Analyzing Insurance Claims for Future Financial Safeguard

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Abstract

In the realm of insurance, the anticipation of claims plays a pivotal role in risk management and financial planning. This project delves into the challenge of predicting insurance claims, a task made intricate by a dataset characterized by its modest sample size and a slight imbalance between claimed and unclaimed instances. The objective is to surmount these obstacles and construct a robust predictive model capable of accurately classifying insurance claims. The project will navigate through methodologies to address imbalances, optimize feature extraction, and employ advanced predictive modeling techniques such as classification and regression trees, random forest, xgboost algorithms, statistical models such as logit and probit, and Support Vector Machines (SVM).

The SVM model, known for its effectiveness in both classification and regression tasks, will be explored to enhance the predictive capabilities of the model. By leveraging SVM's ability to find optimal decision boundaries, we aim to further refine our predictive model. This comprehensive approach, encompassing a variety of advanced modeling techniques, seeks to contribute valuable insights to the field of insurance analytics, enabling more informed decision-making and risk assessment.

Introduction

Within the scope of insurance analytics, the task of predicting insurance claims has emerged as a significant focal point, garnering increased attention in recent years. This heightened interest is attributed to the critical role that accurate predictions play in effective risk management and strategic financial planning within the insurance industry. Numerous research endeavors have been dedicated to the development of robust predictive models, each tailored to address the unique challenges posed by insurance datasets.

The complexity of this endeavor is compounded by the inherent characteristics of the dataset at hand. With a relatively modest sample size, the dataset presents challenges in capturing the diverse scenarios that may lead to insurance claims. Additionally, there is a slight imbalance between instances where claims are made and those where claims are not, adding an extra layer of complexity to the predictive modeling task.

Addressing these challenges requires sophisticated methodologies that can effectively navigate the nuances of the data. Researchers have explored various strategies to optimize predictive model performance, considering factors such as imbalances in the dataset and the need for accurate classification. As we delve into this project, the goal is to overcome these obstacles and construct a predictive model that not only captures the intricacies of the data but also generalizes well to new, unseen instances. The methodologies employed will span techniques for handling imbalanced data, optimizing feature extraction, and leveraging advanced modeling algorithms, including classification and regression trees, random forest, xgboost, support vector machines and statistical models such as logistic regression and probit regression.

By addressing the challenges head-on and employing state-of-the-art methodologies, the project aims to contribute valuable insights to the evolving landscape of insurance analytics. The overarching objective is to empower decision-makers in the insurance industry with accurate and actionable predictions, facilitating more informed choices in risk assessment and financial planning.

Literature Review

Class Imbalance and Sample Size Concerns:

The inherent challenges associated with modest sample sizes and class imbalances in insurance datasets have been widely acknowledged. Researchers have explored various strategies to mitigate these issues, including oversampling techniques, undersampling approaches, and the synthesis of artificial instances to balance the distribution of claimed and unclaimed instances. Notable studies, have demonstrated the efficacy of these methods in enhancing the predictive performance of models in similar contexts.

Feature Extraction and Optimization:

Feature extraction plays a pivotal role in the predictive accuracy of models. Researchers have delved into optimizing feature selection techniques to identify the most informative variables. Dimensionality reduction methods, such as Variable Selection method with forward elimination, backward elimination, both and Variable importance parameter have been explored to enhance model interpretability and generalization performance.

Predictive Modeling Techniques:

The literature is rich with studies employing various predictive modeling techniques for insurance claim prediction. Classification and regression trees (CART), renowned for their interpretability and flexibility, have been extensively utilized. Additionally, ensemble methods such as random forest and xgboost algorithms have gained popularity for their ability to handle complex interactions and improve predictive accuracy. These techniques have been benchmarked against traditional statistical models, including logistic (logit) and probit regression, revealing nuanced insights into the trade-offs between interpretability and predictive power.

Contributions to Insurance Analytics:

By addressing the intricacies of insurance datasets, these studies collectively contribute to the advancement of insurance analytics. Insights gained from predictive models enable stakeholders to make more informed decisions, refine risk assessment strategies, and ultimately bolster the financial stability of insurance providers. The literature underscores the necessity of a multi-faceted approach that integrates advanced statistical learning methodologies to harness the full predictive potential of insurance data.

In summary, the existing body of literature provides a comprehensive foundation for the current project's objectives. By building upon these insights and addressing specific challenges posed by the dataset at hand, this study aspires to add valuable contributions to the ongoing discourse in insurance claim prediction.

Data Description

This data frame contains the following columns:

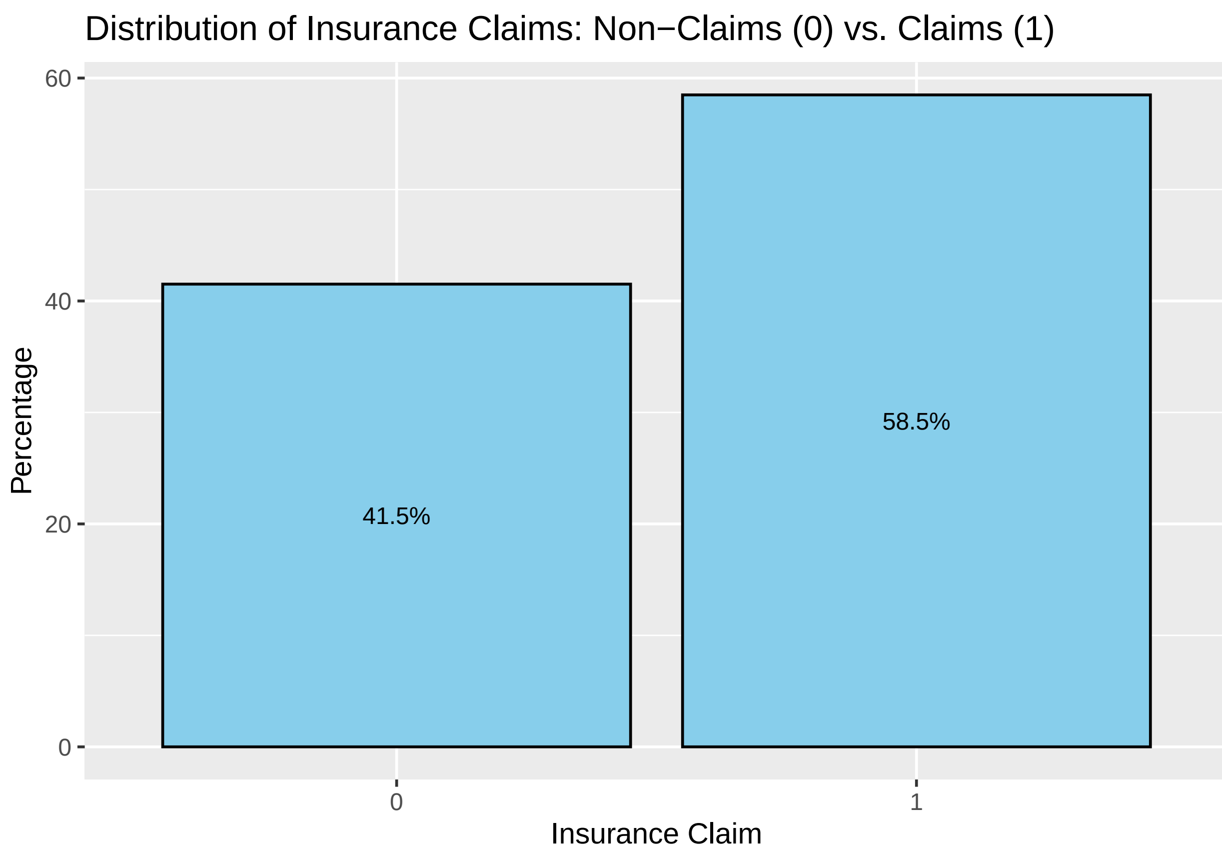
- **age**: Age of the policyholder.
- **sex**: Gender of the policyholder (female=0, male=1).
- **bmi**: Body mass index, providing an understanding of body weight relative to height (kg / m ^ 2).
- **steps**: Average walking steps per day of the policyholder.
- **children**: Number of children/dependents of the policyholder.
- **smoker**: Smoking status of the policyholder (non-smoke=0; smoker=1).
- **region**: The residential area of the policyholder in the US (northeast=0, northwest=1, southeast=2, southwest=3).
- **charges**: Individual medical costs billed by health insurance.
- **insuranceclaim**: Insurance claim status (yes=1, no=0).

The dataset comprises 1338 observations, encompassing explanatory variables such as age, sex, BMI, children, smoker, region, and charges, along with response variables like insurance claim.

Categorical predictor variables, including sex, children, smoker, and region, contain intermediate levels (2, 6, 2, 4, respectively). The dataset consists of 662 females and 675 males. Non-smokers total 1063, while smokers amount to 274. Four regions are represented, with mappings northeast=0, northwest=1, southeast=2, southwest=3, and counts of 324, 324, 364, and 325, respectively. The "children" feature indicates the number of dependents: 573 with no dependents, 324 with 1 dependent, 240 with 2 dependents, 157 with 3 dependents, 25 with 4 dependents, and 18 with 5 dependents.

The response variables exhibit two levels, 0 and 1, denoting no claim and claim, respectively, with counts of 555 and 782.

Dirstribution of the Response variable



Goal

In the domain of insurance, where uncertainty meets financial planning, our mission is crystal clear: predict the unpredictable. The heart of this project beats with the ambition to not just foresee insurance claims but to unravel the variables that wield the most influence in shaping these predictions.

Statistical Methods

1. **Logistic Regression (Logit):** Statistical model for binary classification.

Basis on the response variable with 0's and 1's which is a binomial we can apply binary logit model

A **binary random variable** Y can assume only one of two possible values, a value of 1 (Yes) or a value of 0 (No). and probability mass function (p.m.f.)

$$p(y; \pi) = \pi^y (1-\pi)^{1-y}, \; y = 0 \text{ or } 1; 0 \leq \pi \leq 1.$$

{#eq-pmfBern}

A useful transformation of π is the logit (or, log-odds) transformation:

$$\text{logit}(\pi) = \log\left(\frac{\pi}{1-\pi}\right)$$

{#eq-logitpi}

Let $\eta = \text{logit}(\pi)$. After some algebra, we see that we can uniquely write π as a function of η, i.e., the inverse transformation is

$$\pi = \frac{\exp(\eta)}{1+\exp(\eta)}$$

{#eq-invlogit}

1. Full Binary logit model was fitted on the data where the response variable is insuranceclaims and the remaining variables such as sex, children, bmi, smokers, age, region and charges.

Following are the null and alternative hypothesis.

Null Hypothesis (H_0):

$$H_0 : \beta_j = 0$$

The null hypothesis asserts that there is no association between the independent variable X_j and the log-odds of the dependent variable being in the "success" category.

Alternative Hypothesis (H_1):

$$H_1 : \beta_j \neq 0$$

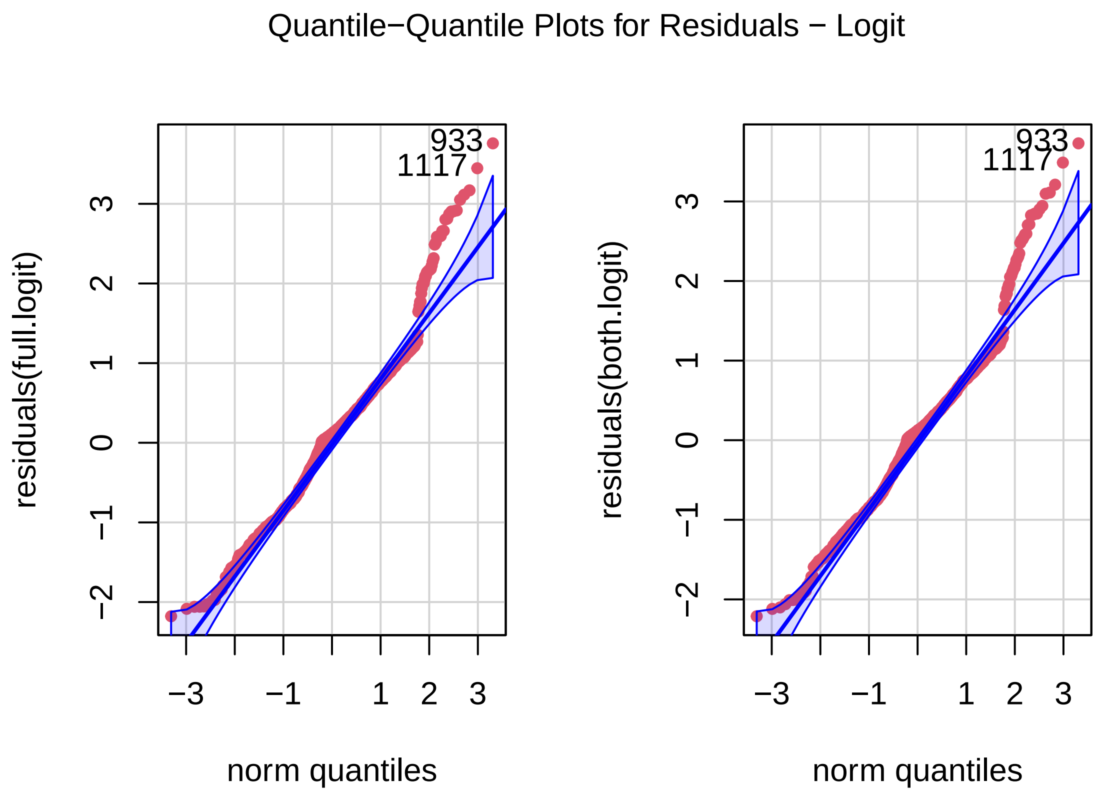
The alternative hypothesis suggests that the independent variable X_j does have a significant association with the log-odds of the event.

After fitting the full and both Logit Model we reject the null hypothesis with extremely less p-value,

Age, BMI, number of children, and smoking status appear to be significant predictors of insurance claims. - Charges and region may not be statistically significant predictors in this model.

```
##   933 1117
##   759  894
```


```
##   933 1117
##   759  894
```



From the above residual plot we can observe most of the data points were normal except few data points. Fitted the model by removing the outliers with the standard deviation greater than 3 times however even though the AIC values got down **normality assumption did not satisfy**.

2. **Probit Regression (Probit):** Alternative statistical model.

Starting with the standard normal c.d.f $\phi(z)$ which lies in the interval $[0,1]$, the probit (or inverse normal c.d.f.) link assumes that

$$\phi^{-1}(\pi_i) = \eta_i$$

{#eq-probit1}

so that

$$\pi_i = \Phi(\eta_i)$$

{#eq-probit2}

where η_i is given by @eq-binarysys as

$$\eta_i = \beta_0 + \sum_{j=1}^{p} \beta_j X_{i,j} = \mathbf{x}_i' \beta.$$

Null Hypothesis (H_0):

$$H_0 : \beta_j = 0$$

The null hypothesis asserts that there is no association between the independent variable X_j and the probability of the dependent variable being in the "success" category.

Alternative Hypothesis (H_1):

$$H_1 : \beta_j \neq 0$$

After fitting the probit model, we reject the null hypothesis as there is a significant asscociation for some variable to the response variable.

The logistic regression model was fitted to predict insurance claims based on various factors. The significant predictors include age, BMI, number of children, smoking status, and certain regions. Age and BMI showed positive associations with the likelihood of making an insurance claim, while having children had a negative impact, with the odds decreasing as the number of children increased. Smoking status was a strong positive predictor, indicating higher odds for smokers. The specific impact of regions varied, with some regions contributing to a decrease in the odds of a claim. The model's overall significance was confirmed by the Wald test (Chi-square = 418.14, df = 13, p < 2e-16). The model's goodness of fit was assessed using the Deviance statistic, with a residual deviance of 765.01 on 1055 degrees of freedom. The AIC value was 793.01, indicating a relatively good fit. Overall, the logistic regression model provides insights into the factors influencing insurance claims, with age, BMI, smoking status, and region being key determinants.

```
##  933 1117
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```
##  933 1117
##  759  894
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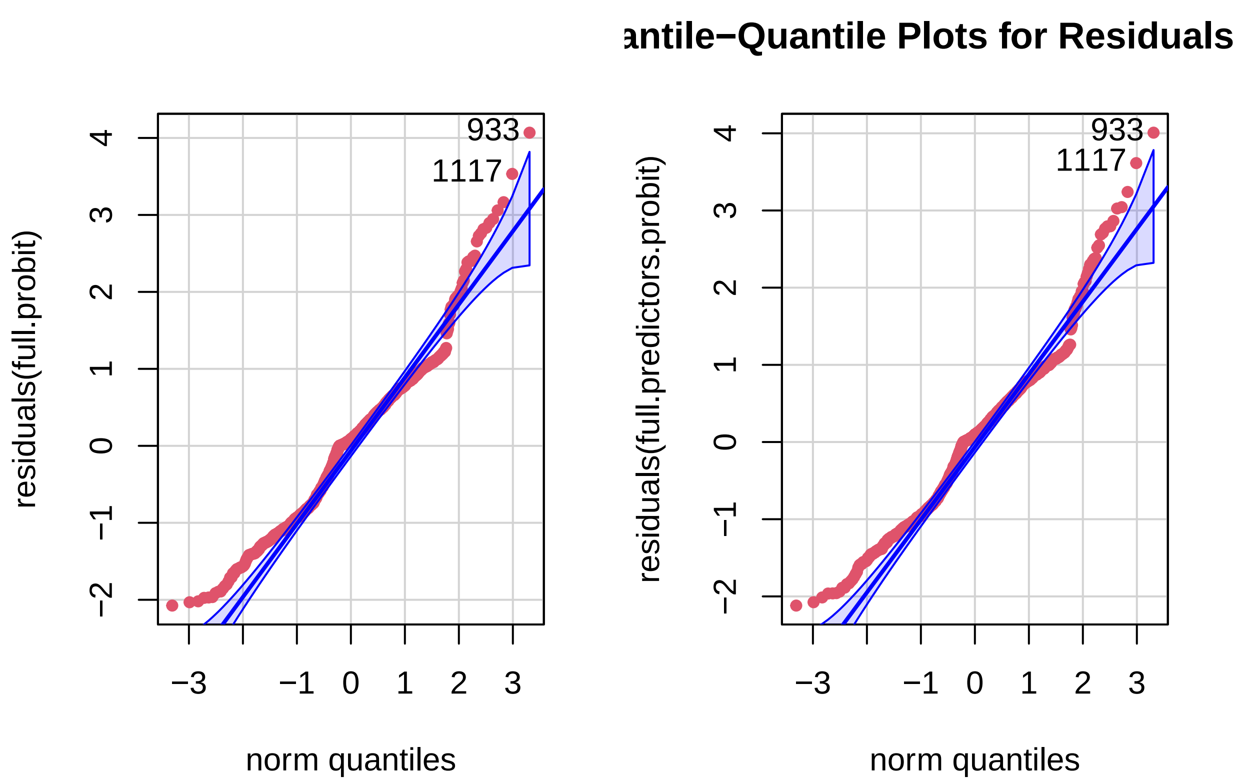


From the above residual plot it is clear that most of the data points were normal except few data points. Fitted the model by removing the outliers with the standard deviation greater than 3 times however even though the AIC values got down **normality assumption did not satisfy**.

3. **Classification and Regression Trees (CART):** Decision tree models for classification.

We define two impurity measures, Gini index and entropy, for classifying a response with J categories. The **Gini index** is defined by

$$\text{Gini index} = 1 - \sum_{j=1}^{J} p_j^2,$$

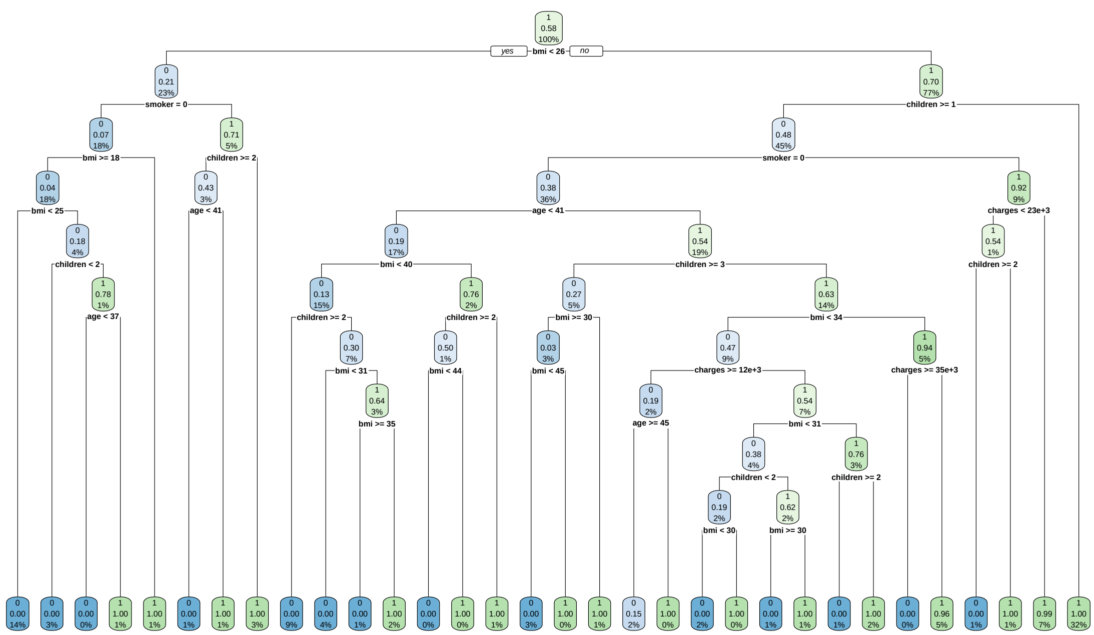
{#eq-gini-index}

where $p_j = P(Y \in \text{class} j),\ j = 1, \ldots, J$. Gini index lies in $[0, 1]$. The value 0 denotes a pure classification where all the cases belong to a single class, while 1 indicates a random distribution of cases across the J classes. A Gini index of 0.5 shows an equal distribution of cases over some classes.

$$\text{Cost}_{CP}(\text{Tree}) = \text{Error}(\text{Tree}) + Cp\ \mathcal{N}(\text{Tree}),$$

where, Error(Tree) is the fraction of misclassified cases and $\mathcal{N}$(Tree) is the number of leaf nodes in the tree.

Pruned Decision Tree



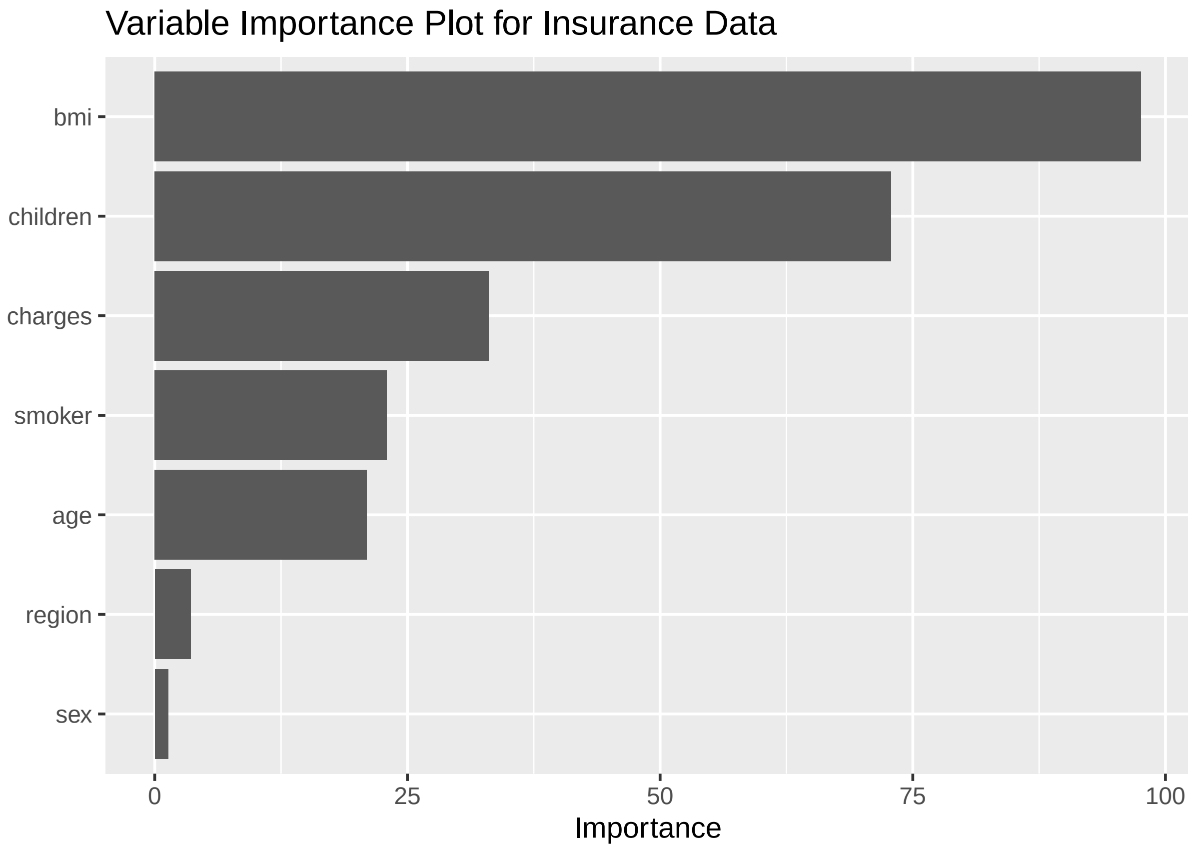
Fitting the CART algorithm and pruning the tree we can view the refined tree with all the conditions at each level including the details of root node error and percent of variability. At the low level of the tree we can view the leaf nodes which classies the response vairables based on the above conditions. Also, implemented tree by various cp values such as 0.0001 and 0.1 which yielded the similar result.

4. **Random Forest:** Ensemble model for enhanced accuracy.

The random forest (RF) is an ensemble learning method which consists of aggregating a large number of decision trees to avoid overfitting and build a better classification model

The Ranger regression model, built on the insurance data, comprises 500 trees with a sample size of 1070 and incorporates seven independent variables. For each split, the model randomly samples three variables, and the target node size is set at 5. The variable importance is assessed based on impurity, and the split rule is determined by variance. The out-of-bag prediction error (mean squared error) is measured at 0.03085552, indicating a relatively low prediction error, while the R-squared value stands at 0.8730195, signifying a high proportion of explained variance in the target variable. These results collectively suggest that the Ranger regression model performs well in predicting insurance claims, offering accuracy and a strong ability to capture variability in the data.

```
## # A tibble: 7 x 2
##   Variable Importance
##   <chr>         <dbl>
## 1 bmi           97.6
## 2 children      72.9
## 3 charges       33.1
## 4 smoker        23.0
## 5 age           21.0
## 6 region         3.55
## 7 sex            1.33
```



Bmi, Children, charges, smoker are having more values from the above **Variable Importance Plot** which indicates the impact those variables shows on predicting the response variable. Implemented the random forest by dropping the columns age, region and sex one after the other and observed improvement in the accuracy on both the train and test data. A popular variant is the gradient boosting algorithm, and XGBoost (acronym for eXtreme Gradient Boosting.

5. **XGBoost Algorithm:** Efficient algorithm for structured data.

For binary response modeling, the idea of boosting was introduced to improve the performance of weak learners. This was done by resampling the training data responses, giving more weight to the misclassified ones, thereby leading to a refined classifier (binary model) which would boost feature performance, especially in ambiguous areas of the feature space.

Plot for the xgboost tree was specified in the following file **tree_plot.html**.

From the above plot we can interpret that the a condition was applied on the chargers column as it's gain value is more with 74 where if it is less than 30175.7773 then it check for the children(gain is 73) else bmi(2.4) and later we have further splits based on this.

By increasing the rounds from 2 to 15 there is an increase in the accuracy on both the train and test dataset.

6. **Support Vector Machines**

Hyperplane: The decision boundary that separates the data into classes. For a two-dimensional space, the hyperplane is a line; for three dimensions, it's a plane, and so on.

Margin: The margin is the distance between the hyperplane and the nearest data point from either class. SVM seeks to maximize this margin, as a larger margin often leads to better generalization to unseen data.

Support Vectors: Support vectors are the data points that are closest to the hyperplane and have a significant influence on its position. These points play a crucial role in determining the optimal hyperplane.

Kernel Trick: SVM can handle non-linear relationships in the data by transforming the features into a higher-dimensional space. This is achieved using a kernel function, which computes the dot product in this higher-dimensional space without explicitly calculating the transformed features.

Regularization Parameter (C): It controls the trade-off between having a smooth decision boundary and correctly classifying the training data. A smaller C value allows for a larger margin but may misclassify some training points, while a larger C value aims to classify all training points correctly but may result in a smaller margin.

The Support Vector Machine (SVM) model is configured as an epsilon-regression with a linear kernel for predicting insurance claims. With 981 identified support vectors, the model demonstrates a nuanced understanding of critical data points. Evaluation on the test set yields an accuracy of approximately 86.64%, with a sensitivity of 83.33% and specificity of 88.98%. These metrics showcase the model's effectiveness in correctly predicting both positive (claims) and negative instances. The SVM decision boundary, visualized through a plot, illustrates the model's ability to discriminate between insurance claim categories in the training set. Overall, the SVM model exhibits robust performance in predicting insurance claims, crucial for risk assessment in the realm of insurance analytics.

Results from the Analyses

Table 1: Decision Trees - Model Performance Results

Model	Test_Acc	Test_sens	Test_spec	Train_Acc	Train_sens	Train_spec
CART	0.82	0.97	0.97	1.00	1.00	1.00
Random Forest	0.98	0.98	0.98	1.00	1.00	1.00
Random Forest Reduced Predictors	0.98	0.98	0.92	1.00	1.00	1.00
XGBoost - 2 Rounds	0.92	0.90	0.93	0.92	0.90	0.93
XGBoost - 10 Rounds	0.88	0.84	0.90	0.92	0.90	0.93
XGBoost - 15 Rounds	0.89	0.90	0.89	0.94	0.93	0.94
SVM	0.86	0.88	0.83	0.86	0.88	0.85

Following are the results of logit and probit models based on the k-fold validations for the train and test data accuracies.

Table 2: Bi-nomial Model Performance Results

Model	Train_Accuracy	Test_Accuracy	AIC	BIC	ROC
Logit - Full	88.49	88.06	779.2900	704.0126	0.916
Logit - Both	87.37	85.45	772.4223	817.1926	0.913
Probit	86.83	86.31	786.4300	862.6500	0.925

Results Summary and Conclusion

Decision Trees - Model Performance Results:

Test Accuracy: Random Forest and XGBoost models exhibit high test accuracy, suggesting their effectiveness in correctly predicting outcomes on new, unseen data. The perfect training accuracy (1.0) for Decision Tree models may indicate potential overfitting, as the models might be memorizing the training data. Bi-nomial Model Performance Results (Logit and Probit):

Train and Test Accuracy:

Logit - Full stands out with the highest train accuracy (88.49%) and test accuracy (88.06%), showcasing its ability to perform well on both the training and test datasets. Probit demonstrates competitive accuracy values, particularly in test accuracy (86.31%). AIC and BIC:

Logit - Full boasts the lowest values for both AIC and BIC. Lower AIC and BIC indicate a better fit with less complexity, making Logit - Full an attractive choice in terms of goodness of fit and model simplicity. ROC (Receiver Operating Characteristic):

Probit achieves the highest ROC value (0.925). ROC is a crucial metric for assessing a model's ability to distinguish between classes, and Probit excels in this regard.

Overall Considerations:

Decision Trees: While showing high test accuracy, the perfect training accuracy signals a potential risk of overfitting. It's important to assess the model's generalization to new data.

Bi-nomial Models: Logit - Full emerges as a strong contender, excelling in accuracy, AIC, and BIC. Probit, with its high ROC, indicates robust discriminatory power.

Decision-Making:

Logit - Full: This model strikes a balance between accuracy and model simplicity, making it a solid choice for a predictive model with favorable goodness of fit.

Probit: Although slightly lower in accuracy than Logit - Full, its superior ROC suggests excellent discriminatory ability. Key contributing variables identified through variable selection and importance analyses include:

- **Age**: Each one-year increase in age corresponds to a 3.51% increase in the odds of making an insurance claim.
- **BMI**: A one-unit increase in BMI results in a 32.37% higher odds of making a claim.
- **Children**: Having no children significantly decreases the odds of an insurance claim.
- **Smoker**: Smokers have approximately 61.2 times higher odds of making a claim compared to non-smokers.

References

- This dataset, titled "Sample Insurance Claim Prediction Dataset," is derived from the "Medical Cost Personal Datasets," and the sample values have been updated accordingly.