

CAR INSURANCE CLAIM PREDICTION

GROUP - 12

Jahnani Nagarajan Sivakumar

Kirthika Kulandaivel Senthilkumar

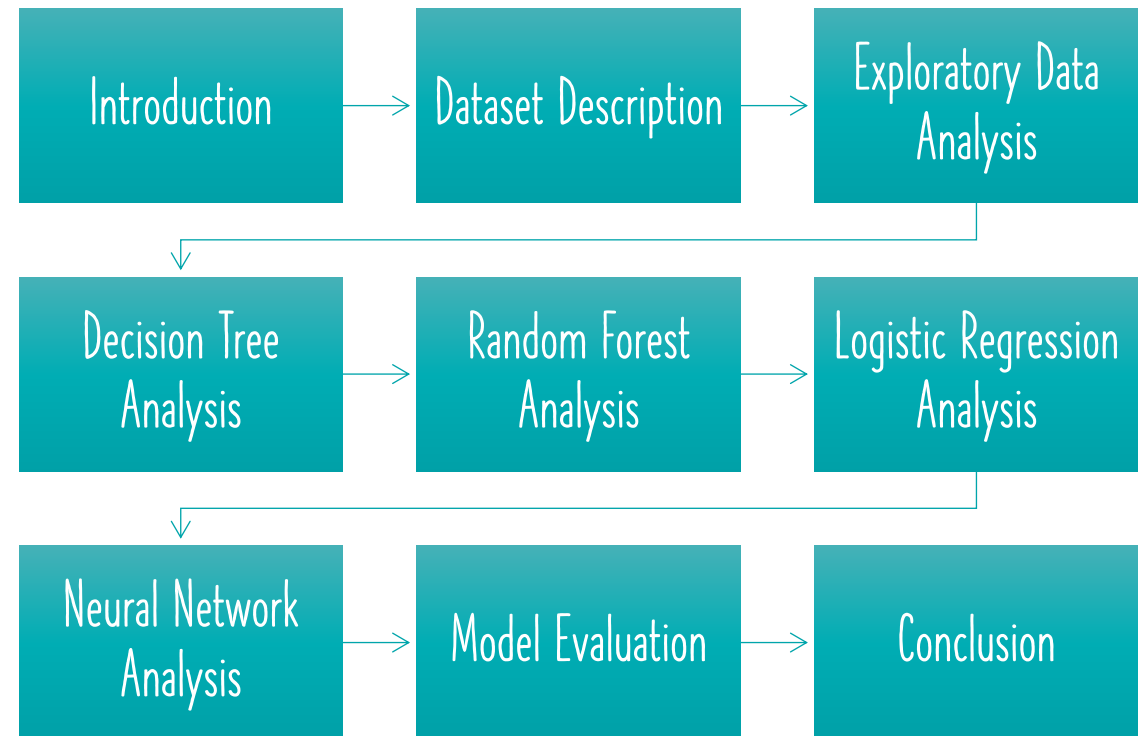
Krishna Apurva

Manusha Medarametla





PROJECT OVERVIEW



INTRODUCTION

- Aims to predict if policyholders will file a claim in the next six months by analyzing a comprehensive dataset.
- Helps insurance companies refine their risk assessment and pricing strategies.
- Revolutionize managing risk in the car insurance industry using Advanced analytics and Machine learning.

Goal:

- The project aims to develop an accurate predictive model using policyholder attributes for data-informed decision-making.

DATASET DESCRIPTION

Data Source: Kaggle

97656 instances and 44 attributes.

Describes policyholder's details like policy tenure, age of the car, age of the car owner, the population density of the city, make and model of the vehicle, power, engine type, etc.,

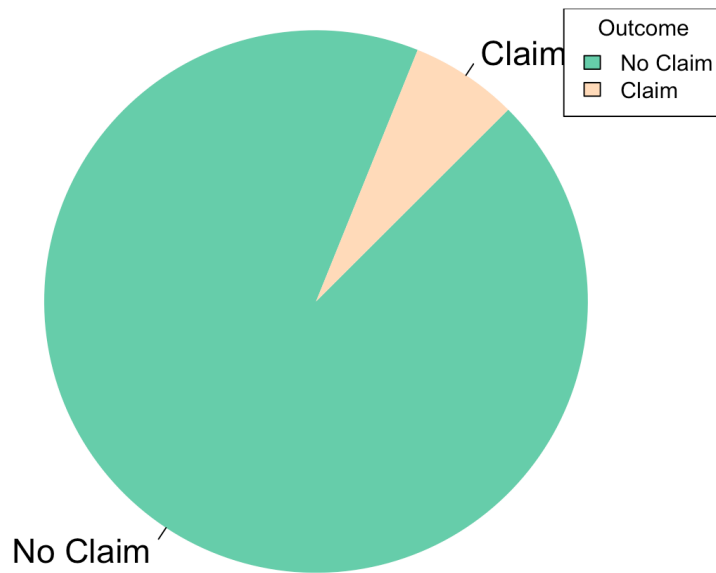
Target variable indicating whether the policyholder files a claim in the next six months.

Split for the training and testing with a ratio of 60:40

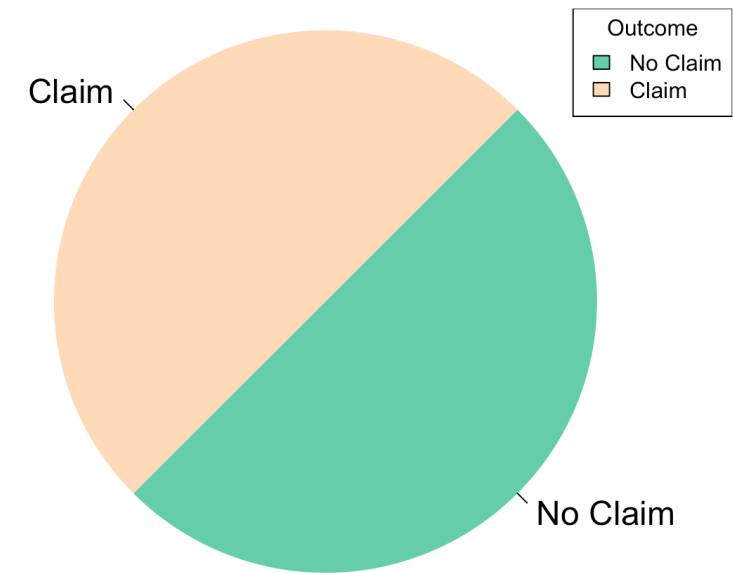
EXPLORATORY DATA ANALYSIS

- An imbalance in the target data distribution occurs
- Oversampled to balance data

Distribution of Claims



Distribution of Claims After oversampling



PRE-PROCESSING PROCEDURES

Identification of null values present, if any

Dropping attributes that are not required for Classification Analysis

Mutated '0' and '1' instead of 'No' and 'Yes' in the dataset

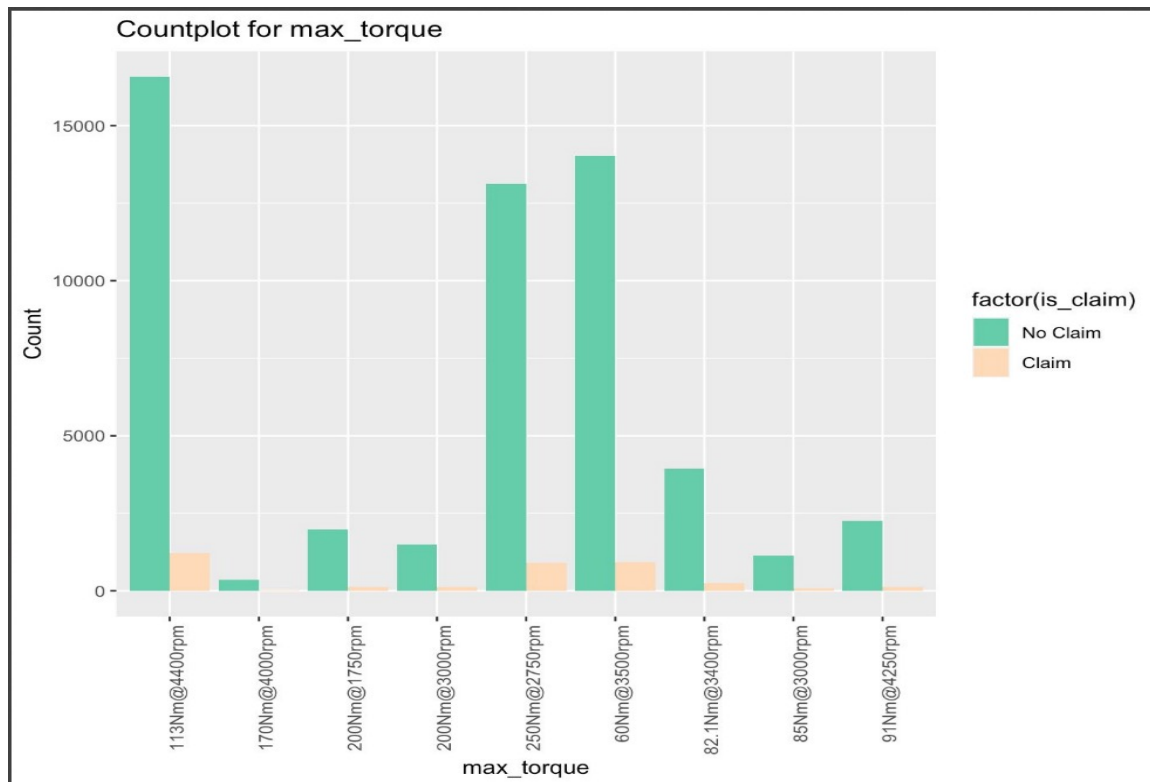
Grouped categorical and numerical attributes

Extracted numerical values from Max torque and Max power to estimate ratio with RPM values

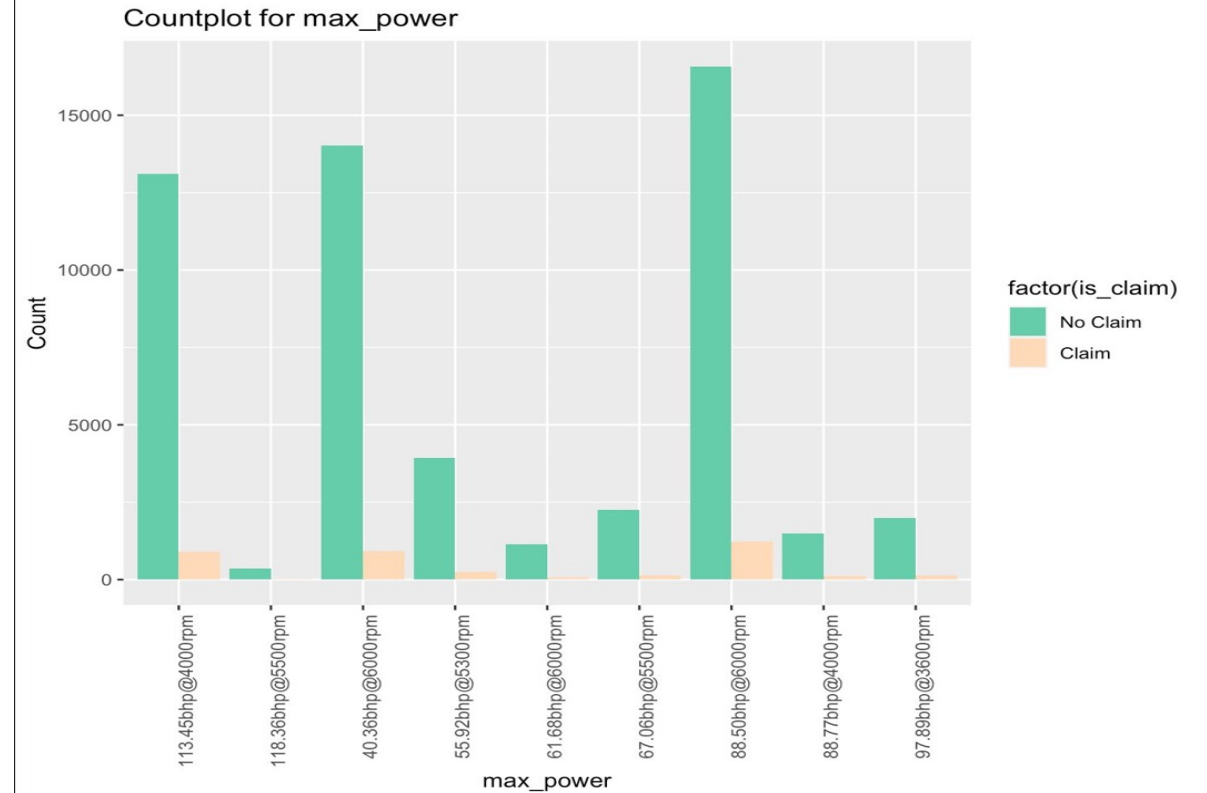
Added new columns to the dataset by splitting the categorical data

DATA DISTRIBUTION ANALYSIS

Max-torque

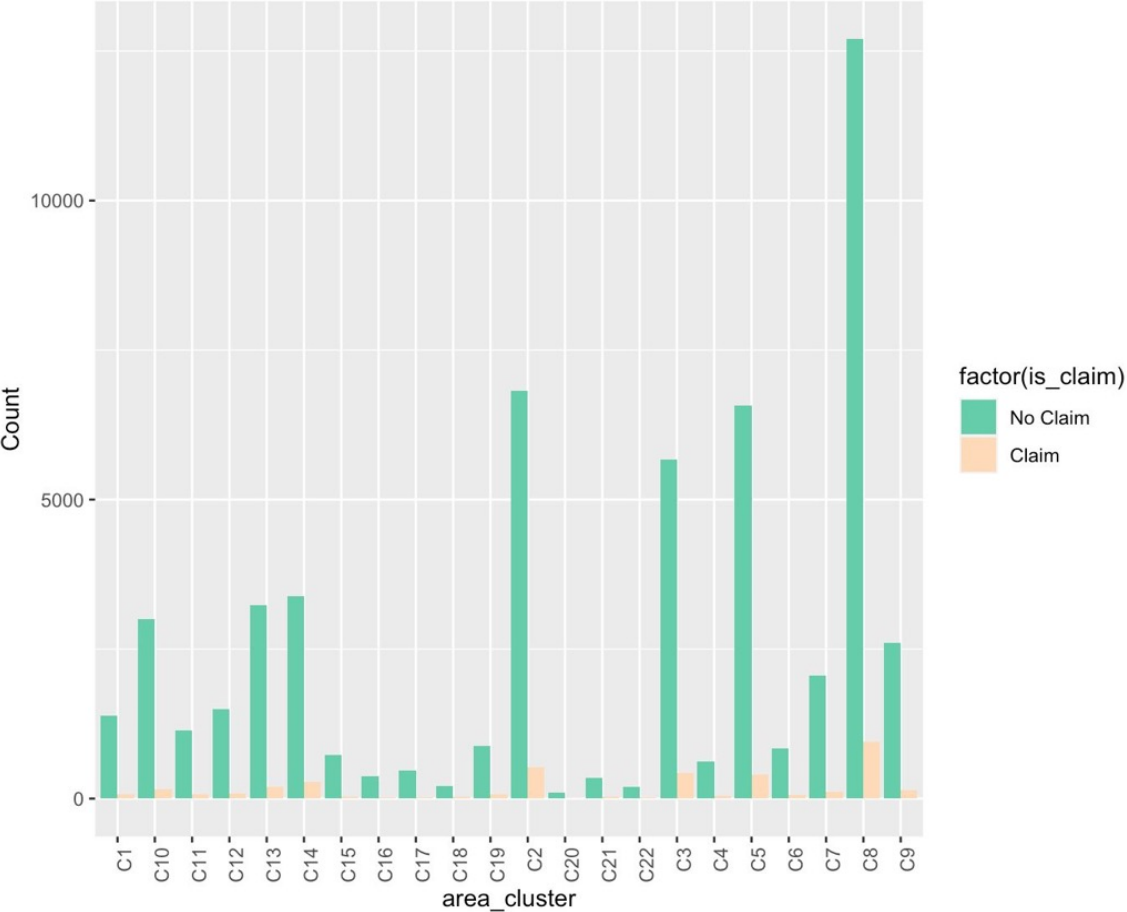


Max-power

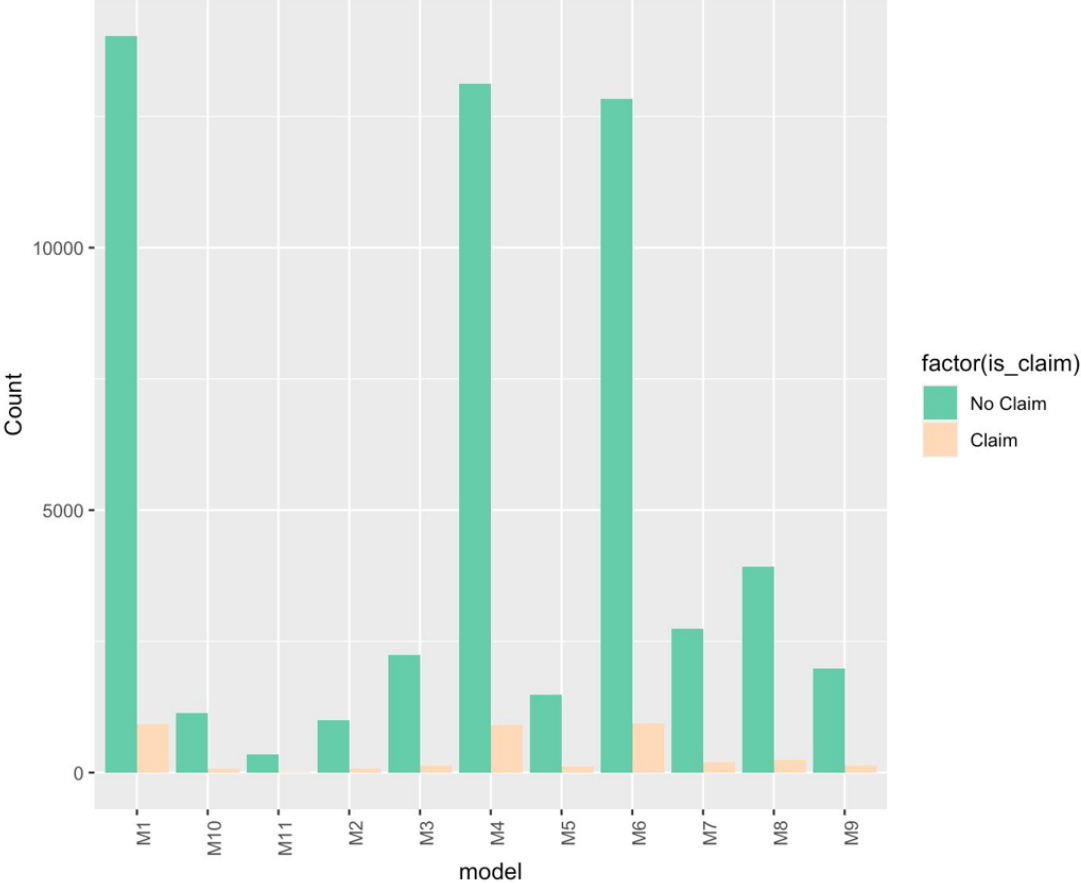


AREA AND MODEL VS CLAIM

Countplot for area_cluster

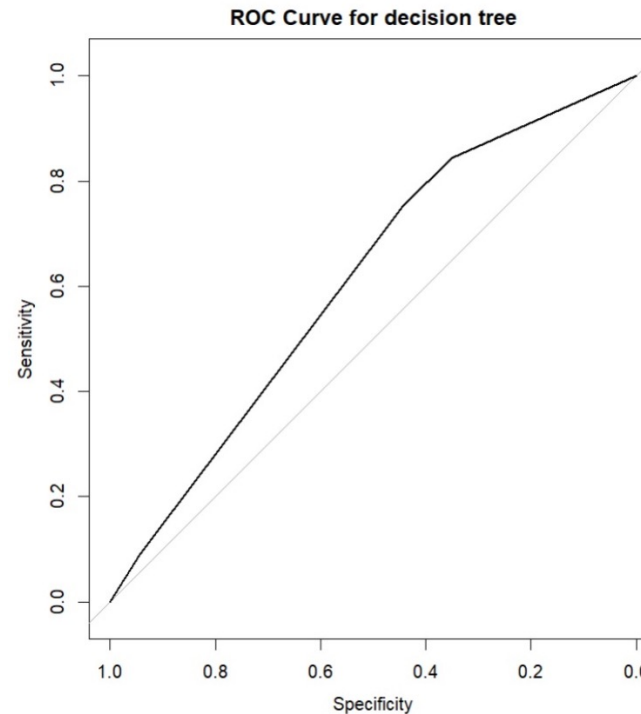
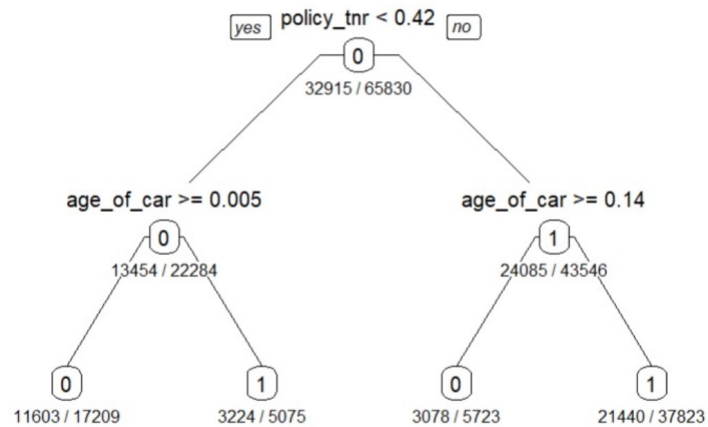


Countplot for model



DECISION TREE ANALYSIS

	Reference	
Prediction	0	1
0	9730	371
1	12199	1137



Car Insurance Claim Prediction

Accuracy : 0.4637
 95% CI : (0.4573, 0.4701)
 No Information Rate : 0.9357
 P-Value [Acc > NIR] : 1

Kappa : 0.0425

Mcnemar's Test P-Value : <2e-16

Sensitivity : 0.44370
 Specificity : 0.75398
 Pos Pred Value : 0.96327
 Neg Pred Value : 0.08526
 Prevalence : 0.93566
 Detection Rate : 0.41516
 Detection Prevalence : 0.43099
 Balanced Accuracy : 0.59884

'Positive' Class : 0

RANDOM FOREST ANALYSIS

Confusion Matrix and Statistics

```

      Reference
Prediction  0    1
0  13512   657
1   8417   851

Accuracy : 0.6128
95% CI : (0.6066, 0.6191)
No Information Rate : 0.9357
P-Value [Acc > NIR] : 1

Kappa : 0.0531

McNemar's Test P-Value : <2e-16

Sensitivity : 0.61617
Specificity : 0.56432
Pos Pred Value : 0.95363
Neg Pred Value : 0.09182
Prevalence : 0.93566
Detection Rate : 0.57652
Detection Prevalence : 0.60456
Balanced Accuracy : 0.59025

'Positive' Class : 0
```

10 TREES CONFUSION MATRIX

Confusion Matrix and Statistics

```

      Reference
Prediction  0    1
0  13610   646
1   8319   862

Accuracy : 0.6175
95% CI : (0.6112, 0.6237)
No Information Rate : 0.9357
P-Value [Acc > NIR] : 1

Kappa : 0.0571

McNemar's Test P-Value : <2e-16

Sensitivity : 0.62064
Specificity : 0.57162
Pos Pred Value : 0.95469
Neg Pred Value : 0.09389
Prevalence : 0.93566
Detection Rate : 0.58071
Detection Prevalence : 0.60827
Balanced Accuracy : 0.59613

'Positive' Class : 0
```

100 TREES CONFUSION MATRIX

Confusion Matrix and Statistics

```

      Reference
Prediction  0    1
0  13567   635
1   8362   873

Accuracy : 0.6161
95% CI : (0.6099, 0.6224)
No Information Rate : 0.9357
P-Value [Acc > NIR] : 1

Kappa : 0.0584

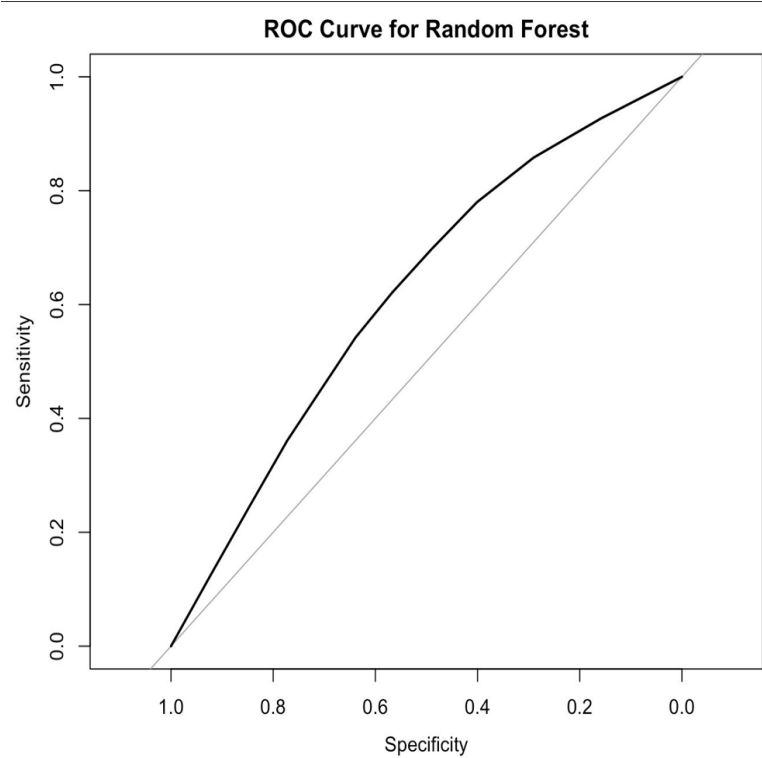
McNemar's Test P-Value : <2e-16

Sensitivity : 0.61868
Specificity : 0.57891
Pos Pred Value : 0.95529
Neg Pred Value : 0.09453
Prevalence : 0.93566
Detection Rate : 0.57887
Detection Prevalence : 0.60596
Balanced Accuracy : 0.59880

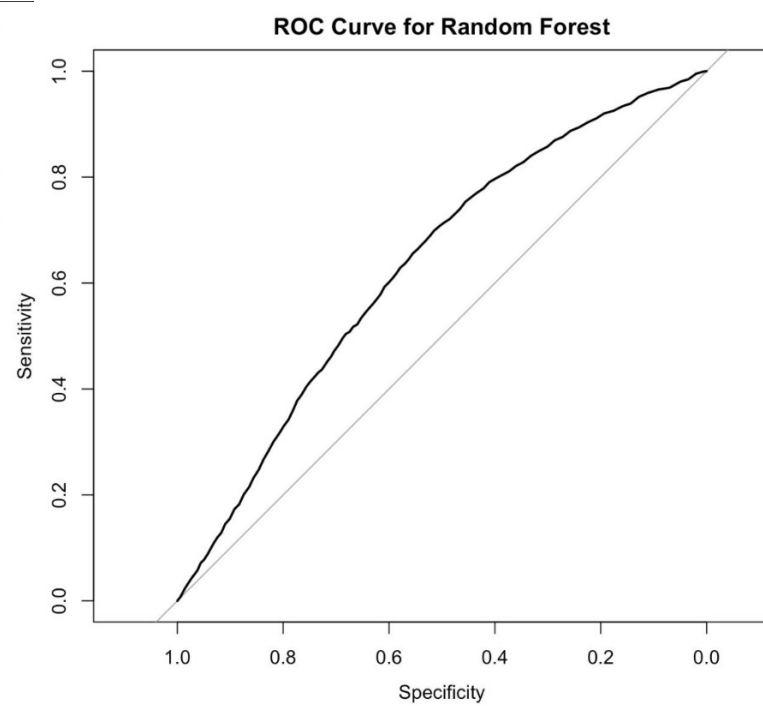
'Positive' Class : 0
```

500 TREES CONFUSION MATRIX

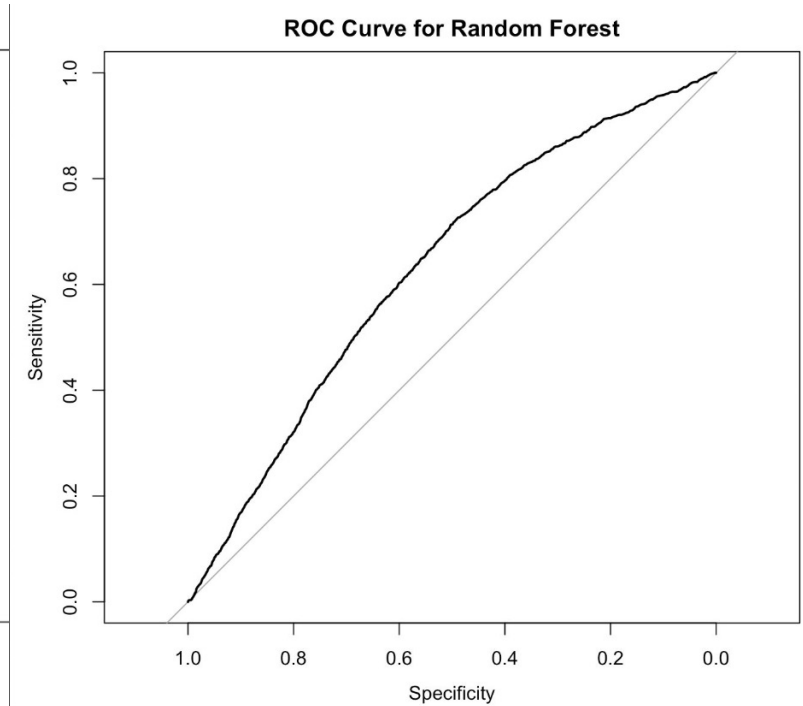
RANDOM FOREST ANALYSIS (CONT..)



10 TREES ROC CURVE



100 TREES ROC CURVE



500 TREES ROC CURVE

LOGISTIC REGRESSION ANALYSIS

Confusion Matrix and Statistics

Prediction	Reference	
	0	1
0	18930	1176
1	2999	332

Accuracy : 0.8219

95% CI : (0.8169, 0.8267)

No Information Rate : 0.9357

P-Value [Acc > NIR] : 1

Kappa : 0.0534

Mcnemar's Test P-Value : <0.0000000000000002

Sensitivity : 0.86324

Specificity : 0.22016

Pos Pred Value : 0.94151

Neg Pred Value : 0.09967

Prevalence : 0.93566

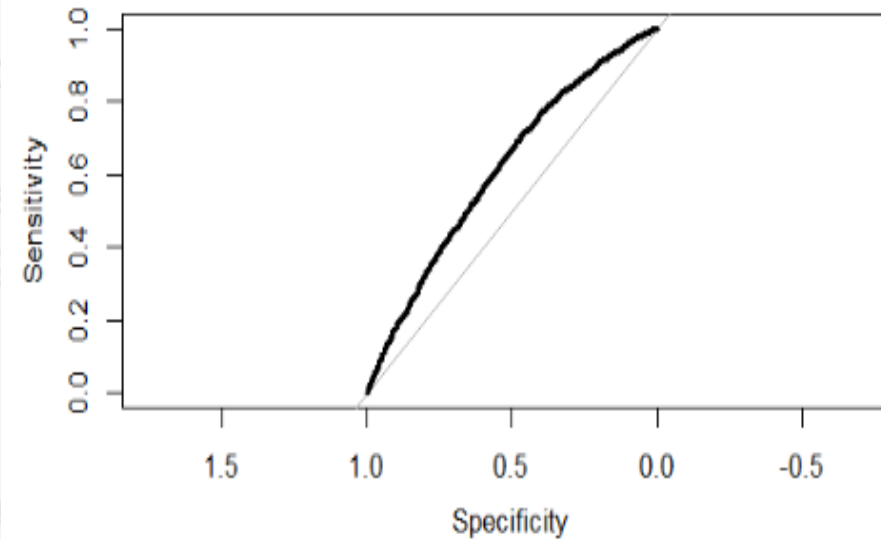
Detection Rate : 0.80770

Detection Prevalence : 0.85787

Balanced Accuracy : 0.54170

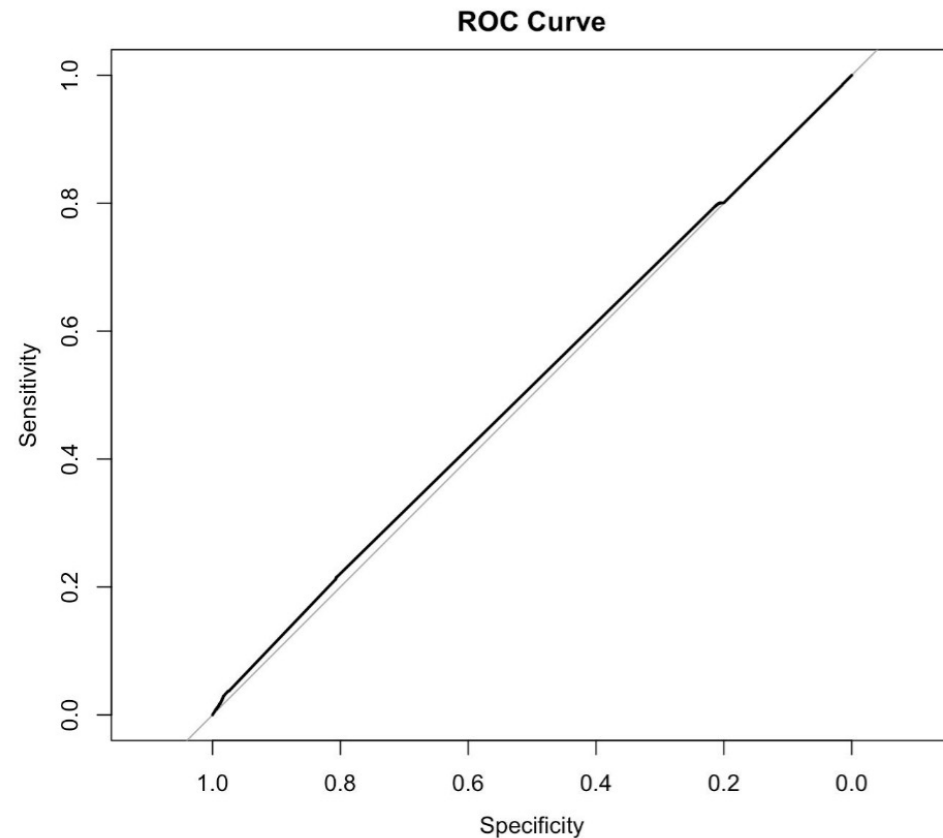
'Positive' class : 0

	actual	predicted
3	0	0.5804978
5	0	0.3813829
6	0	0.5156848
9	0	0.3699288
11	0	0.5901706



Area under the curve: 0.6128

NEURAL NETWORK ANALYSIS



Confusion Matrix and Statistics

Prediction \ Reference	0	1
0	17652	1182
1	4277	326

Accuracy : 0.7671

95% CI : (0.7616, 0.7725)

No Information Rate : 0.9357

P-Value [Acc > NIR] : 1

Kappa : 0.0108

Mcnemar's Test P-Value : <2e-16

Sensitivity : 0.80496

Specificity : 0.21618

Pos Pred Value : 0.93724

Neg Pred Value : 0.07082

Prevalence : 0.93566

Detection Rate : 0.75317

Detection Prevalence : 0.80360

Balanced Accuracy : 0.51057

'Positive' Class : 0

OVERVIEW

	Accuracy	Area Under Curve (ROC)
Decision Tree	46.37%	0.6109
Random Forest	61.62%	0.6316
Logistic Regression	82.19%	0.6128
Neural Network	76.71%	0.5118

SUMMARY

- Logistic regression has the highest accuracy among the models.
- Low AUC may suggest that its ability to discriminate between classes is not as strong as Random Forest
- Random Forest accuracy is lower than logistic regression
- Higher AUC indicates better discrimination between positive and negative cases.
- Random forests are less interpretable than logistic regression.
- Decision trees are prone to overfitting and might have struggled with generalization to new data

CONCLUSION

Based on the business objective, interpretability is crucial to determine what factors influence the policyholder to claim. Therefore, logistic regression clearly explains the attributes that can make a policyholder claim a policy. For example, policy tenure, age of the car, and area have a higher influence on claim prediction than any other attribute.

The insurance company can use this prediction model to charge the policyholder with a premium or higher-cost policy.

Acknowledgement:
Prof. Zhang's R scripts and Notes

THANK YOU