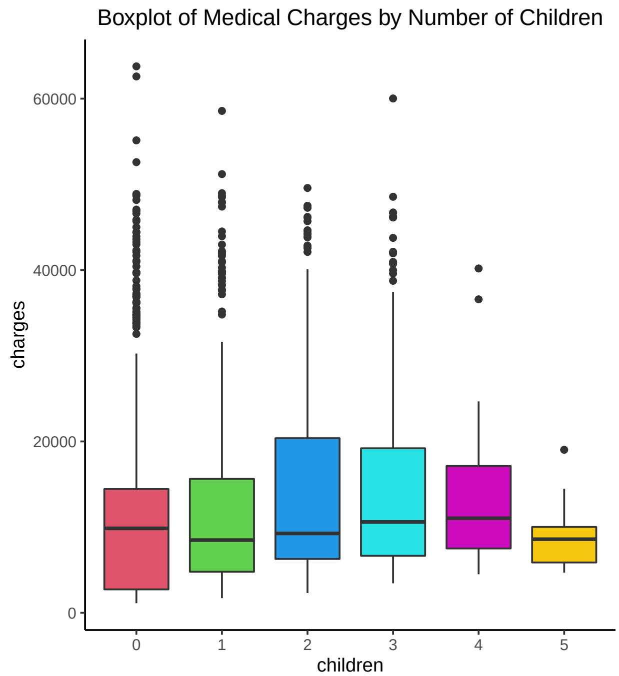
The mean of the response variable is greater than the median of the response variable* that data is right-skewed, also seen in the **histogram of charges** shown below.



From the boxplot of medical **charges** by **sex**, we see that the median value of the **charges** for both males and females is almost the same. However, males tend to have higher medical expenses than females.

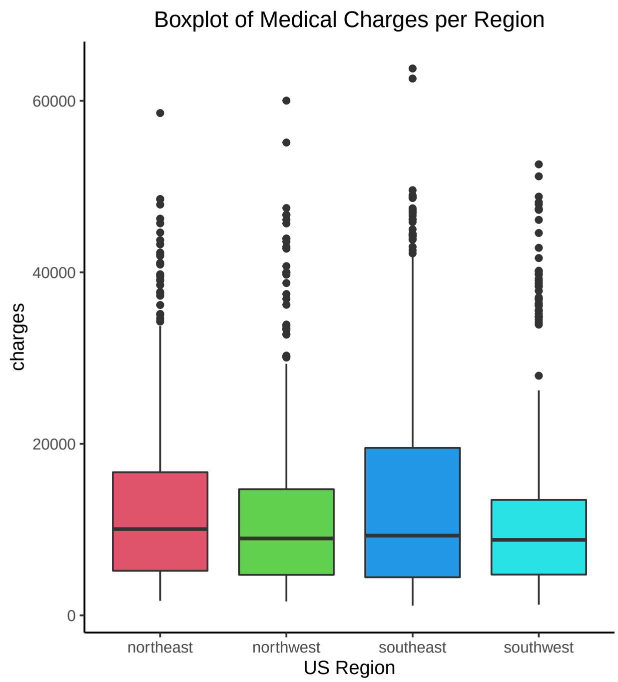
From the boxplot of medical **charges** by **children**, we can make an interesting observation that the medical **charges** for people with five children are less than compared to people with one to four children.

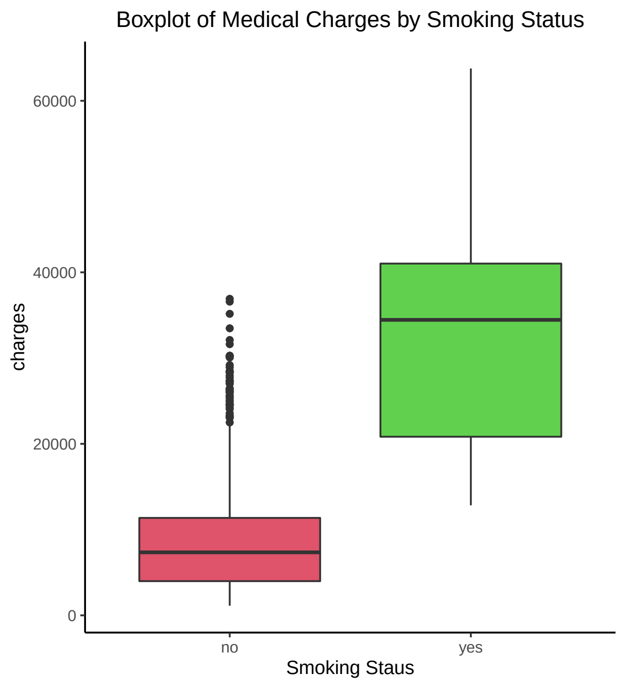




Similarly, the median value of charges across all four regions appears to have the same value. The people in the southeast seem to have higher medical expenses then the people in the other areas.

However, exploring the boxplot of medical **charges** by **smoking** status, we see that the medical **charges** for those who smoke are much higher than those who do not smoke.

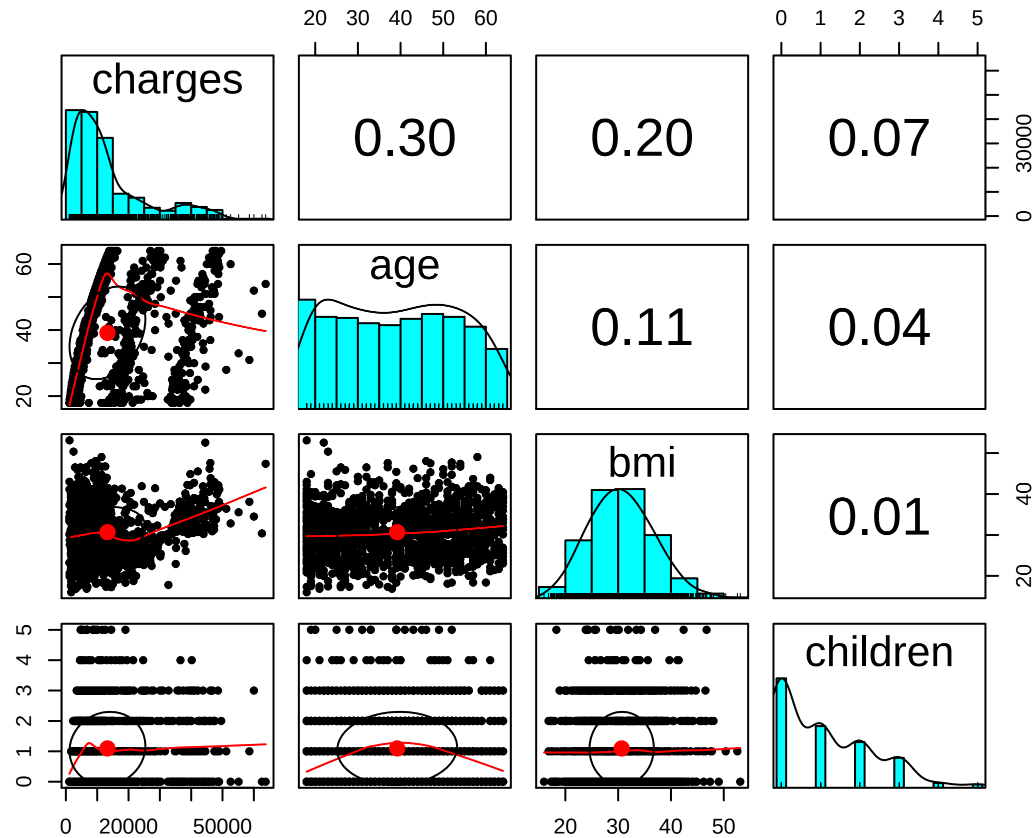




The Correlation matrix:

```
            charges       age       bmi   children
charges  1.00000000 0.2990082 0.1983410 0.06799823
age      0.29900819 1.0000000 0.1092719 0.04246900
bmi      0.19834097 0.1092719 1.0000000 0.01275890
children 0.06799823 0.0424690 0.0127589 1.00000000
```

We see **age** and **charges** are moderately correlated, meaning as age increases, the medical charges also increase moderately. There is also a moderate correlation between **age** and **bmi**, and **children** and **charges**



Computational Exploration One of our project goals is finding the best fit model, but we did not find a strong correlation between the response and predictor variables. So we will search for candidate models applying model automatic predictor search procedures.

We will use the R^2_{adj} and the BIC metrics to identify likely models since these both penalize for adding more terms.

- Following are the two Automatic search procedure recommended models -
  - The model with lowest BIC is: **chareges** $= B_0 + B_1(\text{age}) + B_2(\text{bmi}) + B_3(\text{children}) + B_4(\text{somkeyes})$
  - From the above, we see that our model with the lowest BIC (-1817.233) is the simple regression of **age, bmi, children, smokeyes** against **charges**.

- The model with highest adjusted R^2 is **chareges** = $B_0 + B_1$(age) + B_2(bmi) + B_3(children) + B_4(somkeyes) + B_5(regionsoutheast) + B_6(regionsouthwest)
- The model with the highest adjusted R^2 is **age, bmi,children,smokeyes,regionsoutheast, and regionsouthwest** against medical **charges**.

We also considered the models with the highest R^2, lowest Cp, and lowest MSE values. The best Cp and best MSE are both on the the same model as the best adjusted R^2.

The model with the best R^2 value has all predictors as adjusted R^2 in additon to regionnorthwest

Summary of Exploratory Data Analysis: We can make following observations from the exploratory data analysis:

1. The smokers have more medical expenses than non-smokers
2. None of the correlations from the correlation matrix appear to be strong
3. The quantitative predictors **age**, **bmi**, and **children** are moderately correlated with response variable
4. From computational analysis, we observed that categorical variable sex and region may be considred as significant predictors.
5. And we think that we are dealing with skewed dataset, particularly charges

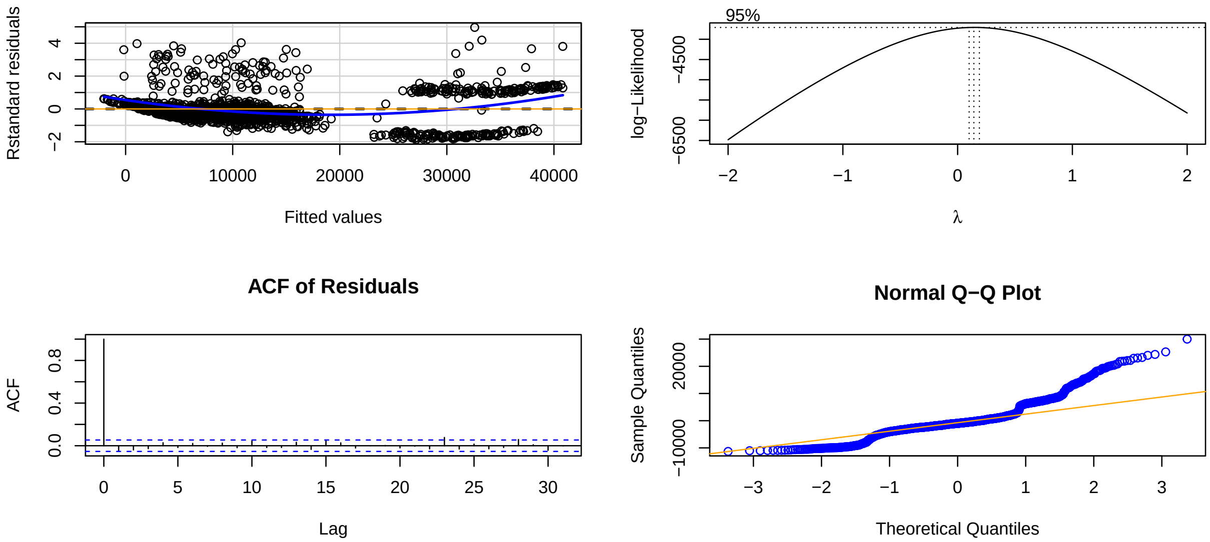
3. Initial Model Considered:

Based on results from the model search procedures, we will will consider our **initial model to be one with the highest adjusted R^2.

```r
initalmodel <- lm(charges ~ age + bmi + children + smoker + region +sex, data=data)
summary(initalmodel)
```

```

Call:
lm(formula = charges ~ age + bmi + children + smoker + region +
    sex, data = data)

Residuals:
     Min       1Q   Median       3Q      Max
-11304.9  -2848.1   -982.1   1393.9  29992.8

Coefficients:
                Estimate Std. Error t value Pr(>|t|)
(Intercept)     -11938.5      987.8 -12.086  < 2e-16 ***
age                256.9       11.9  21.587  < 2e-16 ***
bmi                339.2       28.6  11.860  < 2e-16 ***
children           475.5      137.8   3.451 0.000577 ***
smokeryes        23848.5      413.1  57.723  < 2e-16 ***
regionnorthwest   -353.0      476.3  -0.741 0.458769
regionsoutheast  -1035.0      478.7  -2.162 0.030782 *
regionsouthwest   -960.0      477.9  -2.009 0.044765 *
sexmale           -131.3      332.9  -0.394 0.693348
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 6062 on 1329 degrees of freedom
Multiple R-squared:  0.7509,    Adjusted R-squared:  0.7494
F-statistic: 500.8 on 8 and 1329 DF,  p-value: < 2.2e-16
```

Validating linear regression assumptions:



Looking at the above plots, we observe :
1. ** variance is not constant, as seen in the box-cox plot** and
2. ** non-linearity, as seen in the residual plot.

To fix non-constant variance and non-linearity issues, we will transform y first and the then predictors.

In our hypothesis, we said that old age people, people who smoke, and people with high bmi (bmi>30) might be at high risk. So their medical costs may be higher, based on that hypothesis, and considering that our initial model suffers from non-linearity and non-constant variance issues. We will transform both the response variable and the predictors.

Aligned to our Hypothesis and based on EDA, we will - 1. Transform **charges** (y) to fix non-constant variance 2. Transform age (x1) - by adding a non-linear term for age 3. Create a indicator variable for bmi (obesity indicator) (new categorical predictor) 4. Add and interaction term between smokers and bmi indicator predictor

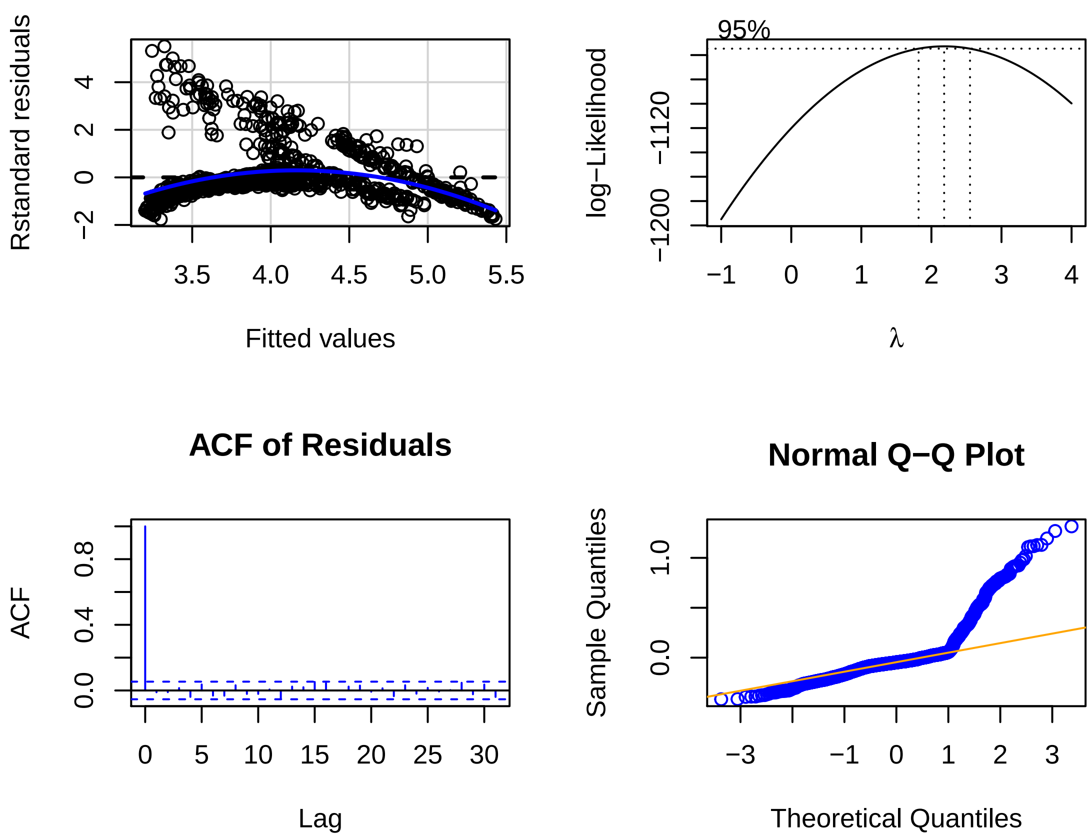
```
[1] TRUE


Call:
lm(formula = charges^0.15 ~ age + age2 + children + bmi + sex +
    bmi30 * smoker + region, data = data)

Residuals:
    Min      1Q  Median      3Q     Max
-0.4167 -0.1094 -0.0469  0.0192  1.3158

Coefficients:
                   Estimate Std. Error t value Pr(>|t|)
(Intercept)       2.816e+00  7.348e-02  38.323  < 2e-16 ***
age               2.428e-02  3.226e-03   7.527 9.53e-14 ***
age2             -6.299e-05  4.024e-05  -1.565 0.117753
children          5.109e-02  5.710e-03   8.948  < 2e-16 ***
bmi               4.007e-03  1.848e-03   2.169 0.030288 *
sexmale          -4.518e-02  1.318e-02  -3.429 0.000625 ***
bmi301           -2.074e-02  2.280e-02  -0.910 0.363243
```

```
smokeryes          7.202e-01  2.372e-02  30.360  < 2e-16 ***
regionnorthwest  -3.253e-02  1.883e-02  -1.727 0.084396 .
regionsoutheast  -8.001e-02  1.896e-02  -4.220 2.61e-05 ***
regionsouthwest  -7.718e-02  1.890e-02  -4.083 4.71e-05 ***
bmi301:smokeryes  4.531e-01  3.261e-02  13.896  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.2397 on 1326 degrees of freedom
Multiple R-squared:  0.8063,    Adjusted R-squared:  0.8047
F-statistic: 501.9 on 11 and 1326 DF,  p-value: < 2.2e-16
```

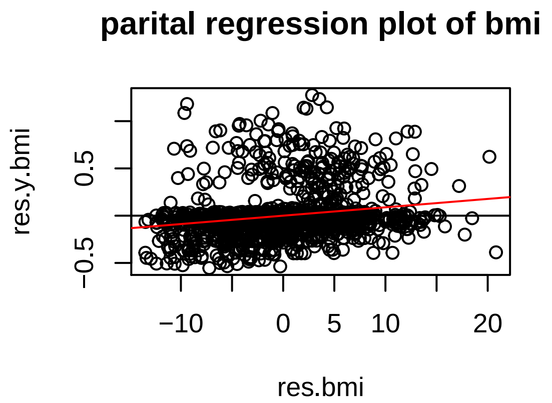
Multiple R^2 and Adjusted R^2 measure how well our model explains the response variable. The transformed model has higher Multiple $R^2 = 0.8063$ and Adjusted $R^2 = 0.8047$ compared to initial model Multiple $R^2 = 0.7509$ and Adjusted $R^2 = 0.7494$

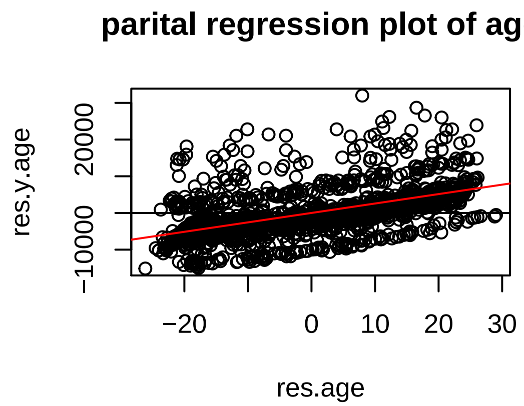
We also observe from the model summary, age2 the second order variable is insignificant based on t value and high p-value greater than 0.05. The interaction term bmi301:somkeryes is significant.

we now verify the linear regression model assumptions:



The bob-cox plot now shows that the non-constant variance issue is fixed. However, from the residual plot, it is not clear have solved the non-constant and non-linearity problem.
So next, we explore which predictors can be removed by creating partial regression plots.

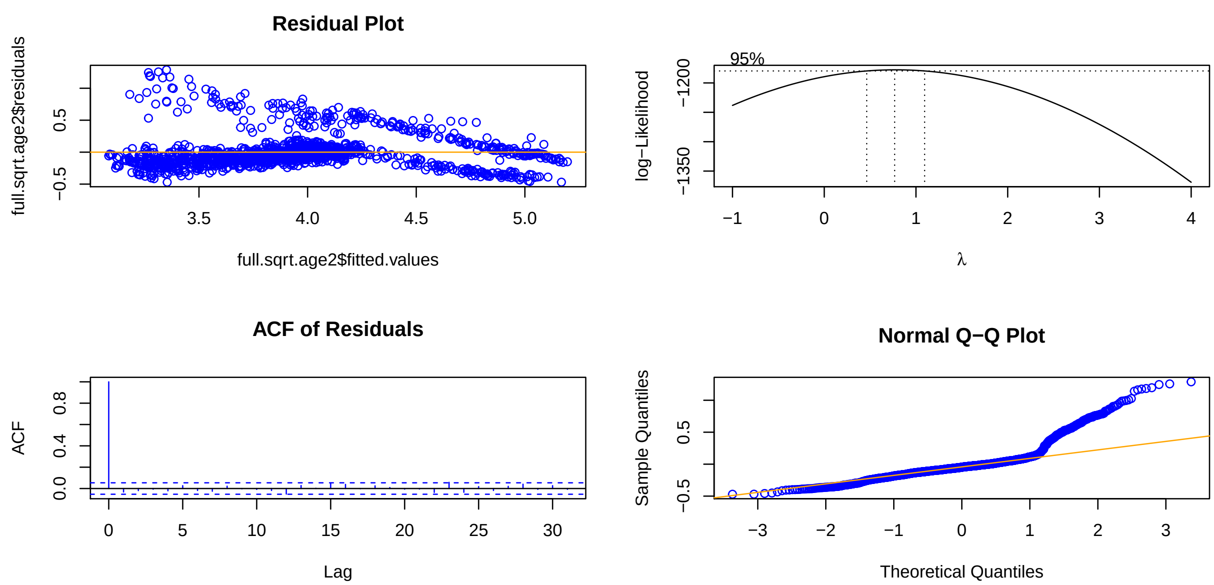




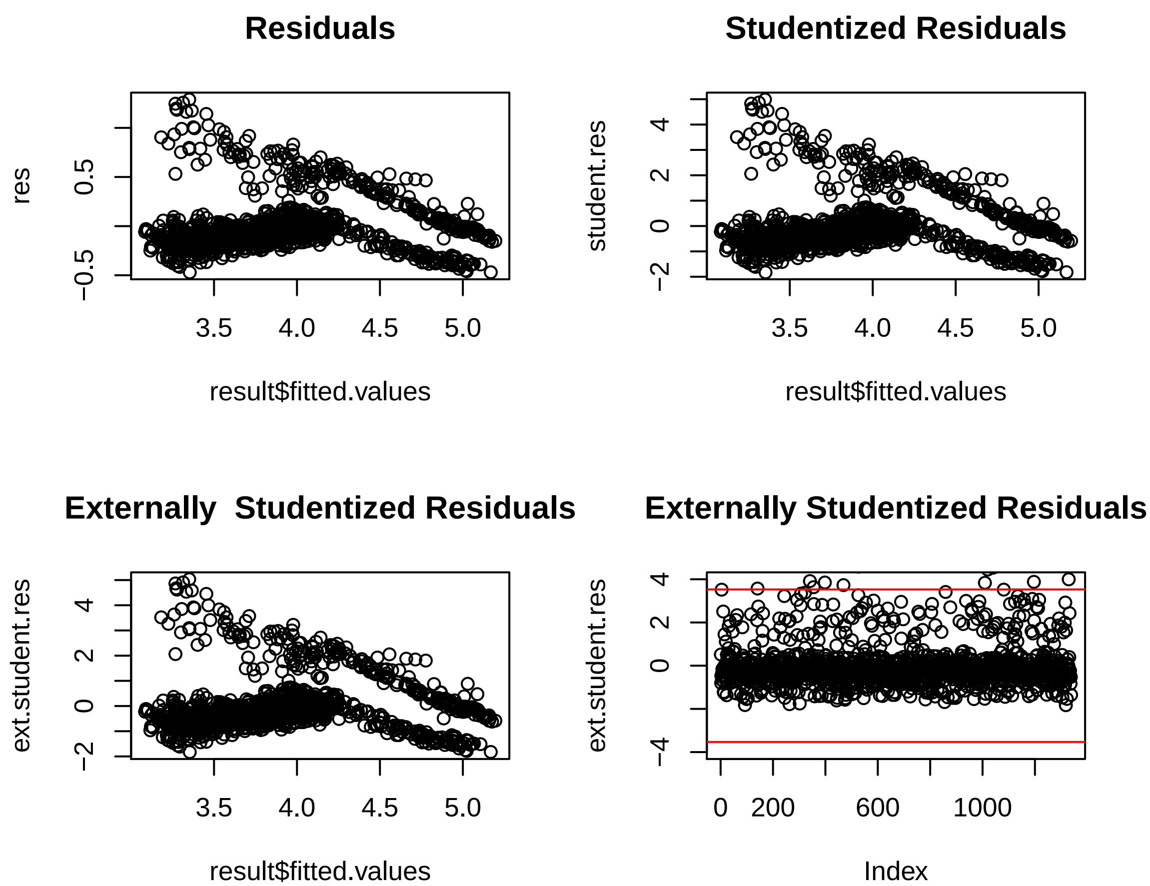
From the above partial regression plots, we still see a leaner pattern for all three quantitative variables, this means the linear terms for the predictors **bmi**, **age** and **children** is appropriate.

```
'data.frame':   1338 obs. of  9 variables:
 $ age     : int  19 18 28 33 32 31 46 37 37 60 ...
 $ sex     : Factor w/ 2 levels "female","male": 1 2 2 2 2 1 1 1 2 1 ...
 $ bmi     : num  27.9 33.8 33 22.7 28.9 ...
 $ children: int  0 1 3 0 0 0 1 3 2 0 ...
 $ smoker  : Factor w/ 2 levels "no","yes": 2 1 1 1 1 1 1 1 1 1 ...
 $ region  : Factor w/ 4 levels "northeast","northwest",..: 4 3 3 2 2 3 3 2 1 2 ...
 $ charges : num  16885 1726 4449 21984 3867 ...
 $ age2    : num  361 324 784 1089 1024 ...
 $ bmi30   : Factor w/ 2 levels "0","1": 1 2 2 1 1 1 2 1 1 1 ...


Call:
lm(formula = charges^0.15 ~ log(age) + children + log(bmi) +
    smoker + region, data = data)

Residuals:
     Min       1Q   Median       3Q      Max
-0.47069 -0.13211 -0.04842  0.04722  1.28840

Coefficients:
```

```
                 Estimate Std. Error t value Pr(>|t|)
(Intercept)      0.318640   0.133283   2.391 0.016955 *
log(age)         0.685523   0.018340  37.379  < 2e-16 ***
children         0.041804   0.005906   7.078 2.36e-12 ***
log(bmi)         0.286829   0.036637   7.829 9.98e-15 ***
smokeryes        0.955017   0.017604  54.249  < 2e-16 ***
regionnorthwest -0.035919   0.020353  -1.765 0.077820 .
regionsoutheast -0.085747   0.020425  -4.198 2.87e-05 ***
regionsouthwest -0.073450   0.020434  -3.595 0.000337 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.259 on 1330 degrees of freedom
Multiple R-squared:  0.7731,    Adjusted R-squared:  0.7719
F-statistic: 647.3 on 7 and 1330 DF,  p-value: < 2.2e-16
```




```
[1] 3.529468
```

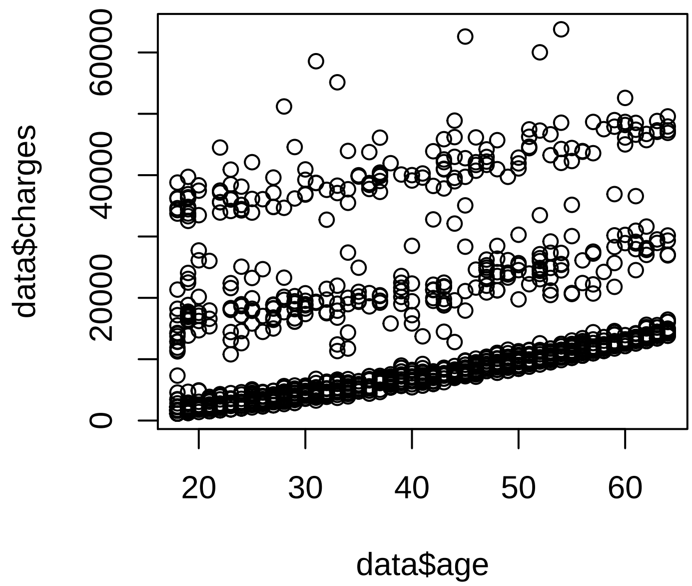



```
     103       141       220       341       355       398       431       469
4.619736 3.570630 4.907768 3.915308 3.631488 3.850610 4.865511 3.728462
     517       527      1009      1020      1028      1040      1196      1329
5.031708 4.585884 3.835164 4.450827 4.672036 4.535482 3.880408 3.997432
```

Even after applying transformations, the model fit is still not satisfying linear regression assumptions. We still see the presence of non-linearity and non-constant variance. It may be due to outliers in the data. This model is good enough to explore the relationship between the predictors and the response variable. However, the predicted values may be unrealistic.

And we notice that the simple scatter plot of charges against age has three distinct relationships, where the medical charges increase with age at a very slight increasing rate in three segments. Since this relationship is odd, we wish to explore if age is the reason for skew in the data.

```
plot(data$age, data$charges)
```



Suppose we remove age from the model and perform transformation on response variable, we do not see any violations of linear regression assumptions.

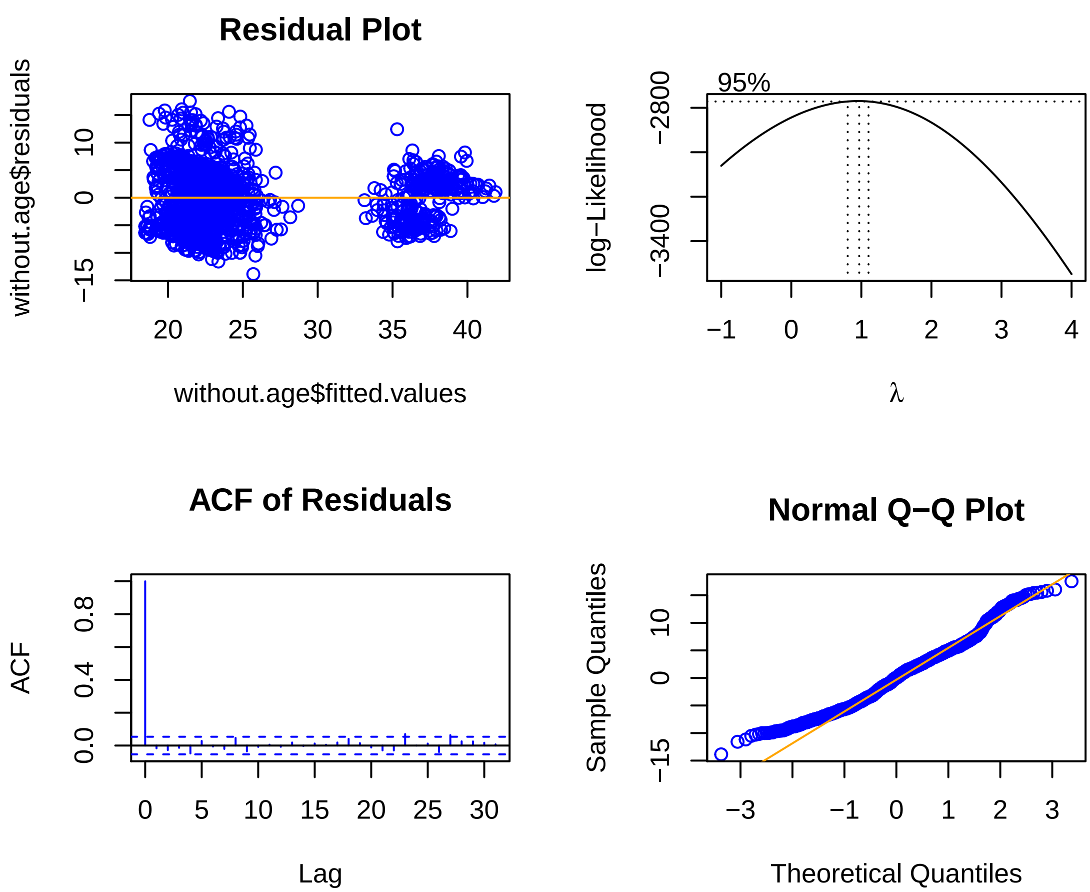
```
without.age <- lm(charges^.35 ~ + children + smoker + sex + region + bmi, data=data)
summary(without.age)
```

```
Call:
lm(formula = charges^0.35 ~ +children + smoker + sex + region +
    bmi, data = data)

Residuals:
     Min       1Q   Median       3Q      Max
-13.8671  -4.2115   0.0291   3.5759  17.5451

Coefficients:
                Estimate Std. Error t value Pr(>|t|)
(Intercept)      15.5451     0.7931  19.600  < 2e-16 ***
children          0.7732     0.1192   6.485 1.25e-10 ***
smokeryes        14.8532     0.3577  41.526  < 2e-16 ***
sexmale          -0.5982     0.2882  -2.076 0.038119 *
regionnorthwest  -0.4948     0.4124  -1.200 0.230442
regionsoutheast  -1.4895     0.4142  -3.596 0.000335 ***
regionsouthwest  -1.0330     0.4138  -2.496 0.012675 *
bmi               0.2304     0.0246   9.367  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 5.249 on 1330 degrees of freedom
Multiple R-squared:  0.5835,    Adjusted R-squared:  0.5813
```

```
F-statistic: 266.2 on 7 and 1330 DF,  p-value: < 2.2e-16
```

However, since age independently had the highest correlation with charges, the adjusted R-squared value falls to 0.5813 in the model without a period. Therefore, we do not believe it makes sense to use this model as a predictor, especially given the significant trade-off in predictability.

```
par(mfrow=c(2,2))
# without.age = without age and with y transformed to achieve lambda = 1 maximized
plot(without.age$fitted.values,without.age$residuals, main="Residual Plot", col='blue')
abline(h=0, col="orange")
boxcox.lambda <- boxcox(without.age, main = "Box-Cox", col='blue',lambda=seq(-1,4, by=0.1))
##ACF plot of residuals
acf(without.age$residuals, main="ACF of Residuals", col='blue')
##Normal probability or QQ plot of residuals
qqnorm(without.age$residuals, col='blue')
qqline(without.age$residuals, col="orange")
```



Initial Model Summary: We were able to increase the adjusted R^2 for our model by transforming the initial model we considered, however the non-constant variance and non-linearity issues in the data set were not fully addressed. So we acknowledged that our initial model could be used to explore the relationship between response and predictor variables. However, predictions may not be accurate.

4 Alternate Model Considered:

We would like to tweak our goal to find a model that predicts the charges to be above or below a certian threshold value. For the example above or below $20,000. convert the problem domain to a logistic regress instead of linear regression.

we begin by converting the response variable to categorical variable and splitting the data into training & testing dataset

and then train the fitted model with the training dataset.

```
lrmodel1<-glm(lrcharges ~ age + bmi + smoker + region + sex + children, family="binomial",
              data = lrdata_train)
summary(lrmodel1)
```

```

Call:
glm(formula = lrcharges ~ age + bmi + smoker + region + sex + 
    children, family = "binomial", data = lrdata_train)

Deviance Residuals: 
    Min       1Q   Median       3Q      Max  
-1.8184  -0.3834  -0.2428  -0.1373   3.1248  

Coefficients:
                Estimate Std. Error z value Pr(>|z|)    
(Intercept)     -7.91973    1.07038  -7.399 1.37e-13 ***
age              0.03953    0.01153   3.428 0.000607 ***
bmi              0.11077    0.02582   4.289 1.79e-05 ***
smokeryes        4.85604    0.37410  12.981  < 2e-16 ***
regionnorthwest  0.22102    0.44125   0.501 0.616451    
regionsoutheast -0.47459    0.41783  -1.136 0.256019    
regionsouthwest -0.81043    0.45047  -1.799 0.072008 .  
sexmale          0.05906    0.30390   0.194 0.845916    
children         0.03180    0.12272   0.259 0.795552    
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 664.52  on 668  degrees of freedom
Residual deviance: 321.06  on 660  degrees of freedom
AIC: 339.06

Number of Fisher Scoring iterations: 6
```

The higher the difference between null deviance and residual deviance, the better the model's predictability. Our data supports' the claim that our logistic regression model is useful in estimating the log odds of whether medical **charges** are greater or less than $20000

The model summary shows, based Z-value (Wald test) age, bmi, and smoker are significant predictors with a p-value of less than 0.05. Furthermore, the region sex and children predictors seem insignificant, hence removing the model.

hypothesis-testing H_0: coefficients for all predictors is $= 0$ and
H_1: at least one coefficient is not zero

```r
1-pchisq(lrmodel1$null.deviance - lrmodel1$deviance,8)
```

```
[1] 0
```

small p-value we reject the null hypothesis that at least one of these coefficients is not zero.

```r
lrmodel2 <-glm(lrcharges ~ age + bmi  + smoker, family="binomial" , data = lrdata_train)
summary(lrmodel2)
```

```

Call:
glm(formula = lrcharges ~ age + bmi + smoker, family = "binomial",
    data = lrdata_train)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.7030  -0.3739  -0.2481  -0.1506   3.1720

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept) -7.86104    1.03377  -7.604 2.87e-14 ***
age          0.04087    0.01150   3.554 0.000379 ***
bmi          0.10134    0.02465   4.111 3.94e-05 ***
smokeryes    4.75564    0.35844  13.268  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 664.52  on 668  degrees of freedom
Residual deviance: 327.44  on 665  degrees of freedom
AIC: 335.44

Number of Fisher Scoring iterations: 6
```

We already know from the Wald test that the region sex and children predictors are insignificant, so we will conduct the delta G^2 test to see if these predictors can be removed from the model.

```r
#test if additional predictors have coefficients equal to 0
1-pchisq(lrmodel2$deviance - lrmodel1$deviance,5)
```

```
[1] 0.2701389
```

p-value is 0.0941 greater than 0.05, so we cannot reject the null so that we will choose the simpler model with just the three predictors **age**, **bmi** and **smoker**.

Logistic Regression model validation Next, we will go over how well-chosen logistic regression model does in predicting an outcome that medical **charges** are greater than or less than $20000 given the values of other predictors, using the probability of the observations in the test data of being in each class, we will choose a threshold of 0.5 for the confusion matrix.

False Positive Rate: When it's actually no, how often does it predict yes = 0.0625

False Negative Rate: When it's actually Yes, how often does it predict yes = 0.2198582

Sensitivity out of all the positive classes, how much we have predicted correctly = 0.7801418

Specificity determines the proportion of actual negatives that are correctly identified = 0.9375

The AUC value for our model is 0.8999704. The AUC value is higher than 0.5, which means the model does better than random guessing the classifying observations.

5. Conclusion:

1. Even after applying transformations, the model fit is still not satisfying linear regression assumptions.
2. We still see non-linearity, and non-constant variance issues are still not addressed in the model.
3. It could be due to skewed data or outliers in the dataset.
4. So we conclude that our initial transformed model is useful for exploring the relationship between predictor and response variables. However, the predicted values will be unreliable.

We recommend to go with the logistic regression model has better predictability.

π = ln(P(charges>20000)==1)

ln(π/(1 - π)) = -7.86104 + 0.04087 (age) + 0.10134 (bmi) + 4.75564 (smokeryes)

And the data is skewed when it comes to age & smokers, producing more balanced dataset may improve the predictability of our initial MLR model.