Final Project

Rules of Engagement:

This is an **honor system assignment**: You may consult your professor, your lab instructor, the textbook, and material on the Internet at any time. You may not consult, collaborate, or seek assistance from any other human besides your professor and lab instructor. Your attribution statement, at the top of your R-code file, should reflect these constraints.

Final Project

The overall goal of the case is to provide actionable insight, based on the data available, as well as accurately predict which people (customers) will be expensive. The dataset contains healthcare cost information from an HMO (Health Management Organization). Each row in the dataset represents a person. Your team's goal is to understand the key drivers for why some people are more expensive (i.e., require more health care), as well as predict which people will be expensive (in terms of health care costs). Hence, at a high level, you have two goals:

- Predict people who will spend a lot of money on health care next year (i.e., which people will have high healthcare costs).
- Provide actionable insight to the HMO, in terms of how to lower their total health care costs, by providing a specific recommendation on how to lower health care costs.

The following report consists of the following items:

1. Data exploration and cleaning
2. Data modeling, prediction and visualizations.
3. Actionable Insights.

The report includes the best working model, models which were tested and not selected. Few steps like using the str(), hist() are repeatedly used to check the new updates on the dataframes.

This report is a combined result of the team effort including:

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Business Overview

The dataset contains healthcare cost information from an HMO (Health Management Organization). Each row in the dataset represents a person. The goal is to understand the key drivers for why some people spend more on healthcare cost , as well as predict which people will be expensive in the next year.

Library

In [ ]:
```
# Setting up directory
dir.create('lib')

# Custom Function
EnsurePackage <- function(x){
  x <- as.character(x)
  if (!require(x, character.only = TRUE, lib.loc = 'lib/')){
    if (!require(x,character.only = TRUE)){
      install.packages(pkgs = x, lib = 'lib/', quiet = TRUE)
      require(x,character.only = TRUE, lib.loc = 'lib/')
    }
  }
}
```

In [ ]:
```
download.file('https://docs.google.com/uc?export=download&id=1FafesVrEhl6WMObKbbhMe
unzip('lib.zip')
```

In [1]:
```
EnsurePackage('imputeTS')
EnsurePackage('ggplot2')
EnsurePackage('Hmisc')
EnsurePackage('dplyr')
EnsurePackage('tidyverse')
EnsurePackage('caret')
EnsurePackage('kernlab')
EnsurePackage('maps')
EnsurePackage('mapproj')
EnsurePackage('ggmap')
EnsurePackage('R.utils')
EnsurePackage('httpuv')
EnsurePackage('googledrive')
# EnsurePackage('rio')
# EnsurePackage('kernlab')
```

In [ ]:
```
# files2zip <- dir('lib', full.names = TRUE)
# zip(zipfile = 'lib', files = files2zip)
```

Data Exploration and Processing

Task 1:

Predict people who will spend a lot of money on health care next year (i.e., which people will have high healthcare costs).

Downloading Data

In [ ]:
```
#storing the source data url
datafile_url <- "https://intro-datascience.s3.us-east-2.amazonaws.com/HMO_data.csv"
#using read.csv() to create dataframe
HMO_data = read.csv(url(datafile_url))
#top 6 rows for data overview
head(HMO_data)
```

A data.frame: 6 × 14

	X	age	bmi	children	smoker	location	location_type	education_level	yearly_p
	<int>	<int>	<dbl>	<int>	<chr>	<chr>	<chr>	<chr>	
1	1	18	27.900	0	yes	CONNECTICUT	Urban	Bachelor	
2	2	19	33.770	1	no	RHODE ISLAND	Urban	Bachelor	
3	3	27	33.000	3	no	MASSACHUSETTS	Urban	Master	
4	4	34	22.705	0	no	PENNSYLVANIA	Country	Master	
5	5	32	28.880	0	no	PENNSYLVANIA	Country	PhD	
6	7	47	33.440	1	no	PENNSYLVANIA	Urban	Bachelor	

In [ ]:
```
#metadata
str(HMO_data)
```

```
'data.frame':	7582 obs. of  14 variables:
 $ X              : int  1 2 3 4 5 7 9 10 11 12 ...
 $ age            : int  18 19 27 34 32 47 36 59 24 61 ...
 $ bmi            : num  27.9 33.8 33 22.7 28.9 ...
 $ children       : int  0 1 3 0 0 1 2 0 0 0 ...
 $ smoker         : chr  "yes" "no" "no" "no" ...
 $ location       : chr  "CONNECTICUT" "RHODE ISLAND" "MASSACHUSETTS" "PENNSYLVANI
A" ...
 $ location_type  : chr  "Urban" "Urban" "Urban" "Country" ...
 $ education_level: chr  "Bachelor" "Bachelor" "Master" "Master" ...
 $ yearly_physical: chr  "No" "No" "No" "No" ...
 $ exercise       : chr  "Active" "Not-Active" "Active" "Not-Active" ...
 $ married        : chr  "Married" "Married" "Married" "Married" ...
 $ hypertension   : int  0 0 0 1 0 0 0 1 0 0 ...
 $ gender         : chr  "female" "male" "male" "male" ...
 $ cost           : int  1746 602 576 5562 836 3842 1304 9724 201 4492 ...
```

Data Exploration

In [ ]:
```
# Making a copy of data
# We will be exploring and cleaning the copy of data
#converting categorical data into factor levels

df_HMO_data <- HMO_data
df_HMO_data$smoker <- as.factor(df_HMO_data$smoker)
df_HMO_data$location <- as.factor(df_HMO_data$location)
df_HMO_data$location_type <- as.factor(df_HMO_data$location_type)
df_HMO_data$education_level <- as.factor(df_HMO_data$education_level)
df_HMO_data$yearly_physical <- as.factor(df_HMO_data$yearly_physical)
df_HMO_data$exercise <- as.factor(df_HMO_data$exercise)
df_HMO_data$married <- as.factor(df_HMO_data$married)
df_HMO_data$gender <- as.factor(df_HMO_data$gender)

#metadata
str(df_HMO_data)
```

```
'data.frame':	7582 obs. of  14 variables:
 $ X              : int  1 2 3 4 5 7 9 10 11 12 ...
 $ age            : int  18 19 27 34 32 47 36 59 24 61 ...
 $ bmi            : num  27.9 33.8 33 22.7 28.9 ...
 $ children       : int  0 1 3 0 0 1 2 0 0 0 ...
 $ smoker         : Factor w/ 2 levels "no","yes": 2 1 1 1 1 1 1 1 1 2 ...
 $ location       : Factor w/ 7 levels "CONNECTICUT",..: 1 7 3 6 6 6 6 6 6 1 ...
 $ location_type  : Factor w/ 2 levels "Country","Urban": 2 2 2 1 1 2 2 1 2 2 ...
 $ education_level: Factor w/ 4 levels "Bachelor","Master",..: 1 1 2 2 4 1 1 1 1 3
...
 $ yearly_physical: Factor w/ 2 levels "No","Yes": 1 1 1 1 1 1 1 1 1 1 ...
 $ exercise       : Factor w/ 2 levels "Active","Not-Active": 1 2 1 2 2 2 1 2 1 1
...
 $ married        : Factor w/ 2 levels "Married","Not_Married": 1 1 1 1 1 1 1 1 1 1
...
 $ hypertension   : int  0 0 0 1 0 0 0 1 0 0 ...
 $ gender         : Factor w/ 2 levels "female","male": 1 2 2 2 2 1 2 1 2 1 ...
 $ cost           : int  1746 602 576 5562 836 3842 1304 9724 201 4492 ...
```

In [ ]:
```
#statistical information of the dataframe
summary(df_HMO_data)
```

```
       X                     age             bmi           children      smoker    
 Min.   :        1   Min.   :18.00   Min.   :15.96   Min.   :0.000   no :6103  
 1st Qu.:     5635   1st Qu.:26.00   1st Qu.:26.60   1st Qu.:0.000   yes:1479  
 Median :    24916   Median :39.00   Median :30.50   Median :1.000             
 Mean   :   712602   Mean   :38.89   Mean   :30.80   Mean   :1.109             
 3rd Qu.:   118486   3rd Qu.:51.00   3rd Qu.:34.77   3rd Qu.:2.000             
 Max.   :131101111   Max.   :66.00   Max.   :53.13   Max.   :5.000             
                                     NA's   :78                                
          location     location_type            education_level yearly_physical
 CONNECTICUT  : 611   Country:1903   Bachelor          :4578   No :5699       
 MARYLAND     : 747   Urban  :5679   Master            :1533   Yes:1883       
 MASSACHUSETTS: 465                  No College Degree: 759                   
 NEW JERSEY   : 498                  PhD               : 712                   
 NEW YORK     : 547                                                            
 PENNSYLVANIA :4010                                                            
 RHODE ISLAND : 704                                                            
       exercise            married       hypertension        gender    
 Active    :1888   Married    :5060   Min.   :0.0000   female:3662  
 Not-Active:5694   Not_Married:2522   1st Qu.:0.0000   male  :3920  
                                      Median :0.0000                
                                      Mean   :0.2005                
                                      3rd Qu.:0.0000                
                                      Max.   :1.0000                
                                      NA's   :80                    
      cost      
 Min.   :    2  
 1st Qu.:  970  
 Median : 2500  
 Mean   : 4043  
 3rd Qu.: 4775  
 Max.   :55715  
```

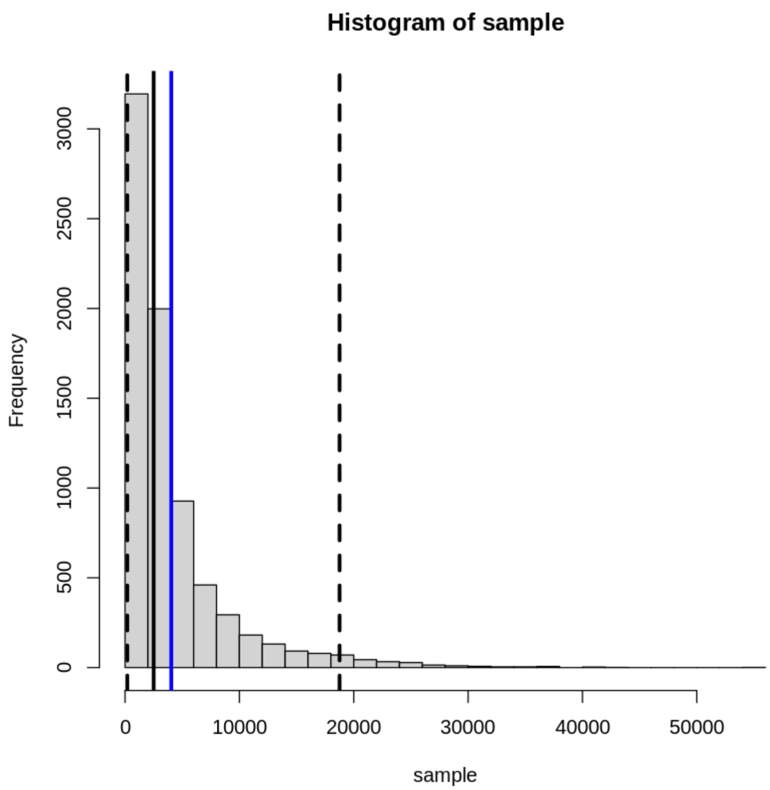
In [ ]:

```
# making a fuction to do the analysis
hist_plot <- function (sample, breaks = 30) {
  # Code
  # 2.5% Threshold
  # the value for 2.5 % Threshold
  min_quantile <- quantile(sample, 0.025, na.rm = TRUE)
  # 97.5% Threshold
  # the value for 97.5 % Threshold
  max_quantile <- quantile(sample, 0.975, na.rm = TRUE)

  # Sample mean
  sample_mean <- mean(sample, na.rm = TRUE)
  sample_median <- median(sample, na.rm = TRUE)

  # Displaying histogram
  hist(sample, breaks = breaks)
  abline(v=sample_mean, lwd=3, col= 'blue') # Population mean line
  abline(v=sample_median, lwd=3) # Population Median line
  abline(v=min_quantile, lwd=3, lty='dashed') # 2.5% line
  abline(v=max_quantile, lwd=3, lty='dashed') # 97.5% line
```

```
  print(paste('Mean:', sample_mean ))
}
```

In [ ]:
```
hist_plot(df_HMO_data$cost)
```

```
[1] "Mean: 4042.96122395146"
```



The blue line indicates the population median of cost at 2500.

The black solid line indicates the population mean of cost at 4043.

The dashed black line indicate the min and max quantile range

In [ ]:
```
# Checking for NAs

check_NA <- function(df){
  for (col in colnames(df)){
    print(paste(col,':', nrow(df[is.na(df[col]),])))
    # print(df[is.na(df[col]),])
  }
}

check_NA(df_HMO_data)

# df[is.na(df$LAPOP1_10),]
```

```
[1] "X : 0"
[1] "age : 0"
[1] "bmi : 78"
[1] "children : 0"
[1] "smoker : 0"
[1] "location : 0"
[1] "location_type : 0"
[1] "education_level : 0"
[1] "yearly_physical : 0"
[1] "exercise : 0"
[1] "married : 0"
[1] "hypertension : 80"
[1] "gender : 0"
[1] "cost : 0"
```

In [ ]:

```
#count of total NA values
nrow(df_HMO_data[((is.na(df_HMO_data$bmi)) | (is.na(df_HMO_data$hypertension))),])
```

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> There are 78 NA in "bmi" and 80 NA in "hypertension"

> These NA in different collumns do not overlap

> For "bmi", we can perform mean value imutation for "hypertension", we can set it to 0

we decided to use the mean interpolation method to fix the nas in the both columns.

In [ ]:

```
# Checking BMI Distribution across location
df_HMO_data %>% filter(!is.na(bmi)) %>% group_by(location) %>% summarise(bmi =mean(
```

A tibble: 7 × 2

location	bmi
<fct>	<dbl>
CONNECTICUT	30.55791
MARYLAND	30.67990
MASSACHUSETTS	30.64881
NEW JERSEY	30.59453
NEW YORK	30.92448
PENNSYLVANIA	30.89284
RHODE ISLAND	30.70580

> BMI of states are similar so we can apply a overall mean imputation

In [ ]:

```
# Checking BMI Distribution across smokers
```

```
df_HMO_data %>% filter(!is.na(bmi)) %>% group_by(smoker) %>% summarise(bmi =mean(bm
```

A tibble: 2 × 2

smoker	bmi
<fct>	<dbl>
no	30.79102
yes	30.81239

In [ ]:
```
# Checking BMI Distribution across smokers
df_HMO_data %>% filter(!is.na(bmi)) %>% group_by(smoker) %>% summarise(bmi =mean(bm
```

A tibble: 6 × 2

children	bmi
<int>	<dbl>
0	30.65592
1	31.15520
2	30.68532
3	31.09279
4	30.94867
5	27.75536

> We will be applying BMI imputation on overall mean

In [ ]:
```
# BMI Imputation
df_HMO_data$bmi <- na_interpolation(df_HMO_data$bmi)
# df_HMO_data$hypertension <- na_interpolation(df_HMO_data$hypertension)

# Null hypertension set to 0
df_HMO_data["hypertension"][is.na(df_HMO_data["hypertension"])] <- 0
```

In [ ]:
```
#data overview of 10 rows
head(df_HMO_data,10)
```

A data.frame: 10 × 14

	X	age	bmi	children	smoker	location	location_type	education_level	yearly_
	<int>	<int>	<dbl>	<int>	<fct>	<fct>	<fct>	<fct>	
1	1	18	27.900	0	yes	CONNECTICUT	Urban	Bachelor	
2	2	19	33.770	1	no	RHODE ISLAND	Urban	Bachelor	
3	3	27	33.000	3	no	MASSACHUSETTS	Urban	Master	
4	4	34	22.705	0	no	PENNSYLVANIA	Country	Master	
5	5	32	28.880	0	no	PENNSYLVANIA	Country	PhD	
6	7	47	33.440	1	no	PENNSYLVANIA	Urban	Bachelor	
7	9	36	29.830	2	no	PENNSYLVANIA	Urban	Bachelor	
8	10	59	25.840	0	no	PENNSYLVANIA	Country	Bachelor	
9	11	24	26.220	0	no	PENNSYLVANIA	Urban	Bachelor	
10	12	61	26.290	0	yes	CONNECTICUT	Urban	No College Degree	

Data Categorization

Cost Category

Expensive or not expensive based on cost median

In [ ]:
```
# Threshold
val_threshold <- median(df_HMO_data$cost)

cost_cat <- function(x){
  r <- case_when((is.na(x)) ~'NA'
    , (val_threshold < x) ~ 'Expensive'
    , (val_threshold >= x) ~ 'Inexpensive')
  return(r)
}
```

In [ ]:
```
```

Age Category

0 - 12: Child

13 - 19: Teen

20 - 30: Young Adult

30 - 50: Adult

50 - 70: Older Adult

70+ : Senior citizen

In [ ]:
```
age_cat <- function(x){
  r <- case_when((is.na(x)) ~'NA'
    , x < 13 ~ 'Child'
    , (x >= 13 & x < 20) ~ 'Teen'
    , (x >= 20 & x < 30) ~ 'Young Adult'
    , (x >= 30 & x < 50) ~ 'Adult'
    , (x >= 50 & x < 70) ~ 'Older Adult'
    , (x >= 70) ~ 'Senior citizen')
  return(r)
}
```

BMI Category

If your BMI is less than 18.5, it falls within the underweight range.

If your BMI is 18.5 to <25, it falls within the healthy weight range.

If your BMI is 25.0 to <30, it falls within the overweight range.

If your BMI is 30.0 or higher, it falls within the obesity range.\

In [ ]:
```
bmi_cat <- function(x){
  r <- case_when((is.na(x)) ~'NA'
    , x < 18.5 ~ 'Underweight'
    , (x >= 18.5 & x < 25.0) ~ 'Healthy'
    , (x >= 25.0 & x < 30.0) ~ 'Overweight'
    , (x >= 30.0) ~ 'Obese')
  return(r)
}
```

Children Category

'> 2 Children: more than 2

'< 2 Children: less than 2

'= 0 Children: no children

In [ ]:
```
#statistical information
summary(df_HMO_data$children)
```

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
  0.000   0.000   1.000   1.109   2.000   5.000 
```

In [ ]:
```
child_cat <- function(x){
  r <- case_when((is.na(x)) ~ 'NA'
    , (x == 0) ~ 'no children'
    , (x > 0 & x <=2) ~ '2 or less'
    , (x > 2) ~ 'more than 2')
  return(r)
}
```

In [ ]:
```
# testing
child_cat(4)
```

'more than 2'

Applying Categories

In [ ]:
```
# Cost Category
df_HMO_data <- df_HMO_data %>% mutate(cost_category = as.factor(cost_cat(cost)))

# Age Category
df_HMO_data <- df_HMO_data %>% mutate(age_category = as.factor(age_cat(age)))

# BMI Category
df_HMO_data <- df_HMO_data %>% mutate(bmi_category = as.factor(bmi_cat(bmi)))

# Child Category
df_HMO_data <- df_HMO_data %>% mutate(child_category = as.factor(child_cat(children
```

In [ ]:
```
# Function to label class
class_label_gen <- function(data, num_bins){
  num_bins = num_bins-1
  # calculate the bin width
  bin_width <- ceiling((max(data) - min(data)) / num_bins)

  # create the bin labels
  bin_labels <- paste0(min(data) + (0:num_bins) * bin_width, "-", min(data) + (1:nu
  # bin_labels <- min(data) + (0:num_bins) * bin_width

  return(bin_labels)
}
```

In [ ]:
```
# Cost Class range
#creating new column segregating cost in classes
break_n = 10
df_HMO_data$cost_class <- cut(df_HMO_data$cost, breaks = break_n, labels = class_la
```

In [ ]:
```
#overview of top 6 rows
head(df_HMO_data)
```

	X	age	bmi	children	smoker	location	location_type	education_level	yearly_p
	<int>	<int>	<dbl>	<int>	<fct>	<chr>	<fct>	<fct>	
1	1	18	27.900	0	yes	CONNECTICUT	Urban	Bachelor	
2	2	19	33.770	1	no	RHODE ISLAND	Urban	Bachelor	
3	3	27	33.000	3	no	MASSACHUSETTS	Urban	Master	
4	4	34	22.705	0	no	PENNSYLVANIA	Country	Master	
5	5	32	28.880	0	no	PENNSYLVANIA	Country	PhD	
6	7	47	33.440	1	no	PENNSYLVANIA	Urban	Bachelor	

In [ ]:

```
#metadata
str(df_HMO_data)
```

```
'data.frame':	7582 obs. of  19 variables:
 $ X              : int  1 2 3 4 5 7 9 10 11 12 ...
 $ age            : int  18 19 27 34 32 47 36 59 24 61 ...
 $ bmi            : num  27.9 33.8 33 22.7 28.9 ...
 $ children       : int  0 1 3 0 0 1 2 0 0 0 ...
 $ smoker         : Factor w/ 2 levels "no","yes": 2 1 1 1 1 1 1 1 1 2 ...
 $ location       : chr  "CONNECTICUT" "RHODE ISLAND" "MASSACHUSETTS" "PENNSYLVANI
A" ...
 $ location_type  : Factor w/ 2 levels "Country","Urban": 2 2 2 1 1 2 2 1 2 2 ...
 $ education_level: Factor w/ 4 levels "Bachelor","Master",..: 1 1 2 2 4 1 1 1 1 3
...
 $ yearly_physical: Factor w/ 2 levels "No","Yes": 1 1 1 1 1 1 1 1 1 1 ...
 $ exercise       : Factor w/ 2 levels "Active","Not-Active": 1 2 1 2 2 2 1 2 1 1
...
 $ married        : Factor w/ 2 levels "Married","Not_Married": 1 1 1 1 1 1 1 1 1 1
...
 $ hypertension   : num  0 0 0 1 0 0 0 1 0 0 ...
 $ gender         : Factor w/ 2 levels "female","male": 1 2 2 2 2 1 2 1 2 1 ...
 $ cost           : int  1746 602 576 5562 836 3842 1304 9724 201 4492 ...
 $ cost_category  : Factor w/ 2 levels "Expensive","Inexpensive": 2 2 2 1 2 1 2 1 2
1 ...
 $ age_category   : Factor w/ 4 levels "Adult","Older Adult",..: 3 3 4 1 1 1 1 2 4
2 ...
 $ bmi_category   : Factor w/ 4 levels "Healthy","Obese",..: 3 2 2 1 3 2 3 3 3 3
...
 $ child_category : Factor w/ 3 levels "2 or less","more than 2",..: 3 1 2 3 3 1 1
3 3 3 ...
 $ cost_class     : Factor w/ 10 levels "2-6192","6193-12383",..: 1 1 1 1 1 1 1 2 1
1 ...
```

Making deciles cateogroies

In [ ]:
```
# Calculting deciles
# deciling patients based on cost
df_HMO_data$cost_decile <- as.factor(ntile(-df_HMO_data$cost, 10))#, weights = df_H
```

In [ ]:
```
#overview of top 6 rows
head(df_HMO_data)
```

	X	age	bmi	children	smoker	location	location_type	education_level	yearly_p
	<int>	<int>	<dbl>	<int>	<fct>	<chr>	<fct>	<fct>	
1	1	18	27.900	0	yes	CONNECTICUT	Urban	Bachelor	
2	2	19	33.770	1	no	RHODE ISLAND	Urban	Bachelor	
3	3	27	33.000	3	no	MASSACHUSETTS	Urban	Master	
4	4	34	22.705	0	no	PENNSYLVANIA	Country	Master	
5	5	32	28.880	0	no	PENNSYLVANIA	Country	PhD	
6	7	47	33.440	1	no	PENNSYLVANIA	Urban	Bachelor	

In [ ]:
```
# Decile stats
df_top_spenders <- df_HMO_data %>%  group_by(cost_decile) %>%
  summarise(count = n_distinct(X), avg_cost =mean(cost), sum_cost = sum(cost)) %>%
    summarise(cost_decile, count, avg_cost, sum_cost
    , cum_sum_cost = cumsum(sum_cost)
    , patient_perc = round(100*cumsum(count)/sum(count),2)
    , cost_perc = round(100*cumsum(sum_cost)/sum(sum_cost),2))

df_top_spenders
```

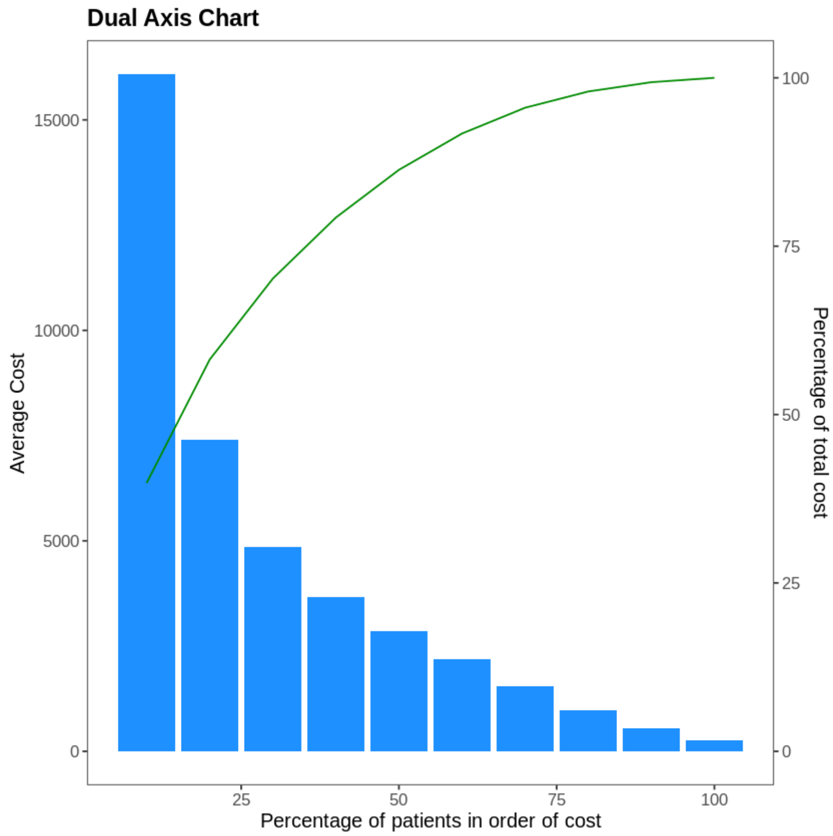
```
Warning message:
“Returning more (or less) than 1 row per `summarise()` group was deprecated in
dplyr 1.1.0.
ℹ Please use `reframe()` instead.
ℹ When switching from `summarise()` to `reframe()`, remember that `reframe()`
  always returns an ungrouped data frame and adjust accordingly.”
```

A tibble: 10 × 7

cost_decile	count	avg_cost	sum_cost	cum_sum_cost	patient_perc	cost_perc
<fct>	<int>	<dbl>	<int>	<int>	<dbl>	<dbl>
1	759	16085.6653	12209020	12209020	10.01	39.83
2	759	7411.7194	5625495	17834515	20.02	58.18
3	758	4856.0369	3680876	21515391	30.02	70.19
4	758	3668.7084	2780881	24296272	40.02	79.26
5	758	2862.6755	2169908	26466180	50.01	86.34
6	758	2180.5198	1652834	28119014	60.01	91.73
7	758	1547.9644	1173357	29292371	70.01	95.56
8	758	973.6913	738058	30030429	80.01	97.97
9	758	557.7124	422746	30453175	90.00	99.35
10	758	264.5871	200557	30653732	100.00	100.00

In [ ]:

```r
# Create the plot
my_plot <- ggplot(df_top_spenders, aes(x = patient_perc))


# Add the second y-axis (left)
my_plot <- my_plot + geom_bar(aes(y = avg_cost), stat = "identity", fill = "dodgerb


# Add the first y-axis (right)
my_plot <- my_plot + geom_line(aes(y = cost_perc*160), color = "green4")

my_plot <- my_plot + scale_y_continuous(
  name = "Average Cost",
  sec.axis = sec_axis(~ ./160, name = "Percentage of total cost")
)

# Add labels and titles
my_plot <- my_plot + labs(x = "Percentage of patients in order of cost", y = "Perce
my_plot <- my_plot + ggtitle("Dual Axis Chart")

# Customize the theme
my_plot <- my_plot + theme_bw() + theme(
  plot.title = element_text(size = 14, face = "bold"),
  axis.title.x = element_text(size = 12),
  axis.title.y = element_text(size = 12),
  axis.text = element_text(size = 10),
  panel.grid.major = element_blank(),
  panel.grid.minor = element_blank(),
  legend.position = "none"
)

# Display the plot
my_plot
```



> The table summarizes the patient count, average cost, total cost, cumulative total cost, percentage of patients, and percentage of costs for each cost decile.

> 10% of the top paying patients contribute to approx 40% of the overall cost.

> 40% of the top paying patients contribute to approx 60% of the overall cost

The green line indicates the bin percentage out of the total percentage. It eventually goes to 100 as the bins increase.

The blue bars represent each decile's cost value.

In [ ]:
```
#data overview
head(df_HMO_data)
```

	X	age	bmi	children	smoker	location	location_type	education_level	yearly_p
	<int>	<int>	<dbl>	<int>	<fct>	<chr>	<fct>	<fct>	
1	1	18	27.900	0	yes	CONNECTICUT	Urban	Bachelor	
2	2	19	33.770	1	no	RHODE ISLAND	Urban	Bachelor	
3	3	27	33.000	3	no	MASSACHUSETTS	Urban	Master	
4	4	34	22.705	0	no	PENNSYLVANIA	Country	Master	
5	5	32	28.880	0	no	PENNSYLVANIA	Country	PhD	
6	7	47	33.440	1	no	PENNSYLVANIA	Urban	Bachelor	

In [ ]:

```
#statistical information for top 2 cost_deciles
summary(df_HMO_data[which(df_HMO_data$cost_decile %in% c('1', '2')),])
```

```
       X                  age             bmi           children      smoker  
 Min.   :       10   Min.   :18.00   Min.   :17.77   Min.   :0.000   no :528  
 1st Qu.:     5405   1st Qu.:36.00   1st Qu.:29.83   1st Qu.:0.000   yes:990  
 Median :    22826   Median :47.00   Median :33.33   Median :1.000            
 Mean   :   838977   Mean   :45.11   Mean   :33.10   Mean   :1.227            
 3rd Qu.:   115611   3rd Qu.:57.00   3rd Qu.:36.77   3rd Qu.:2.000            
 Max.   :114211111   Max.   :66.00   Max.   :52.58   Max.   :5.000            
                                                                              
   location         location_type          education_level yearly_physical
 Length:1518        Country: 386   Bachelor         :907   No :1123       
 Class :character   Urban  :1132   Master           :291   Yes: 395       
 Mode  :character                  No College Degree:166                  
                                   PhD              :154                  
                                                                          
                                                                          
       exercise          married      hypertension       gender   
 Active    : 195   Married    :1002   Min.   :0.0000   female:629  
 Not-Active:1323   Not_Married: 516   1st Qu.:0.0000   male  :889  
                                      Median :0.0000               
                                      Mean   :0.2312               
                                      3rd Qu.:0.0000               
                                      Max.   :1.0000               
                                                                   
      cost          cost_category       age_category      bmi_category 
 Min.   : 5779   Expensive  :1518   Adult      :620   Healthy    : 133  
 1st Qu.: 7228   Inexpensive:   0   Older Adult:644   Obese      :1114  
 Median : 9602                      Teen       : 76   Overweight : 261  
 Mean   :11749                      Young Adult:178   Underweight:  10  
 3rd Qu.:14246                                                          
 Max.   :55715                                                          
                                                                        
     child_category       cost_class   cost_decile
 2 or less  :680    6193-12383 :920   1      :759  
 more than 2:267    12384-18574:325   2      :759  
 no children:571    18575-24765:172   3      :  0  
                    24766-30956: 64   4      :  0  
                    30957-37147: 21   5      :  0  
                    37148-43338: 11   6      :  0  
                    (Other)    :  5   (Other):  0  
```

> Most of the high payers are **obese** and of age category of **adult** and **older adult**.

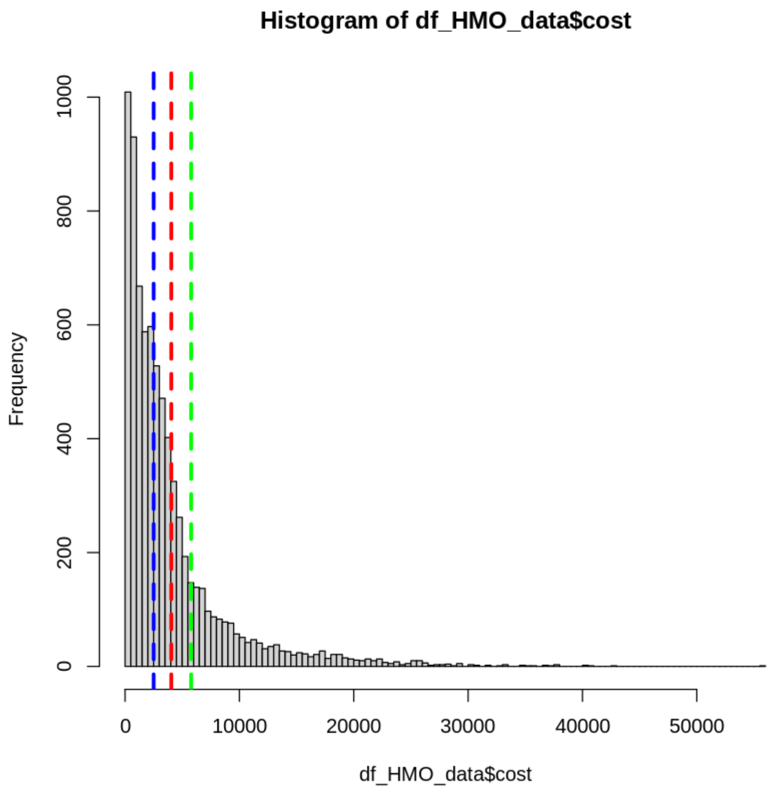
In [ ]:

Plots

Histograms

Plot: Cost Histogram

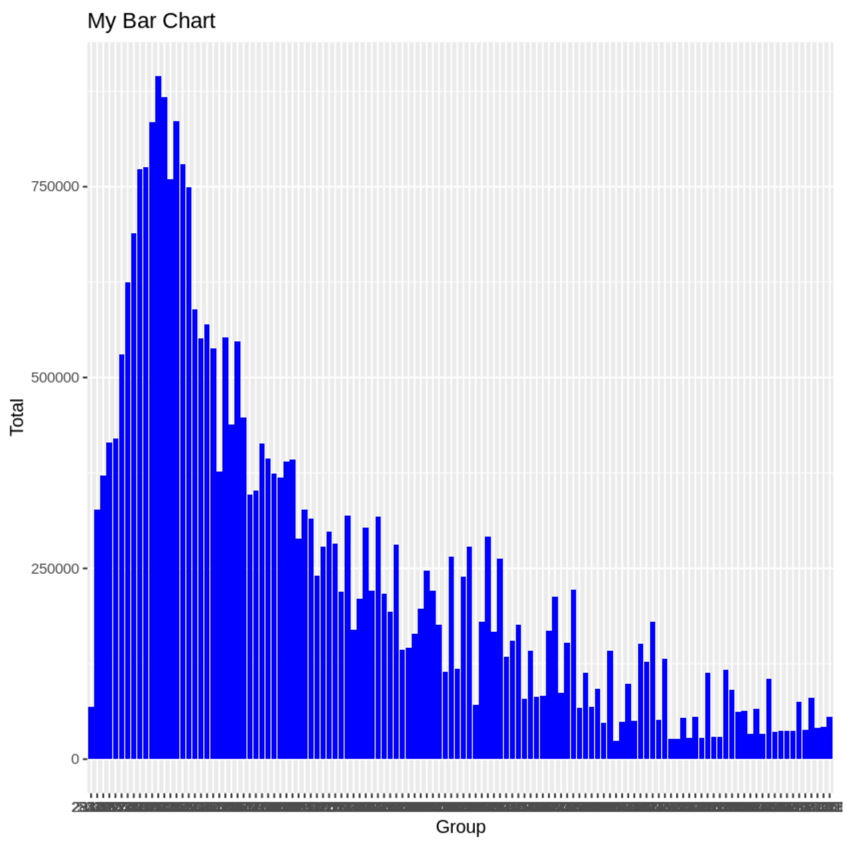
In [ ]:
```
# Histogram of cost distibution
hist(df_HMO_data$cost, breaks = 100)#, xlim = c(0,10000))
#abline for mean
abline(v=mean(df_HMO_data$cost), col='red', lwd=3, lty='dashed')
#abline for median
abline(v=median(df_HMO_data$cost), col='blue', lwd=3, lty='dashed')
#abline showing 80th percentile
abline(v=quantile(df_HMO_data$cost, c(.8)), col='Green', lwd=3, lty='dashed')
```



The cost is right skewed indicating majority of the cost is concentrated in the first few deciles of the population.

In [ ]:
```
n = 200

#create visualization of the distribution of costs across different categories,
df_HMO_data$cost_categories <- cut(df_HMO_data$cost, breaks = n, labels = class_lab

freq_table <- df_HMO_data %>% group_by(cost_categories) %>% summarise(cost = sum(co

# create a bar chart of the frequency table
ggplot(freq_table, aes(x = cost_categories, y = cost)) +
```

```
  geom_bar(stat = "identity", fill = "blue") +
  labs(title = "My Bar Chart", x = "Group", y = "Total")
```



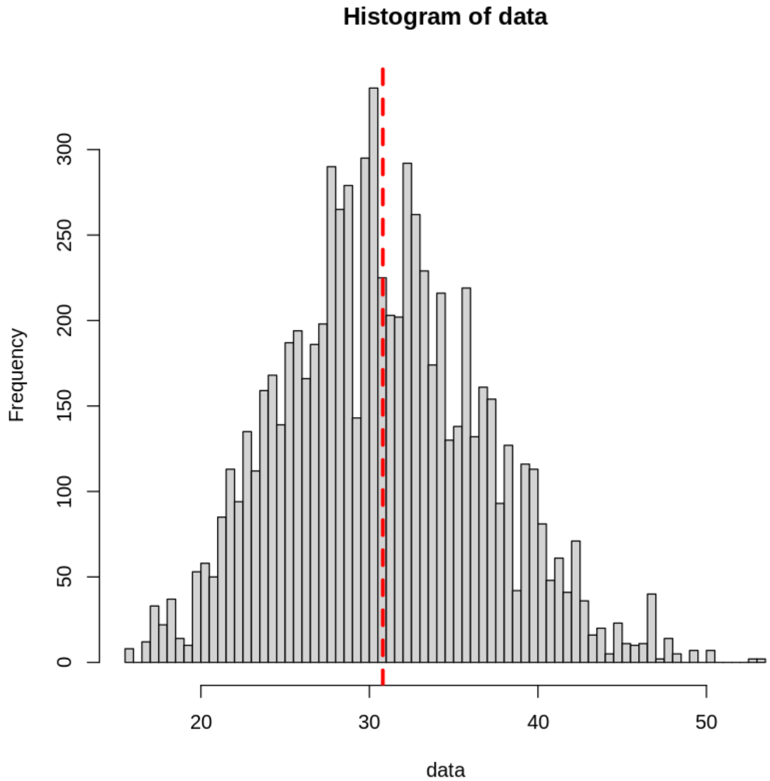
In [ ]:
```
#cost distrubution for maximum cost
freq_table[which.max(freq_table$cost),]
```

A tibble: 1 × 2

cost_categories	cost
<fct>	<int>
3082-3361	894432

Histogram of BMI Distribution

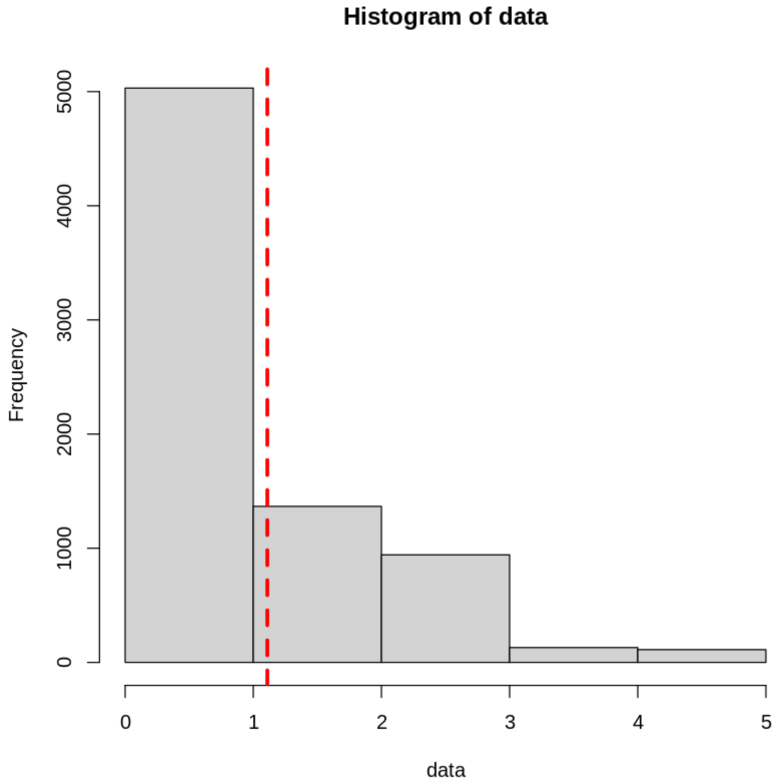
In [ ]:
```
# BMI

data = df_HMO_data$bmi
hist(data, breaks = 100)
abline(v=mean(data), col='red', lwd=3, lty='dashed')
```



Red line indicating the mean of the bmi

Histogram: children

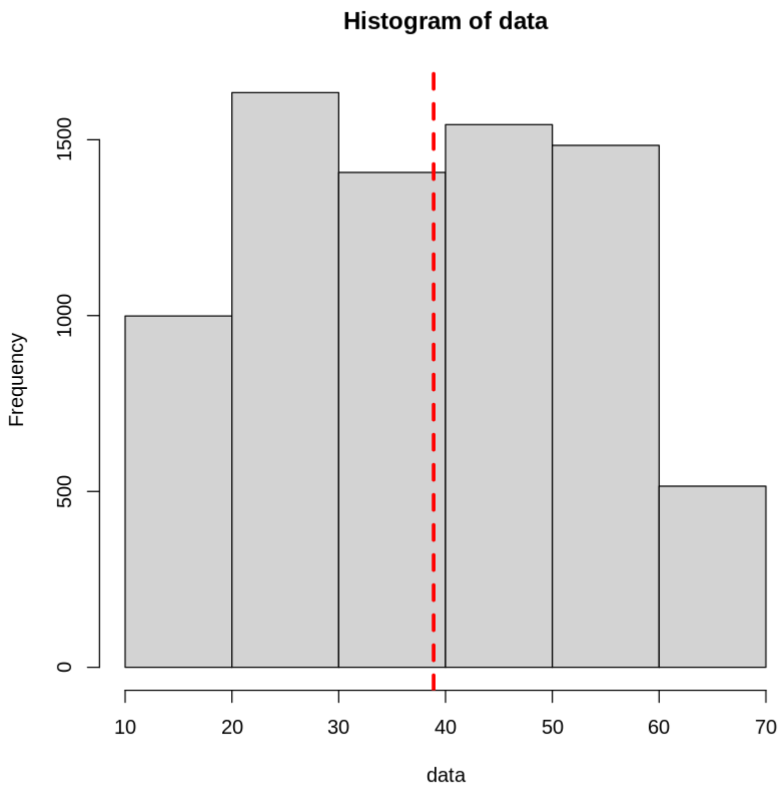
In [ ]:
```
# Children

data = df_HMO_data$children
hist(data, breaks = 6)
abline(v=mean(data), col='red', lwd=3, lty='dashed')
```



Red line indicating the mean of the no. of children

Histogram: Age

In [ ]:
```
# Age

data = df_HMO_data$age
hist(data, breaks = 6)
abline(v=mean(data), col='red', lwd=3, lty='dashed')
```



Red line indicating the mean of the age

In [ ]:
```
#metadata
str(df_HMO_data)
```

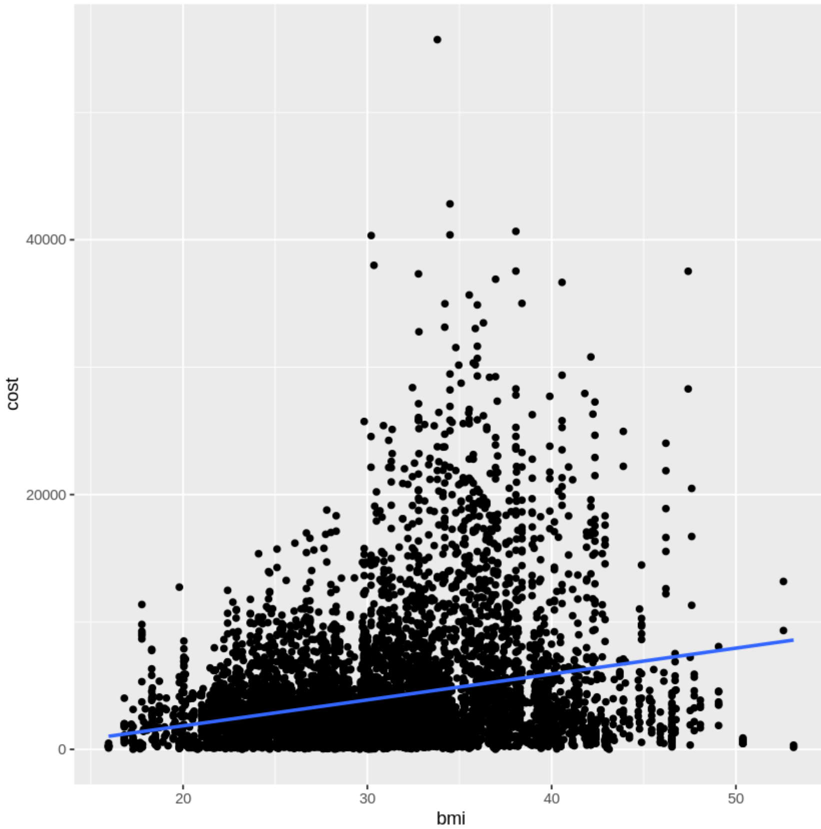
```
'data.frame':	7582 obs. of  21 variables:
 $ X              : int  1 2 3 4 5 7 9 10 11 12 ...
 $ age            : int  18 19 27 34 32 47 36 59 24 61 ...
 $ bmi            : num  27.9 33.8 33 22.7 28.9 ...
 $ children       : int  0 1 3 0 0 1 2 0 0 0 ...
 $ smoker         : Factor w/ 2 levels "no","yes": 2 1 1 1 1 1 1 1 1 2 ...
 $ location       : chr  "CONNECTICUT" "RHODE ISLAND" "MASSACHUSETTS" "PENNSYLVANI
A" ...
 $ location_type  : Factor w/ 2 levels "Country","Urban": 2 2 2 1 1 2 2 1 2 2 ...
 $ education_level: Factor w/ 4 levels "Bachelor","Master",..: 1 1 2 2 4 1 1 1 1 3
...
 $ yearly_physical: Factor w/ 2 levels "No","Yes": 1 1 1 1 1 1 1 1 1 1 ...
 $ exercise       : Factor w/ 2 levels "Active","Not-Active": 1 2 1 2 2 2 1 2 1 1
...
 $ married        : Factor w/ 2 levels "Married","Not_Married": 1 1 1 1 1 1 1 1 1 1
...
 $ hypertension   : num  0 0 0 1 0 0 0 1 0 0 ...
 $ gender         : Factor w/ 2 levels "female","male": 1 2 2 2 2 1 2 1 2 1 ...
 $ cost           : int  1746 602 576 5562 836 3842 1304 9724 201 4492 ...
 $ cost_category  : Factor w/ 2 levels "Expensive","Inexpensive": 2 2 2 1 2 1 2 1 2
1 ...
 $ age_category   : Factor w/ 4 levels "Adult","Older Adult",..: 3 3 4 1 1 1 1 2 4
2 ...
 $ bmi_category   : Factor w/ 4 levels "Healthy","Obese",..: 3 2 2 1 3 2 3 3 3 3
...
 $ child_category : Factor w/ 3 levels "2 or less","more than 2",..: 3 1 2 3 3 1 1
3 3 3 ...
 $ cost_class     : Factor w/ 10 levels "2-6192","6193-12383",..: 1 1 1 1 1 1 1 2 1
1 ...
 $ cost_decile    : Factor w/ 10 levels "1","2","3","4",..: 7 9 9 3 8 4 7 1 10 3
...
 $ cost_categories: Factor w/ 200 levels "2-281","282-561",..: 7 3 3 20 3 14 5 35 1
17 ...
```

Scatter plots

Scatter plot of BMI and Cost

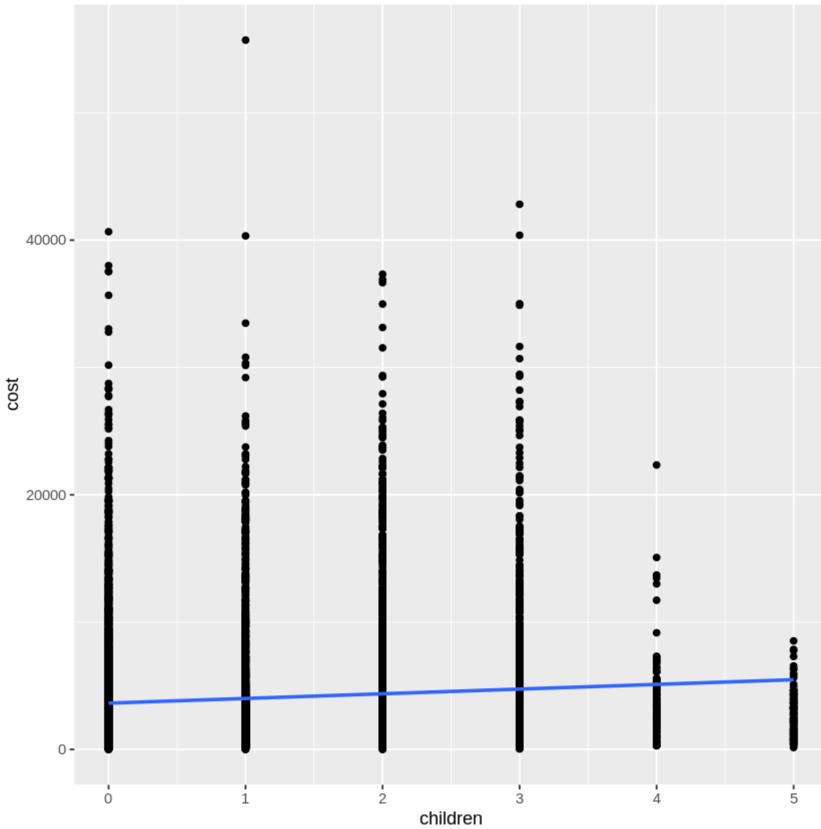
In [ ]:
```r
# BMI
ggplot(data=df_HMO_data) + aes(x=bmi, y=cost) + geom_point() +
 geom_smooth(method="lm", se=FALSE)
#line fitting the linear equation
```

```
`geom_smooth()` using formula = 'y ~ x'
```



In [ ]:
```
# AGE
ggplot(data=df_HMO_data) + aes(x=children, y=cost) + geom_point() +
 geom_smooth(method="lm", se=FALSE)
#line fitting the linear equation
```

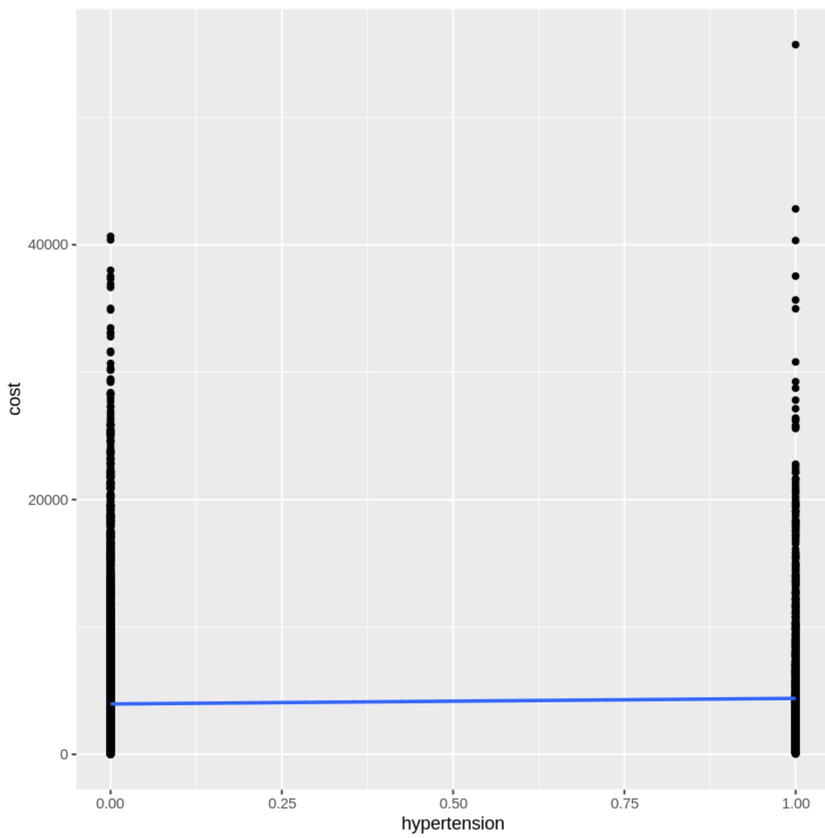
```
`geom_smooth()` using formula = 'y ~ x'
```



In [ ]:

```
# hypertension
ggplot(data=df_HMO_data) + aes(x=hypertension, y=cost) + geom_point() +
 geom_smooth(method="lm", se=FALSE)
#line fitting the linear equation
```

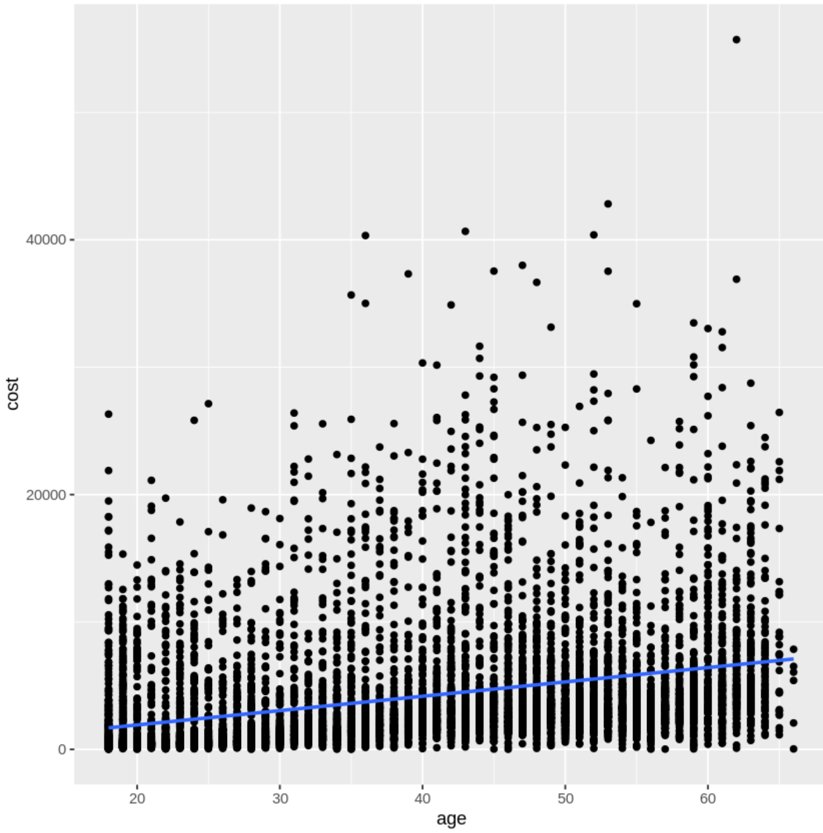
```
`geom_smooth()` using formula = 'y ~ x'
```



In [ ]:

```
# Children
ggplot(data=df_HMO_data) + aes(x=age, y=cost) + geom_point() +
 geom_smooth(method="lm", se=FALSE)
#line fitting the linear equation
```

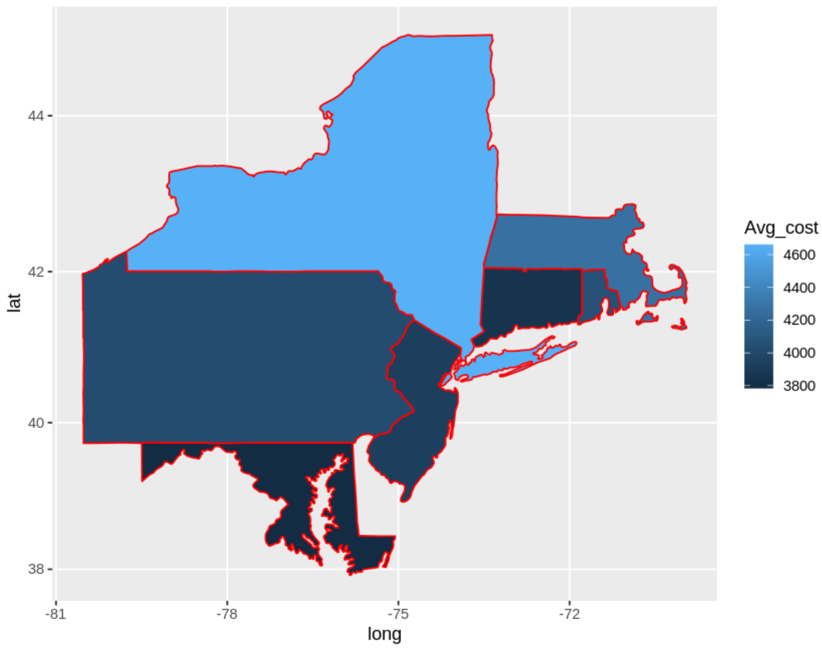
```
`geom_smooth()` using formula = 'y ~ x'
```



Plot: GGmap location and Cost

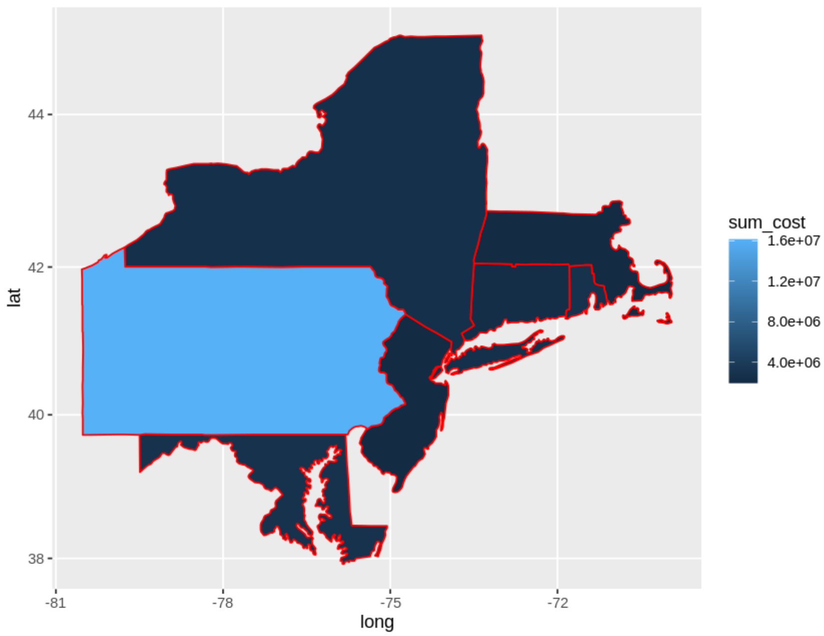
```
In [ ]: EnsurePackage('ggplot2')
        EnsurePackage('maps')
        EnsurePackage('mapproj')
        EnsurePackage('ggmap')
        EnsurePackage('tidyverse')
```

```
In [ ]: #map plot for location and average cost data
        GroupedData <- df_HMO_data%>%group_by(location)%>%summarise(Avg_cost =mean(cost))
        state <- map_data("state")
        # colnames(GroupedData)[6]<- "region"
        GroupedData$region <- GroupedData$location
        GroupedData$region <- tolower(GroupedData$region)
        MergedData <- merge(state,GroupedData, on="region")
        MergedData <- MergedData%>%arrange(order)
        #To create a filled map
        MyMap <- ggplot(MergedData)+coord_map()+geom_polygon(aes(x=long,y=lat,group=group,
        MyMap
```



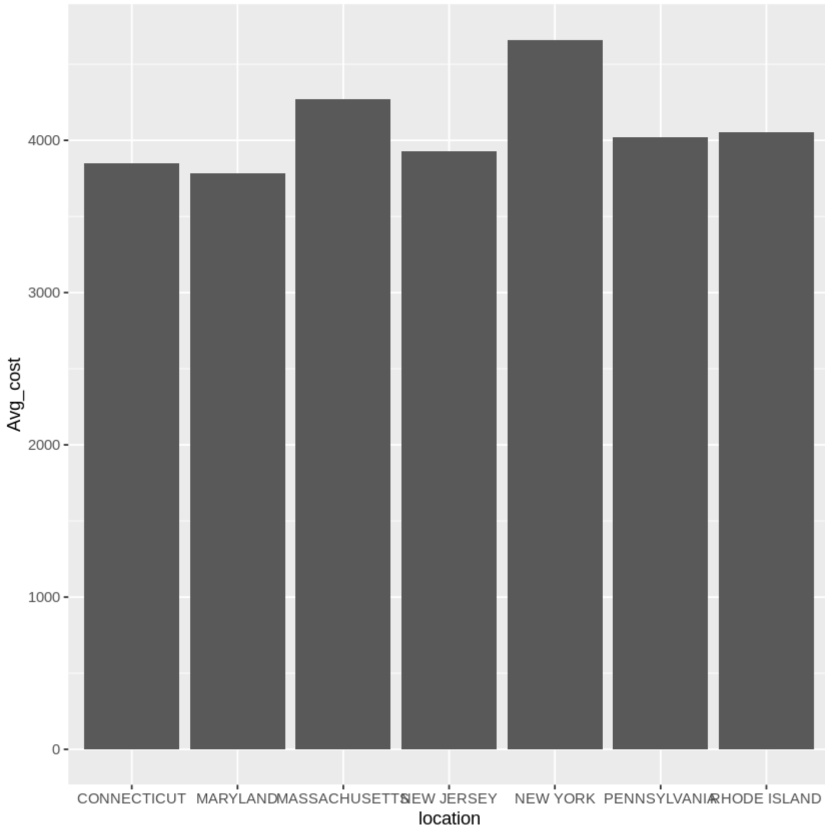
In [ ]:

```
#map plot for location and total cost data
GroupedData <- df_HMO_data%>%group_by(location)%>%summarise(sum_cost =sum(cost))
state <- map_data("state")
# colnames(GroupedData)[6]<- "region"
GroupedData$region <- GroupedData$location
GroupedData$region <- tolower(GroupedData$region)
MergedData <- merge(state,GroupedData, on="region")
MergedData <- MergedData%>%arrange(order)
#To create a filled map
MyMap <- ggplot(MergedData)+coord_map()+geom_polygon(aes(x=long,y=lat,group=group,
MyMap
```



Plot:

In [ ]:
```
#Location and average cost
GroupedData <- df_HMO_data%>%group_by(location)%>%summarise(Avg_cost =mean(cost))

ggplot(data=GroupedData, aes(x=location, y=Avg_cost)) + geom_bar(stat="identity")
```



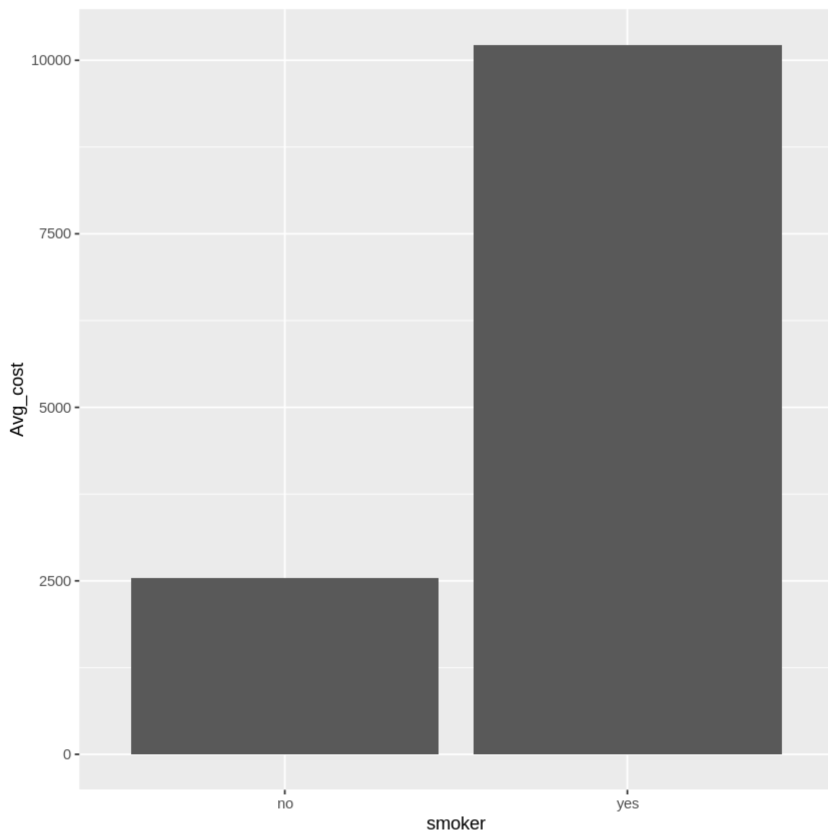
In [ ]:

```
#metadata
str(df_HMO_data)
```

```
'data.frame':	7582 obs. of  21 variables:
 $ X              : int  1 2 3 4 5 7 9 10 11 12 ...
 $ age            : int  18 19 27 34 32 47 36 59 24 61 ...
 $ bmi            : num  27.9 33.8 33 22.7 28.9 ...
 $ children       : int  0 1 3 0 0 1 2 0 0 0 ...
 $ smoker         : Factor w/ 2 levels "no","yes": 2 1 1 1 1 1 1 1 1 2 ...
 $ location       : chr  "CONNECTICUT" "RHODE ISLAND" "MASSACHUSETTS" "PENNSYLVANI
A" ...
 $ location_type  : Factor w/ 2 levels "Country","Urban": 2 2 2 1 1 2 2 1 2 2 ...
 $ education_level: Factor w/ 4 levels "Bachelor","Master",..: 1 1 2 2 4 1 1 1 1 3
...
 $ yearly_physical: Factor w/ 2 levels "No","Yes": 1 1 1 1 1 1 1 1 1 1 ...
 $ exercise       : Factor w/ 2 levels "Active","Not-Active": 1 2 1 2 2 2 1 2 1 1
...
 $ married        : Factor w/ 2 levels "Married","Not_Married": 1 1 1 1 1 1 1 1 1 1
...
 $ hypertension   : num  0 0 0 1 0 0 0 1 0 0 ...
 $ gender         : Factor w/ 2 levels "female","male": 1 2 2 2 2 1 2 1 2 1 ...
 $ cost           : int  1746 602 576 5562 836 3842 1304 9724 201 4492 ...
 $ cost_category  : Factor w/ 2 levels "Expensive","Inexpensive": 2 2 2 1 2 1 2 1 2
1 ...
 $ age_category   : Factor w/ 4 levels "Adult","Older Adult",..: 3 3 4 1 1 1 1 2 4
2 ...
 $ bmi_category   : Factor w/ 4 levels "Healthy","Obese",..: 3 2 2 1 3 2 3 3 3 3
...
 $ child_category : Factor w/ 3 levels "2 or less","more than 2",..: 3 1 2 3 3 1 1
3 3 3 ...
 $ cost_class     : Factor w/ 10 levels "2-6192","6193-12383",..: 1 1 1 1 1 1 1 2 1
1 ...
 $ cost_decile    : Factor w/ 10 levels "1","2","3","4",..: 7 9 9 3 8 4 7 1 10 3
...
 $ cost_categories: Factor w/ 200 levels "2-281","282-561",..: 7 3 3 20 3 14 5 35 1
17 ...
```

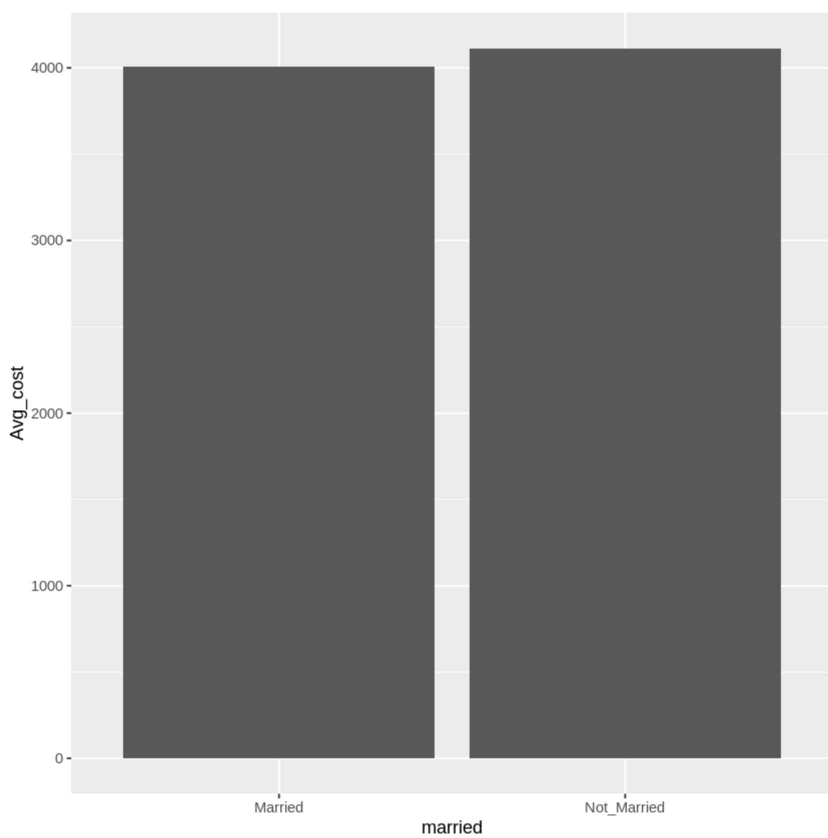
In [ ]:

```r
#smoker and average cost
GroupedData1 <- df_HMO_data%>%group_by(smoker)%>%summarise(Avg_cost =mean(cost))

ggplot(data=GroupedData1, aes(x=smoker, y=Avg_cost)) + geom_bar(stat="identity")
```

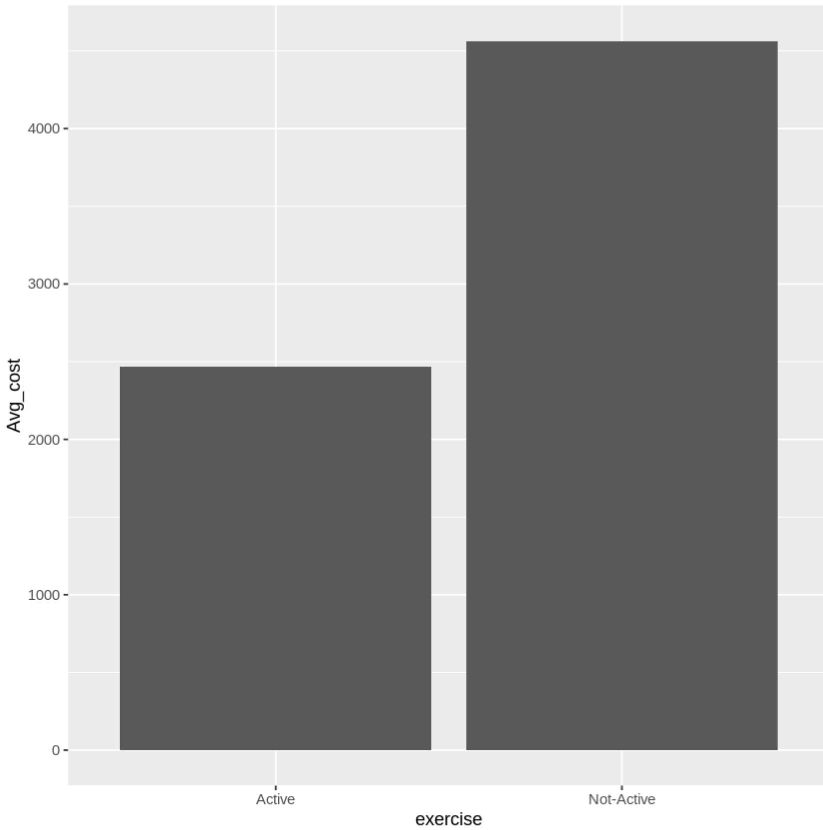


In [ ]:

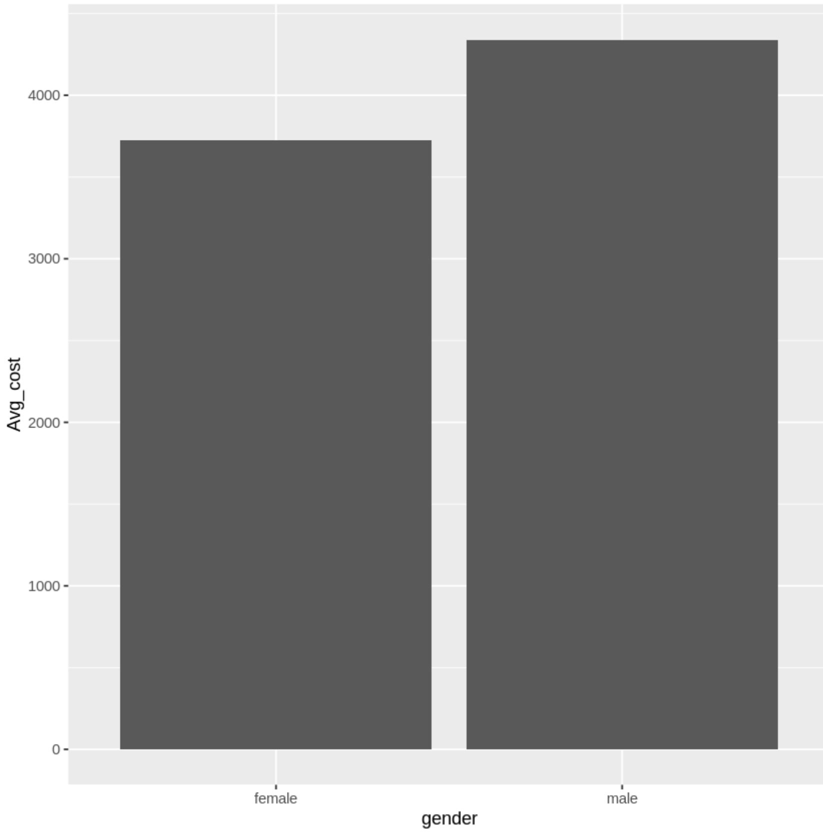
```
#Marital Status and Average Cost
GroupedData2 <- df_HMO_data%>%group_by(married)%>%summarise(Avg_cost =mean(cost))

ggplot(data=GroupedData2, aes(x=married, y=Avg_cost)) + geom_bar(stat="identity")
```



In [ ]:
```
#Exercise and Average Cost
GroupedData3 <- df_HMO_data%>%group_by(exercise)%>%summarise(Avg_cost =mean(cost))

ggplot(data=GroupedData3, aes(x=exercise, y=Avg_cost)) + geom_bar(stat="identity")
```

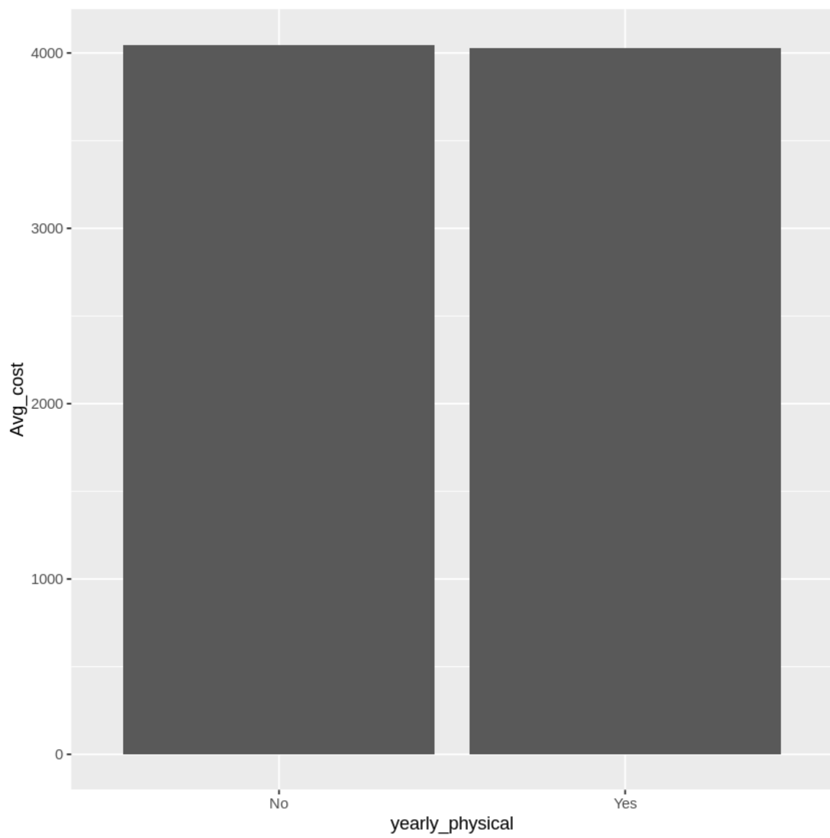


In [ ]:
```
#Gender and Average Cost
GroupedData4 <- df_HMO_data%>%group_by(gender)%>%summarise(Avg_cost =mean(cost))

ggplot(data=GroupedData4, aes(x=gender, y=Avg_cost)) + geom_bar(stat="identity")
```



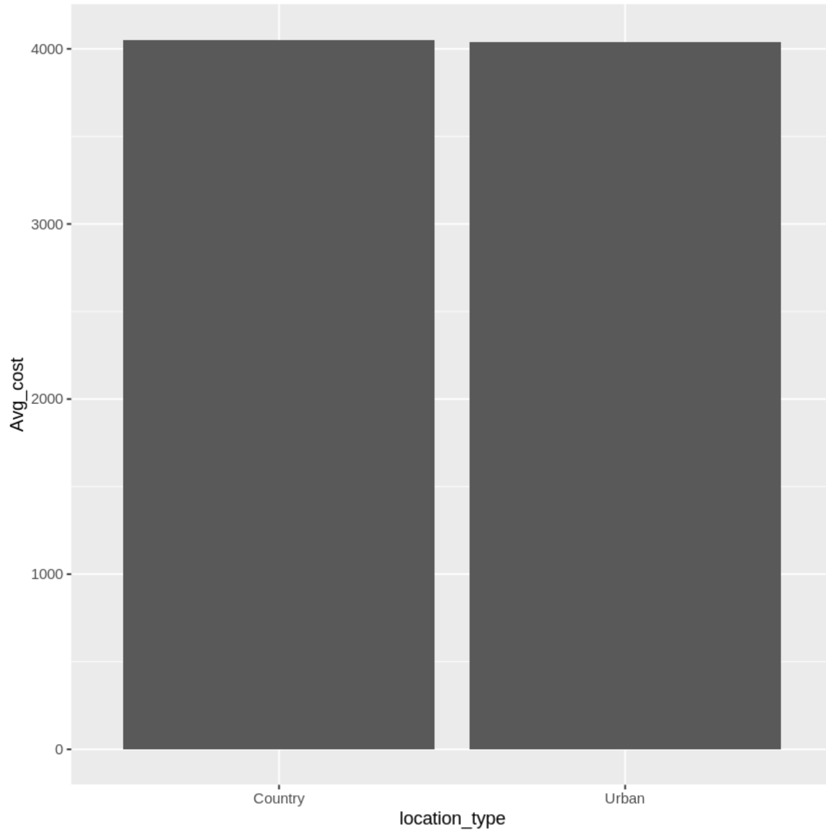
In [ ]:

```
# yearly_physical and average cost

GroupedData4 <- df_HMO_data%>%group_by(yearly_physical)%>%summarise(Avg_cost =mean(

ggplot(data=GroupedData4, aes(x=yearly_physical, y=Avg_cost)) + geom_bar(stat="iden
```

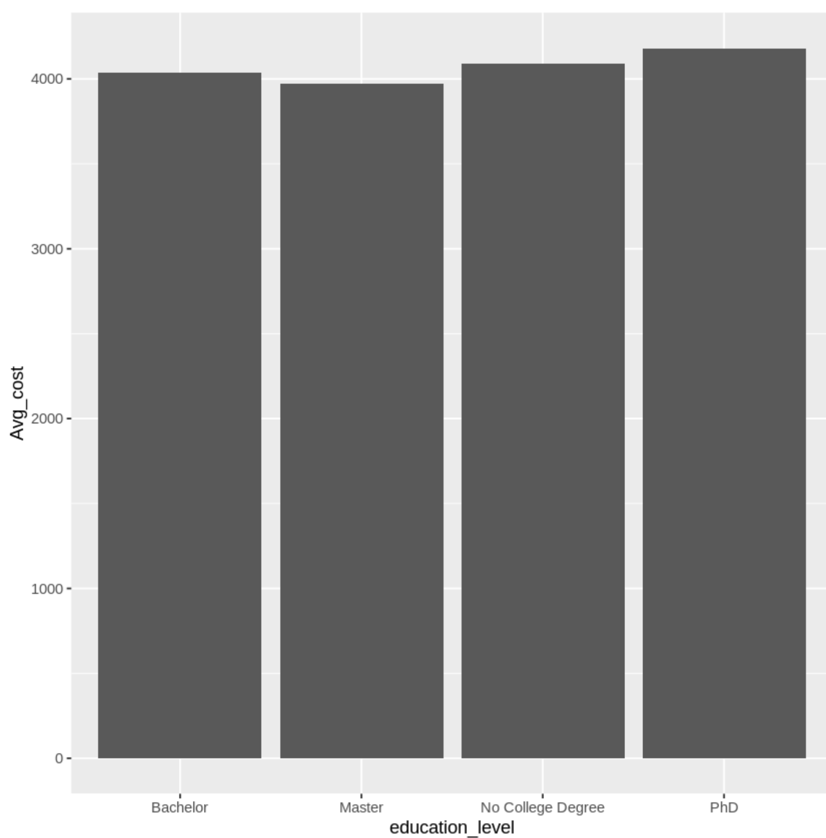


In [ ]:

```
# location_type

GroupedData4 <- df_HMO_data%>%group_by(location_type)%>%summarise(Avg_cost =mean(co

ggplot(data=GroupedData4, aes(x=location_type, y=Avg_cost)) + geom_bar(stat="identi
```



In [ ]:
```
# education_level and average cost
GroupedData5 <- df_HMO_data%>%group_by(education_level)%>%summarise(Avg_cost =mean(

ggplot(data=GroupedData5, aes(x=education_level, y=Avg_cost)) + geom_bar(stat="iden
```



Linear models to check correlation:

A simple corr() cannot account for casual relationship, thus using other models

In [ ]:
```
#predictor is bmi
lm_out <- lm(cost ~ bmi, data = df_HMO_data)
print(lm_out)
summary(lm_out)
```

```
Call:
lm(formula = cost ~ bmi, data = df_HMO_data)

Coefficients:
(Intercept)          bmi
    -2216.6        203.3

Call:
lm(formula = cost ~ bmi, data = df_HMO_data)

Residuals:
   Min     1Q Median     3Q    Max
 -8425  -2800  -1237    995  51062

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) -2216.572    288.005  -7.696 1.58e-14 ***
bmi           203.253      9.181  22.139  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 4777 on 7580 degrees of freedom
Multiple R-squared:  0.06074,	Adjusted R-squared:  0.06061
F-statistic: 490.2 on 1 and 7580 DF,  p-value: < 2.2e-16
```

In [ ]:
```
#predictor is age
lm_out <- lm(cost ~ age, data = df_HMO_data)
print(lm_out)
summary(lm_out)
```

```
Call:
lm(formula = cost ~ age, data = df_HMO_data)

Coefficients:
(Intercept)          age
     -335.7        112.6
```

```
Call:
lm(formula = cost ~ age, data = df_HMO_data)

Residuals:
   Min     1Q Median     3Q    Max 
 -7062  -2286  -1506    293  49069 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept) -335.748    156.358  -2.147   0.0318 *  
age          112.605      3.778  29.807   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 4663 on 7580 degrees of freedom
Multiple R-squared:  0.1049,	Adjusted R-squared:  0.1048 
F-statistic: 888.5 on 1 and 7580 DF,  p-value: < 2.2e-16
```

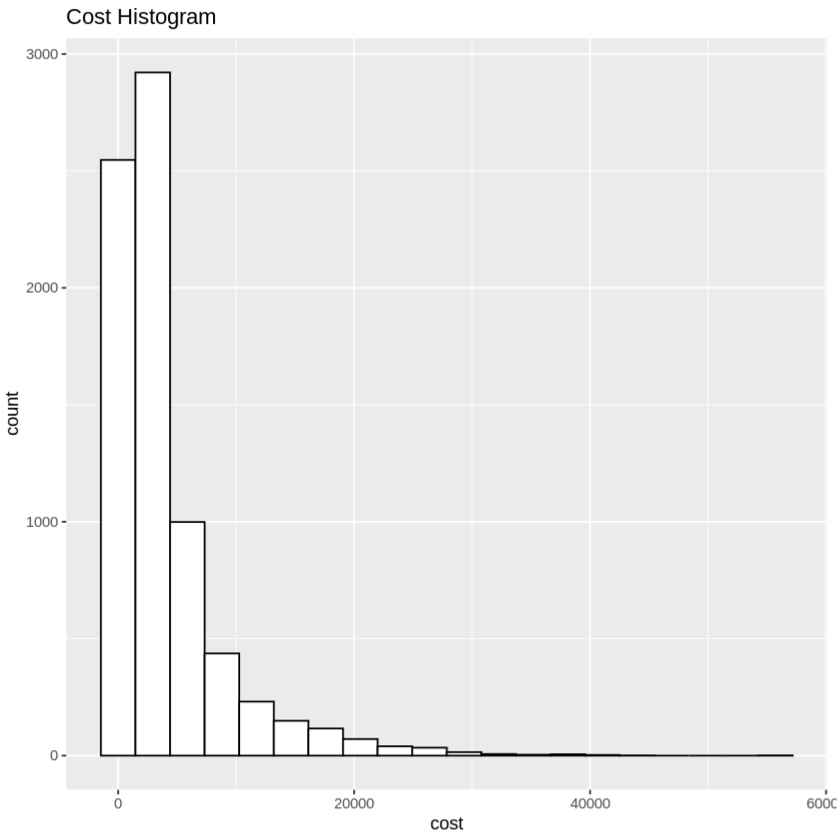
In [ ]:

```r
#predictor is bmi and age
lm_out <- lm(cost ~ age + bmi, data = df_HMO_data)
print(lm_out)
summary(lm_out)
```

```
Call:
lm(formula = cost ~ age + bmi, data = df_HMO_data)

Coefficients:
(Intercept)          age          bmi  
    -5589.7        105.5        179.6  

Call:
lm(formula = cost ~ age + bmi, data = df_HMO_data)

Residuals:
   Min     1Q Median     3Q    Max 
 -8153  -2376  -1307    607  48695 

Coefficients:
             Estimate Std. Error t value Pr(>|t|)    
(Intercept) -5589.743    298.102  -18.75   <2e-16 ***
age           105.455      3.694   28.55   <2e-16 ***
bmi           179.630      8.763   20.50   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 4539 on 7579 degrees of freedom
Multiple R-squared:  0.1519,	Adjusted R-squared:  0.1517 
F-statistic: 678.9 on 2 and 7579 DF,  p-value: < 2.2e-16
```

In [ ]:

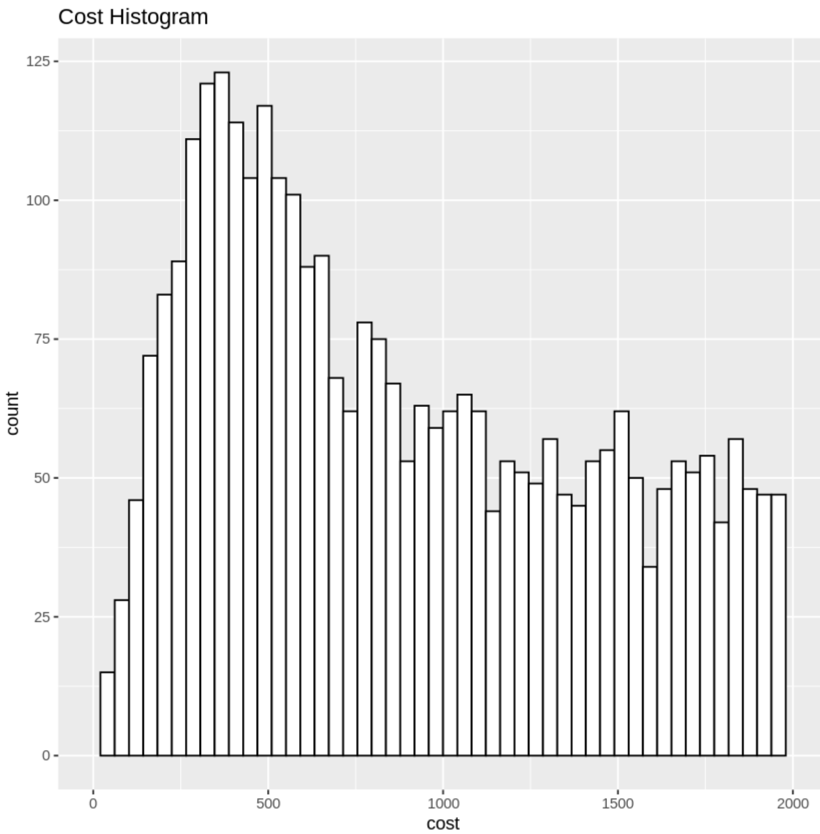
```r
library(tidyverse)
HistPlotCost1 <- ggplot(df_HMO_data, aes(x=cost)) + geom_histogram(bins = 20,color=
HistPlotCost1 <- HistPlotCost1 + ggtitle("Cost Histogram")
HistPlotCost1
```



In [ ]:

```
#removing skewness by increasing bins
library(tidyverse)
HistPlotCost2 <- ggplot(df_HMO_data, aes(x=cost)) + geom_histogram(bins = 50,color=
HistPlotCost2 <- HistPlotCost2 + ggtitle("Cost Histogram")
HistPlotCost2
```

```
Warning message:
“Removed 4387 rows containing non-finite values (`stat_bin()`).”
Warning message:
“Removed 2 rows containing missing values (`geom_bar()`).”
```



hypertension_cat <- function(x){ r <- case_when((is.na(x)) ~'NA' , x = 0 ~ 'no' , (x = 1) ~ 'yes') return(r) } df_HMO_data <- df_HMO_data %>% mutate(hypertension_category = hypertension_cat(hypertension))

LINEAR MODELS

Linear Model: All the variables as the independent variable to find out which variables have a statistically significant relationship with cost. Also checked other combinations of independent variables against cost

In [ ]:
```
lm_all <- lm(cost ~age+bmi+children+smoker+location+location_type+education_level+y
print(lm_all)
summary(lm_all)
```

```
Call:
lm(formula = cost ~ age + bmi + children + smoker + location + 
    location_type + education_level + yearly_physical + exercise + 
    married + hypertension + gender, data = df_HMO_data)

Coefficients:
                     (Intercept)                                age  
                        -9146.73                             102.43  
                             bmi                           children  
                          181.40                             232.98  
                       smokeryes                   locationMARYLAND  
                         7664.40                            -130.44  
           locationMASSACHUSETTS                 locationNEW JERSEY  
                            9.23                             112.88  
                locationNEW YORK               locationPENNSYLVANIA  
                          468.52                              16.59  
             locationRHODE ISLAND                location_typeUrban  
                          114.55                             -10.80  
           education_levelMaster  education_levelNo College Degree  
                          -97.32                              41.21  
              education_levelPhD                 yearly_physicalYes  
                         -234.02                             139.52  
              exerciseNot-Active                  marriedNot_Married  
                         2263.59                             134.45  
                    hypertension                         gendermale  
                          347.52                              29.60  
```

```
Call:
lm(formula = cost ~ age + bmi + children + smoker + location + 
    location_type + education_level + yearly_physical + exercise + 
    married + hypertension + gender, data = df_HMO_data)

Residuals:
   Min     1Q Median     3Q    Max 
-11987  -1481   -356   1008  41747 

Coefficients:
                                  Estimate Std. Error t value Pr(>|t|)    
(Intercept)                      -9146.733    269.404 -33.952  < 2e-16 ***
age                                102.434      2.630  38.949  < 2e-16 ***
bmi                                181.403      6.232  29.109  < 2e-16 ***
children                           232.984     30.477   7.645 2.35e-14 ***
smokeryes                         7664.403     93.752  81.752  < 2e-16 ***
locationMARYLAND                  -130.442    175.776  -0.742 0.458054    
locationMASSACHUSETTS                9.230    198.370   0.047 0.962889    
locationNEW JERSEY                 112.878    194.544   0.580 0.561784    
locationNEW YORK                   468.522    189.779   2.469 0.013580 *  
locationPENNSYLVANIA                16.590    139.980   0.119 0.905663    
locationRHODE ISLAND               114.545    178.199   0.643 0.520377    
location_typeUrban                 -10.805     85.431  -0.126 0.899361    
education_levelMaster              -97.316     95.115  -1.023 0.306277    
education_levelNo College Degree    41.214    126.291   0.326 0.744178    
education_levelPhD                -234.019    129.880  -1.802 0.071616 .  
yearly_physicalYes                 139.522     85.692   1.628 0.103531    
exerciseNot-Active                2263.587     85.625  26.436  < 2e-16 ***
marriedNot_Married                 134.452     78.591   1.711 0.087163 .  
hypertension                       347.517     92.825   3.744 0.000183 ***
gendermale                          29.601     74.530   0.397 0.691250    
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 3220 on 7562 degrees of freedom
Multiple R-squared:  0.5742,	Adjusted R-squared:  0.5731 
F-statistic: 536.7 on 19 and 7562 DF,  p-value: < 2.2e-16
```

In [ ]:
```r
lm_out <- lm(cost ~ smoker, data = df_HMO_data)
print(lm_out)
summary(lm_out)
```

```
Call:
lm(formula = cost ~ smoker, data = df_HMO_data)

Coefficients:
(Intercept)    smokeryes  
       2545         7681  
```

```
Call:
lm(formula = cost ~ smoker, data = df_HMO_data)

Residuals:
   Min     1Q Median     3Q    Max
-10148  -1974   -681   1214  45489

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  2544.62      49.62   51.28   <2e-16 ***
smokeryes    7681.14     112.36   68.36   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 3877 on 7580 degrees of freedom
Multiple R-squared:  0.3814,    Adjusted R-squared:  0.3813
F-statistic:  4674 on 1 and 7580 DF,  p-value: < 2.2e-16
```

In [ ]:
```
lm_out <- lm(cost ~ exercise, data = df_HMO_data)
print(lm_out)
summary(lm_out)
```

```
Call:
lm(formula = cost ~ exercise, data = df_HMO_data)

Coefficients:
       (Intercept)  exerciseNot-Active
              2469                2095


Call:
lm(formula = cost ~ exercise, data = df_HMO_data)

Residuals:
   Min     1Q Median     3Q    Max
 -4468  -2732  -1384    688  51150

Coefficients:
                   Estimate Std. Error t value Pr(>|t|)
(Intercept)          2469.3      111.5   22.15   <2e-16 ***
exerciseNot-Active   2095.4      128.7   16.29   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 4845 on 7580 degrees of freedom
Multiple R-squared:  0.0338,    Adjusted R-squared:  0.03368
F-statistic: 265.2 on 1 and 7580 DF,  p-value: < 2.2e-16
```

In [ ]:
```
lm_out <- lm(cost ~ hypertension, data = df_HMO_data)
print(lm_out)
summary(lm_out)
```

```
Call:
lm(formula = cost ~ hypertension, data = df_HMO_data)

Coefficients:
 (Intercept)  hypertension  
      3955.6         440.2  

Call:
lm(formula = cost ~ hypertension, data = df_HMO_data)

Residuals:
   Min     1Q Median     3Q    Max 
 -4355  -3065  -1529    762  51319 

Coefficients:
             Estimate Std. Error t value Pr(>|t|)    
(Intercept)   3955.64      63.18  62.605  < 2e-16 ***
hypertension   440.22     141.86   3.103  0.00192 ** 
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 4926 on 7580 degrees of freedom
Multiple R-squared:  0.001269,	Adjusted R-squared:  0.001137 
F-statistic: 9.629 on 1 and 7580 DF,  p-value: 0.001922
```

In [ ]:

```r
lm_out <- lm(cost ~ children, data = df_HMO_data)
print(lm_out)
summary(lm_out)
```

```
Call:
lm(formula = cost ~ children, data = df_HMO_data)

Coefficients:
(Intercept)     children  
     3634.6        368.1  

Call:
lm(formula = cost ~ children, data = df_HMO_data)

Residuals:
   Min     1Q Median     3Q    Max 
 -5327  -3030  -1563    782  51712 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept)  3634.57      76.23  47.681  < 2e-16 ***
children      368.10      46.25   7.959 1.98e-15 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 4909 on 7580 degrees of freedom
Multiple R-squared:  0.008289,	Adjusted R-squared:  0.008158 
F-statistic: 63.35 on 1 and 7580 DF,  p-value: 1.98e-15
```

In [ ]:

```r
lm_out <- lm(cost ~ age + bmi + smoker, data = df_HMO_data)
print(lm_out)
```

```
summary(lm_out)
```

```
Call:
lm(formula = cost ~ age + bmi + smoker, data = df_HMO_data)

Coefficients:
(Intercept)          age          bmi    smokeryes  
    -6975.2        103.5        178.7       7639.4  

Call:
lm(formula = cost ~ age + bmi + smoker, data = df_HMO_data)

Residuals:
   Min     1Q Median     3Q    Max 
-13950  -1484   -261    928  42594 

Coefficients:
             Estimate Std. Error t value Pr(>|t|)    
(Intercept) -6975.207    222.841  -31.30   <2e-16 ***
age           103.512      2.753   37.60   <2e-16 ***
bmi           178.683      6.530   27.36   <2e-16 ***
smokeryes    7639.434     98.040   77.92   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 3383 on 7578 degrees of freedom
Multiple R-squared:  0.5292,	Adjusted R-squared:  0.529 
F-statistic:  2839 on 3 and 7578 DF,  p-value: < 2.2e-16
```

In [ ]:
```
lm_out <- lm(cost ~ age + bmi+ exercise, data = df_HMO_data)
print(lm_out)
summary(lm_out)
```

```
Call:
lm(formula = cost ~ age + bmi + exercise, data = df_HMO_data)

Coefficients:
       (Intercept)                 age                 bmi  exerciseNot-Active  
           -7256.3               105.5               181.6              2134.6  
```

```
Call:
lm(formula = cost ~ age + bmi + exercise, data = df_HMO_data)

Residuals:
   Min     1Q Median     3Q    Max 
 -6789  -2479  -1341    801  48157 

Coefficients:
                    Estimate Std. Error t value Pr(>|t|)    
(Intercept)        -7256.286    306.096  -23.71   <2e-16 ***
age                  105.497      3.617   29.17   <2e-16 ***
bmi                  181.638      8.581   21.17   <2e-16 ***
exerciseNot-Active  2134.635    118.054   18.08   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 4445 on 7578 degrees of freedom
Multiple R-squared:  0.187,	Adjusted R-squared:  0.1867 
F-statistic:   581 on 3 and 7578 DF,  p-value: < 2.2e-16
```

In [ ]:

```
lm_out <- lm(cost ~ smoker+ bmi+exercise+hypertension, data = df_HMO_data)
print(lm_out)
summary(lm_out)
```

```
Call:
lm(formula = cost ~ smoker + bmi + exercise + hypertension, data = df_HMO_data)

Coefficients:
       (Intercept)           smokeryes                 bmi  exerciseNot-Active  
           -5501.0              7715.6               203.9              2265.3  
      hypertension  
             300.3  


Call:
lm(formula = cost ~ smoker + bmi + exercise + hypertension, data = df_HMO_data)

Residuals:
   Min     1Q Median     3Q    Max 
-10814  -1971   -281   1334  44044 

Coefficients:
                    Estimate Std. Error t value Pr(>|t|)    
(Intercept)        -5501.015    228.010 -24.126  < 2e-16 ***
smokeryes           7715.584    102.920  74.966  < 2e-16 ***
bmi                  203.857      6.824  29.876  < 2e-16 ***
exerciseNot-Active  2265.280     94.308  24.020  < 2e-16 ***
hypertension         300.332    102.256   2.937  0.00332 ** 
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 3550 on 7577 degrees of freedom
Multiple R-squared:  0.4814,	Adjusted R-squared:  0.4812 
F-statistic:  1759 on 4 and 7577 DF,  p-value: < 2.2e-16
```

In [ ]:

```
lm_out <- lm(cost ~ exercise+hypertension, data = df_HMO_data)
print(lm_out)
```

```
summary(lm_out)
```

```
Call:
lm(formula = cost ~ exercise + hypertension, data = df_HMO_data)

Coefficients:
       (Intercept)  exerciseNot-Active        hypertension  
            2385.7              2093.4               428.9  

Call:
lm(formula = cost ~ exercise + hypertension, data = df_HMO_data)

Residuals:
   Min     1Q Median     3Q    Max 
 -4751  -2754  -1373    676  50807 

Coefficients:
                   Estimate Std. Error t value Pr(>|t|)    
(Intercept)          2385.7      114.7  20.798  < 2e-16 ***
exerciseNot-Active   2093.4      128.6  16.279  < 2e-16 ***
hypertension          428.9      139.5   3.076  0.00211 ** 
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 4842 on 7579 degrees of freedom
Multiple R-squared:  0.03501,	Adjusted R-squared:  0.03475 
F-statistic: 137.5 on 2 and 7579 DF,  p-value: < 2.2e-16
```

In [ ]:

```
lm_out <- lm(cost ~ age + smoker, data = df_HMO_data)
print(lm_out)
summary(lm_out)
```

```
Call:
lm(formula = cost ~ age + smoker, data = df_HMO_data)

Coefficients:
(Intercept)          age    smokeryes  
    -1749.8        110.6       7644.4  
```

```
Call:
lm(formula = cost ~ age + smoker, data = df_HMO_data)

Residuals:
   Min     1Q Median     3Q    Max 
-12664  -1234   -291    519  42962 

Coefficients:
             Estimate Std. Error t value Pr(>|t|)    
(Intercept) -1749.845    120.390  -14.54   <2e-16 ***
age           110.623      2.872   38.51   <2e-16 ***
smokeryes    7644.428    102.763   74.39   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 3546 on 7579 degrees of freedom
Multiple R-squared:  0.4827,	Adjusted R-squared:  0.4825 
F-statistic:  3535 on 2 and 7579 DF,  p-value: < 2.2e-16
```

In [ ]:
```
str(df_HMO_data)
```

```
'data.frame':	7582 obs. of  21 variables:
 $ X              : int  1 2 3 4 5 7 9 10 11 12 ...
 $ age            : int  18 19 27 34 32 47 36 59 24 61 ...
 $ bmi            : num  27.9 33.8 33 22.7 28.9 ...
 $ children       : int  0 1 3 0 0 1 2 0 0 0 ...
 $ smoker         : Factor w/ 2 levels "no","yes": 2 1 1 1 1 1 1 1 1 2 ...
 $ location       : chr  "CONNECTICUT" "RHODE ISLAND" "MASSACHUSETTS" "PENNSYLVANI
A" ...
 $ location_type  : Factor w/ 2 levels "Country","Urban": 2 2 2 1 1 2 2 1 2 2 ...
 $ education_level: Factor w/ 4 levels "Bachelor","Master",..: 1 1 2 2 4 1 1 1 1 3
...
 $ yearly_physical: Factor w/ 2 levels "No","Yes": 1 1 1 1 1 1 1 1 1 1 ...
 $ exercise       : Factor w/ 2 levels "Active","Not-Active": 1 2 1 2 2 2 1 2 1 1
...
 $ married        : Factor w/ 2 levels "Married","Not_Married": 1 1 1 1 1 1 1 1 1 1
...
 $ hypertension   : num  0 0 0 1 0 0 0 1 0 0 ...
 $ gender         : Factor w/ 2 levels "female","male": 1 2 2 2 2 1 2 1 2 1 ...
 $ cost           : int  1746 602 576 5562 836 3842 1304 9724 201 4492 ...
 $ cost_category  : Factor w/ 2 levels "Expensive","Inexpensive": 2 2 2 1 2 1 2 1 2
1 ...
 $ age_category   : Factor w/ 4 levels "Adult","Older Adult",..: 3 3 4 1 1 1 1 2 4
2 ...
 $ bmi_category   : Factor w/ 4 levels "Healthy","Obese",..: 3 2 2 1 3 2 3 3 3 3
...
 $ child_category : Factor w/ 3 levels "2 or less","more than 2",..: 3 1 2 3 3 1 1
3 3 3 ...
 $ cost_class     : Factor w/ 10 levels "2-6192","6193-12383",..: 1 1 1 1 1 1 1 2 1
1 ...
 $ cost_decile    : Factor w/ 10 levels "1","2","3","4",..: 7 9 9 3 8 4 7 1 10 3
...
 $ cost_categories: Factor w/ 200 levels "2-281","282-561",..: 7 3 3 20 3 14 5 35 1
17 ...
```

BEST LM MODEL

In [ ]:
```
# BEST MODEL
lm_out <- lm(cost ~ age + bmi + smoker + hypertension + children + exercise, data =
print(lm_out)
summary(lm_out)
```

```
Call:
lm(formula = cost ~ age + bmi + smoker + hypertension + children +
    exercise, data = df_HMO_data)

Coefficients:
       (Intercept)                  age                  bmi            smokeryes
           -9040.2                102.3                181.3               7666.9
      hypertension             children  exerciseNot-Active
             338.7                235.2               2260.0

Call:
lm(formula = cost ~ age + bmi + smoker + hypertension + children +
    exercise, data = df_HMO_data)

Residuals:
   Min     1Q Median     3Q    Max
-12188  -1490   -356   1012  41783

Coefficients:
                    Estimate Std. Error t value Pr(>|t|)
(Intercept)        -9040.156    225.143 -40.153  < 2e-16 ***
age                  102.281      2.629  38.912  < 2e-16 ***
bmi                  181.348      6.222  29.147  < 2e-16 ***
smokeryes           7666.889     93.438  82.053  < 2e-16 ***
hypertension         338.720     92.825   3.649 0.000265 ***
children             235.154     30.441   7.725 1.26e-14 ***
exerciseNot-Active  2260.047     85.602  26.402  < 2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 3222 on 7575 degrees of freedom
Multiple R-squared:  0.5729,    Adjusted R-squared:  0.5726
F-statistic:  1694 on 6 and 7575 DF,  p-value: < 2.2e-16
```

In [ ]:
```
lm_out <- lm(cost ~ age + bmi + smoker + children + exercise, data = df_HMO_data)
print(lm_out)
summary(lm_out)
```

```
Call:
lm(formula = cost ~ age + bmi + smoker + children + exercise,
    data = df_HMO_data)

Coefficients:
       (Intercept)                  age                  bmi            smokeryes
           -8977.3                102.2                181.5               7671.6
          children    exerciseNot-Active
             236.4               2261.7

Call:
lm(formula = cost ~ age + bmi + smoker + children + exercise,
    data = df_HMO_data)

Residuals:
   Min      1Q Median      3Q     Max
-12257  -1484   -367   1001   42053

Coefficients:
                    Estimate Std. Error t value Pr(>|t|)
(Intercept)        -8977.331    224.666  -39.96  < 2e-16 ***
age                  102.153      2.630   38.84  < 2e-16 ***
bmi                  181.537      6.227   29.16  < 2e-16 ***
smokeryes           7671.606     93.505   82.05  < 2e-16 ***
children             236.409     30.464    7.76 9.58e-15 ***
exerciseNot-Active  2261.677     85.670   26.40  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 3225 on 7576 degrees of freedom
Multiple R-squared:  0.5722,    Adjusted R-squared:  0.5719
F-statistic:  2026 on 5 and 7576 DF,  p-value: < 2.2e-16
```

SVM MODELS

In [ ]:
```
EnsurePackage('rio')
EnsurePackage('caret')
EnsurePackage('kernlab')
EnsurePackage('e1071')
```

```
Loading required package: rio

Warning message in library(package, lib.loc = lib.loc, character.only = TRUE, logic
al.return = TRUE, :
“there is no package called ‘rio’”
Loading required package: rio

Warning message in library(package, lib.loc = lib.loc, character.only = TRUE, logic
al.return = TRUE, :
“there is no package called ‘rio’”
also installing the dependency ‘openxlsx’


Loading required package: rio

Loading required package: e1071


Attaching package: ‘e1071’


The following object is masked from ‘package:Hmisc’:

    impute

```

In [ ]:

```
library(rio)
library(caret)
library(kernlab)
library(e1071)
```

In [ ]:

```
df_HMO_sub <- df_HMO_data
cols <- c("age", "bmi", "children","cost", "smoker", "exercise", "hypertension" )
df_HMO_sub<-df_HMO_sub[,cols]
head(df_HMO_sub)

set.seed(111)
subHMO<- df_HMO_sub
trainList <- createDataPartition(y=subHMO$cost,p=0.70,list=FALSE)
trainSet <- subHMO[trainList,]
testSet <- subHMO[-trainList,]
```

A data.frame: 6 × 7

	age	bmi	children	cost	smoker	exercise	hypertension
	<int>	<dbl>	<int>	<int>	<fct>	<fct>	<dbl>
1	18	27.900	0	1746	yes	Active	0
2	19	33.770	1	602	no	Not-Active	0
3	27	33.000	3	576	no	Active	0
4	34	22.705	0	5562	no	Not-Active	1
5	32	28.880	0	836	no	Not-Active	0
6	47	33.440	1	3842	no	Not-Active	0

In [ ]:

```
fit1 <- train(cost~.,data = trainSet, method="svmRadial",preProc=c("center","scale"
fit1
```

```
Support Vector Machines with Radial Basis Function Kernel

5310 samples
   6 predictor

Pre-processing: centered (6), scaled (6)
Resampling: Bootstrapped (25 reps)
Summary of sample sizes: 5310, 5310, 5310, 5310, 5310, 5310, ...
Resampling results across tuning parameters:

  C     RMSE      Rsquared   MAE
  0.25  2613.046  0.7333921  1405.297
  0.50  2600.813  0.7336134  1401.378
  1.00  2596.782  0.7330647  1402.356

Tuning parameter 'sigma' was held constant at a value of 0.1676783
RMSE was used to select the optimal model using the smallest value.
The final values used for the model were sigma = 0.1676783 and C = 1.
```

In [ ]:

```
str(df_HMO_data)
```

```
'data.frame':	7582 obs. of  21 variables:
 $ X              : int  1 2 3 4 5 7 9 10 11 12 ...
 $ age            : int  18 19 27 34 32 47 36 59 24 61 ...
 $ bmi            : num  27.9 33.8 33 22.7 28.9 ...
 $ children       : int  0 1 3 0 0 1 2 0 0 0 ...
 $ smoker         : Factor w/ 2 levels "no","yes": 2 1 1 1 1 1 1 1 1 2 ...
 $ location       : chr  "CONNECTICUT" "RHODE ISLAND" "MASSACHUSETTS" "PENNSYLVANI
A" ...
 $ location_type  : Factor w/ 2 levels "Country","Urban": 2 2 2 1 1 2 2 1 2 2 ...
 $ education_level: Factor w/ 4 levels "Bachelor","Master",..: 1 1 2 2 4 1 1 1 1 3
...
 $ yearly_physical: Factor w/ 2 levels "No","Yes": 1 1 1 1 1 1 1 1 1 1 ...
 $ exercise       : Factor w/ 2 levels "Active","Not-Active": 1 2 1 2 2 2 1 2 1 1
...
 $ married        : Factor w/ 2 levels "Married","Not_Married": 1 1 1 1 1 1 1 1 1 1
...
 $ hypertension   : num  0 0 0 1 0 0 0 1 0 0 ...
 $ gender         : Factor w/ 2 levels "female","male": 1 2 2 2 2 1 2 1 2 1 ...
 $ cost           : int  1746 602 576 5562 836 3842 1304 9724 201 4492 ...
 $ cost_category  : Factor w/ 2 levels "Expensive","Inexpensive": 2 2 2 1 2 1 2 1 2
1 ...
 $ age_category   : Factor w/ 4 levels "Adult","Older Adult",..: 3 3 4 1 1 1 1 2 4
2 ...
 $ bmi_category   : Factor w/ 4 levels "Healthy","Obese",..: 3 2 2 1 3 2 3 3 3 3
...
 $ child_category : Factor w/ 3 levels "2 or less","more than 2",..: 3 1 2 3 3 1 1
3 3 3 ...
 $ cost_class     : Factor w/ 10 levels "2-6192","6193-12383",..: 1 1 1 1 1 1 1 2 1
1 ...
 $ cost_decile    : Factor w/ 10 levels "1","2","3","4",..: 7 9 9 3 8 4 7 1 10 3
...
 $ cost_categories: Factor w/ 200 levels "2-281","282-561",..: 7 3 3 20 3 14 5 35 1
17 ...
```

In [ ]:

```
df_HMO_sub <- df_HMO_data
cols <- c("age", "bmi", "children","cost_class", "smoker", "exercise", "hypertensio
df_HMO_sub<-df_HMO_sub[,cols]
# head(df_HMO_sub)

set.seed(111)
subHMO<- df_HMO_sub
trainList <- createDataPartition(y=subHMO$cost_class,p=0.70,list=FALSE)
trainSet <- subHMO[trainList,]
df_HMO_sub$cost_class <- as.factor(df_HMO_sub$cost_class)
testSet <- subHMO[-trainList,]
testSet <- testSet[-which(testSet$cost_class == '49530-55720'),]
head(testSet)
```

```
Warning message in createDataPartition(y = subHMO$cost_class, p = 0.7, list = FALS
E):
“Some classes have no records ( 49530-55720 ) and these will be ignored”
Warning message in createDataPartition(y = subHMO$cost_class, p = 0.7, list = FALS
E):
“Some classes have a single record ( 55721-6192 ) and these will be selected for th
e sample”
```

A data.frame: 0 × 7

age	bmi	children	cost_class	smoker	exercise	hypertension
<int>	<dbl>	<int>	<fct>	<fct>	<fct>	<dbl>

In [ ]:
```
summary(testSet)
```

```
      age             bmi           children             cost_class    smoker    
 Min.   :18.00   Min.   :15.96   Min.   :0.000   2-6192      :1798   no :1820  
 1st Qu.:26.00   1st Qu.:26.46   1st Qu.:0.000   6193-12383 : 296   yes: 451  
 Median :40.00   Median :30.40   Median :1.000   12384-18574:  97             
 Mean   :39.45   Mean   :30.75   Mean   :1.113   18575-24765:  51             
 3rd Qu.:52.00   3rd Qu.:34.48   3rd Qu.:2.000   24766-30956:  19             
 Max.   :66.00   Max.   :53.13   Max.   :5.000   30957-37147:   6             
                                                 (Other)    :   4             
       exercise     hypertension   
 Active    : 572   Min.   :0.0000  
 Not-Active:1699   1st Qu.:0.0000  
                   Median :0.0000  
                   Mean   :0.1968  
                   3rd Qu.:0.0000  
                   Max.   :1.0000  
```

In [ ]:
```
fit1 <- train(cost_class~.,data = trainSet, method="svmRadial",preProc=c("center","
fit1
```

```
Error: One or more factor levels in the outcome has no data: '49530-55720'
Traceback:

1. train(cost_class ~ ., data = trainSet, method = "svmRadial", 
 .     preProc = c("center", "scale"))
2. train.formula(cost_class ~ ., data = trainSet, method = "svmRadial", 
 .     preProc = c("center", "scale"))
3. train(x, y, weights = w, ...)
4. train.default(x, y, weights = w, ...)
5. stop(paste("One or more factor levels in the outcome has no data:", 
 .     xtab_msg), call. = FALSE)
```

In [ ]:
```
df_HMO_sub <- df_HMO_data
cols <- c("age", "bmi", "children","cost_category", "smoker", "exercise", "hyperten
df_HMO_sub<-df_HMO_sub[,cols]
df_HMO_sub$cost_category <- as.factor(df_HMO_sub$cost_category)
head(df_HMO_sub)
```

A data.frame: 6 × 7

	age	bmi	children	cost_category	smoker	exercise	hypertension
	<int>	<dbl>	<int>	<fct>	<fct>	<fct>	<dbl>
1	18	27.900	0	Inexpensive	yes	Active	0
2	19	33.770	1	Inexpensive	no	Not-Active	0
3	27	33.000	3	Inexpensive	no	Active	0
4	34	22.705	0	Expensive	no	Not-Active	1
5	32	28.880	0	Inexpensive	no	Not-Active	0
6	47	33.440	1	Expensive	no	Not-Active	0

Training Test split

In [ ]:
```
library(rio)
library(caret)
library(kernlab)

set.seed(111)
subHMO<- df_HMO_sub
trainList <- createDataPartition(y=subHMO$cost_category,p=0.70,list=FALSE)
trainSet <- subHMO[trainList,]
testSet <- subHMO[-trainList,]
```

In [ ]:
```
dim(trainSet)
dim(testSet)
```

5308 · 7

2274 · 7

In [ ]:
```
fit1 <- train(cost_category~.,data = trainSet, method="svmRadial",preProc=c("center
fit1
```

In [ ]:
```
library(caret)
library(kernlab)

fit1 <- train(cost_category~.,data = trainSet, method="svmRadial",preProc=c("center
fit1
```

```
Support Vector Machines with Radial Basis Function Kernel

5308 samples
   6 predictor
   2 classes: 'Expensive', 'Inexpensive'

Pre-processing: centered (6), scaled (6)
Resampling: Bootstrapped (25 reps)
Summary of sample sizes: 5308, 5308, 5308, 5308, 5308, 5308, ...
Resampling results across tuning parameters:

  C     Accuracy   Kappa
  0.25  0.8479854  0.6959078
  0.50  0.8481425  0.6962155
  1.00  0.8483527  0.6966497

Tuning parameter 'sigma' was held constant at a value of 0.1724707
Accuracy was used to select the optimal model using the largest value.
The final values used for the model were sigma = 0.1724707 and C = 1.
```

In [ ]:

```
summary(fit1)
```

```
Length  Class   Mode
     1   ksvm     S4
```

Best Model SVM

In [ ]:

```
# library(caret)
# library(kernlab)

svmPred <-predict(fit1,testSet)
confusion1 <- table(svmPred, testSet$cost_category)
confusion1
prop.table(confusion1)
confusion2 <- confusionMatrix(svmPred, testSet$cost_category)
confusion2
```

```
svmPred       Expensive Inexpensive
  Expensive         956         158
  Inexpensive       181         979

svmPred        Expensive Inexpensive
  Expensive   0.42040457  0.06948109
  Inexpensive 0.07959543  0.43051891
```

```
Confusion Matrix and Statistics

             Reference
Prediction    Expensive Inexpensive
  Expensive         956         158
  Inexpensive       181         979

               Accuracy : 0.8509
                 95% CI : (0.8356, 0.8653)
    No Information Rate : 0.5
    P-Value [Acc > NIR] : <2e-16

                  Kappa : 0.7018

 Mcnemar's Test P-Value : 0.2321

            Sensitivity : 0.8408
            Specificity : 0.8610
         Pos Pred Value : 0.8582
         Neg Pred Value : 0.8440
             Prevalence : 0.5000
         Detection Rate : 0.4204
   Detection Prevalence : 0.4899
      Balanced Accuracy : 0.8509

       'Positive' Class : Expensive
```

In [ ]:

```
# library(caret)
# library(kernlab)

fit <- train(cost_category~age+bmi+smoker,data = trainSet, method="svmRadial",prePr
fit
svmPred <-predict(fit,testSet)
confusion1 <- table(svmPred, testSet$cost_category)
confusion1
prop.table(confusion1)
confusion2 <- confusionMatrix(svmPred, testSet$cost_category)
confusion2
```

```
Support Vector Machines with Radial Basis Function Kernel

5308 samples
   3 predictor
   2 classes: 'Expensive', 'Inexpensive'

Pre-processing: centered (3), scaled (3)
Resampling: Bootstrapped (25 reps)
Summary of sample sizes: 5308, 5308, 5308, 5308, 5308, 5308, ...
Resampling results across tuning parameters:

  C     Accuracy   Kappa
  0.25  0.8035611  0.6072065
  0.50  0.8040540  0.6081800
  1.00  0.8041408  0.6083544

Tuning parameter 'sigma' was held constant at a value of 0.8391853
Accuracy was used to select the optimal model using the largest value.
The final values used for the model were sigma = 0.8391853 and C = 1.

svmPred       Expensive Inexpensive
  Expensive         977         284
  Inexpensive       160         853

svmPred       Expensive Inexpensive
  Expensive   0.4296394   0.1248901
  Inexpensive 0.0703606   0.3751099
Confusion Matrix and Statistics

             Reference
Prediction    Expensive Inexpensive
  Expensive         977         284
  Inexpensive       160         853

               Accuracy : 0.8047
                 95% CI : (0.7878, 0.8209)
    No Information Rate : 0.5
    P-Value [Acc > NIR] : < 2.2e-16

                  Kappa : 0.6095

 Mcnemar's Test P-Value : 5.305e-09

            Sensitivity : 0.8593
            Specificity : 0.7502
         Pos Pred Value : 0.7748
         Neg Pred Value : 0.8421
             Prevalence : 0.5000
         Detection Rate : 0.4296
   Detection Prevalence : 0.5545
      Balanced Accuracy : 0.8047

       'Positive' Class : Expensive
```

In [ ]:
```
library(caret)
library(kernlab)
fit <- train(cost_category~age+bmi+exercise,data = trainSet, method="svmRadial",pre
fit
svmPred <-predict(fit,testSet)
confusion1 <- table(svmPred, testSet$cost_category)
confusion1
prop.table(confusion1)
confusion2 <- confusionMatrix(svmPred, testSet$cost_category)
confusion2
```

```
Support Vector Machines with Radial Basis Function Kernel

5308 samples
   3 predictor
   2 classes: 'Expensive', 'Inexpensive'

Pre-processing: centered (3), scaled (3)
Resampling: Bootstrapped (25 reps)
Summary of sample sizes: 5308, 5308, 5308, 5308, 5308, 5308, ...
Resampling results across tuning parameters:

  C     Accuracy   Kappa
  0.25  0.7673739  0.5343628
  0.50  0.7670460  0.5336986
  1.00  0.7668787  0.5333642

Tuning parameter 'sigma' was held constant at a value of 0.7235525
Accuracy was used to select the optimal model using the largest value.
The final values used for the model were sigma = 0.7235525 and C = 0.25.

svmPred       Expensive Inexpensive
  Expensive         801         171
  Inexpensive       336         966

svmPred        Expensive Inexpensive
  Expensive   0.35224274  0.07519789
  Inexpensive 0.14775726  0.42480211
```

```
Confusion Matrix and Statistics

             Reference
Prediction    Expensive Inexpensive
  Expensive         801         171
  Inexpensive       336         966

               Accuracy : 0.777
                 95% CI : (0.7594, 0.794)
    No Information Rate : 0.5
    P-Value [Acc > NIR] : < 2.2e-16

                  Kappa : 0.5541

 Mcnemar's Test P-Value : 3.253e-13

            Sensitivity : 0.7045
            Specificity : 0.8496
         Pos Pred Value : 0.8241
         Neg Pred Value : 0.7419
             Prevalence : 0.5000
         Detection Rate : 0.3522
   Detection Prevalence : 0.4274
      Balanced Accuracy : 0.7770

       'Positive' Class : Expensive
```

In [ ]:

```
library(caret)
library(kernlab)
fit <- train(cost_category~bmi+smoker+(exercise=="Not-Active")+hypertension,data =
fit
svmPred <-predict(fit,testSet)
confusion1 <- table(svmPred, testSet$cost_category)
confusion1
prop.table(confusion1)
confusion2 <- confusionMatrix(svmPred, testSet$cost_category)
confusion2
```

```
Support Vector Machines with Radial Basis Function Kernel

5308 samples
   4 predictor
   2 classes: 'Expensive', 'Inexpensive'

Pre-processing: centered (4), scaled (4)
Resampling: Bootstrapped (25 reps)
Summary of sample sizes: 5308, 5308, 5308, 5308, 5308, 5308, ...
Resampling results across tuning parameters:

  C     Accuracy   Kappa
  0.25  0.6828712  0.3660663
  0.50  0.6828748  0.3660504
  1.00  0.6828086  0.3659685

Tuning parameter 'sigma' was held constant at a value of 1.335887
Accuracy was used to select the optimal model using the largest value.
The final values used for the model were sigma = 1.335887 and C = 0.5.

svmPred       Expensive Inexpensive
  Expensive         712         289
  Inexpensive       425         848

svmPred       Expensive Inexpensive
  Expensive   0.3131047   0.1270888
  Inexpensive 0.1868953   0.3729112
Confusion Matrix and Statistics

             Reference
Prediction    Expensive Inexpensive
  Expensive         712         289
  Inexpensive       425         848

               Accuracy : 0.686
                 95% CI : (0.6665, 0.7051)
    No Information Rate : 0.5
    P-Value [Acc > NIR] : < 2.2e-16

                  Kappa : 0.372

 Mcnemar's Test P-Value : 4.366e-07

            Sensitivity : 0.6262
            Specificity : 0.7458
         Pos Pred Value : 0.7113
         Neg Pred Value : 0.6661
             Prevalence : 0.5000
         Detection Rate : 0.3131
   Detection Prevalence : 0.4402
      Balanced Accuracy : 0.6860

       'Positive' Class : Expensive
```

In [ ]:

```
library(caret)
library(kernlab)
fit <- train(cost_category~bmi+smoker+exercise+hypertension,data = trainSet, method
fit
svmPred <-predict(fit,testSet)
confusion1 <- table(svmPred, testSet$cost_category)
confusion1
prop.table(confusion1)
confusion2 <- confusionMatrix(svmPred, testSet$cost_category)
confusion2
```

```
Support Vector Machines with Radial Basis Function Kernel

5308 samples
   4 predictor
   2 classes: 'Expensive', 'Inexpensive'

Pre-processing: centered (4), scaled (4)
Resampling: Bootstrapped (25 reps)
Summary of sample sizes: 5308, 5308, 5308, 5308, 5308, 5308, ...
Resampling results across tuning parameters:

  C     Accuracy   Kappa
  0.25  0.6793699  0.3593907
  0.50  0.6792690  0.3591815
  1.00  0.6797436  0.3601109

Tuning parameter 'sigma' was held constant at a value of 1.351174
Accuracy was used to select the optimal model using the largest value.
The final values used for the model were sigma = 1.351174 and C = 1.

svmPred       Expensive Inexpensive
  Expensive         716         289
  Inexpensive       421         848

svmPred       Expensive Inexpensive
  Expensive   0.3148637   0.1270888
  Inexpensive 0.1851363   0.3729112
```

```
Confusion Matrix and Statistics

             Reference
Prediction    Expensive Inexpensive
  Expensive         716         289
  Inexpensive       421         848

               Accuracy : 0.6878
                 95% CI : (0.6683, 0.7068)
    No Information Rate : 0.5
    P-Value [Acc > NIR] : < 2.2e-16

                  Kappa : 0.3755

 Mcnemar's Test P-Value : 8.818e-07

            Sensitivity : 0.6297
            Specificity : 0.7458
         Pos Pred Value : 0.7124
         Neg Pred Value : 0.6682
             Prevalence : 0.5000
         Detection Rate : 0.3149
   Detection Prevalence : 0.4420
      Balanced Accuracy : 0.6878

       'Positive' Class : Expensive
```

KSVM MODELS

In [ ]:
```
library(caret)
library(kernlab)
modksvm <- ksvm(cost_category~.,data=trainSet, C=5,cross=3,prob.model=TRUE)
modksvm
predout <-predict(modksvm,testSet)
confusion1 <- table(predout, testSet$cost_category)
prop.table(confusion1)
confusion2 <- confusionMatrix(predout, testSet$cost_category)
confusion2
```

```
Support Vector Machine object of class "ksvm"

SV type: C-svc  (classification)
 parameter : cost C = 5

Gaussian Radial Basis kernel function.
 Hyperparameter : sigma =  0.228794490504832

Number of Support Vectors : 1890

Objective Function Value : -8623.44
Training error : 0.13847
Cross validation error : 0.150905
Probability model included.
```

```
predout        Expensive Inexpensive
  Expensive   0.42392260  0.07651715
  Inexpensive 0.07607740  0.42348285
Confusion Matrix and Statistics

             Reference
Prediction    Expensive Inexpensive
  Expensive         964         174
  Inexpensive       173         963

               Accuracy : 0.8474
                 95% CI : (0.832, 0.862)
    No Information Rate : 0.5
    P-Value [Acc > NIR] : <2e-16

                  Kappa : 0.6948

 Mcnemar's Test P-Value : 1

            Sensitivity : 0.8478
            Specificity : 0.8470
         Pos Pred Value : 0.8471
         Neg Pred Value : 0.8477
             Prevalence : 0.5000
         Detection Rate : 0.4239
   Detection Prevalence : 0.5004
      Balanced Accuracy : 0.8474

       'Positive' Class : Expensive
```

In [ ]:

```
library(caret)
library(kernlab)
modksvm <- ksvm(cost_category~bmi+smoker+exercise,data=trainSet, C=5,cross=3,prob.m
modksvm
predout <-predict(modksvm,testSet)
confusion1 <- table(predout, testSet$cost_category)
prop.table(confusion1)
confusion2 <- confusionMatrix(predout, testSet$cost_category)
confusion2
```

```
Support Vector Machine object of class "ksvm"

SV type: C-svc  (classification)
 parameter : cost C = 5

Gaussian Radial Basis kernel function.
 Hyperparameter : sigma =  2.96093710633448

Number of Support Vectors : 3525

Objective Function Value : -16331.47
Training error : 0.301997
Cross validation error : 0.302939
Probability model included.
```

```
predout       Expensive Inexpensive
  Expensive   0.3069481   0.1165347
  Inexpensive 0.1930519   0.3834653
Confusion Matrix and Statistics

             Reference
Prediction    Expensive Inexpensive
  Expensive         698         265
  Inexpensive       439         872

               Accuracy : 0.6904
                 95% CI : (0.671, 0.7094)
    No Information Rate : 0.5
    P-Value [Acc > NIR] : < 2.2e-16

                  Kappa : 0.3808

 Mcnemar's Test P-Value : 7.022e-11

            Sensitivity : 0.6139
            Specificity : 0.7669
         Pos Pred Value : 0.7248
         Neg Pred Value : 0.6651
             Prevalence : 0.5000
         Detection Rate : 0.3069
   Detection Prevalence : 0.4235
      Balanced Accuracy : 0.6904

       'Positive' Class : Expensive
```

In [ ]:

```
library(caret)
library(kernlab)
modksvm <- ksvm(cost_category~bmi+smoker+hypertension,data=trainSet, C=5,cross=3,pr
modksvm
predout <-predict(modksvm,testSet)
confusion1 <- table(predout, testSet$cost_category)
prop.table(confusion1)
confusion2 <- confusionMatrix(predout, testSet$cost_category)
confusion2
```

```
Support Vector Machine object of class "ksvm"

SV type: C-svc  (classification)
 parameter : cost C = 5

Gaussian Radial Basis kernel function.
 Hyperparameter : sigma =  3.52965247539185

Number of Support Vectors : 3739

Objective Function Value : -17293.12
Training error : 0.320271
Cross validation error : 0.330634
Probability model included.
```

```
predout        Expensive Inexpensive
  Expensive   0.22295515  0.06948109
  Inexpensive 0.27704485  0.43051891
Confusion Matrix and Statistics

             Reference
Prediction    Expensive Inexpensive
  Expensive         507         158
  Inexpensive       630         979

               Accuracy : 0.6535
                 95% CI : (0.6335, 0.673)
    No Information Rate : 0.5
    P-Value [Acc > NIR] : < 2.2e-16

                  Kappa : 0.3069

 Mcnemar's Test P-Value : < 2.2e-16

            Sensitivity : 0.4459
            Specificity : 0.8610
         Pos Pred Value : 0.7624
         Neg Pred Value : 0.6085
             Prevalence : 0.5000
         Detection Rate : 0.2230
   Detection Prevalence : 0.2924
      Balanced Accuracy : 0.6535

       'Positive' Class : Expensive
```

In [ ]:

```
library(caret)
library(kernlab)
modksvm <- ksvm(cost_category~bmi+exercise+hypertension,data=trainSet, C=5,cross=3,
modksvm
predout <-predict(modksvm,testSet)
confusion1 <- table(predout, testSet$cost_category)
prop.table(confusion1)
confusion2 <- confusionMatrix(predout, testSet$cost_category)
confusion2
```

```
Support Vector Machine object of class "ksvm"

SV type: C-svc  (classification)
 parameter : cost C = 5

Gaussian Radial Basis kernel function.
 Hyperparameter : sigma =  2.58660565204118

Number of Support Vectors : 4336

Objective Function Value : -20448.69
Training error : 0.385833
Cross validation error : 0.393934
Probability model included.
```

```
predout        Expensive Inexpensive
  Expensive   0.40061566  0.28715919
  Inexpensive 0.09938434  0.21284081
Confusion Matrix and Statistics

             Reference
Prediction    Expensive Inexpensive
  Expensive         911         653
  Inexpensive       226         484

               Accuracy : 0.6135
                 95% CI : (0.5931, 0.6335)
    No Information Rate : 0.5
    P-Value [Acc > NIR] : < 2.2e-16

                  Kappa : 0.2269

 Mcnemar's Test P-Value : < 2.2e-16

            Sensitivity : 0.8012
            Specificity : 0.4257
         Pos Pred Value : 0.5825
         Neg Pred Value : 0.6817
             Prevalence : 0.5000
         Detection Rate : 0.4006
   Detection Prevalence : 0.6878
      Balanced Accuracy : 0.6135

       'Positive' Class : Expensive
```

In [ ]:

```
library(caret)
library(kernlab)
modksvm <- ksvm(cost_category~age+exercise+hypertension,data=trainSet, C=5,cross=3,
modksvm
predout <-predict(modksvm,testSet)
confusion1 <- table(predout, testSet$cost_category)
prop.table(confusion1)
confusion2 <- confusionMatrix(predout, testSet$cost_category)
confusion2
```

```
Support Vector Machine object of class "ksvm"

SV type: C-svc  (classification)
 parameter : cost C = 5

Gaussian Radial Basis kernel function.
 Hyperparameter : sigma =  2.86433666503225

Number of Support Vectors : 2732

Objective Function Value : -12747.52
Training error : 0.235682
Cross validation error : 0.240201
Probability model included.
```

```
predout        Expensive Inexpensive
  Expensive   0.34872471  0.08443272
  Inexpensive 0.15127529  0.41556728
Confusion Matrix and Statistics

             Reference
Prediction    Expensive Inexpensive
  Expensive         793         192
  Inexpensive       344         945

               Accuracy : 0.7643
                 95% CI : (0.7463, 0.7816)
    No Information Rate : 0.5
    P-Value [Acc > NIR] : < 2.2e-16

                  Kappa : 0.5286

 Mcnemar's Test P-Value : 6.928e-11

            Sensitivity : 0.6974
            Specificity : 0.8311
         Pos Pred Value : 0.8051
         Neg Pred Value : 0.7331
             Prevalence : 0.5000
         Detection Rate : 0.3487
   Detection Prevalence : 0.4332
      Balanced Accuracy : 0.7643

       'Positive' Class : Expensive
```

In [ ]:

```
library(caret)
library(kernlab)
modksvm <- ksvm(cost_category~bmi+smoker+exercise+hypertension,data=trainSet, C=5,c
modksvm
predout <-predict(modksvm,testSet)
confusion1 <- table(predout, testSet$cost_category)
prop.table(confusion1)
confusion2 <- confusionMatrix(predout, testSet$cost_category)
confusion2
```

```
Support Vector Machine object of class "ksvm"

SV type: C-svc  (classification)
 parameter : cost C = 5

Gaussian Radial Basis kernel function.
 Hyperparameter : sigma =  1.60430150230418

Number of Support Vectors : 3551

Objective Function Value : -16481.03
Training error : 0.306895
Cross validation error : 0.307838
Probability model included.
```

```
predout       Expensive Inexpensive
  Expensive   0.3021108   0.1156552
  Inexpensive 0.1978892   0.3843448
Confusion Matrix and Statistics

             Reference
Prediction    Expensive Inexpensive
  Expensive         687         263
  Inexpensive       450         874

               Accuracy : 0.6865
                 95% CI : (0.6669, 0.7055)
    No Information Rate : 0.5
    P-Value [Acc > NIR] : < 2.2e-16

                  Kappa : 0.3729

 Mcnemar's Test P-Value : 3.266e-12

            Sensitivity : 0.6042
            Specificity : 0.7687
         Pos Pred Value : 0.7232
         Neg Pred Value : 0.6601
             Prevalence : 0.5000
         Detection Rate : 0.3021
   Detection Prevalence : 0.4178
      Balanced Accuracy : 0.6865

       'Positive' Class : Expensive
```

BUSINESS RULES

In [ ]:

```
hypertension_cat <- function(x){
  r <- case_when((is.na(x)) ~'NA'
    , (x == 0) ~ 'no'
    , (x == 1) ~ 'yes')
  return(r)
}
df_HMO_data <- df_HMO_data %>% mutate(hypertension_category = hypertension_cat(hype
head(df_HMO_data)
```

	X	age	bmi	children	smoker	location	location_type	education_level	yearly_p
	<int>	<int>	<dbl>	<int>	<fct>	<chr>	<fct>	<fct>	
1	1	18	27.900	0	yes	CONNECTICUT	Urban	Bachelor	
2	2	19	33.770	1	no	RHODE ISLAND	Urban	Bachelor	
3	3	27	33.000	3	no	MASSACHUSETTS	Urban	Master	
4	4	34	22.705	0	no	PENNSYLVANIA	Country	Master	
5	5	32	28.880	0	no	PENNSYLVANIA	Country	PhD	
6	7	47	33.440	1	no	PENNSYLVANIA	Urban	Bachelor	

In [ ]:

```
df_HMO_one <- df_HMO_data
cols <- c("age_category", "bmi_category", "child_category","cost_category", "smoker
"location_type", "education_level", "yearly_physical", "exercise", "married","hyper
df_HMO_one<-df_HMO_one[,cols]
head(df_HMO_one)
```

A data.frame: 6 ×

	age_category	bmi_category	child_category	cost_category	smoker	location	location_ty
	<fct>	<fct>	<fct>	<fct>	<fct>	<chr>	<f
1	Teen	Overweight	no children	Inexpensive	yes	CONNECTICUT	Ur
2	Teen	Obese	2 or less	Inexpensive	no	RHODE ISLAND	Ur
3	Young Adult	Obese	more than 2	Inexpensive	no	MASSACHUSETTS	Ur
4	Adult	Healthy	no children	Expensive	no	PENNSYLVANIA	Cour
5	Adult	Overweight	no children	Inexpensive	no	PENNSYLVANIA	Cour
6	Adult	Obese	2 or less	Expensive	no	PENNSYLVANIA	Ur

In [ ]:

```
EnsurePackage('arules')
EnsurePackage('arulesViz')
```

```
Loading required package: arules

Warning message in library(package, lib.loc = lib.loc, character.only = TRUE, logic
al.return = TRUE, :
“there is no package called ‘arules’”
Loading required package: arules

Warning message in library(package, lib.loc = lib.loc, character.only = TRUE, logic
al.return = TRUE, :
“there is no package called ‘arules’”
Loading required package: arules

Loading required package: Matrix


Attaching package: ‘Matrix’


The following objects are masked from ‘package:tidyr’:

    expand, pack, unpack



Attaching package: ‘arules’


The following object is masked from ‘package:kernlab’:

    size


The following object is masked from ‘package:dplyr’:

    recode


The following objects are masked from ‘package:base’:

    abbreviate, write


Loading required package: arulesViz

Warning message in library(package, lib.loc = lib.loc, character.only = TRUE, logic
al.return = TRUE, :
“there is no package called ‘arulesViz’”
Loading required package: arulesViz

Warning message in library(package, lib.loc = lib.loc, character.only = TRUE, logic
al.return = TRUE, :
“there is no package called ‘arulesViz’”
also installing the dependencies ‘tweenr’, ‘polyclip’, ‘RcppEigen’, ‘TSP’, ‘qap’,
‘gclus’, ‘ca’, ‘registry’, ‘ggforce’, ‘ggrepel’, ‘tidygraph’, ‘graphlayouts’, ‘cros
stalk’, ‘lazyeval’, ‘seriation’, ‘vcd’, ‘igraph’, ‘scatterplot3d’, ‘ggraph’, ‘DT’,
‘plotly’, ‘visNetwork’
```

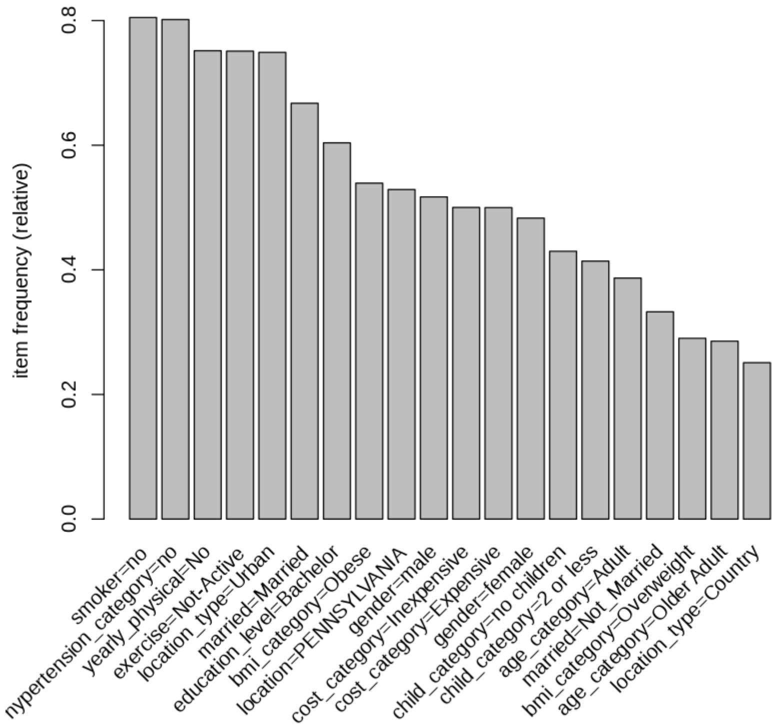
```
Loading required package: arulesViz
```

In [ ]:

```
library(arules)
library(arulesViz)
HMOX <-as(df_HMO_one, "transactions")
itemFrequency(HMOX)
itemFrequencyPlot(HMOX, topN = 20)
```

```
Warning message:
“Column(s) 6, 12 not logical or factor. Applying default discretization (see '? dis
cretizeDF').”
```

age_category=Adult: 0.386837246109206 **age_category=Older Adult:** 0.285544711158006 **age_category=Teen:** 0.0994460564494856 **age_category=Young Adult:** 0.228171986283303 **bmi_category=Healthy:** 0.157478237931944 **bmi_category=Obese:** 0.539171722500659 **bmi_category=Overweight:** 0.290160907412292 **bmi_category=Underweight:** 0.0131891321551042 **child_category=2 or less:** 0.414006858348721 **child_category=more than 2:** 0.156159324716434 **child_category=no children:** 0.429833816934846 **cost_category=Expensive:** 0.499868108678449 **cost_category=Inexpensive:** 0.500131891321551 **smoker=no:** 0.804932735426009 **smoker=yes:** 0.195067264573991 **location=CONNECTICUT:** 0.0805855974676866 **location=MARYLAND:** 0.0985228171986283 **location=MASSACHUSETTS:** 0.0613294645212345 **location=NEW JERSEY:** 0.0656818781324189 **location=NEW YORK:** 0.0721445528884199 **location=PENNSYLVANIA:** 0.528884199419678 **location=RHODE ISLAND:** 0.0928514903719335 **location_type=Country:** 0.250989184911633 **location_type=Urban:** 0.749010815088367 **education_level=Bachelor:** 0.60379847006067 **education_level=Master:** 0.202189395937747 **education_level=No College Degree:** 0.100105513057241 **education_level=PhD:** 0.0939066209443419 **yearly_physical=No:** 0.751648641519388 **yearly_physical=Yes:** 0.248351358480612 **exercise=Active:** 0.249010815088367 **exercise=Not-Active:** 0.750989184911633 **married=Married:** 0.667370087048272 **married=Not_Married:** 0.332629912951728 **hypertension_category=no:** 0.801635452387233 **hypertension_category=yes:** 0.198364547612767 **gender=female:** 0.482986019519916 **gender=male:** 0.517013980480084



In [ ]:

```
library(arules)
library(arulesViz)
inspect(HMOX[1:5])
```

```
    items                             transactionID
[1] {age_category=Teen,
     bmi_category=Overweight,
     child_category=no children,
     cost_category=Inexpensive,
     smoker=yes,
     location=CONNECTICUT,
     location_type=Urban,
     education_level=Bachelor,
     yearly_physical=No,
     exercise=Active,
     married=Married,
     hypertension_category=no,
     gender=female}                            1
[2] {age_category=Teen,
     bmi_category=Obese,
     child_category=2 or less,
     cost_category=Inexpensive,
     smoker=no,
     location=RHODE ISLAND,
     location_type=Urban,
     education_level=Bachelor,
     yearly_physical=No,
     exercise=Not-Active,
     married=Married,
     hypertension_category=no,
     gender=male}                              2
[3] {age_category=Young Adult,
     bmi_category=Obese,
     child_category=more than 2,
     cost_category=Inexpensive,
     smoker=no,
     location=MASSACHUSETTS,
     location_type=Urban,
     education_level=Master,
     yearly_physical=No,
     exercise=Active,
     married=Married,
     hypertension_category=no,
     gender=male}                              3
[4] {age_category=Adult,
     bmi_category=Healthy,
     child_category=no children,
     cost_category=Expensive,
     smoker=no,
     location=PENNSYLVANIA,
     location_type=Country,
     education_level=Master,
     yearly_physical=No,
     exercise=Not-Active,
     married=Married,
     hypertension_category=yes,
     gender=male}                              4
[5] {age_category=Adult,
     bmi_category=Overweight,
     child_category=no children,
```

```
     cost_category=Inexpensive,
     smoker=no,
     location=PENNSYLVANIA,
     location_type=Country,
     education_level=PhD,
     yearly_physical=No,
     exercise=Not-Active,
     married=Married,
     hypertension_category=no,
     gender=male}                            5
```

In [ ]:

```
library(arules)
library(arulesViz)
rules1 <- apriori(HMOX,
 parameter=list(supp=0.25, conf=0.5),
 control=list(verbose=F),
 appearance=list(default="lhs",rhs=("cost_category=Expensive")))
```

In [ ]:

```
library(arules)
library(arulesViz)
inspectedHMOX<-inspect(rules1)
inspectedHMOX
```

```
     lhs                               rhs                           support  confidence
coverage     lift count
[1]  {gender=male}                  => {cost_category=Expensive} 0.2647059  0.5119898
0.5170140 1.024250  2007
[2]  {bmi_category=Obese}           => {cost_category=Expensive} 0.3048008  0.5653131
0.5391717 1.130925  2311
[3]  {exercise=Not-Active}          => {cost_category=Expensive} 0.4264046  0.5677907
0.7509892 1.135881  3233
[4]  {yearly_physical=No}           => {cost_category=Expensive} 0.3768135  0.5013160
0.7516486 1.002897  2857
[5]  {bmi_category=Obese,
      exercise=Not-Active}          => {cost_category=Expensive} 0.2533632  0.6283939
0.4031918 1.257119  1921
[6]  {education_level=Bachelor,
      exercise=Not-Active}          => {cost_category=Expensive} 0.2557373  0.5656359
0.4521235 1.131570  1939
[7]  {exercise=Not-Active,
      married=Married}              => {cost_category=Expensive} 0.2850171  0.5640825
0.5052757 1.128463  2161
[8]  {location_type=Urban,
      exercise=Not-Active}          => {cost_category=Expensive} 0.3175943  0.5628799
0.5642311 1.126057  2408
[9]  {yearly_physical=No,
      exercise=Not-Active}          => {cost_category=Expensive} 0.3218148  0.5686320
0.5659457 1.137564  2440
[10] {exercise=Not-Active,
      hypertension_category=no}     => {cost_category=Expensive} 0.3383012  0.5627468
0.6011606 1.125791  2565
[11] {location_type=Urban,
      exercise=Not-Active,
      hypertension_category=no}     => {cost_category=Expensive} 0.2517805  0.5593320
0.4501451 1.118959  1909
[12] {yearly_physical=No,
      exercise=Not-Active,
      hypertension_category=no}     => {cost_category=Expensive} 0.2548140  0.5629371
0.4526510 1.126171  1932
NULL
```

Decision trees

In [ ]:

```
library(rio)
library(caret)
library(kernlab)

set.seed(111)
subHMO<- df_HMO_data
trainList <- createDataPartition(y=subHMO$cost_category,p=0.70,list=FALSE)

trainData <- subHMO[trainList,]
testData <- subHMO[-trainList,]
```

In [ ]:

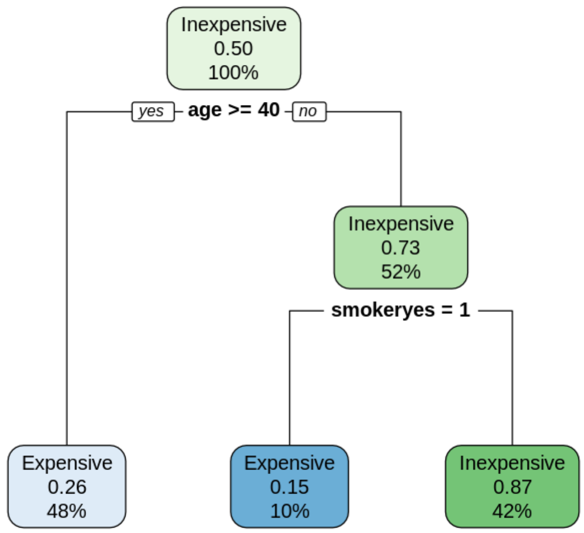
```
install.packages('rpart.plot')
```

```
Installing package into '/usr/local/lib/R/site-library'
(as 'lib' is unspecified)
```

In [ ]:
```
str(trainData)
```

```
'data.frame':	5308 obs. of  21 variables:
 $ X              : int  1 3 4 7 9 10 11 12 13 14 ...
 $ age            : int  18 27 34 47 36 59 24 61 22 57 ...
 $ bmi            : num  27.9 33 22.7 33.4 29.8 ...
 $ children       : int  0 3 0 1 2 0 0 0 0 0 ...
 $ smoker         : Factor w/ 2 levels "no","yes": 2 1 1 1 1 1 1 2 1 1 ...
 $ location       : chr  "CONNECTICUT" "MASSACHUSETTS" "PENNSYLVANIA" "PENNSYLVANI
A" ...
 $ location_type  : Factor w/ 2 levels "Country","Urban": 2 2 1 2 2 1 2 2 2 2 ...
 $ education_level: Factor w/ 4 levels "Bachelor","Master",..: 1 2 2 1 1 1 1 3 1 1
...
 $ yearly_physical: Factor w/ 2 levels "No","Yes": 1 1 1 1 1 1 1 1 1 2 ...
 $ exercise       : Factor w/ 2 levels "Active","Not-Active": 1 1 2 2 1 2 1 1 2 2
...
 $ married        : Factor w/ 2 levels "Married","Not_Married": 1 1 1 1 1 1 1 1 1 1
...
 $ hypertension   : num  0 0 1 0 0 1 0 0 0 0 ...
 $ gender         : Factor w/ 2 levels "female","male": 1 2 2 1 2 1 2 1 2 1 ...
 $ cost           : int  1746 576 5562 3842 1304 9724 201 4492 717 4153 ...
 $ cost_category  : Factor w/ 2 levels "Expensive","Inexpensive": 2 2 1 1 2 1 2 1 2
1 ...
 $ age_category   : Factor w/ 4 levels "Adult","Older Adult",..: 3 4 1 1 1 2 4 2 4
2 ...
 $ bmi_category   : Factor w/ 4 levels "Healthy","Obese",..: 3 2 1 2 3 3 3 3 2 2
...
 $ child_category : Factor w/ 3 levels "2 or less","more than 2",..: 3 2 3 1 1 3 3
3 3 3 ...
 $ cost_class     : Factor w/ 10 levels "2-6192","6193-12383",..: 1 1 1 1 1 2 1 1 1
1 ...
 $ cost_decile    : Factor w/ 10 levels "1","2","3","4",..: 7 9 3 4 7 1 10 3 9 4
...
 $ cost_categories: Factor w/ 200 levels "2-281","282-561",..: 7 3 20 14 5 35 1 17
3 15 ...
```

In [ ]:
```
library(e1071)
library(rpart)
library(rpart.plot)
library(caret)
library(rio)

Tree <- train(cost_category ~smoker + bmi + age + children + location + location_ty
  , method = "rpart"
  , data =trainData)

rpart.plot(Tree$finalModel)
```



In [ ]:
```
Tree
```

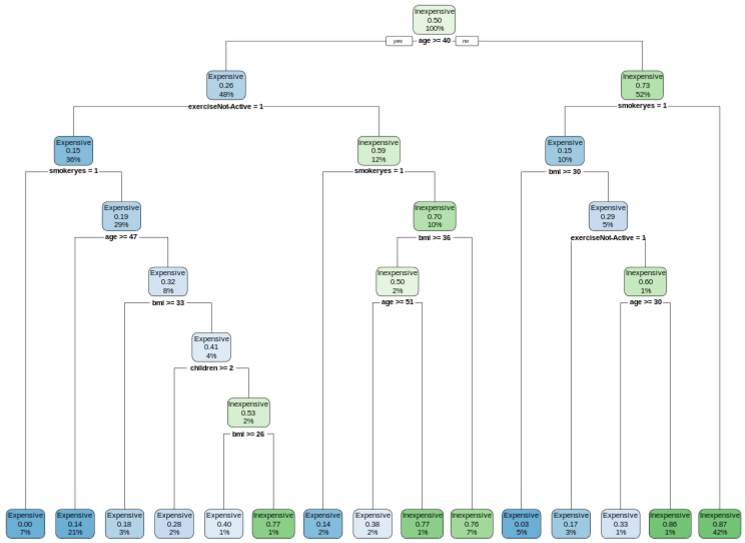
```
CART

5308 samples
  12 predictor
   2 classes: 'Expensive', 'Inexpensive'

No pre-processing
Resampling: Bootstrapped (25 reps)
Summary of sample sizes: 5308, 5308, 5308, 5308, 5308, 5308, ...
Resampling results across tuning parameters:

  cp          Accuracy   Kappa
  0.04183943  0.8128968  0.6257205
  0.13908783  0.7525272  0.5051763
  0.46852620  0.5950894  0.1994012

Accuracy was used to select the optimal model using the largest value.
The final value used for the model was cp = 0.04183943.
```

In [ ]:
```
pred <- predict(Tree,testData)

confusionMatrix(pred,as.factor(testData$cost_category))
```

```
Confusion Matrix and Statistics

             Reference
Prediction    Expensive Inexpensive
  Expensive        1013         330
  Inexpensive       124         807

               Accuracy : 0.8004
                 95% CI : (0.7833, 0.8166)
    No Information Rate : 0.5
    P-Value [Acc > NIR] : < 2.2e-16

                  Kappa : 0.6007

 Mcnemar's Test P-Value : < 2.2e-16

            Sensitivity : 0.8909
            Specificity : 0.7098
         Pos Pred Value : 0.7543
         Neg Pred Value : 0.8668
             Prevalence : 0.5000
         Detection Rate : 0.4455
   Detection Prevalence : 0.5906
      Balanced Accuracy : 0.8004

       'Positive' Class : Expensive
```

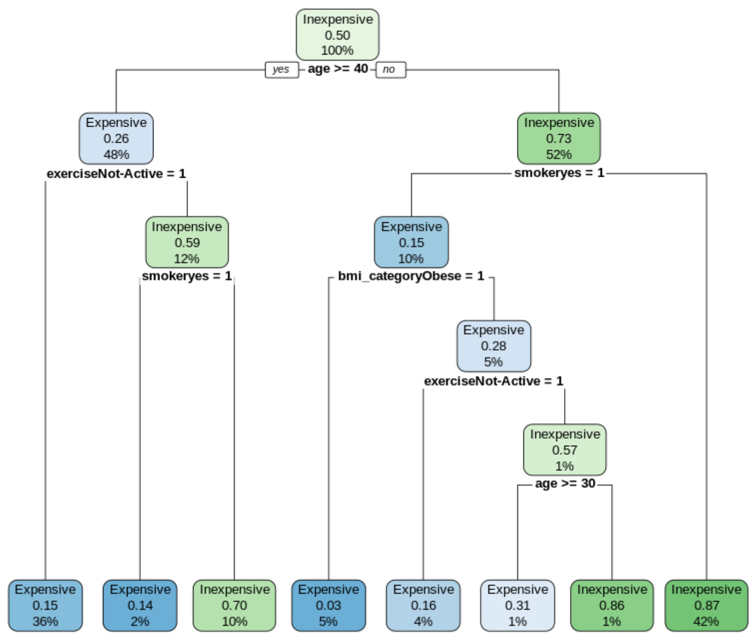
In [ ]:

```
Tree<- train(cost_category ~smoker + bmi + age + children + location_type + educati
  , method = "rpart"
  , data =trainData
  , tuneLength=10)

rpart.plot(Tree$finalModel)
```



In [ ]:

```
Tree<- train(cost_category ~smoker + bmi_category + age + children + exercise + mar
  , method = "rpart"
  , data =trainData
  , tuneLength=6)

rpart.plot(Tree$finalModel)
```



In [ ]:
```
str(trainData)
```

```
'data.frame':	5308 obs. of  21 variables:
 $ X              : int  1 3 4 7 9 10 11 12 13 14 ...
 $ age            : int  18 27 34 47 36 59 24 61 22 57 ...
 $ bmi            : num  27.9 33 22.7 33.4 29.8 ...
 $ children       : int  0 3 0 1 2 0 0 0 0 0 ...
 $ smoker         : Factor w/ 2 levels "no","yes": 2 1 1 1 1 1 1 2 1 1 ...
 $ location       : chr  "CONNECTICUT" "MASSACHUSETTS" "PENNSYLVANIA" "PENNSYLVANI
A" ...
 $ location_type  : Factor w/ 2 levels "Country","Urban": 2 2 1 2 2 1 2 2 2 2 ...
 $ education_level: Factor w/ 4 levels "Bachelor","Master",..: 1 2 2 1 1 1 1 3 1 1
...
 $ yearly_physical: Factor w/ 2 levels "No","Yes": 1 1 1 1 1 1 1 1 1 2 ...
 $ exercise       : Factor w/ 2 levels "Active","Not-Active": 1 1 2 2 1 2 1 1 2 2
...
 $ married        : Factor w/ 2 levels "Married","Not_Married": 1 1 1 1 1 1 1 1 1 1
...
 $ hypertension   : num  0 0 1 0 0 1 0 0 0 0 ...
 $ gender         : Factor w/ 2 levels "female","male": 1 2 2 1 2 1 2 1 2 1 ...
 $ cost           : int  1746 576 5562 3842 1304 9724 201 4492 717 4153 ...
 $ cost_category  : Factor w/ 2 levels "Expensive","Inexpensive": 2 2 1 1 2 1 2 1 2
1 ...
 $ age_category   : Factor w/ 4 levels "Adult","Older Adult",..: 3 4 1 1 1 2 4 2 4
2 ...
 $ bmi_category   : Factor w/ 4 levels "Healthy","Obese",..: 3 2 1 2 3 3 3 3 2 2
...
 $ child_category : Factor w/ 3 levels "2 or less","more than 2",..: 3 2 3 1 1 3 3
3 3 3 ...
 $ cost_class     : Factor w/ 10 levels "2-6192","6193-12383",..: 1 1 1 1 1 2 1 1 1
1 ...
 $ cost_decile    : Factor w/ 10 levels "1","2","3","4",..: 7 9 3 4 7 1 10 3 9 4
...
 $ cost_categories: Factor w/ 200 levels "2-281","282-561",..: 7 3 20 14 5 35 1 17
3 15 ...
```

To conclude, We built linear model (with multiple combinations),

SVM (with multiple combinations),

decision tree,

Apriori,

on the HMO dataset. The best model is SVM and it is what will be used for us to determine the actionable insights.

Actionable Insights

We want to target obese old adults and old adults to have a reduced premium cost if they take a part in HMO collaborations for health services. These collaborations will be established in selected locations based on our cost and location map plotting.

Similarly, young adults and adults would be targetted for corresponding health programs for reduced premiums and dependent cost if they sign up for partnet exercise plans, partner yearly physical tests. These programs would be promoted in locations with high concetration of adults and young adults.