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# CAR INSURANCE CLAIMS CLASSIFICATION

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## ABSTRACT

This report describes the project of analysis and prediction of the car insurance claims dataset. The dataset includes historical data of the policyholders (e.g., age, gender, vehicle details , etc.), among which the variable of interest is the outcome of insurance, indicating whether a customer's claim is approved or not. The `aiinsurance` R package [1] is developed to make this work reproducible, accessible, and equipped with advanced features, e.g., a pipeline that performs the main steps of this work in a single command, and an interactive app that displays the performance of the models. Using package's functions, two machine learning models, i.e., logistic regression and random forest are implemented to classify the outcomes based on solely the historical data. The results indicate promising prediction power with various evaluation metrics (e.g., accuracy, precision, recall, etc.) of over 80 percent. In addition to classification, informative insights from the dataset and models have been drawn, e.g., by dint of the both models, statistical significance level of the variables of the dataset can be measured to determine the variables that perform more effective role in the prediction.

## 1 Introduction



Rapid advances in artificial intelligence (AI) and machine learning are creating products and services with the potential not only to change the environment in which actuaries operate but also to provide new opportunities within actuarial science [2].

The use of statistical learning models has been a common practice in actuarial science since the 1980s. It was not long after since the field adopted classical models, such as linear models and generalized linear models (GLMs). While actuaries use GLMs frequently in practice, it was

in the past few years that the use of AI and machine learning, and hence more modern models garnered significant attention in the field [3].

The goal of this work is to predict status of policyholders' claims. The status lies at the "outcome" column of the car insurance dataset, indicating whether a customer has claimed his loan or not.

A classical linear model and a modern nonlinear model is used and compared. The former model is logistic regression, which is an example of GLMs, accommodated to classification setting, i.e., for predicting discrete classes, in this work's case, status of claims. The latter model is a nonlinear tree-based model.

The remainder of this work is organized as the following: In section 2, main concepts included in the work are explained. In 2.1, the concept of car insurance is introduced followed by an elaboration on claims and how they interact among an insurer and a policyholder. Subsequently, the two machine learning models, logistic regression 2.2, and random forest 2.3 are briefly explained. As a contribution of this work, the `aiinsurance` package [1], introduced in 3, is developed, which automates many of the classification tasks, uses advanced features, e.g., runs a pipeline that performs the main steps of this work in a single command, and it provides an interactive shiny app to display the performance of the models.

## 2 Preliminary Concepts

### 2.1 Car Insurance Claims

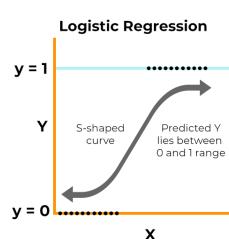


Car insurance is a type of insurance policy that financially protects drivers in the event of an accident or theft. There are several types of car insurance coverage, including liability insurance, collision insurance, comprehensive insurance, and personal injury protection.

An insurance claim is a formal request by a policyholder to an insurance company for coverage or compensation for a covered loss or policy event, in this work's case, a car accident. The insurance company either accepts or rejects the claim. If it is approved, the insurance company will issue payment to the insured or an approved interested party on behalf of the insured.

Predicting the outcome of claims can be utilized to better understand the customer strata and incorporate the findings throughout the insurance policy enrollment (including the underwriting and approval or rejection stages), triage claims and automate where possible, gradually obviating the need for human interaction, and optimize the entire insurance policy enrollment process flow [4].

### 2.2 Model: Logistic Regression

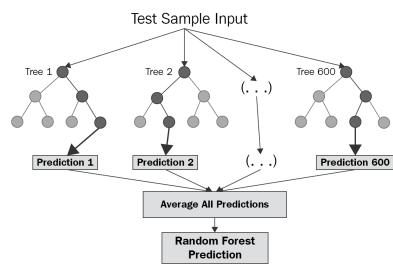


Logistic regression (logit), which is type of GLM, uses the logistic function to model the probability of the binary outcome by creating a model that takes in the input variable (e.g., client's information) and produces a probability that a "outcome" (the variable we aim to predict) is 1. The "outcome" in this work is whether a customer's claim is approved or not. The logistic function is defined as the following:

$$\frac{1}{1 + e^{-x}}$$

This probability can then be used to make a prediction about the outcome. For instance, if the probability that the client's claim will be approved is greater than a certain threshold (e.g., 0.5), we predict that the claim will be approved. In another words, the goal of logit is to find the best set of coefficients for a set of independent variables that maximizes the likelihood (measuring how well parameters of a model fit the data) of the observed data.

### 2.3 Model: Random Forest



An ensemble learning model is a model that is constructed from multiple models, to obtain combined results, expected to be improved compared to any of the constituent models. The random forest is an ensemble model built from decision trees, i.e., flowchart-like tree structures, wherein each internal node represents a "test" on a variable (e.g., vehicle type), each branch represents the outcome of the test, and each leaf node represents a class label (e.g., 1 for claim approval and 0 for claim rejection). The intuition behind a decision tree is to recursively split the data into subsets based on the values of the input variables, such that the subsets are as "pure" as possible in terms of their class labels. The less pure a subset is, the more the data belongs to the same class, and the more pure it is, the more data is evenly split among all classes. The goal is to create a tree

that can accurately classify new examples by traversing the tree from the root to a leaf node, making decisions at each internal node based on the values of the input variables.

As a single random tree might not be able to capture the proper inherent complexity of a data, and may either overfit (become too complex and remembers data rather than learning from it) or underfit (become too simple and hence unable to learn the inherent complicated patterns in the data). By training multiple decision trees and combining their predictions by taking a majority vote, a random forest is able to capture a more robust and accurate representation of the data. The randomness in the random forest comes from randomly selecting subsets of the data to train each

decision tree, and randomly selecting subsets of input variables to consider at each split point in the decision tree. This helps to decorrelate the trees, i.e., reducing the correlation or dependence between the trees, consequently, make the model more robust to overfitting.

### 3 aiinsurance Package



[Icon Source](#)

The `aiinsurance` R package [1] is developed to make this work reproducible, accessible, and equipped with advanced features.

Instructions on how to install and use the package's functions and features is provided in the [README part of package's Github repository](#).

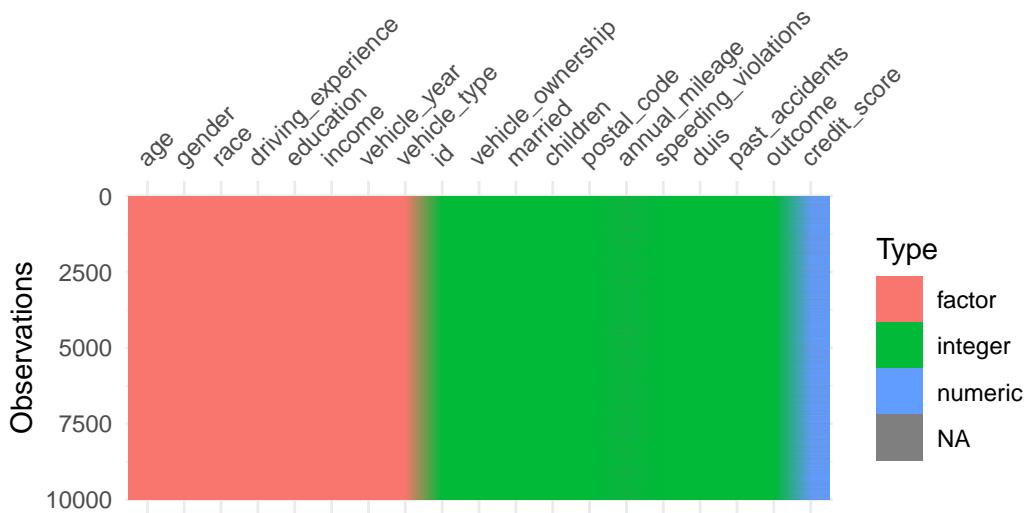
Noteworthy features of the package are explained in the following: A pipeline that performs the main steps of this work in a single command, and an interactive app that displays the performance of the models. Using package's functions

### 4 Exploratory Data Analysis (EDA)

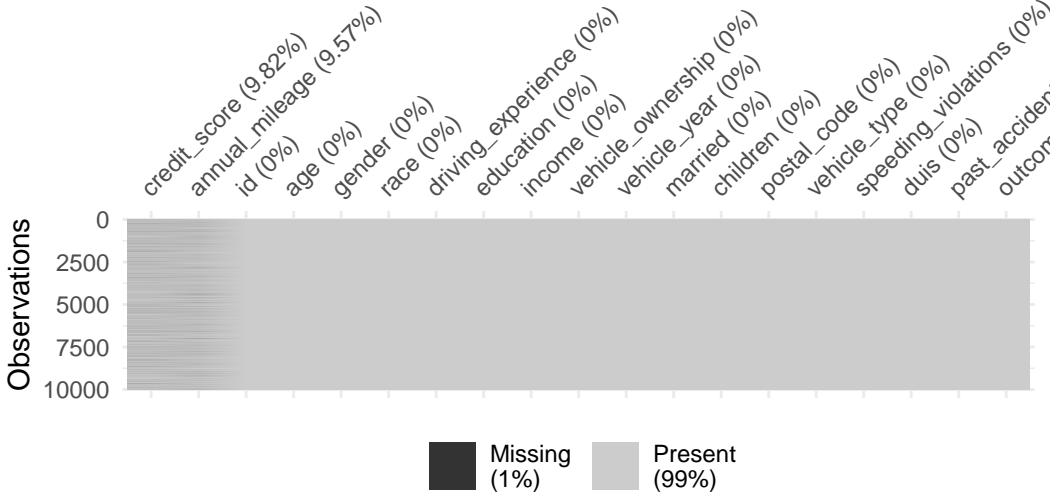
An overview of the car insurance dataset is provided in the following:

```
## Rows: 10,000
## Columns: 19
## $ id           <int> 569520, 750365, 199901, 478866, 731664, 877557, 93~  
## $ age          <chr> "65+", "16-25", "16-25", "16-25", "26-39", "40-64"~  
## $ gender       <chr> "female", "male", "female", "male", "male", "femail~  
## $ race          <chr> "majority", "majority", "majority", "majority", "m~  
## $ driving_experience <chr> "0-9y", "0-9y", "0-9y", "0-9y", "10-19y", "20-29y"~  
## $ education     <chr> "high school", "none", "high school", "university"~  
## $ income         <chr> "upper class", "poverty", "working class", "workin~  
## $ credit_score   <dbl> 0.6290273, 0.3577571, 0.4931458, 0.2060129, 0.3883~  
## $ vehicle_ownership <int> 1, 0, 1, 1, 1, 0, 0, 0, 1, 1, 1, 1, 1, 0, 1,~  
## $ vehicle_year    <chr> "after 2015", "before 2015", "before 2015", "befor~  
## $ married        <int> 0, 0, 0, 0, 0, 1, 0, 1, 1, 1, 0, 1, 1, 1, 1,~  
## $ children        <int> 1, 0, 0, 1, 0, 1, 1, 0, 1, 1, 0, 1, 1, 0, 1,~  
## $ postal_code     <int> 10238, 10238, 10238, 32765, 32765, 10238, 10238, 1~  
## $ annual_mileage  <int> 12000, 16000, 11000, 11000, 12000, 13000, 13000, 1~  
## $ vehicle_type     <chr> "sedan", "sedan", "sedan", "sedan", "sedan", "sed~  
## $ speeding_violations <int> 0, 0, 0, 2, 3, 7, 0, 0, 0, 6, 4, 4, 0, 0, 0, 10~  
## $ duis            <int> 0, 0, 0, 0, 0, 0, 0, 0, 0, 2, 0, 1, 0, 2, 0, 2,~  
## $ past_accidents  <int> 0, 0, 0, 1, 3, 3, 0, 0, 0, 7, 0, 2, 0, 1, 0, 1,~  
## $ outcome          <int> 0, 1, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0,~
```

The following plot visualizes proportion of data types within the dataset.



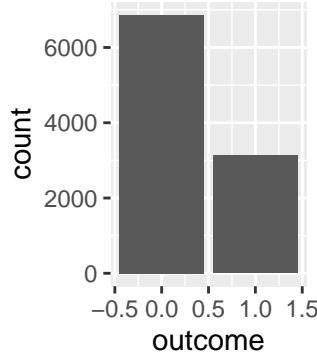
The “factor” types of the plot represent categorical variables contain classes as characters, e.g., gender variable contains characters male or female. However, there are some categorical variables in the integer type as well, e.g., married.



## 5 Preprocessing

### 5.1 Class Imbalance

The proportion of outcome classes are shown in the following:



The number of class 0 and class 1 labels are respectively 6867, 3133

Imbalance ratio is defined as size of minority class (1 in our case) over size of majority class (0). Therefore, the ideal number for this quantity is 1. Imbalance ratio: 0.45624

After oversampling, the number of class 0 and class 1 labels are respectively 5484, 5516. Imbalance ratio is approximately 1 now.

To make the dataset balanced, oversampling methods can be used, which are methods that generate samples from the dataset with the minority class (having outcome = 1). The key challenge in these methods is that the samples should be similar to the original dataset, as their information, i.e., distribution and other statistical properties should align with the original data, however, they should be different to a small extent too, so that they would resemble new data available in the dataset, not merely a copy of what exists in it. A promising oversampling method that is used for this work is the RaCog algorithm. Prior to explaining the algorithm in 5.3, the process of representing the categorical columns of the dataset as numerical ones is explained in 5.2, as this process is a prerequisite for many oversampling methods. For RaCog, the dataset should be discretized and numeric, and a one-hot-encoded dataset satisfies this property.

## 5.2 Encoding Categorical Columns

As mentioned earlier, a prerequisite of RaCog algorithm is a discretized and numeric dataset. In addition to this, there are other reasons for encoding the dataset to only contain numbers. Firstly, most machine learning algorithms require that input and output variables are numbers. Secondly, even if the dataset only contain numbers, and yet a categorical variable is represented with natural numbers, the following two cases might occur: Either the variable has a natural order, e.g., age which contains four age groups can be represented with numbers {1,2,3,4}, such that higher numbers correspond to older age group. However, the variables `vehicle_type`, `gender`, `race`, etc are not suitable to be represented with natural numbers, as higher or lower numbers do not indicate any inherent order, and this might mislead a machine learning model. One-hot-encoding is used to encode (represent) categorical variables as numerical values but not natural numbers. This is done by creating a new binary column for each unique category in the data, with a value of 1 in the column corresponding to the category and 0 in all other columns. One-hot-encoding wouldn't contain any order for classes of columns, and therefore overcomes the ordering issue mentioned earlier.

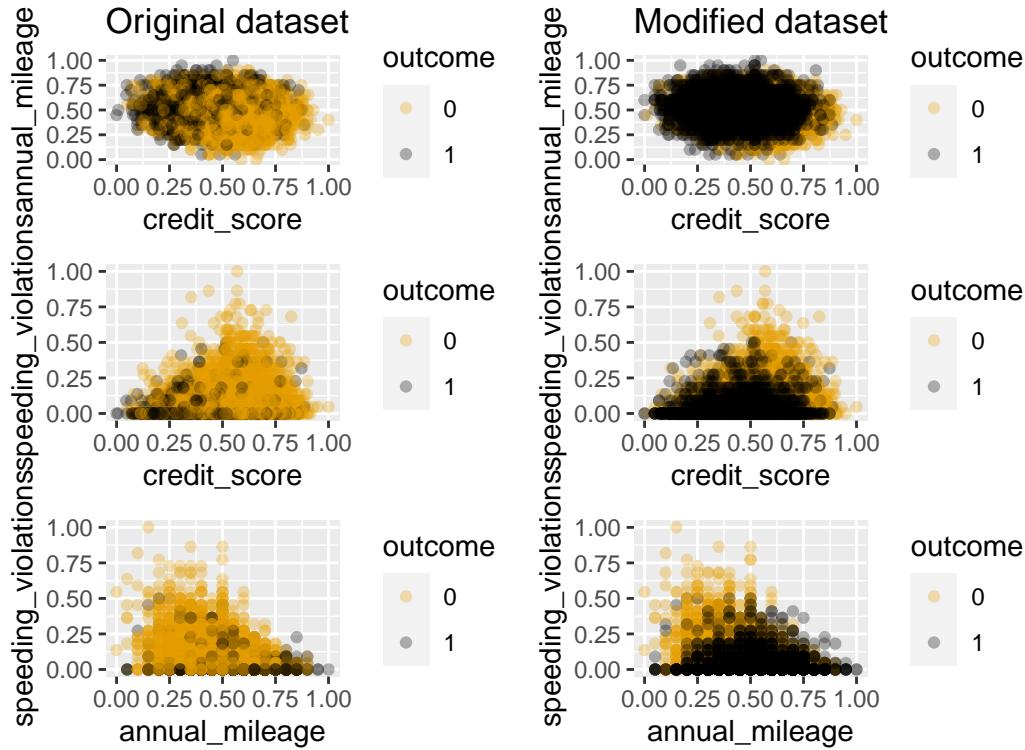
## 5.3 RaCog

Existing oversampling approaches for addressing imbalanced dataset (explained in [5.1](#)) typically do not consider the probability distribution of the minority class while synthetically generating new samples. This leads to poor representation of the minority class, and hence to poor classification performance.

Rapidly converging Gibbs algorithm (RaCog) uses the joint probability distribution of input variables as well as Gibbs sampling to generate new minority class samples. Gibbs sampling is a Markov Chain Monte Carlo (MCMC) method [\[5\]](#) that is used to sample from a multi-dimensional distribution. The basic idea behind Gibbs sampling is that in order to sample from a probability distribution with multiple random variables, instead of directly sampling from the joint distribution of all the variables, the algorithm iteratively sample from the conditional distributions of each variable given the current values of the other variables. By dint of this, the computational difficulties of sampling from the full joint distribution are avoided. The result of the algorithm is a sequence of samples from the joint distribution of all the variables, which can be used to estimate various properties of the distribution, such as the mean and variance of each variable.

In summary, Gibbs sampling is a way to iteratively sample from the conditional distributions of each variable given the current values of the other variables, to estimate properties of a multi-dimensional distribution. For more rigorous and detailed information on RaCog algorithm, the interested reader is referred to [\[6\]](#).

In following, a grid of one to one variable comparison is presented, wherein the prior imbalanced dataset is placed graphics next to the balanced one, for each pair of variables.



## 6 Classification Models

### 6.1 Logistic Regression

When applying the logistic regression model (explained in)

Among results of fitting logistic regression (logit) on the dataset, the significance level of variables are reported, obtained by perturbing a small change in the variable under study while holding all other variables constant. The most significant variables that affects the prediction of outcomes, i.e., 1 for approval and 0 for rejection of car insurance claims are listed below. The high significance levels were determined by observing small p-values. However, the direction of the variables' impact remains yet to be determined. The aim is to answer the following question. Would a significant have an effective role in increasing the chance of approval (class 1), or chance of rejection (class 0). The answer of this question lies at the sign of the coefficient of the variable in the model. The significant variables and their direction of significance are reported below. Positive effect means the variable increased chance in class 1.

- `driving_experience .0 .9y`: Having driving experience between 0-9 years, positive.
- `vehicle_ownership`: Whether the policyholder owns the vehicle or not, negative.
- `vehicle_year.after.2015`: The vehicle was built after 2015, negative.
- `postal_code`: Postal code of the policyholder.

### 6.2 Random Forest

The random forest model can also report significance level of variables using different measures, two of which will be reported, accuracy, and Gini.

The following plot visualizes significance level of variables. The left part shows how much accuracy the model loses by excluding each variable. The more the accuracy suffers (higher MeanDecreaseAccuracy), the more important the variable is for the successful classification. The variables are presented in descending quantity order of importance. The right part shows the mean decrease in Gini coefficient. The Gini coefficient is a measure of how each variable contributes to the homogeneity of the nodes and leaves in the resulting random forest. Again, higher MeanDecreaseGini indicates more significance.

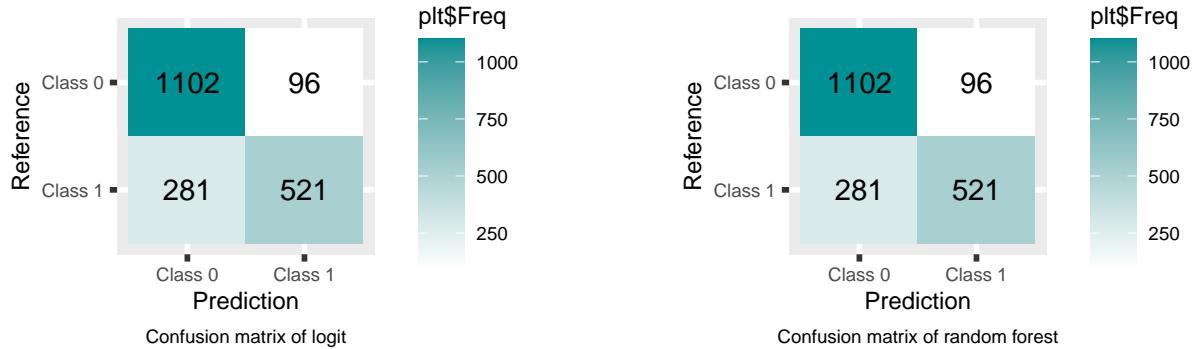
A salient point to take into account is that almost all variables for which both the logit model 6.1 considered high significance level also have high significance in random forest 6.2 based on at least one of the accuracy or Gini measurements. The only variable considered significant by logit but not by random forest was `gender.female`. And the variables that were considered significant by random forest but not by logit were the following: `age`, `speeding_violations`, and `credit_score`.

### 6.3 Hyper-parameter tuning

## 7 Evaluation

In the following, various evaluation metrics were employed to measure and compare the classification performance of the models.

### 7.1 Confusion Matrix

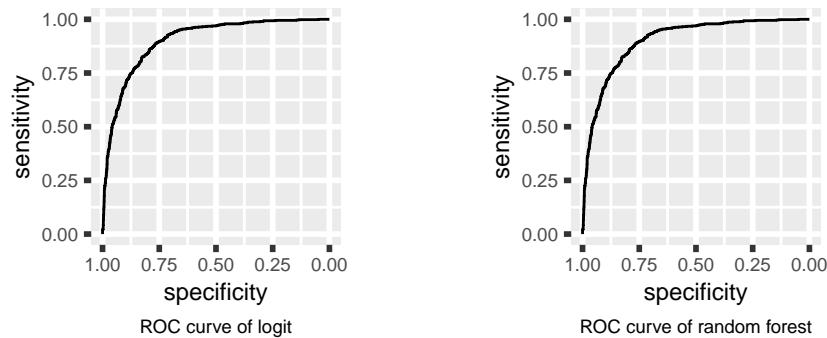


### 7.2 Accuracy, Precision, Recall, ROC

Metric	Logit	Random Forest
Accuracy	0.8115	0.8115
Precision	0.8444084	0.8444084
Recall	0.6496259	0.6496259

Table 1: Comparison of Evaluation Metrics for Two Models

### 7.3 ROC Curve



## 8 Conclusion

## References

- [1] Hamed Vaheb. aiinsurance Package. Available at <http://github.com/berserkhmdvhb/aiinsurance>.
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