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**[ X ] I have read and accept the above.**

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*For each question, please start your answer in a new page.*

# Answer to Q1:

**Create the BMI variable based on CDC definition . Show your code.**

From the website, BMI is a person’s weight in kilograms divided by the square of height in meters. We shall implement this formula to create the BMI variable.

We reference Appendix A of CBA Question Paper.pdf and see that the Height variable is given in cm, while the Weight variable is given in kg. Therefore, we will have to perform some conversion for the height variable before using it.

The formula is therefore BMI = Weight / (Height/100)^2. We will keep BMI as a variable type of Double because the decimal points are important. However, we will round off to just one decimal point.

Graphical user interface, text, application, email

Description automatically generated

# Answer to Q2:

**There are many categorical variables with integer coded values (e.g. Diabetes, HighBloodPressure, Transplant…etc.) Is it necessary to convert them to factor datatype in R?**

Yes, it is necessary to convert them into factor datatype in R. If we wrongly interpret the categorical variables as continuous variables, this allows for numeric concepts on continuous numbers such as fractions to become applicable.

Taking the example of the Gender variable, a value of 0.5 would mean that the person is halfway male and female, which is not possible. Or for the Allergy variable, the interpretation would be that the person has half an allergy which makes no sense as well.

Hence, it is necessary to convert categorical variables with integer coded values into factor datatype in R.

# Answer to Q3:

**Explore the data and report on your key findings.**

A lot of exploratory data analysis was conducted. The most important ones will be mentioned here.

# Chart, histogram Description automatically generatedNumMajorSurgeries

**Findings**

NumMajorSurgeries is continuous variable of integer variable type.

However, while NumMajorSurgeries could theoretically take on any continuous integer value, it practically is limited to very few values because a human can only go through that many major surgeries. Therefore, an argument can be made for this to be a factor variable.

Particularly in this case, where NumMajorSurgeries only takes on integers 0,1,2,3, we should treat it as a factor variable. It is closer to a factor variable than a continuous variable in the context of this dataset.

Conversion to factor is performed!

# Calendar Description automatically generatedCorrelation for continuous variables

**Findings**

There is high correlation between Age and Premium, suggesting that Age could be one of the most important predictors for Premium within the continuous variables.

BMI has high correlation with Weight and moderately high correlation with Height, which could result in BMI being removed in the models subsequently. This makes sense - BMI was derived from Height and Weight

# Graphical user interface, application Description automatically generatedPremium

**Findings**

Most of the population have a premium between $1100 to $1400, but the majority has a premium of around $1150. However, we can also note that the Premium variable takes only several distinct values (24 unique ones) between the range of 750-2000.

Having very few unique values of Premium might affect our model’s error later on.

# Continuous variables

Graphical user interface, chart, scatter chart

Description automatically generated**Findings**

Age - The older you are, the higher the premium tends to be. Likely an important variable

Height - There is very little observable relationship between height and premium

Weight - The heavier you are, the higher the premium tends to be. Likely an important variable

BMI - The higher the BMI, the higher the premium tends to be. Likely an important variable

# Categorical variables

Chart, diagram, box and whisker chart

Description automatically generatedChart, diagram, box and whisker chart

Description automatically generated

* Diabetes
  + Having diabetes means that premium will generally be higher. However, the distribution remains similar
  + Likely an important variable
* HighBloodPressure
  + Having high blood pressure means that premium will almost certainly be higher. Almost all high blood pressure persons will pay a premium above the mean/median of someone without high blood pressure
  + Likely an important variable
* Transplant
  + Having had transplants before means that premium will almost certainly be higher. Almost all persons with a history of transplants will pay a premium above the 75 percentile of someone without transplants
  + Likely an important variable
* ChronicDisease
  + Having chronic disease means that premium will almost certainly be higher. Almost all persons with chronic disease will pay a premium above the mean/median of someone without chronic disease
  + Likely an important variable
* Allergy
  + Allergies do not seem to affect premium
* CancerInFamily
  + Having cancer in family members means that premium will generally be higher based on mean and median premiums
  + Likely an important variable
* NumMajorSurgeries
  + The more the number of major surgeries, the higher the premium will be. However there is almost no difference between having 2 major surgeries, and having 3. However, this could be because of a lack of data.
  + Likely an important variable
* Gender
  + Gender does not affect premium too much

# Answer to Q4:

**Using 1 SE optimal CART and one other technique learnt in this course:**

Given that the dependent variable is Premium, which is a continuous variable, the other technique chosen is linear regression.

1. **What is the 10-fold cross validation RMSE and number of splits in the 1SE Optimal CART?**

# Short answer

10-fold CV RMSE in 1SE Optimal CART = 161.6693

Number of splits in 1SE Optimal CART = 7

Read on for explanation

# CART

The optimal tree was generated based on the full dataset. Checking the cp table, the root node error was obtained, and the xerror at the final split was obtained. These will allow us to calculate the 10-fold cross validation RMSE for the 1SE Optimal CART. The number of splits in the tree can also be determined by reading the cp table.

Table

Description automatically generated

Graphical user interface, text

Description automatically generated

# Linear regression (can skip this part)

For completeness sake, we can also obtain the 10-fold CV RMSE for the linear regression model. Cross-validation was performed for linear regression using the *caret* library, and the printout provides us with the RMSE.

10-fold CV RMSE in Optimal linear regression = 186.655

Graphical user interface, text

Description automatically generated

1. **Identify the key predictors of premium.**

# Short answer

Age, Transplant, NumMajorSurgeries, Weight, ChronicDisease, CancerInFamily

Read on for explanation

# CART

Using the optimal tree that was trained on the full dataset, we can check the most important variables by simply calling up the variable importance table from the 1SE optimal cart model.

Graphical user interface, text, application

Description automatically generated

However, the 1SE optimal tree does not use all these variables. Therefore, we can refer to the optimal tree to pick just the key predictors, which are variables actually used in the optimal tree.

Diagram

Description automatically generated

From this, the order of variable importance for the key predictors of Premium are:

Age > Transplant > NumMajorSurgeries > Weight > ChronicDisease > CancerInFamily

Six variables have been selected

# Linear regression

Using the optimal linear regression model that was trained on the full dataset, we can check the most important variables by checking what variables were preserved in the final linear regression model.

Text, table

Description automatically generated

From this, the key predictors of Premium are:

Age, Transplant, NumMajorSurgeries, Weight, ChronicDisease, CancerInFamily

However, it should be noted that we can only tell what the key predictors are, but not the order of importance between them.

# CART vs Linear regression

Given that the key predictors of Premium for both CART and linear regression are the exact same, we can confirm that the key predictors of Premium are definitely the following six variables

Age, Transplant, NumMajorSurgeries, Weight, ChronicDisease, CancerInFamily

1. **Is BMI or Gender important in determining premium?**

# Short answer

|  |  |  |
| --- | --- | --- |
|  | CART | Linear regression |
| BMI | Important  (as surrogate) | Not important |
| Gender | Not important | Not important |

Read on for explanation

# CART

From part b, we established that the key predictors of Premium for both models are:

Age, Transplant, NumMajorSurgeries, Weight, ChronicDisease, CancerInFamily

We might be tempted to say that BMI or Gender are unimportant because they do not appear in the six variables above. However, they are still important because they can be used as **surrogates** in CART. This is in the event where the key predictor is missing for a record, then we will need the next best alternative variable to make the split decision at a node that requires the missing key predictor.

Below shows the details for node number 13 of the 1SE optimal CART.

Text

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As we can see, BMI can be used as a surrogate at node number 13, when the primary split of Age is missing. Node number 6 and 27 also uses BMI as a surrogate variable. This means that BMI is important in determining Premium, and why it appears in the cart2$variable.importance call despite not appearing in the optimal tree.

Gender however does not appear even as a surrogate, hence unimportant in CART.

# Linear regression

BMI and Gender both do not appear in the optimal linear regression model. This means the two variables are not statistically significant enough to be considered when performing linear regression.

There are no concepts of surrogates in linear regression, therefore both BMI and Gender are unimportant in linear regression

1. **Evaluate and compare the predictive accuracy of the two techniques on a 70-30 train-test split. Present testset RMSE results in a table.**

|  |  |  |
| --- | --- | --- |
|  | CART (train-test) | Linear regression (train-test) |
| Testset RMSE | 160.9869 | 182.4656 |

The testset RMSE was calculated as per the screenshots, using models trained on trainset data. From the table above, we can see that CART has a lower testset RMSE than linear regression. Therefore, we conclude that the predictive accuracy of the CART model is better than the linear regression model.

It might appear strange that the CART model has a lower RMSE than the linear regression, even though the dependent variable Premium is a continuous variable, and CART model we have only has eight leaf nodes, hence can only predict eight values. One should expect linear regression to perform better.

However, this can be explained by the distribution of Premium. Looking at the histograms and density plots for Premium, we can see that Premium does not take on many unique values, as seen from the large spikes. Indeed, there are actually only 24 unique values for Premium, out of 988 records.

Chart, histogram, waterfall chart

Description automatically generatedGraphical user interface, text, application

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Graphical user interface, text, application, email

Description automatically generatedTherefore for the testset, the fewer values (7) that the CART model predicts actually match the 20 unique values of Premium better, versus the many values (295) that the linear regression model predicts.

This results in a lower RMSE value for the CART model.

# Answer to Q5:

**Explain the limitations of your analysis. [Max 1 page.]**

# Answer to Q6:

**Is CART successful in this application? Explain. [Max 1 page.]**

# References:

**plotgrid** references

<https://wilkelab.org/cowplot/articles/plot_grid.html>

**ggplot** references

<https://ggplot2.tidyverse.org/reference/ggplot.html>

Histogram code

<http://www.sthda.com/english/wiki/ggplot2-histogram-plot-quick-start-guide-r-software-and-data-visualization>

Boxplot code

<https://stackoverflow.com/questions/19876505/boxplot-show-the-value-of-mean>

Line of best fit code

<https://stackoverflow.com/questions/15633714/adding-a-regression-line-on-a-ggplot>

Decision trees are immune to multicollinearity

<https://towardsdatascience.com/why-feature-correlation-matters-a-lot-847e8ba439c4#:~:text=Multicollinearity%20happens%20when%20one%20predictor,immune%20to%20multicollinearity%20by%20nature%20>.

Linear regression with k-fold cross validation using **caret** library

<http://www.sthda.com/english/articles/38-regression-model-validation/157-cross-validation-essentials-in-r/>

CART and linear regression code

RE6013 slides