Ronaldlee Ejalu

Student ID: 2020637

DSC424: Assignment1

Defining the different matrices and vectors

problem2

```
Z = matrix(c(1, -1, 1, 2, 1, -2, 1, 0), nrow = 4, ncol = 2, byrow = T)
Z

##      [,1] [,2]
## [1,]    1   -1
## [2,]    1    2
## [3,]    1   -2
## [4,]    1    0

Y = matrix(c(0, 5, 0, 8), nrow = 4, ncol = 1)
Y

##      [,1]
## [1,]    0
## [2,]    5
## [3,]    0
## [4,]    8

M = matrix(c(11, 5, 0, 25, 20, 5, 0, 15, 11), nrow = 3, ncol = 3, byro
w = T)
M

##      [,1] [,2] [,3]
## [1,]   11    5    0
## [2,]   25   20    5
## [3,]    0   15   11

N = matrix(c(-11, -5, 0, 0, 11, 5, 11, 11, -11), nrow = 3, ncol = 3, b
yrow = T)
N

##      [,1] [,2] [,3]
## [1,]  -11   -5    0
## [2,]    0   11    5
## [3,]   11   11  -11
```

```r
v = matrix(c(-6, 0, 8), nrow = 3, ncol = 1)
v
```

```
##      [,1]
## [1,]   -6
## [2,]    0
## [3,]    8
```

```r
w = matrix(c(3, 1, 0), nrow = 3, ncol = 1)
w
```

```
##      [,1]
## [1,]    3
## [2,]    1
## [3,]    0
```

#(a)v.w (dot product)

```r
dotproduct = v * w
dotproduct
```

```
##      [,1]
## [1,]  -18
## [2,]    0
## [3,]    0
```

#(b)-3*w

```r
b = -3 * w
b
```

```
##      [,1]
## [1,]   -9
## [2,]   -3
## [3,]    0
```

#(c)M * v

```r
Mv = M %*% v
Mv
```

```
##      [,1]
## [1,]  -66
## [2,] -110
## [3,]   88
```

#(d) M + N

```r
sum = M + N
sum
```

```
##      [,1] [,2] [,3]
## [1,]    0    0    0
## [2,]   25   31   10
## [3,]   11   26    0
```

#(e) M - N

```
diff = M - N
diff
```

```
##      [,1] [,2] [,3]
## [1,]   22   10    0
## [2,]   25    9    0
## [3,]  -11    4   22
```

#(f)Z^T z

```
result = t(Z) %*% Z
result
```

```
##      [,1] [,2]
## [1,]    4   -1
## [2,]   -1    9
```

#(g) Compute beta = (Z^T * Z)^-1

```
beta = solve(t(Z) %*% Z)
beta
```

```
##            [,1]       [,2]
## [1,] 0.25714286 0.02857143
## [2,] 0.02857143 0.11428571
```

#(h) transpose of Z * Y

```
result = t(Z) %*% Y
result
```

```
##      [,1]
## [1,]   13
## [2,]   10
```

#(i) Compute Beta = (Z^T * Z)^-1 * Z^T * Y

```
beta2 = solve((t(Z) %*% Z)) %*% t(Z) %*% Y
beta2
```

```
##          [,1]
## [1,] 3.628571
## [2,] 1.514286
```

#(j) compute det(Z^T * Z)

```
determ = det(t(Z) %*% Z)
determ

## [1] 35
```

Problem 3:

The journal article addresses the problem of multicollinearity through the use of bias estimation procedures like ridge regression and generalized inverse regression. Most of the time we have no control of how the source data, which are trying to analyze is collected, especially when data has missing values, correlated errors. Bias estimation starts with understanding the problem or research question, and this raises the need to identify the variables to be operationalized so that the question at hand can answered. VIF values that exceed 10 are regarded as indicating multicollinearity. Also, in weaker models values greater 2.5 are of a concern to multicollinearity.

Marquardt (1970) assessed that in order to develop a set of stable coefficients and minimize the effects of predictor variable correlation, biased estimation procedures like ridge regression are considered instead of the LSE when the VIF values are large amongst the predictor variables (p. 22). Also, the nonessential ill conditioning exists in the raw source data set and with the existence of the constant term in raw data set, Marquardt (1975) emphasizes the use of standardization of the predictors to extract out the ill conditioning (p. 2).

Marquardt, and Snee (1975) demonstrated how ridge and generalized regression achieve a small mean square error through the reduction of the variance, which is obtained by introducing a little bit of bias (pp. 4 - 17).

This explained why ridge regression gave the smallest regression coefficients consistent with a given degree of increase in the residual sum of error.

According to Marquardt, and Snee (1975), ”both the predictor variables and response variable have to scaled to the correlation form so that to select the required amount of bias” (p. 5). Variable selection procedure was performed at least twice with curvilinear models with an objective to determine which, if either, gave a simple, well behaved model. More than ten coefficient traces were plotted on a given graph and the variance of the coefficients was a decreasing function of k and bias was an increasing function of k. This meant that as k increased, the coefficient means square error decreased to a minimum and then increased. The goal was to determine a value of k which gave a set of coefficients with smaller Mean Square Error than the ordinary least square regression model. This proved to be a good strategy to develop a set of stable coefficients, which do a good job of predicting future observations Marquardt, and Snee (1975, p. 10).

References

1. Marquardt, D. W., & Snee, R. D. (1975). Ridge regression in practice. *The American Statistician*, *29*(1), 3-20. https://doi.org/10.2307/2683673
2. Marquaridt, D. W. (1970). Generalized inverses, ridge regression, biased linear estimation, and nonlinear estimation. *Technometrics*, *12*(3), 591-612.

Problem 4

According to Leon (2019), “Big data refers to the processing of large volumes of data with the goal of discovering patterns and deriving useful insights” (p. 1). A variety of technological tools are used to capture, analyze and interlink the volume and variety of this data.

The health care domain has embraced Big data mining because of the critical factors, which are the huge potential it contributes to advanced research, biomedical practices, and the promotion of public health and on the other hand increasing awareness of the issues of vulnerability Big data comes with (Leon, 2019). However, there are incident errors which arise in the machine learning algorithms procedures, which must be corrected by a data professional before these algorithms are used either in our society or to administer patient care. If these errors are not addressed, a lot of bioethical issues arise from the use of this data. For health care professional to benefit from the accuracy and statistical power of the data analyzed, they shouldn’t extrapolate the results beyond the scope of the study. Otherwise, the information obtained may be subject to errors, which would raise a lot of questions when it is applied in the health area (Tavani, 2011).

First, Leon (2011) discussed how transparency was critical in the use of the data; stakeholders should understand the origin of data as well as the complexity of the algorithms applied and the implications of the operations (p. 3). This was done for society to be able to rely on the good practices of these results of these analyses especially in the field of public health. Second, Leon (2011) discusses how as far confidentiality is concerned, special attention is given to the protection of genetic data; personal information doesn’t have to be disclosed without their authorization except in situations established ethically and legally (p. 3). Provided that the data is either in a public domain or are anonymous, it doesn't need the approval of the interested parties for its use. Third, data users should respect the right "Not to Be Profiled" as a new right of persons. This is important to avoid the discrimination of individuals or groups of people within the scope of big data, for example the use of big data in public health to find patterns and correlations between social behaviors and Morbi-mortality on a certain race group (Leon, 2011). Furthermore, this is done in order to respect the freedom of the individual actions. Healthcare researchers or data stake holders have to put precautions in place that enforce the confidentiality of data or requires personal consent to participate in the studies, which is very important. Research by Nuffield Council on Bioethics (2015) supported that correlated information on disability, mental illness, genetic diseases, sexual orientation, drug addictions, juvenile delinquency, political or religious issues, was especially sensitive (pp. 107 – 108). Fourth, although big data analysis has been used to implement effective systems for cost containment, risk management, patient safety and quality assurance program, ethical paradigms should be enforced because private and public health care organizations use the information to exclusively control costs and to evaluate the practice of professional instead of guaranteeing the quality of care (Leon, 2011, p. 5).

In addition to the data ethics and Integrity, automated transfer of data or the "Opting Out" approach should not be used as suitable way to protect people because people's data ends in the cloud when one publishes a page on the internet, or provides ones information on social networks. Also, crowdsourcing should be avoided unless when people are educated on how their personal data is going to be used. Governance, education, capacity building and benefit sharing are considered as four crucial measures for protecting individual rights and fostering public good while recognizing the unavoidable loss of control by individuals about the use of their data in terms of Big data. Lean (2011) supports the importance of data ethics through the quality, accuracy, and validity of the data and algorithms, the need for adequate information for the different stakeholders to understand the implications of big data, the respect to privacy of individuals and good data security practices (p. 10).

References

1. Leon-Sanz, P. (2019). Key Points for an Ethical Evaluation of Healthcare Big Data. *Processes*, *7*(8), 493.
2. Tavani, H. T. (2011). *Ethics and technology: Controversies, questions, and strategies for ethical computing*. John Wiley & Sons.
3. Nuffield Council on Bioethics. (2015). *The Collection, Linking and Use of Data in Biomedical Research and Health Care: Ethical Issues: a Guide to the Report*. Nuffield Council on Bioethics. Available online: http://nu

eldbioethics.org/wp-content/uploads/Biological_and_health_data_web.

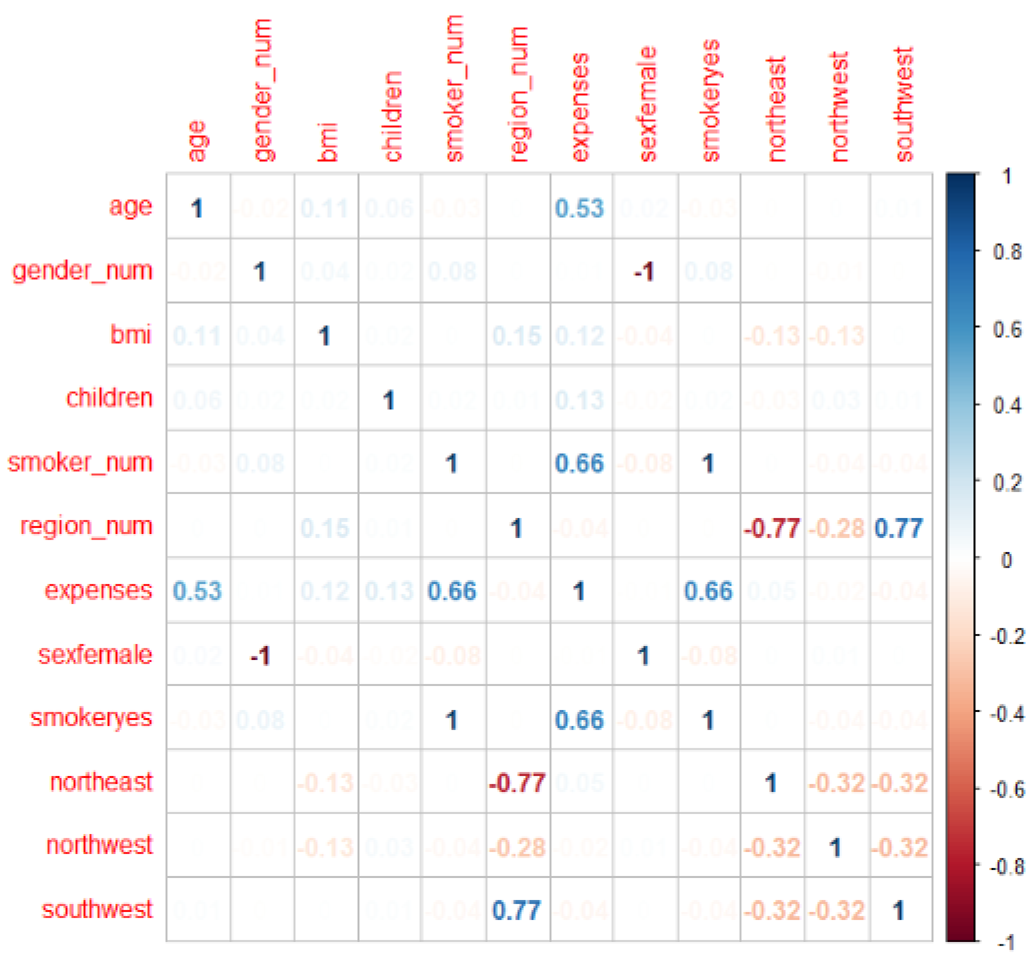
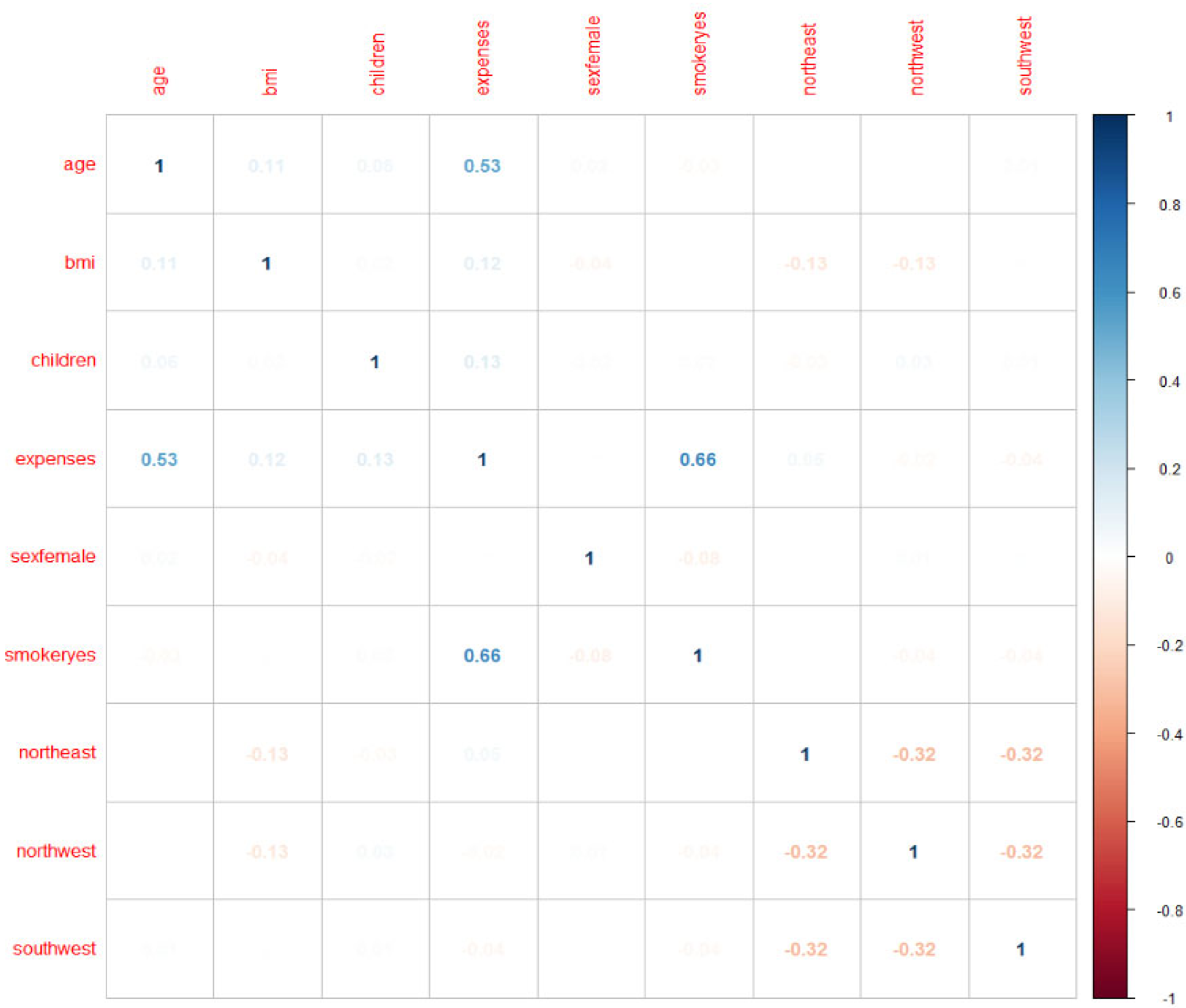
pdf (accessed on 1/16/2021).

Problem 5: (15 pts – regression analysis, visualization, and interpretation): The insurance_dataset.csv dataset contains 1338 observations (rows) and 7 features (columns). The insurance data contains 4 numerical features (age, bmi, children and expenses) and 3 nominal features (sex, smoker and region) that were converted into factors with numerical value designated for each level.

We are interested in which independent variables are significant for **predicting the insurance expenses** by the other predictor.

a. (5 points) Before running any regressions make sure to check for multicollinearity. How did you check for multicollinearity?

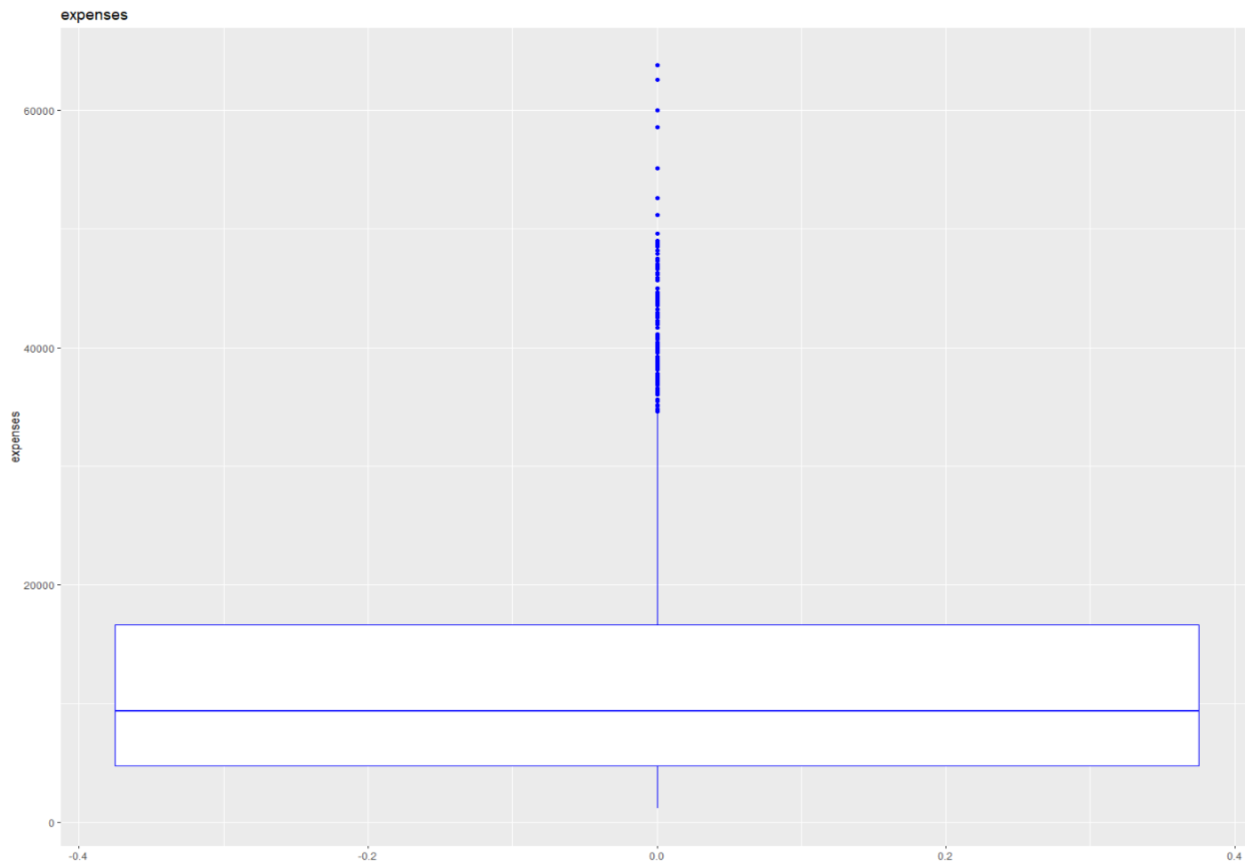
   I loaded my data set into Rstudio then converted the 3 nominal features into factors and also specified particular levels first for each of the factors variable with the relevel function then converted of them into dummy variables.

```
# data cleaning
```{r}
insurance.clean <- insurance_dataset %>%
  transmute(age = age
            , sex = as.factor(sex)
            , gender_num = gender_num
            , bmi = bmi
            , children = children
            , smoker = as.factor(smoker)
            , smoker_num = smoker_num
            , region = as.factor(region)
            , region_num = region_num
            , expenses = expenses) %>%
  mutate(
    sex = relevel(sex, ref = 'male')
    , smoker = relevel(smoker, ref = 'no')
    , region = relevel(region, ref = 'southeast')
  )

# Create a matrix for sex
sexdummies.matrix <- model.matrix(~insurance.clean$sex)

# Convert the model matrix into a data frame
sexdummies.frame <- data.frame(sexdummies.matrix)

# bind the data frame to data set
insurance.clean <- cbind(insurance.clean, sexdummies.frame)

# create a matrix for smoker
smokerdummies.matrix <- model.matrix(~insurance.clean$smoker)

#Convert the model matrix into a data frame
smokerdummies.frame <- data.frame(smokerdummies.matrix)

#bind the data frame to data set
insurance.clean <- cbind(insurance.clean, smokerdummies.frame)

# create a matrix for region
regiondummies.matrix <- model.matrix(~insurance.clean$region)

# Convert the model matrix into a data frame
regiondummies.frame <- data.frame(regiondummies.matrix)

# bind the data frame to a data set
insurance.clean <- cbind(insurance.clean, regiondummies.frame)
```
```

I created a new dataset called insurancecleansed by renaming and selecting all the necessary features of interest with the following R syntax:

```
# rename and select all the variables interest
```{r}
insurancecleansed <- insurance.clean %>%
  select(age = age
            , gender_num = gender_num
            , bmi = bmi
            , children = children
            , smoker_num = smoker_num
            , region_num = region_num
            , expenses = expenses
            , sexfemale = insurance.clean.sexfemale
            , smokeryes = insurance.clean.smokeryes
            , northeast = insurance.clean.regionnortheast
            , northwest = insurance.clean.regionnorthwest
            , southwest = insurance.clean.regionsouthwest)
```
```

Used the corrplot function to display the graphical representation of the correlation matrix



From the graphical representation above you can see that the following variable correlations

- Sexfemale and gender_num

- Smokeryes and smoker_num
- Northeast and region_num
- Southwest and region_num

are strongly correlated either negatively or positively, in that regards there is a lot of multicollinearity so it's not appropriate to have both of these pairs when you are building your model.

If there is multicollinearity, how do you plan to resolve it?

To resolve the issue of multicollinearity, I removed gender_num, smoker_num, and region_num from my data set and retested again for multicollinearity:



So, right now the issue of multicollinearity has been resolved.

Also, when I run a full model and run the VIF R syntax, you would see that the issue of multicollinearity has been resolved as below:

```
Call:
lm(formula = expenses ~ ., data = insurancewithselectedvars)

Residuals:
     Min       1Q   Median       3Q      Max 
-11302.7  -2850.9   -979.6   1383.9  29981.7 

Coefficients:
             Estimate Std. Error t value Pr(>|t|)    
(Intercept) -13108.51    1090.51 -12.021  < 2e-16 ***
age            256.84      11.90  21.586  < 2e-16 ***
bmi            339.29      28.60  11.864  < 2e-16 ***
children       475.69     137.80   3.452 0.000574 ***
sexfemale      131.35     332.94   0.395 0.693255    
smokeryes    23847.48     413.14  57.723  < 2e-16 ***
northeast     1035.60     478.68   2.163 0.030685 *  
northwest      682.81     478.95   1.426 0.154211    
southwest       76.29     470.64   0.162 0.871253    
---
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: 500.9 on 8 and 1329 DF,  p-value: < 2.2e-16

      age       bmi  children sexfemale smokeryes northeast northwest southwest 
 1.016843  1.106682  1.004008  1.008900  1.012067  1.531084  1.536030  1.483177 
```

As shown above the VIF values for age, bmi, children, sexfemale, smokeryes, northeast, northwest and southwest are below 5 implying that we should not be worried of any multicollinearity.

Are there any other issues with the dataset we must consider before running the regressions?



From the boxplot above the data set has some outliers, which need to be removed.

b. Run a multiple regression of price on the variables listed above.

The screenshot below shows a model built without using any automatic procedure:

```
# model building after removing the outliers.
```{r}
model3 <- lm(expenses ~ ., data = insurancewithselectedvars.withoutliers)
summary(model3)
```
```

```
Call:
lm(formula = expenses ~ ., data = insurancewithselectedvars.withoutliers)

Residuals:
    Min      1Q  Median      3Q     Max 
-3400.6  -911.0  -512.9    77.5 15971.3 

Coefficients:
             Estimate Std. Error t value Pr(>|t|)    
(Intercept) -4061.330    459.687  -8.835  < 2e-16 ***
age           240.347      5.057  47.525  < 2e-16 ***
bmi            36.218     12.147   2.982 0.002932 ** 
children      476.477     56.228   8.474  < 2e-16 ***
sexfemale     469.862    137.709   3.412 0.000669 ***
smokeryes   13012.777    309.396  42.059  < 2e-16 ***
northeast     609.983    201.904   3.021 0.002579 ** 
northwest     358.805    199.860   1.795 0.072895 .  
southwest    -192.527    195.892  -0.983 0.325921    
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 2243 on 1055 degrees of freedom
Multiple R-squared:  0.7744,	Adjusted R-squared:  0.7727 
F-statistic: 452.7 on 8 and 1055 DF,  p-value: < 2.2e-16
```

i. (5 points) Run the model **using an automatic method** (i.e. stepwise, forward, backward). Explain why you chose the method. Comment on the overall significance of the regression fit. Which predictors have coefficients that are significantly different from zero at the .05 level?

Using forward selection

```
Call:
lm(formula = expenses ~ age + smokeryes + children + sexfemale + 
    southwest + bmi + northeast + northwest, data = insurancewithselectedvars.withoutliers)

Residuals:
    Min      1Q  Median      3Q     Max 
-3400.6  -911.0  -512.9    77.5 15971.3 

Coefficients:
             Estimate Std. Error t value Pr(>|t|)    
(Intercept) -4061.330    459.687  -8.835  < 2e-16 ***
age           240.347      5.057  47.525  < 2e-16 ***
smokeryes   13012.777    309.396  42.059  < 2e-16 ***
children      476.477     56.228   8.474  < 2e-16 ***
sexfemale     469.862    137.709   3.412 0.000669 ***
southwest    -192.527    195.892  -0.983 0.325921    
bmi            36.218     12.147   2.982 0.002932 ** 
northeast     609.983    201.904   3.021 0.002579 ** 
northwest     358.805    199.860   1.795 0.072895 .  
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 2243 on 1055 degrees of freedom
Multiple R-squared:  0.7744,	Adjusted R-squared:  0.7727 
F-statistic: 452.7 on 8 and 1055 DF,  p-value: < 2.2e-16
```

Using backward

```
Step:  AIC=16426.59
expenses ~ age + bmi + children + sexfemale + smokeryes + northeast + 
    northwest

            Df  Sum of Sq        RSS   AIC
<none>                    5.3122e+09 16427
- northwest  1 3.6238e+07 5.3485e+09 16432
- bmi        1 5.2198e+07 5.3644e+09 16435
- sexfemale  1 5.8136e+07 5.3704e+09 16436
- northeast  1 8.4389e+07 5.3966e+09 16441
- children   1 3.5932e+08 5.6715e+09 16494
- smokeryes  1 8.9465e+09 1.4259e+10 17475
- age        1 1.1374e+10 1.6687e+10 17642

Call:
lm(formula = expenses ~ age + bmi + children + sexfemale + smokeryes + 
    northeast + northwest, data = insurancewithselectedvars.withoutliers)

Residuals:
    Min      1Q  Median      3Q     Max 
-3391.4  -917.9  -508.4    76.4 15878.8 

Coefficients:
             Estimate Std. Error t value Pr(>|t|)    
(Intercept) -4213.938    432.661  -9.740  < 2e-16 ***
age           240.054      5.048  47.551  < 2e-16 ***
bmi            38.442     11.934   3.221  0.00132 ** 
children      475.040     56.208   8.452  < 2e-16 ***
sexfemale     468.098    137.695   3.400  0.00070 ***
smokeryes   13028.969    308.952  42.172  < 2e-16 ***
northeast     711.222    173.648   4.096 4.53e-05 ***
northwest     459.903    171.353   2.684  0.00739 ** 
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 2243 on 1056 degrees of freedom
Multiple R-squared:  0.7742,	Adjusted R-squared:  0.7727 
F-statistic: 517.3 on 7 and 1056 DF,  p-value: < 2.2e-16
```

Using stepwise

```
Step:  AIC=16426.59
expenses ~ age + smokeryes + children + sexfemale + bmi + northeast + 
    northwest

            Df  Sum of Sq        RSS   AIC
<none>                    5.3122e+09 16427
+ southwest  1 4.8593e+06 5.3074e+09 16428
- northwest  1 3.6238e+07 5.3485e+09 16432
- bmi        1 5.2198e+07 5.3644e+09 16435
- sexfemale  1 5.8136e+07 5.3704e+09 16436
- northeast  1 8.4389e+07 5.3966e+09 16441
- children   1 3.5932e+08 5.6715e+09 16494
- smokeryes  1 8.9465e+09 1.4259e+10 17475
- age        1 1.1374e+10 1.6687e+10 17642

Call:
lm(formula = expenses ~ age + smokeryes + children + sexfemale + 
    bmi + northeast + northwest, data = insurancewithselectedvars.withoutliers)

Residuals:
    Min      1Q  Median      3Q     Max 
-3391.4  -917.9  -508.4    76.4 15878.8 

Coefficients:
             Estimate Std. Error t value Pr(>|t|)    
(Intercept) -4213.938    432.661  -9.740  < 2e-16 ***
age           240.054      5.048  47.551  < 2e-16 ***
smokeryes   13028.969    308.952  42.172  < 2e-16 ***
children      475.040     56.208   8.452  < 2e-16 ***
sexfemale     468.098    137.695   3.400  0.00070 ***
bmi            38.442     11.934   3.221  0.00132 ** 
northeast     711.222    173.648   4.096 4.53e-05 ***
northwest     459.903    171.353   2.684  0.00739 ** 
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 2243 on 1056 degrees of freedom
Multiple R-squared:  0.7742,	Adjusted R-squared:  0.7727 
F-statistic: 517.3 on 7 and 1056 DF,  p-value: < 2.2e-16
```

From the above output, I choose to use stepwise regression because it ends up giving me only the required significant predictors, which are different zero at 0.05 level of significance.

Furthermore, using either Backward, forward, or stepwise regression, I ended up getting the same multiple R squared, but because Stepwise gives me significant predictors at 0.05 level of significance, I would go with that.

I have to keep in mind of the issues stepwise regression experiences, multicollinearity and Computational power. Before I ran this model, I had already resolved the issue of multicollinearity and being that my data set is very small, I didn't experience any computational power issues on my laptop when running the stepwise regression process.

On the overall significance of the model, the stepwise regression process produces a multiple regression model, which minimizes the sum of squares of errors:

```
Step:  AIC=16426.59
expenses ~ age + smokeryes + children + sexfemale + bmi + northeast +
    northwest

            Df  Sum of Sq        RSS   AIC
<none>                    5.3122e+09 16427
+ southwest  1 4.8593e+06 5.3074e+09 16428
- northwest  1 3.6238e+07 5.3485e+09 16432
- bmi        1 5.2198e+07 5.3644e+09 16435
- sexfemale  1 5.8136e+07 5.3704e+09 16436
- northeast  1 8.4389e+07 5.3966e+09 16441
- children   1 3.5932e+08 5.6715e+09 16494
- smokeryes  1 8.9465e+09 1.4259e+10 17475
- age        1 1.1374e+10 1.6687e+10 17642

Call:
lm(formula = expenses ~ age + smokeryes + children + sexfemale +
    bmi + northeast + northwest, data = insurancewithselectedvars.withoutliers)

Residuals:
    Min      1Q  Median      3Q     Max
-3391.4  -917.9  -508.4    76.4 15878.8

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) -4213.938    432.661  -9.740  < 2e-16 ***
age           240.054      5.048  47.551  < 2e-16 ***
smokeryes   13028.969    308.952  42.172  < 2e-16 ***
children      475.040     56.208   8.452  < 2e-16 ***
sexfemale     468.098    137.695   3.400  0.00070 ***
bmi            38.442     11.934   3.221  0.00132 **
northeast     711.222    173.648   4.096 4.53e-05 ***
northwest     459.903    171.353   2.684  0.00739 **
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 2243 on 1056 degrees of freedom
Multiple R-squared:  0.7742,	Adjusted R-squared:  0.7727
F-statistic: 517.3 on 7 and 1056 DF,  p-value: < 2.2e-16
```

Looking at the F statistic value of 517.3 and the p-value of less than 2.2e-16. The p-value is the probability that given the null hypothesis, that all the Betas associated with the independent variables are equal to zero. We would observer the data as extreme as it is. Since the p-value is very small, so we are going to reject the null hypothesis and accept the alternative, at least one of the Betas is not equal to zero. We don’t know which beta or they are not equal to zero. It is not the F-test, which tells us that. This is a test of the model itself, which tells me that something in my model is working. Multiple R squared is 0.7742, meaning that 77.42 percent of the variability in the expenses is explained by the model.

Looking at the individual p-value for age, smokeryes, children, sexfemale, bmi, northeast, northwest from the t-test, those are the p-values for the null hypothesis the betas associated with those variables are equal to zero. Because the p-values are low, we are going to reject the null hypothesis and accept the alternative that the betas associated with those parameters are not equal to zero and their use their estimations.

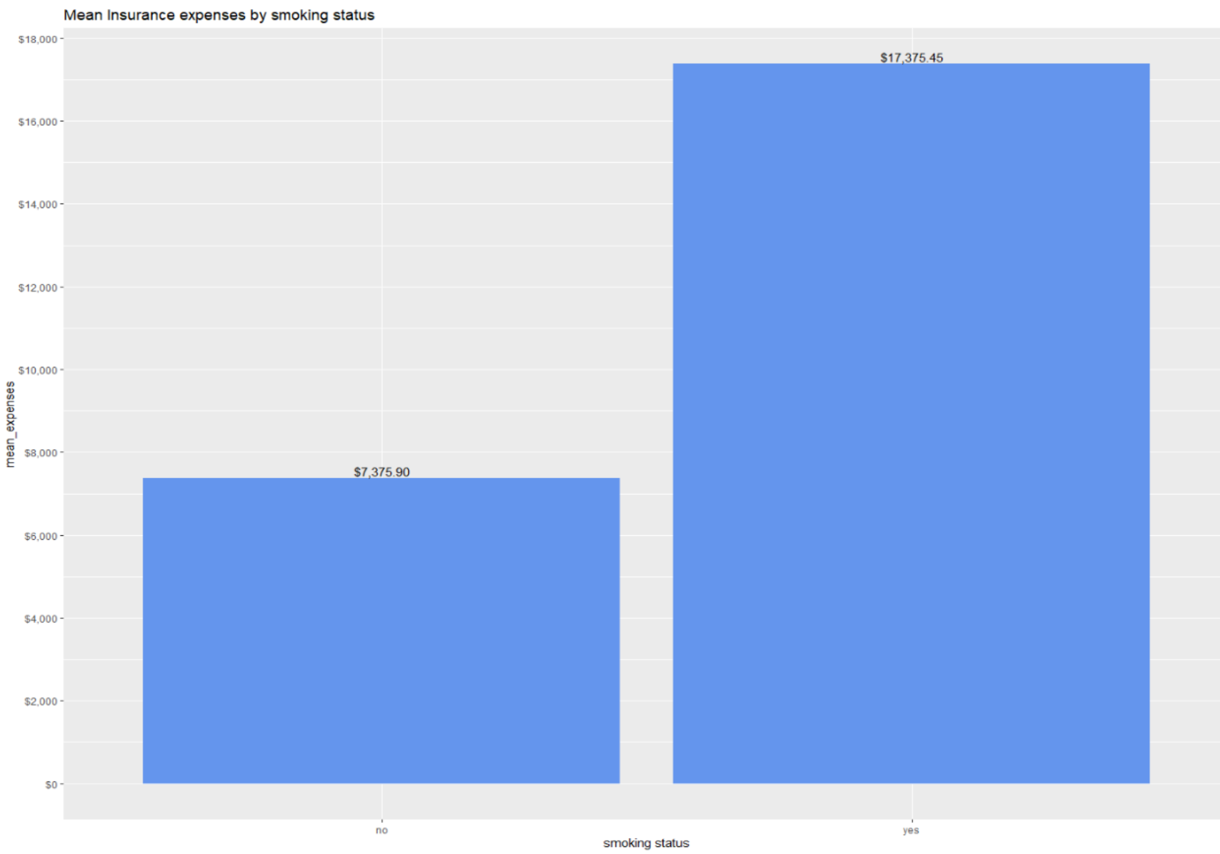
Remember sex, smoker and region are dummy variables therefore, male, smokerno and southeast region with have an estimation of -4213.938. Age will have an estimation of 240.054 + (-4213.938) = -3973.884, smokeryes will have an estimation of 13028.969 + (-4213.938) = 8815.031, children will have an estimation of 475.040 + (-4213.938) = -3738.898, sexfemale will have an estimation of 468.098 + (-4213.938) = -3750.84, northeast will have an estimation of 711.222 + (-4213.938) = -3502.716, northwest will have an estimation of 459.903 + (-4213.938) = -3754.035.

A unit increase in the number of male population from the Southeast region who don't smoke, their insurance expenses will decrease by the beta coefficients.

Also, people who smoke are likely to pay high insurance premiums.

sex, smoker and region, age, children, bmi are all have coefficients different from zero at 0.05 level of significance.

ii. (5 points) Using the variables above, **create a visualization**, which will provide an interesting story or insight within this data.



Looking at the above bar chart, people who are smoke pay higher insurances expenses than folks who don't smoke.

Appendix is my R code:

DSC424HomeWork1

Ronaldlee Ejalu

1/15/2021

Load all the necessary libraries

```
library(readr)
library(tidyverse)

## -- Attaching packages ---------------------------------------------
------------------------- tidyverse 1.3.0 --
```

```
## v ggplot2 3.3.2     v dplyr   1.0.2
## v tibble  3.0.3     v stringr 1.4.0
## v tidyr   1.1.2     v forcats 0.5.0
## v purrr   0.3.4

## -- Conflicts -------------------------------------------------------
-------------------- tidyverse_conflicts() --
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()    masks stats::lag()

library(gtsummary)

## Warning: package 'gtsummary' was built under R version 4.0.3

## #BlackLivesMatter

library(tableone)

## Warning: package 'tableone' was built under R version 4.0.3

library(broom)
library(dplyr) #dplryr calculations
library(corrplot) # Plot Correlations

## Warning: package 'corrplot' was built under R version 4.0.3

## corrplot 0.84 loaded

library(DescTools) # VIF Function

## Warning: package 'DescTools' was built under R version 4.0.3
```

Read data into R studio

```
insurance_dataset <- read_csv("C:\\Users\\rejalu1\\OneDrive - Henry Fo
rd Health System\\DSC424\\Data Sets\\insurance_dataset.csv")

## Parsed with column specification:
## cols(
##   age = col_double(),
##   sex = col_character(),
##   gender_num = col_double(),
##   bmi = col_double(),
##   children = col_double(),
##   smoker = col_character(),
##   smoker_num = col_double(),
##   region = col_character(),
##   region_num = col_double(),
```

```
##   expenses = col_double()
## )
```

#view the 10 data observations

```
head(insurance_dataset)

## # A tibble: 6 x 10
##     age sex    gender_num   bmi children smoker smoker_num region re
gion_num
##   <dbl> <chr>       <dbl> <dbl>    <dbl> <chr>       <dbl> <chr>
<dbl>
## 1    19 fema~           0  27.9        0 yes             1 south~
4
## 2    18 male            1  33.8        1 no              0 south~
3
## 3    28 male            1  33          3 no              0 south~
3
## 4    33 male            1  22.7        0 no              0 north~
2
## 5    32 male            1  28.9        0 no              0 north~
2
## 6    31 fema~           0  25.7        0 no              0 south~
3
## # ... with 1 more variable: expenses <dbl>
```

#view the last 10 data observations

```
tail(insurance_dataset)

## # A tibble: 6 x 10
##     age sex    gender_num   bmi children smoker smoker_num region re
gion_num
##   <dbl> <chr>       <dbl> <dbl>    <dbl> <chr>       <dbl> <chr>
<dbl>
## 1    52 fema~           0  44.7        3 no              0 south~
4
## 2    50 male            1  31          3 no              0 north~
2
## 3    18 fema~           0  31.9        0 no              0 north~
1
## 4    18 fema~           0  36.9        0 no              0 south~
3
## 5    21 fema~           0  25.8        0 no              0 south~
4
## 6    61 fema~           0  29.1        0 yes             1 north~
```

```
2
## # ... with 1 more variable: expenses <dbl>
```

#data structure

```
str(insurance_dataset)

## tibble [1,338 x 10] (S3: spec_tbl_df/tbl_df/tbl/data.frame)
##  $ age       : num [1:1338] 19 18 28 33 32 31 46 37 37 60 ...
##  $ sex       : chr [1:1338] "female" "male" "male" "male" ...
##  $ gender_num: num [1:1338] 0 1 1 1 1 0 0 0 1 0 ...
##  $ bmi       : num [1:1338] 27.9 33.8 33 22.7 28.9 25.7 33.4 27.7 2
9.8 25.8 ...
##  $ children  : num [1:1338] 0 1 3 0 0 0 1 3 2 0 ...
##  $ smoker    : chr [1:1338] "yes" "no" "no" "no" ...
##  $ smoker_num: num [1:1338] 1 0 0 0 0 0 0 0 0 0 ...
##  $ region    : chr [1:1338] "southwest" "southeast" "southeast" "no
rthwest" ...
##  $ region_num: num [1:1338] 4 3 3 2 2 3 3 2 1 2 ...
##  $ expenses  : num [1:1338] 16885 1726 4449 21984 3867 ...
##  - attr(*, "spec")=
##   .. cols(
##   ..   age = col_double(),
##   ..   sex = col_character(),
##   ..   gender_num = col_double(),
##   ..   bmi = col_double(),
##   ..   children = col_double(),
##   ..   smoker = col_character(),
##   ..   smoker_num = col_double(),
##   ..   region = col_character(),
##   ..   region_num = col_double(),
##   ..   expenses = col_double()
##   .. )
```

summarized statistical data from the data set

```
summary(insurance_dataset)

##       age             sex              gender_num          bmi
##  Min.   :18.00   Length:1338        Min.   :0.0000   Min.   :16.00
##  1st Qu.:27.00   Class :character   1st Qu.:0.0000   1st Qu.:26.30
##  Median :39.00   Mode  :character   Median :1.0000   Median :30.40
##  Mean   :39.21                      Mean   :0.5052   Mean   :30.67
##  3rd Qu.:51.00                      3rd Qu.:1.0000   3rd Qu.:34.70
##  Max.   :64.00                      Max.   :1.0000   Max.   :53.10
##     children         smoker            smoker_num        region
##  Min.   :0.000   Length:1338        Min.   :0.0000   Length:1338
```

```
##  1st Qu.:0.000   Class :character   1st Qu.:0.0000   Class :charact
er
##  Median :1.000   Mode  :character   Median :0.0000   Mode  :charact
er
##  Mean   :1.095                      Mean   :0.2048
##  3rd Qu.:2.000                      3rd Qu.:0.0000
##  Max.   :5.000                      Max.   :1.0000
##    region_num       expenses
##  Min.   :1.000   Min.   : 1122
##  1st Qu.:2.000   1st Qu.: 4740
##  Median :3.000   Median : 9382
##  Mean   :2.516   Mean   :13270
##  3rd Qu.:3.000   3rd Qu.:16640
##  Max.   :4.000   Max.   :63770
```

#check for any missing value #There are no missing values

```
sum(is.na(insurance_dataset))
```

```
## [1] 0
```

#get specific column index in R

```
as.data.frame(colnames(insurance_dataset))
```

```
##    colnames(insurance_dataset)
## 1                          age
## 2                          sex
## 3                   gender_num
## 4                          bmi
## 5                     children
## 6                       smoker
## 7                   smoker_num
## 8                       region
## 9                   region_num
## 10                    expenses
```

#distinct values of each factor column # gender_num, smoker_num, region_num

```
insurance_dataset.sex <- count(distinct(insurance_dataset), sex)
insurance_dataset.sex
```

```
## # A tibble: 2 x 2
##   sex        n
##   <chr>  <int>
## 1 female   662
## 2 male     675
```

```r
insurance_dataset.smoker <- count(distinct(insurance_dataset), smoker)
insurance_dataset.smoker
```

```
## # A tibble: 2 x 2
##   smoker     n
##   <chr>  <int>
## 1 no      1063
## 2 yes      274
```

```r
insurance_dataset.region <- count(distinct(insurance_dataset), region)
insurance_dataset.region
```

```
## # A tibble: 4 x 2
##   region        n
##   <chr>     <int>
## 1 northeast   324
## 2 northwest   324
## 3 southeast   364
## 4 southwest   325
```

data cleaning

```r
insurance.clean <- insurance_dataset %>%
  transmute(age = age
            , sex = as.factor(sex)
            , gender_num = gender_num
            , bmi = bmi
            , children = children
            , smoker = as.factor(smoker)
            , smoker_num = smoker_num
            , region = as.factor(region)
            , region_num = region_num
            , expenses = expenses) %>%
  mutate(
    sex = relevel(sex, ref = 'male')
    , smoker = relevel(smoker, ref = 'no')
    , region = relevel(region, ref = 'southeast')
  )

# Create a matrix for sex
sexdummies.matrix <- model.matrix(~insurance.clean$sex)

# Convert the model matrix into a data frame
sexdummies.frame <- data.frame(sexdummies.matrix)

# bind the data frame to data set
insurance.clean <- cbind(insurance.clean, sexdummies.frame)
```

```
# create a matrix for smoker
smokerdummies.matrix <- model.matrix(~insurance.clean$smoker)

#Convert the model matrix into a data frame
smokerdummies.frame <- data.frame(smokerdummies.matrix)

#bind the data frame to data set
insurance.clean <- cbind(insurance.clean, smokerdummies.frame)

# create a matrix for region
regiondummies.matrix <- model.matrix(~insurance.clean$region)

# Convert the model matrix into a data frame
regiondummies.frame <- data.frame(regiondummies.matrix)

# bind the data frame to a data set
insurance.clean <- cbind(insurance.clean, regiondummies.frame)
```

rename and select all the variables interest

```
insurancecleansed <- insurance.clean %>%
  select(age = age
            , gender_num = gender_num
            , bmi = bmi
            , children = children
            , smoker_num = smoker_num
            , region_num = region_num
            , expenses = expenses
            , sexfemale = insurance.clean.sexfemale
            , smokeryes = insurance.clean.smokeryes
            , northeast = insurance.clean.regionnortheast
            , northwest = insurance.clean.regionnorthwest
            , southwest = insurance.clean.regionsouthwest)
```

#extract out all numerical variables

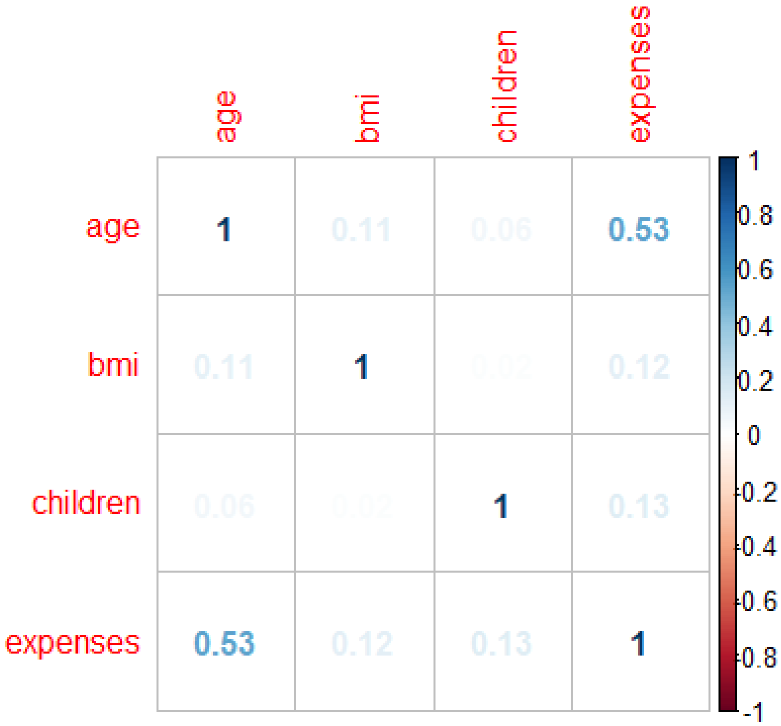
```
insurance.numvariables <- insurance_dataset[,c(1,4:5,10)]
```

check for multicollinearity amongst the numerical variables

```
M <- cor(insurance.numvariables, method = "spearman")
M

##                 age        bmi   children  expenses
## age      1.00000000 0.10769164 0.05699222 0.5343921
## bmi      0.10769164 1.00000000 0.01558886 0.1194189
```

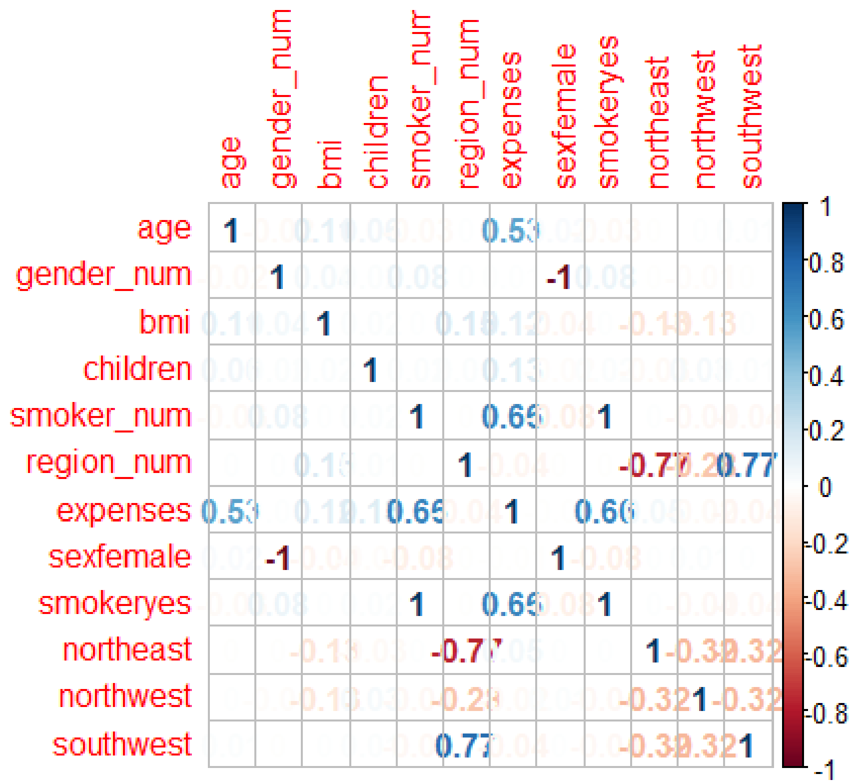
```
## children 0.05699222 0.01558886 1.00000000 0.1333389
## expenses 0.53439213 0.11941885 0.13333894 1.0000000
```

```r
corrplot(M, method = "number")
```



Check for multicollinearity amongst all the variables

```r
m2 <- cor(insurancecleansed, method = "spearman")
corrplot(m2, method = "number")
```

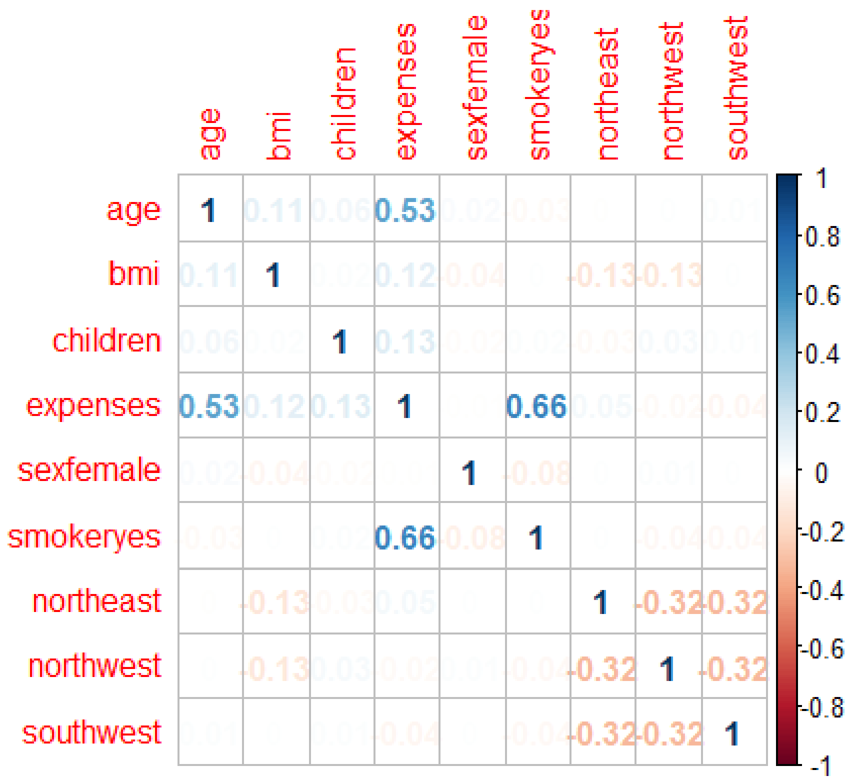


#Altering my data set after sensing multicollinearity in the original data # I select the variables of interest

```
insurancewithselectedvars <- insurancecleansed %>%
  select(age = age
            , bmi = bmi
            , children = children
            , expenses = expenses
            , sexfemale = sexfemale
            , smokeryes = smokeryes
            , northeast = northeast
            , northwest = northwest
            , southwest = southwest)
```

Again check for multicollinearity

```
#summary(insurancewithselectedvars)
m3 <- cor(insurancewithselectedvars, method = "spearman")
#m3
corrplot(m3, method = "number")
```




```r
model2 <- lm(expenses ~ ., data = insurancewithselectedvars)
summary(model2)

##
## Call:
## lm(formula = expenses ~ ., data = insurancewithselectedvars)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -11302.7  -2850.9   -979.6   1383.9  29981.7
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) -13108.51    1090.51 -12.021  < 2e-16 ***
## age            256.84      11.90  21.586  < 2e-16 ***
## bmi            339.29      28.60  11.864  < 2e-16 ***
## children       475.69     137.80   3.452 0.000574 ***
## sexfemale      131.35     332.94   0.395 0.693255
## smokeryes    23847.48     413.14  57.723  < 2e-16 ***
## northeast     1035.60     478.68   2.163 0.030685 *
## northwest      682.81     478.95   1.426 0.154211
## southwest       76.29     470.64   0.162 0.871253
## ---
## 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: 500.9 on 8 and 1329 DF,  p-value: < 2.2e-16
```

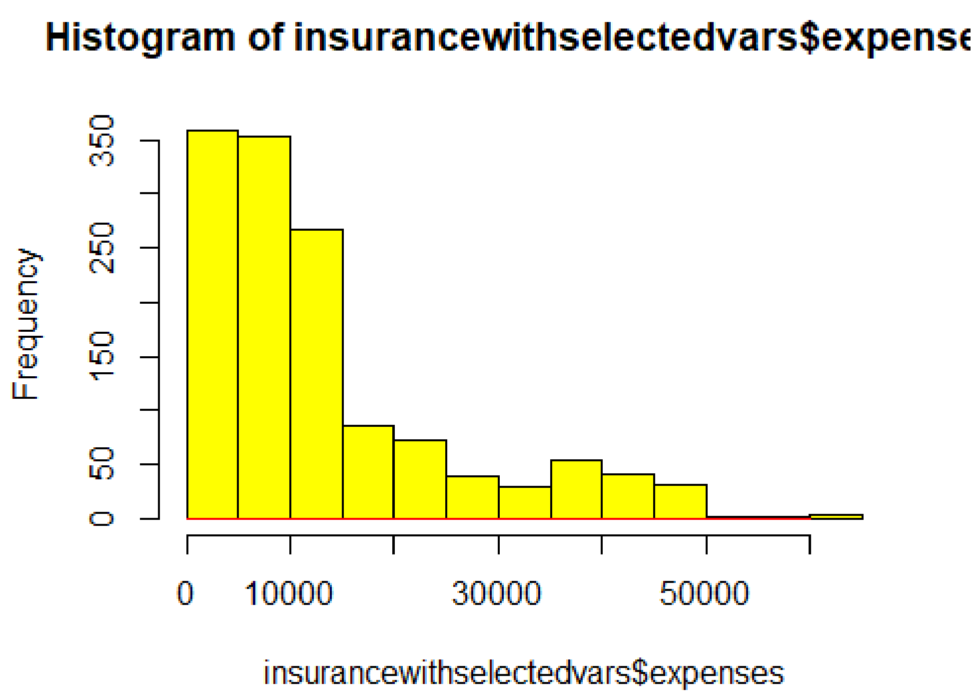
```
VIF(model2)
```

```
##       age       bmi  children sexfemale smokeryes northeast northwe
st southwest
##  1.016843  1.106682  1.004008  1.008900  1.012067  1.531084  1.5360
30  1.483177
```

Explanatory analysis

#Histogram

```
hist(insurancewithselectedvars$expenses, col="yellow", freq=TRUE)
x <- seq(0, 60000, length.out = 50)
y <- with(insurancewithselectedvars, dnorm(x, mean(expenses), sd(expen
ses)))
lines(x, y, col="red")
```

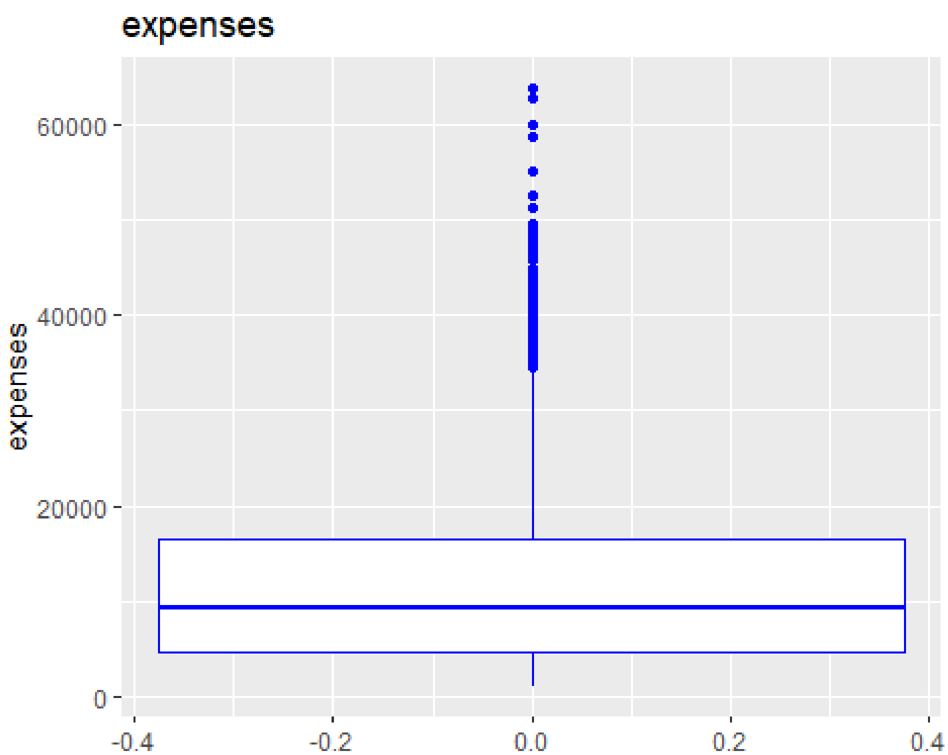


Five - Number Summary for the Boxplot

```
summary(insurancewithselectedvars$expenses)
```

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

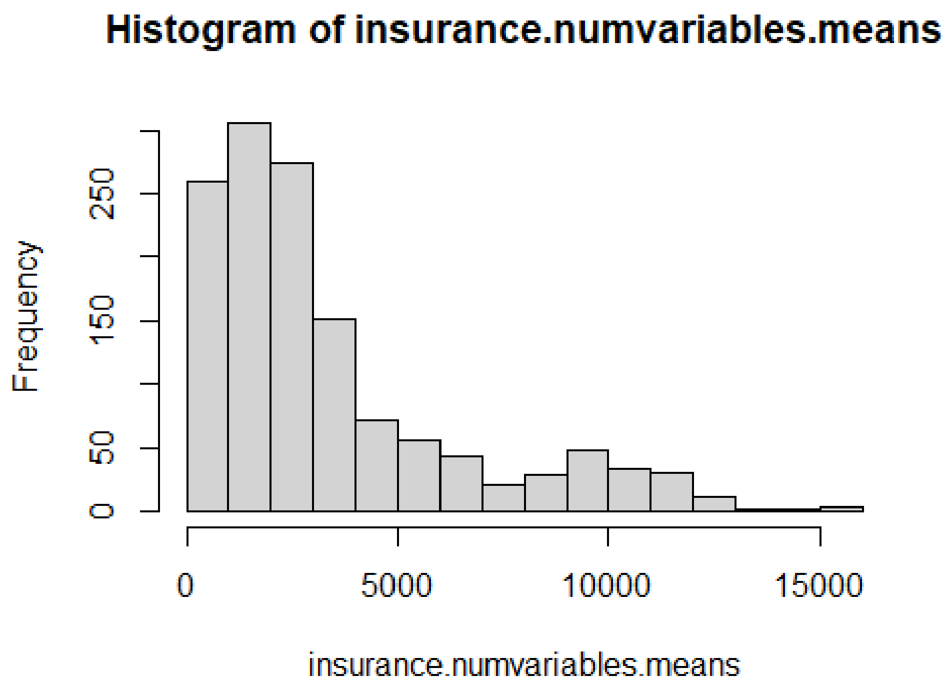
```
# Boxplots
insuranxebloxplot <-ggplot(insurancewithselectedvars, aes(y=expenses))
+
  geom_boxplot(col="blue") +
  labs(
    title="expenses",
    y="expenses")
insuranxebloxplot
```




```
ggsave("insuranxebloxplot.png")

## Saving 5 x 4 in image
```

Return a vector with a mean value across each row of the insurance.numvariables data set

```
insurance.numvariables.means <- rowMeans(insurance.numvariables, na.rm
=TRUE)
hist(insurance.numvariables.means)
```



#remove entries with the means greater than 5000

```
insurance.keep <- insurance.numvariables.means < 5000
```

remove outliers from the original data frame

```
insuracedataset <- insurance_dataset[insurance.keep,]
```

remove outliers from the numerical insurance data set

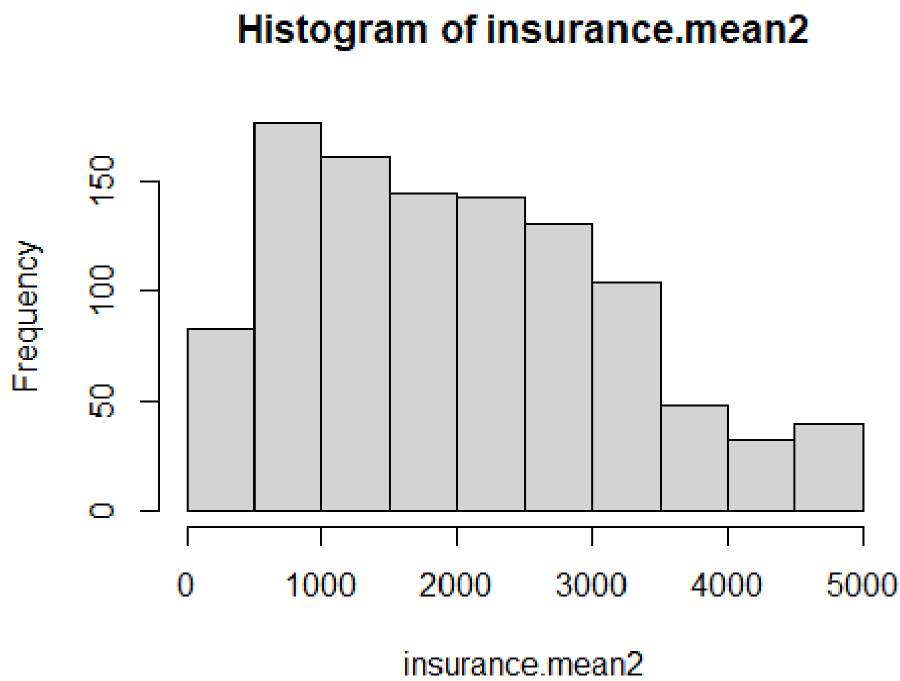
```
insurance.numvariables.withoutliers <- insurance.numvariables[insuranc
e.keep,]
```

#remove outliers from the insurance with selected vars data set

```
insurancewithselectedvars.withoutliers <- insurancewithselectedvars[in
surance.keep, ]
```

#plot the means with outliers removed

```
insurance.mean2 <- rowMeans(insurance.numvariables.withoutliers, na.rm
= TRUE)
hist(insurance.mean2)
```

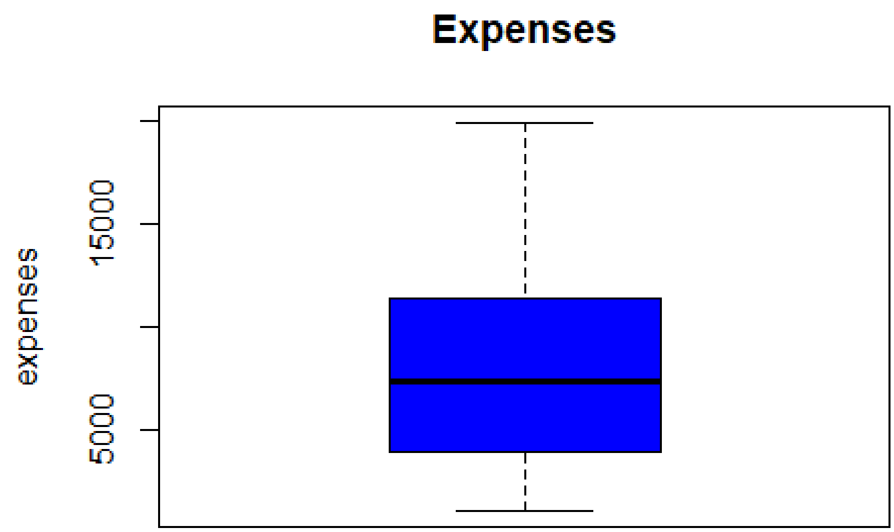


#five number summary

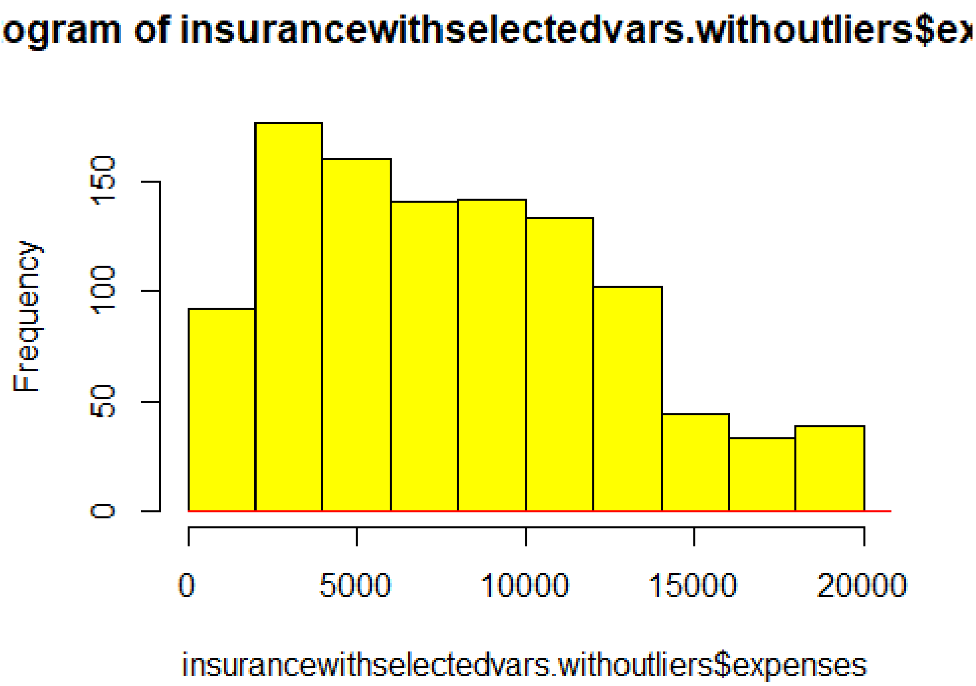
```
summary(insurancewithselectedvars.withoutliers$expenses,)

##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##    1122    3986    7345    7949   11363   19933
```

#box plot

```
boxplot(insurancewithselectedvars.withoutliers$expenses, col = "blue",
main = "Expenses", ylab = "expenses")
```




```
hist(insurancewithselectedvars.withoutliers$expenses, col="yellow", fr
eq=TRUE)
x <- seq(0, 60000, length.out = 50)
y <- with(insurancewithselectedvars.withoutliers, dnorm(x, mean(expens
es), sd(expenses)))
lines(x, y, col="red")
```



model building after removing the outliers.

```
model3 <- lm(expenses ~ ., data = insurancewithselectedvars.withoutlie
rs)
summary(model3)

##
## Call:
## lm(formula = expenses ~ ., data = insurancewithselectedvars.without
liers)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -3400.6  -911.0  -512.9    77.5 15971.3
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) -4061.330    459.687  -8.835  < 2e-16 ***
## age           240.347      5.057  47.525  < 2e-16 ***
## bmi            36.218     12.147   2.982 0.002932 **
## children      476.477     56.228   8.474  < 2e-16 ***
## sexfemale     469.862    137.709   3.412 0.000669 ***
## smokeryes   13012.777    309.396  42.059  < 2e-16 ***
## northeast     609.983    201.904   3.021 0.002579 **
```

```
## northwest     358.805    199.860   1.795 0.072895 .
## southwest    -192.527    195.892  -0.983 0.325921
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2243 on 1055 degrees of freedom
## Multiple R-squared:  0.7744, Adjusted R-squared:  0.7727
## F-statistic: 452.7 on 8 and 1055 DF,  p-value: < 2.2e-16
```

Creating the automatic models

```
null = lm(expenses ~ 1, data = insurancewithselectedvars.withoutliers)
null

##
## Call:
## lm(formula = expenses ~ 1, data = insurancewithselectedvars.without
liers)
##
## Coefficients:
## (Intercept)
##        7949

full = lm(expenses ~ ., data = insurancewithselectedvars.withoutliers)

#Forward regression
train_forward = step(null, scope = list(lower=null, upper=full),direct
ion="forward")

## Start:  AIC=17995.95
## expenses ~ 1
##
##              Df  Sum of Sq        RSS   AIC
## + age         1 8574022947 1.4953e+10 17516
## + smokeryes   1 5749769984 1.7777e+10 17700
## + children    1  548799328 2.2978e+10 17973
## + northeast   1   80416879 2.3446e+10 17994
## + sexfemale   1   80368634 2.3446e+10 17994
## <none>                     2.3527e+10 17996
## + southwest   1   15517598 2.3511e+10 17997
## + bmi         1    2601381 2.3524e+10 17998
## + northwest   1     890445 2.3526e+10 17998
##
## Step:  AIC=17515.7
## expenses ~ age
##
```

```
##             Df  Sum of Sq        RSS   AIC
## + smokeryes  1 9119040316 5.8336e+09 16516
## + children   1  375396047 1.4577e+10 17491
## + bmi        1  231703142 1.4721e+10 17501
## + northeast  1   71880163 1.4881e+10 17513
## + southwest  1   51420675 1.4901e+10 17514
## + sexfemale  1   44433177 1.4908e+10 17515
## <none>                    1.4953e+10 17516
## + northwest  1     280125 1.4952e+10 17518
##
## Step:  AIC=16516.21
## expenses ~ age + smokeryes
##
##             Df Sum of Sq        RSS   AIC
## + children   1 346670490 5486943917 16453
## + sexfemale  1  52197142 5781417265 16509
## + southwest  1  42744521 5790869886 16510
## + northeast  1  38271526 5795342880 16511
## + bmi        1  23782172 5809832234 16514
## <none>                   5833614407 16516
## + northwest  1   5818288 5827796119 16517
##
## Step:  AIC=16453.02
## expenses ~ age + smokeryes + children
##
##             Df Sum of Sq        RSS   AIC
## + sexfemale  1  54448427 5432495489 16444
## + southwest  1  51445266 5435498651 16445
## + northeast  1  45705618 5441238299 16446
## + bmi        1  24338028 5462605889 16450
## <none>                   5486943917 16453
## + northwest  1   5247104 5481696812 16454
##
## Step:  AIC=16444.41
## expenses ~ age + smokeryes + children + sexfemale
##
##             Df Sum of Sq        RSS   AIC
## + southwest  1  53224973 5379270517 16436
## + northeast  1  45666344 5386829146 16437
## + bmi        1  26777953 5405717536 16441
## <none>                   5432495489 16444
## + northwest  1   5317643 5427177847 16445
##
## Step:  AIC=16435.93
## expenses ~ age + smokeryes + children + sexfemale + southwest
##
```

```
##              Df Sum of Sq        RSS   AIC
## + bmi         1  25631742 5353638775 16433
## + northeast  1  21444599 5357825918 16434
## <none>                     5379270517 16436
## + northwest  1     21474 5379249043 16438
##
## Step:  AIC=16432.85
## expenses ~ age + smokeryes + children + sexfemale + southwest +
##     bmi
##
##              Df Sum of Sq        RSS   AIC
## + northeast  1  30061483 5323577292 16429
## <none>                     5353638775 16433
## + northwest  1    358961 5353279814 16435
##
## Step:  AIC=16428.86
## expenses ~ age + smokeryes + children + sexfemale + southwest +
##     bmi + northeast
##
##              Df Sum of Sq        RSS   AIC
## + northwest  1  16214040 5307363251 16428
## <none>                     5323577292 16429
##
## Step:  AIC=16427.61
## expenses ~ age + smokeryes + children + sexfemale + southwest +
##     bmi + northeast + northwest
```

```
summary(train_forward)
```

```
##
## Call:
## lm(formula = expenses ~ age + smokeryes + children + sexfemale +
##     southwest + bmi + northeast + northwest, data = insurancewithse
lectedvars.withoutliers)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -3400.6  -911.0  -512.9    77.5 15971.3
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept) -4061.330    459.687  -8.835  < 2e-16 ***
## age           240.347      5.057  47.525  < 2e-16 ***
## smokeryes   13012.777    309.396  42.059  < 2e-16 ***
## children      476.477     56.228   8.474  < 2e-16 ***
## sexfemale     469.862    137.709   3.412 0.000669 ***
```

```
## southwest    -192.527    195.892  -0.983 0.325921
## bmi            36.218     12.147   2.982 0.002932 **
## northeast     609.983    201.904   3.021 0.002579 **
## northwest     358.805    199.860   1.795 0.072895 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2243 on 1055 degrees of freedom
## Multiple R-squared:  0.7744, Adjusted R-squared:  0.7727
## F-statistic: 452.7 on 8 and 1055 DF,  p-value: < 2.2e-16
```

using backward

```
train_backward = step(full, dierction="backward")

## Start:  AIC=16427.61
## expenses ~ age + bmi + children + sexfemale + smokeryes + northeast
+
##     northwest + southwest
##
##              Df  Sum of Sq        RSS   AIC
## - southwest   1 4.8593e+06 5.3122e+09 16427
## <none>                     5.3074e+09 16428
## - northwest   1 1.6214e+07 5.3236e+09 16429
## - bmi         1 4.4725e+07 5.3521e+09 16435
## - northeast   1 4.5917e+07 5.3533e+09 16435
## - sexfemale   1 5.8566e+07 5.3659e+09 16437
## - children    1 3.6125e+08 5.6686e+09 16496
## - smokeryes   1 8.8989e+09 1.4206e+10 17473
## - age         1 1.1362e+10 1.6670e+10 17643
##
## Step:  AIC=16426.59
## expenses ~ age + bmi + children + sexfemale + smokeryes + northeast
+
##     northwest
##
##              Df  Sum of Sq        RSS   AIC
## <none>                     5.3122e+09 16427
## - northwest   1 3.6238e+07 5.3485e+09 16432
## - bmi         1 5.2198e+07 5.3644e+09 16435
## - sexfemale   1 5.8136e+07 5.3704e+09 16436
## - northeast   1 8.4389e+07 5.3966e+09 16441
## - children    1 3.5932e+08 5.6715e+09 16494
## - smokeryes   1 8.9465e+09 1.4259e+10 17475
## - age         1 1.1374e+10 1.6687e+10 17642
```

```r
summary(train_backward)
```

```
##
## Call:
## lm(formula = expenses ~ age + bmi + children + sexfemale + smokerye
s +
##     northeast + northwest, data = insurancewithselectedvars.without
liers)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -3391.4  -917.9  -508.4    76.4 15878.8
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) -4213.938    432.661  -9.740  < 2e-16 ***
## age           240.054      5.048  47.551  < 2e-16 ***
## bmi            38.442     11.934   3.221  0.00132 **
## children      475.040     56.208   8.452  < 2e-16 ***
## sexfemale     468.098    137.695   3.400  0.00070 ***
## smokeryes   13028.969    308.952  42.172  < 2e-16 ***
## northeast     711.222    173.648   4.096 4.53e-05 ***
## northwest     459.903    171.353   2.684  0.00739 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2243 on 1056 degrees of freedom
## Multiple R-squared:  0.7742, Adjusted R-squared:  0.7727
## F-statistic: 517.3 on 7 and 1056 DF,  p-value: < 2.2e-16
```

using stepwise Regression

```r
train_step = step(null, scope = list(upper=full), direction = "both")
```

```
## Start:  AIC=17995.95
## expenses ~ 1
##
##              Df  Sum of Sq        RSS   AIC
## + age         1 8574022947 1.4953e+10 17516
## + smokeryes   1 5749769984 1.7777e+10 17700
## + children    1  548799328 2.2978e+10 17973
## + northeast   1   80416879 2.3446e+10 17994
## + sexfemale   1   80368634 2.3446e+10 17994
## <none>                     2.3527e+10 17996
## + southwest   1   15517598 2.3511e+10 17997
## + bmi         1    2601381 2.3524e+10 17998
```

```
## + northwest  1     890445 2.3526e+10 17998
##
## Step:  AIC=17515.7
## expenses ~ age
##
##             Df  Sum of Sq        RSS   AIC
## + smokeryes  1 9119040316 5.8336e+09 16516
## + children   1  375396047 1.4577e+10 17491
## + bmi        1  231703142 1.4721e+10 17501
## + northeast  1   71880163 1.4881e+10 17513
## + southwest  1   51420675 1.4901e+10 17514
## + sexfemale  1   44433177 1.4908e+10 17515
## <none>                    1.4953e+10 17516
## + northwest  1     280125 1.4952e+10 17518
## - age        1 8574022947 2.3527e+10 17996
##
## Step:  AIC=16516.21
## expenses ~ age + smokeryes
##
##             Df  Sum of Sq        RSS   AIC
## + children   1 3.4667e+08 5.4869e+09 16453
## + sexfemale  1 5.2197e+07 5.7814e+09 16509
## + southwest  1 4.2745e+07 5.7909e+09 16510
## + northeast  1 3.8272e+07 5.7953e+09 16511
## + bmi        1 2.3782e+07 5.8098e+09 16514
## <none>                    5.8336e+09 16516
## + northwest  1 5.8183e+06 5.8278e+09 16517
## - smokeryes  1 9.1190e+09 1.4953e+10 17516
## - age        1 1.1943e+10 1.7777e+10 17700
##
## Step:  AIC=16453.02
## expenses ~ age + smokeryes + children
##
##             Df  Sum of Sq        RSS   AIC
## + sexfemale  1 5.4448e+07 5.4325e+09 16444
## + southwest  1 5.1445e+07 5.4355e+09 16445
## + northeast  1 4.5706e+07 5.4412e+09 16446
## + bmi        1 2.4338e+07 5.4626e+09 16450
## <none>                    5.4869e+09 16453
## + northwest  1 5.2471e+06 5.4817e+09 16454
## - children   1 3.4667e+08 5.8336e+09 16516
## - smokeryes  1 9.0903e+09 1.4577e+10 17491
## - age        1 1.1739e+10 1.7226e+10 17668
##
## Step:  AIC=16444.41
## expenses ~ age + smokeryes + children + sexfemale
```

```
##
##              Df  Sum of Sq        RSS   AIC
## + southwest  1 5.3225e+07 5.3793e+09 16436
## + northeast  1 4.5666e+07 5.3868e+09 16437
## + bmi        1 2.6778e+07 5.4057e+09 16441
## <none>                    5.4325e+09 16444
## + northwest  1 5.3176e+06 5.4272e+09 16445
## - sexfemale  1 5.4448e+07 5.4869e+09 16453
## - children   1 3.4892e+08 5.7814e+09 16509
## - smokeryes  1 9.0982e+09 1.4531e+10 17489
## - age        1 1.1694e+10 1.7127e+10 17664
##
## Step:  AIC=16435.93
## expenses ~ age + smokeryes + children + sexfemale + southwest
##
##              Df  Sum of Sq        RSS   AIC
## + bmi        1 2.5632e+07 5.3536e+09 16433
## + northeast  1 2.1445e+07 5.3578e+09 16434
## <none>                    5.3793e+09 16436
## + northwest  1 2.1474e+04 5.3792e+09 16438
## - southwest  1 5.3225e+07 5.4325e+09 16444
## - sexfemale  1 5.6228e+07 5.4355e+09 16445
## - children   1 3.5784e+08 5.7371e+09 16503
## - smokeryes  1 9.0883e+09 1.4468e+10 17487
## - age        1 1.1732e+10 1.7111e+10 17665
##
## Step:  AIC=16432.85
## expenses ~ age + smokeryes + children + sexfemale + southwest +
##     bmi
##
##              Df  Sum of Sq        RSS   AIC
## + northeast  1 3.0061e+07 5.3236e+09 16429
## <none>                    5.3536e+09 16433
## + northwest  1 3.5896e+05 5.3533e+09 16435
## - bmi        1 2.5632e+07 5.3793e+09 16436
## - southwest  1 5.2079e+07 5.4057e+09 16441
## - sexfemale  1 5.8632e+07 5.4123e+09 16442
## - children   1 3.5837e+08 5.7120e+09 16500
## - smokeryes  1 8.8877e+09 1.4241e+10 17472
## - age        1 1.1483e+10 1.6836e+10 17650
##
## Step:  AIC=16428.86
## expenses ~ age + smokeryes + children + sexfemale + southwest +
##     bmi + northeast
##
##              Df  Sum of Sq        RSS   AIC
```

```
## + northwest  1 1.6214e+07 5.3074e+09 16428
## <none>                    5.3236e+09 16429
## - southwest  1 2.4883e+07 5.3485e+09 16432
## - northeast  1 3.0061e+07 5.3536e+09 16433
## - bmi        1 3.4249e+07 5.3578e+09 16434
## - sexfemale  1 5.8535e+07 5.3821e+09 16439
## - children   1 3.6266e+08 5.6862e+09 16497
## - smokeryes  1 8.8970e+09 1.4221e+10 17472
## - age        1 1.1419e+10 1.6742e+10 17646
##
## Step:  AIC=16427.61
## expenses ~ age + smokeryes + children + sexfemale + southwest +
##     bmi + northeast + northwest
##
##             Df  Sum of Sq        RSS   AIC
## - southwest  1 4.8593e+06 5.3122e+09 16427
## <none>                    5.3074e+09 16428
## - northwest  1 1.6214e+07 5.3236e+09 16429
## - bmi        1 4.4725e+07 5.3521e+09 16435
## - northeast  1 4.5917e+07 5.3533e+09 16435
## - sexfemale  1 5.8566e+07 5.3659e+09 16437
## - children   1 3.6125e+08 5.6686e+09 16496
## - smokeryes  1 8.8989e+09 1.4206e+10 17473
## - age        1 1.1362e+10 1.6670e+10 17643
##
## Step:  AIC=16426.59
## expenses ~ age + smokeryes + children + sexfemale + bmi + northeast
+
##     northwest
##
##             Df  Sum of Sq        RSS   AIC
## <none>                    5.3122e+09 16427
## + southwest  1 4.8593e+06 5.3074e+09 16428
## - northwest  1 3.6238e+07 5.3485e+09 16432
## - bmi        1 5.2198e+07 5.3644e+09 16435
## - sexfemale  1 5.8136e+07 5.3704e+09 16436
## - northeast  1 8.4389e+07 5.3966e+09 16441
## - children   1 3.5932e+08 5.6715e+09 16494
## - smokeryes  1 8.9465e+09 1.4259e+10 17475
## - age        1 1.1374e+10 1.6687e+10 17642
```

```
summary(train_step)
```

```
##
## Call:
## lm(formula = expenses ~ age + smokeryes + children + sexfemale +
```

```
##     bmi + northeast + northwest, data = insurancewithselectedvars.w
ithoutliers)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -3391.4  -917.9  -508.4    76.4 15878.8
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) -4213.938    432.661  -9.740  < 2e-16 ***
## age           240.054      5.048  47.551  < 2e-16 ***
## smokeryes   13028.969    308.952  42.172  < 2e-16 ***
## children      475.040     56.208   8.452  < 2e-16 ***
## sexfemale     468.098    137.695   3.400  0.00070 ***
## bmi            38.442     11.934   3.221  0.00132 **
## northeast     711.222    173.648   4.096 4.53e-05 ***
## northwest     459.903    171.353   2.684  0.00739 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2243 on 1056 degrees of freedom
## Multiple R-squared:  0.7742, Adjusted R-squared:  0.7727
## F-statistic: 517.3 on 7 and 1056 DF,  p-value: < 2.2e-16
```

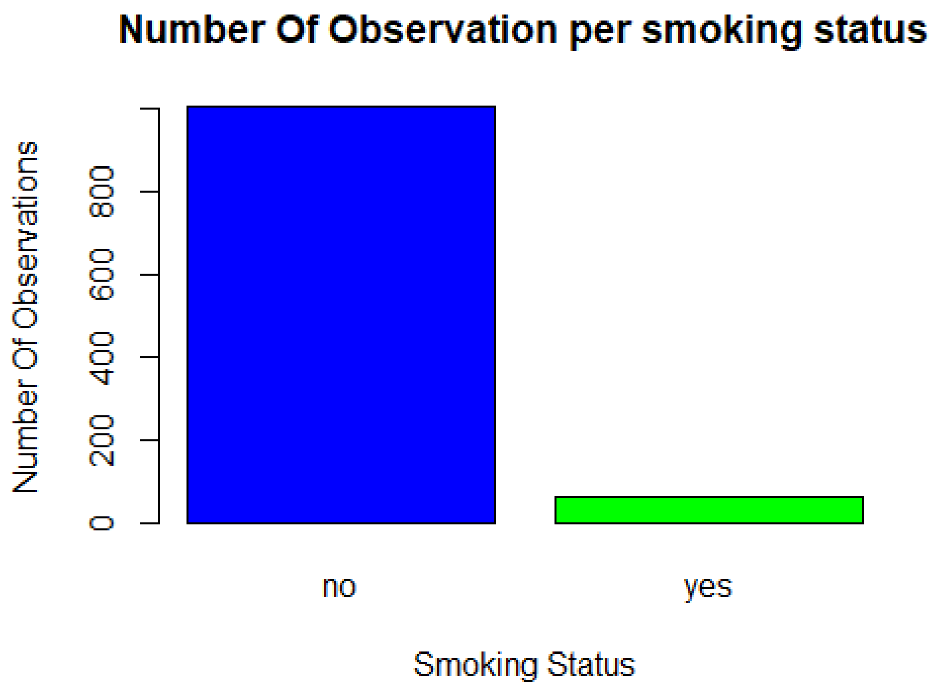
Data Visualization

plot a box plot

```
counts <- table(insuracedataset$smoker)
counts
```

```
##
##   no  yes
## 1003   61
```

```
barplot(counts, main="Number Of Observation per smoking status",ylab="
Number Of Observations", xlab="Smoking Status", col=c("blue","green"))
```



calculate the mean expense by smoking status

plot a bar chart

```
library(scales)

##
## Attaching package: 'scales'

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

## The following object is masked from 'package:readr':
##
##     col_factor

plotdata <- insuracedataset %>%
  group_by(smoker) %>%
  summarize(mean_expenses = mean(expenses))

## `summarise()` ungrouping output (override with `.groups` argument)

#plotdata
```

```r
# plot the means
ggplot(plotdata,
       aes(x = smoker,
           y = mean_expenses)) +
  geom_bar(stat = "identity",
           fill = "cornflowerblue") +
  geom_text(aes(label = dollar(mean_expenses)),
            vjust = -0.25) +
  scale_y_continuous(breaks = seq(0, 30000, 2000),
                     label = dollar
                     ) +
  labs(title = "Mean Insurance expenses by smoking status",
       x = "smoking status",
       y = "mean_expenses")
```