Data Analysis Project for Medical Insurance Forecast

By
Ayush Sharma 8A
Nittin Kakkar 21A

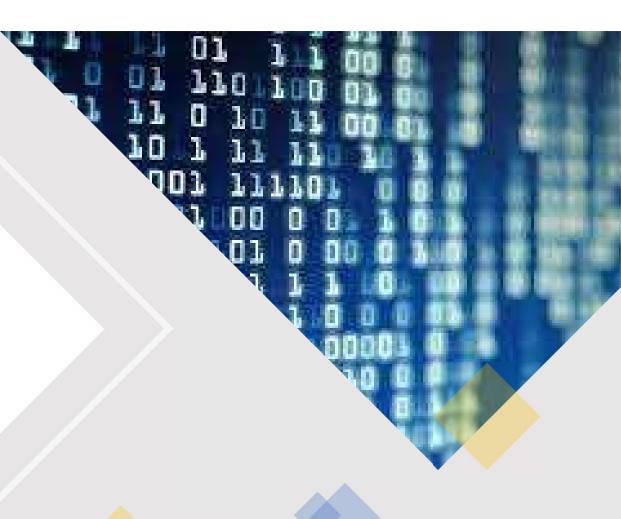


About Dataset

- Despite knowing little about the insured population, insurance companies must determine premiums based on demographic trends to make a profit.
- Our objective is to estimate the cost that the insured will incur.
- Using Different Linear Regression and Methods available in R.
- The link to original dataset can be found here.

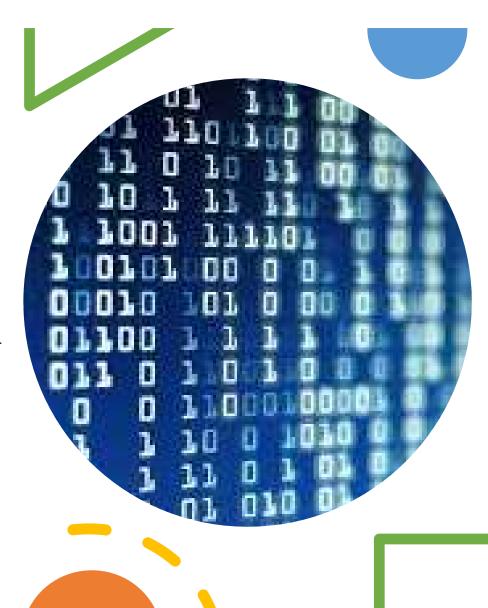


- ☐ This dataset consists of 1338 observations on 7 variables
- Dependent variable charges
- ☐ Independent variables age, bmi, smoker ,etc.
- Also, the dataset contains some categorical variable like sex, children(number of children), and smoker, region.



DATASET

- •Age: the age of the insured (recipients).
- •Sex: sex of insured persons; "male" or "female".
- •bmi: body mass index, providing an understanding of the body, relatively high or low weights relative to height, objective body weight index (kg / m $^{\circ}$ 2) using the height / weight ratio.
- •children: number of children covered by health insurance / number of dependents.
- •smoker: does the insured smoke or not.
- •region: the recipient's residential area in the United States; northeast, southeast, southwest, northwest.
- •charges: Individual medical costs billed by health insurance.



Summary of Data

```
> summary(dataset)
                                                  children.
                                                                 smoker
     age
                   sex
                                                                                   region
Min. :18.00 Length:1338
                                 Min. :15.96 Min. :0.000 Length:1338
                                                                                Length:1338
1st Qu.:27.00 Class :character 1st Qu.:26.30 1st Qu.:0.000 Class :character Class :character
                                                             Mode :character Mode :character
Median :30.00 Mode :character Median :30.40 Median :1.000
Mean :39.21
                                 Mean :30.66 Mean :1.095
3rd Ou.:51.00
                                 3rd Ou.:34.69 3rd Ou.:2.000
Max. :64.00
                                 Max. :53.13 Max. :5.000
   charges
Min. : 1122
1st Qu.: 4740
Median: 9382
Mean :13270
3rd Ou.:16640
Max. :63770
> dim(dataset)
[1] 1338 7
> str(dataset)
'data.frame': 1338 obs. of 7 variables:
$ age : int 19 18 28 33 32 31 46 37 37 60 ...
         : chr "female" "male" "male" "male" ...
         : num 27.9 33.8 33 22.7 28.9 ...
$ children: int 0 1 3 0 0 0 1 3 2 0 ...
$ smoker : chr "yes" "no" "no" "no" ...
$ region : chr "southwest" "southeast" "southeast" "northwest" ...
$ charges : num 16885 1726 4449 21984 3867 ...
```

Objective

- Examine the relationship between the cost of insurance and the variables that affect it, including age, sex, BMI, the number of children covered by health insurance, smoking, and geographic location.
- We will examine and make predictions about the factors influencing health insurance premiums in this paper. Linear Regression will be used to achieve it. Data preparation, exploratory data analysis, model building, prediction alternative model, and conclusion are all steps in the process.
- Response Variable: Charges
- <u>Predictor Variables</u>: Age, BMI, children, smoker

DATA PRE - PROCESSING

NO MISSING VALUES WERE FOUND

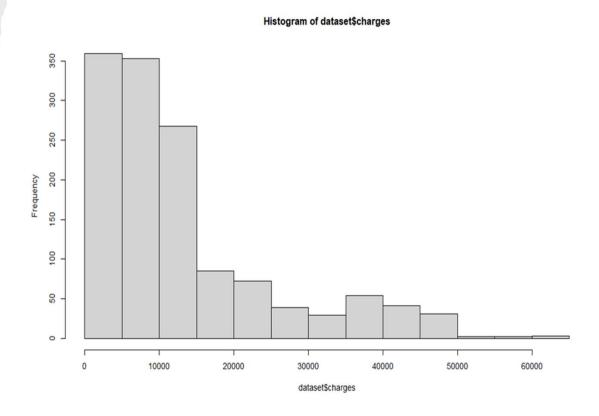
TRANSFORMED CHARACTER
VARIABLES AS FACTORS
AND CREATED NEW
COLUMN TO CATEGORIZE
BMI FOR BETTER ANALYSIS



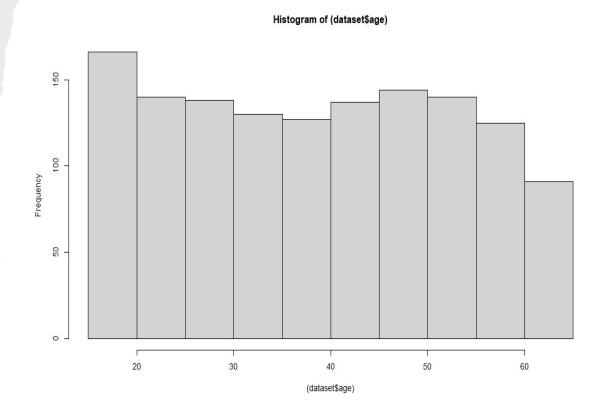
DATA ANALYSIS

☐ Scatter plots, co-relations plots are frequently used to identify any relationships between data since they make it simple to see any correlation.

Histogram ~ Charges



Histogram ~ Age



Distribution ~ Region wise Percentage

- Gender is equally distributed
- 20% of individuals are smokers
- 54% of individuals have 1-3 children

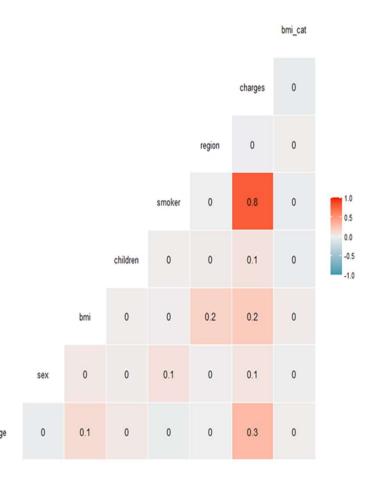
region count percent	
<fct> <int> <dbl></dbl></int></fct>	
1 northeast 324 24	smoker count percent
2 northwest 325 24	<fct> <int> <dbl></dbl></int></fct>
3 southeast 364 27	1 no 1064 80
4 southwest 325 24	2 yes 274 20
	children count percent

sex count percent				
<fct> <int> <dbl></dbl></int></fct>				
1 fem	nale	662	2	49
2 ma	le	676		51

<int><int><int><int> percent10574432132424322401843157125425265181

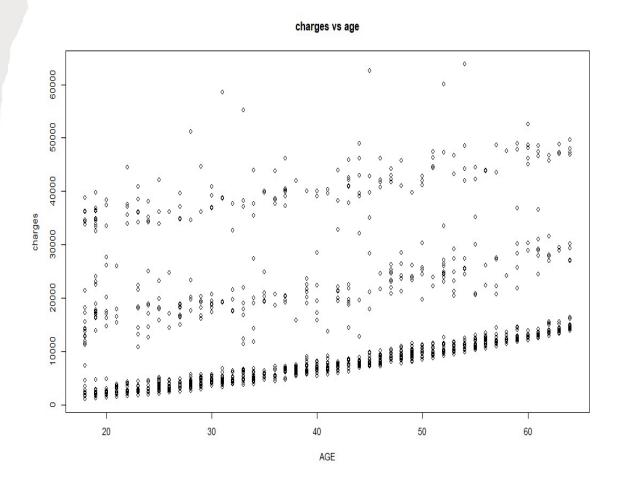
Correlation Charge vs Age vs BMI

As can be seen from the correlation plot, smoker, age and bmi are positively related to charges. So, we are going to analyse their relationship further.



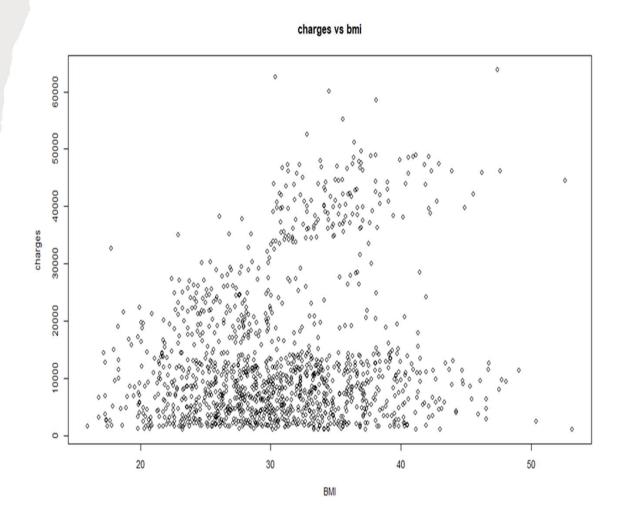
Scatter Plot Charge vs Age

 According to the graph, charges slightly increases with increase in age



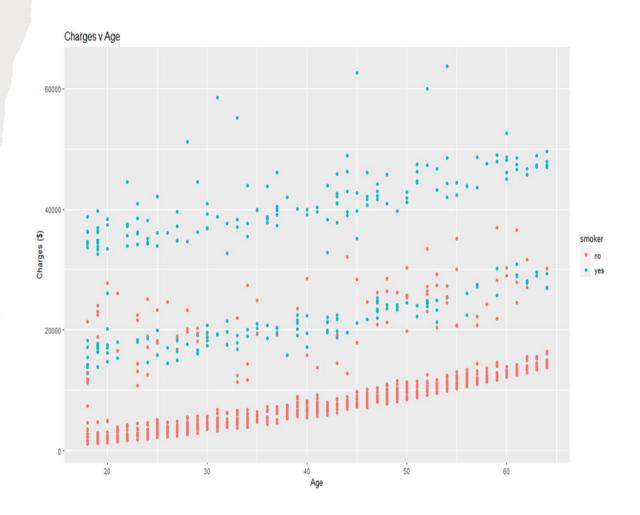
Scatter Plot Charge vs BMI

• According to the graph, BMI the relationship gets stronger after 30.



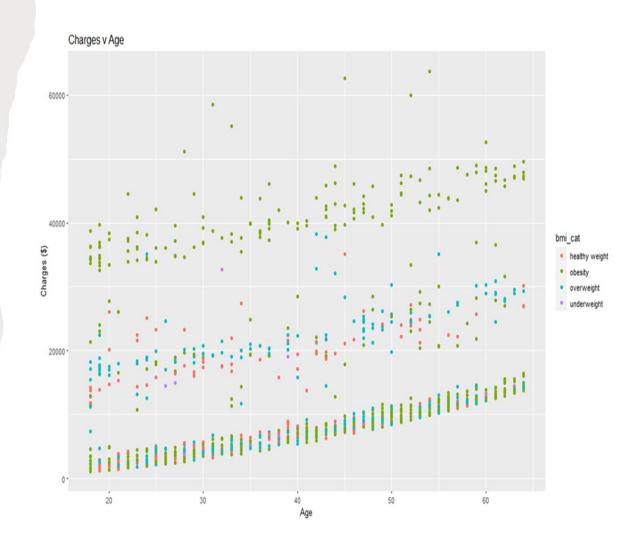
Scatter Plot Charge vs Age vs Smoker

It is clear from the plot that the charges rise in price with age.
Additionally, it is evident that smokers paid more in fees than non-smokers did.



Scatter Plot Charge vs Age vs BMI

It is clear from the plot that the charges rise in price with age and obesity (higher bmi)



Regression Analysis:

- ❖The goal of linear regression is to mathematically represent a continuous variable Y as a function of one or more variables X, allowing us to use this regression model to predict the Y when only the X is known.
- Initial Linear regression model.
 - ❖ Outcome: Charges
 - ❖Predictors: Age, Sex, BMI, Smokers

Here, we attempt to build a model using one significant predictor at a time. Based on the correlation plot, we can see that age is the second important predictor, as the most significant predictor, smoking, is a categorical variable.

Linear Regression Analysis:

```
Call:
lm(formula = charges ~ age, data = training_set)
Residuals:
  Min
          10 Median
 -8106 -6704 -5933 5775 47338
Coefficients:
           Estimate Std. Error t value Pr(>|t|)
(Intercept) 3381.74
                       1079.16 3.134 0.00178 **
             253.27
                         25.79 9.821 < 2e-16 ***
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Residual standard error: 11420 on 1002 degrees of freedom
Multiple R-squared: 0.08781, Adjusted R-squared: 0.0869
F-statistic: 96.46 on 1 and 1002 DF, p-value: < 2.2e-16
```

We can see from the Pr(>|t|) column that the regression coefficient (2.2e-16) is significant from zero (po.oo1) and that there should be an increase in charges of 253.27 for every year that a person gets older. The model only accounts for 8.78 percent of the variance in charges, which is quite low and suggests that it is not a very good model. The squared correlation between the actual and anticipated value is also known as the multiple R-squared. Because of how large the residual standard error (11420) is, it can be regarded as the typical error in estimating charges from age using this model.

Regression Analysis:

```
data = training_set)
> summary(rg)
Call:
lm(formula = charges ~ ., data = training_set)
Residuals:
    Min
              10 Median
                                3Q
-11484.8 -3615.8
                  -234.1 1625.2 25646.6
Coefficients:
                  Estimate Std. Error t value Pr(>|t|)
(Intercept)
                  -6147.85
                             1641.88 -3.744 0.000191 ***
                    258.90
                               13.70 18.900 < 2e-16 ***
age
sexmale
                   -504.27
                              382.39 -1.319 0.187565
bmi
                     79.69
                              64.12 1.243 0.214248
children
                              157.03 3.068 0.002210 **
                    481.83
smokeryes
                              471.98 49.609 < 2e-16 ***
                  23414.39
regionnorthwest
                  -567.62
                              547.94 -1.036 0.300499
regionsoutheast
                              549.69 -2.101 0.035872 *
                  -1155.03
regionsouthwest
                              553.28 -1.963 0.049886 *
                  -1086.28
bmi_catobesity
                   4114.28
                              951.76 4.323 1.7e-05 ***
bmi_catoverweight
                    691.76
                              669.98 1.033 0.302086
bmi_catunderweight
                   363.15
                             1656.70 0.219 0.826541
Signif, codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Residual standard error: 6030 on 992 degrees of freedom
Multiple R-squared: 0.7485,
                             Adjusted R-squared: 0.7457
F-statistic: 268.3 on 11 and 992 DF, p-value: < 2.2e-16
```

Final Model:

- Final model can be written as follow:
- charges= -12102.77 + 257.85(age) + 321.85(bmi) + 23811.40(smoker-yes) +473.50(children)

```
> summary(model_3)
Call:
lm(formula = dataset$charges ~ dataset$age + dataset$bmi + dataset$smoker +
   dataset$children, data = training_set)
Residuals:
    Min
             10 Median
-11897.9 -2920.8 -986.6 1392.2 29509.6
Coefficients:
                 Estimate Std. Error t value Pr(>|t|)
                -12102.77 941.98 -12.848 < 2e-16 ***
(Intercept)
dataset$age
                  257.85 11.90 21.675 < 2e-16 ***
dataset$bmi
                  321.85 27.38 11.756 < 2e-16 ***
dataset$smokeryes 23811.40 411.22 57.904 < 2e-16 ***
dataset$children 473.50 137.79 3.436 0.000608 ***
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' '1
Residual standard error: 6068 on 1333 degrees of freedom
Multiple R-squared: 0.7497, Adjusted R-squared: 0.7489
F-statistic: 998.1 on 4 and 1333 DF, p-value: < 2.2e-16
```

- Using R, we fitted a linear regression model to the dataset and used the model to predict the values under various situations.
- With an Adjusted R-Squared value of 0.7489, the constructed linear regression model can account for 74.89 percent of the variance in the target variable (insurance charges).
- As a result, expanding the data collection may be necessary because there may not be enough data or predictors to fully explain the target variables.
- The most important factors in determining insurance charges, according to both models, are age, bmi, and smoker status. As a result, the beneficiary's insurance premiums will be higher if they smoke frequently, are older, have a higher BMI, or are obese.

