Overview

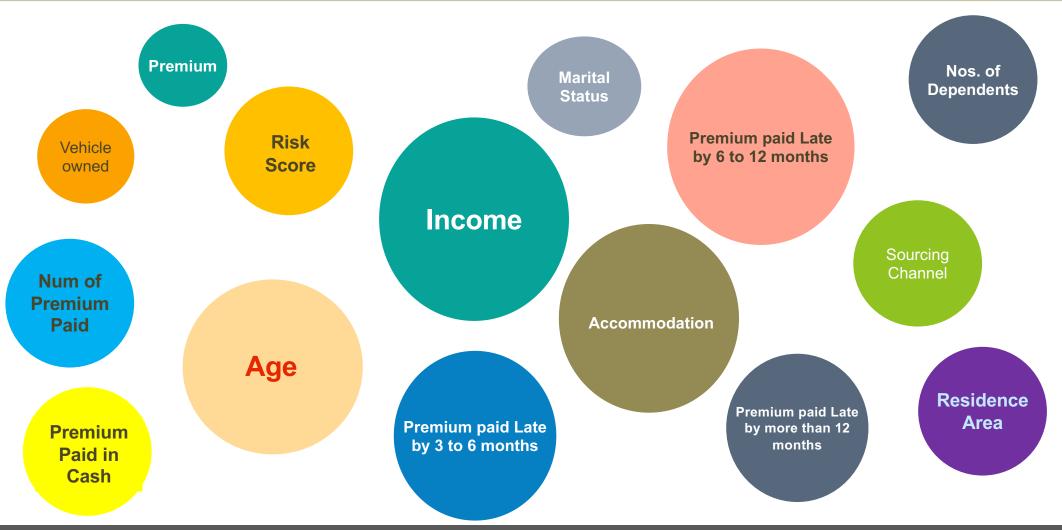
Premium paid by the customer is the major revenue source for insurance companies. Default in premium payments results in significant revenue losses and hence insurance companies would like to know upfront which type of customers would default premium payments.





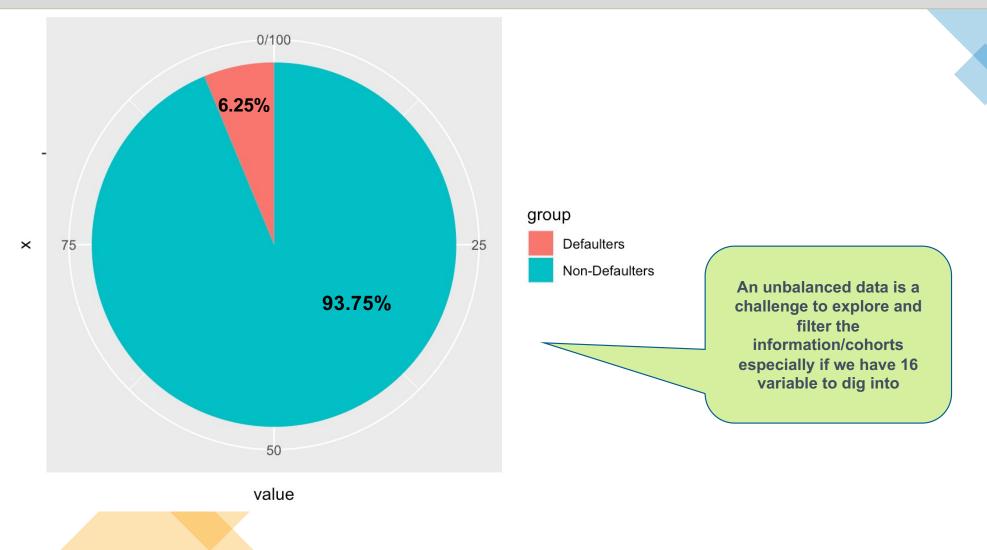
Explore the data to identify customers with the propensity to default on the Premiums to be paid to the Insurance company.

Independent Variables to be explored

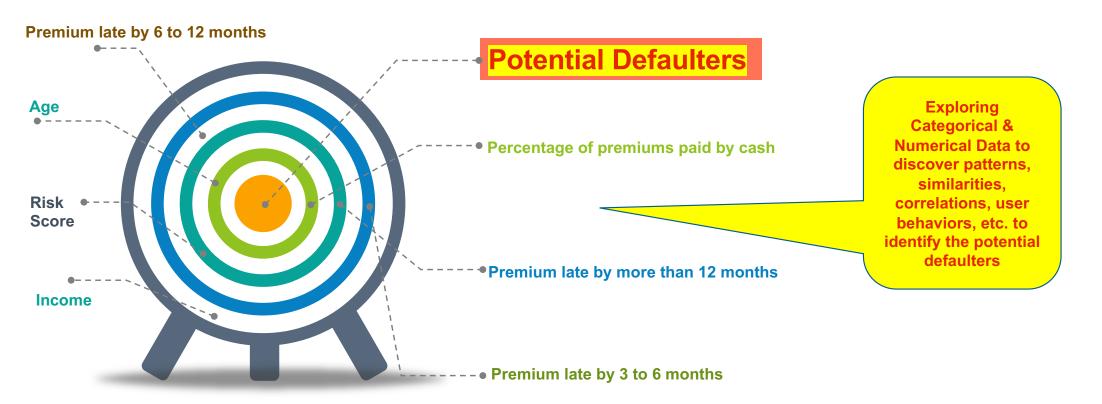


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Exploring the unbalanced Data



Exploring various attributes to identify the potential defaulters among the cohorts



Solution Design

The journey of exploring the data for identifying the potential defaulters

Building Insights Clean & Filter **Bi Variant** Correlation Identify **Uni Variant** Finalize/ Select **Analysis Analytical Important** Data **Analysis Analysis** Model Models Recommendations variables 5 2 3 4 6 8

Data **Treatment**

- Missing Value
- **Outlier Treatment**
- Variable **Transformation**
- Adding/removing variables
- Column Names

EDA **Uni Variant**

The categorical and numerical variables explored to check on aspects like the mean, median, mode. outliers and other influencina aspect of each variable individually.

EDA Bi Variant

see how the dependent variable (Defaulter) is behaving amidst all the categorical and numerical variables.

Correlation

understand the dearee of correlation and any high correlations which we need to consider for our analysis.

if they would be

Building Basic Models, **Bagging & Boosting**

- CART model Logistic Rearession Model
- Naïve Bayes
- KNN
- Random Forest
- Gradient Boostina
- XG Boost

Best Model for Analysis

Model performing best of aspects like: Confusion

- Matrix
- Accuracy
- Specificity
- Sensitivity
- Precision
- AUC Gini
- Concordance

Important Variables

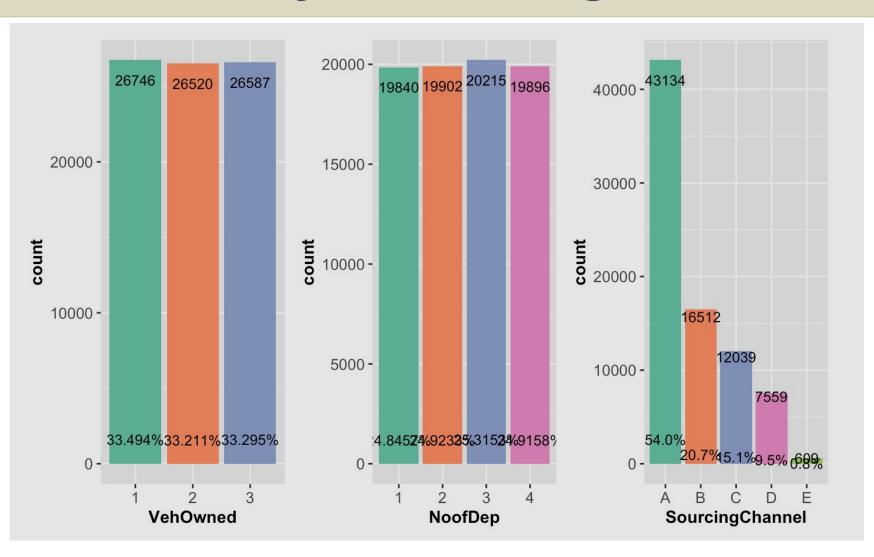
Discover the important influencina variables which indicate pattern. user behavior. tendency. characteristics and introspect to come out with solutions &

recommendations

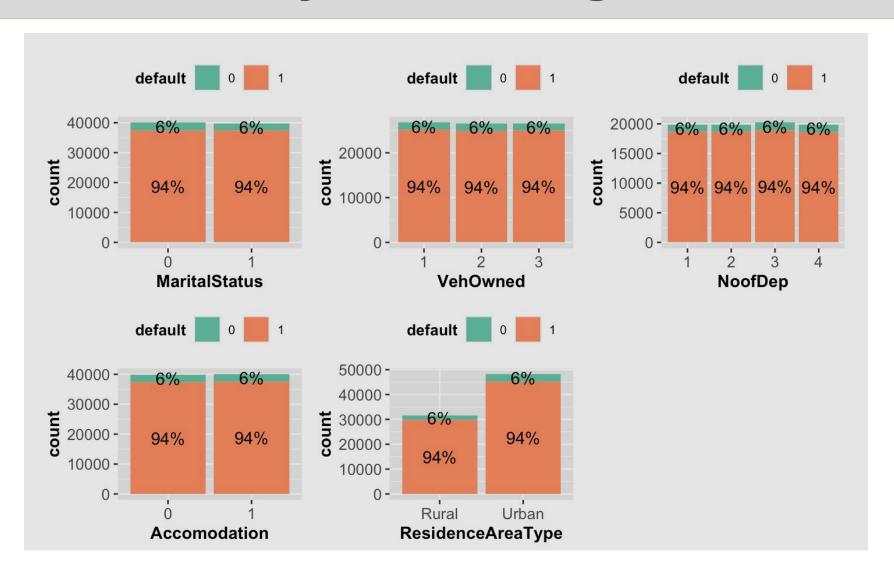
Findings & **Solutions**

- Long Term Short term
- One Fit or tailored solution model
- Conclusion
- Recommend ations with some realworld example

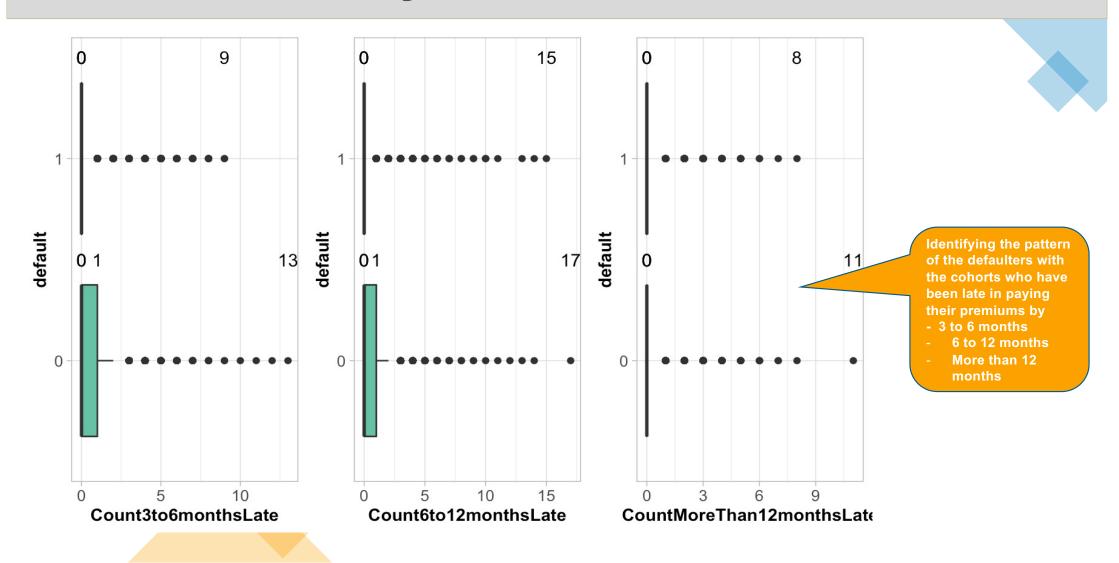
Uni Variant Analysis of Categorical variables



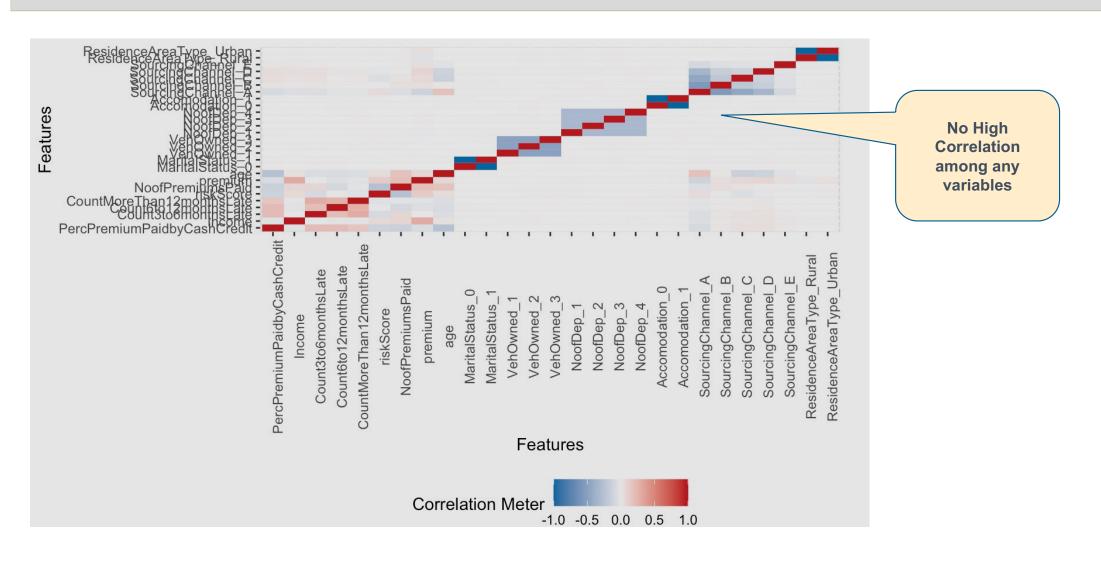
Bi Variant Analysis of Categorical variables



Bi Variant Analysis – old vs new defaulters



Correlations among all variables



Analytical Models

Basic Models

Will apply a Supervised Machine Learning Technique for a Descriptive, Predictive & Prescriptive Analysis



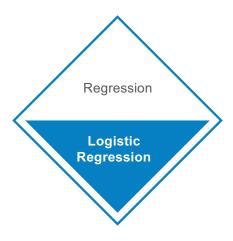
Supervised Machine Learning Technique

Built a CART model on the train data.
-- create CART model 1 & validate for accuracy.

 Tuning the model: further tune the model for further accuracy
 Model Validation: validate the new model

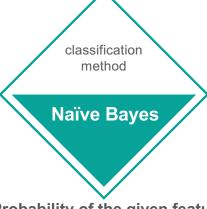
Model Evaluation: evaluate both the models on the test data & compare their accuracy.

- + Tune the model and prune the tree, if required.
 - + Test the data on test set.



Logistic function to model the conditional probability

In the case of binary classification the probability of defaulting premiums and not defaulting premiums will sum up to 1



Probability of the given feature vector being associated with a label

the algorithm expects the features to be independent which is not always is the case.



classify new data points based on similarity measure

Classification is done by a majority vote to its neighbors. The data is assigned to the class which has the nearest neighbors.

As you increase the number of nearest neighbors, the value of k, accuracy might increase.

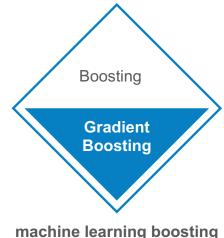
Analytical Models Bagging & Boosting

Process will involve creating a Train & Test Data set from the original data set. The training data set will be used to validate each model and the same will later be used to evaluate the model on the test data set.



an ensemble method that trains several decision trees in parallel with bootstrapping followed by aggregation

- -- Incase there is no significant improvement in the CART model from the baseline model, we build the Random Forest.
 - -- Tune the Model
 - -- Model Validation: validate the new model
- -- Model Evaluation: evaluate both the models on the test data & compare their accuracy.



It relies on the intuition that the best possible next model, when combined with previous models, minimizes the overall prediction error.



Efficient to the Gradient Boosting

Extreme Gradient Boosting (XGBoost) is similar to gradient boosting framework but more efficient. It has both linear model solver and tree learning algorithms. What makes it fast is its capacity to do parallel computation on a single machine..

Confusion Matrix

Indication towards extracting "defaulters" & 'non-defaulters

| | CART MODEL 1 | Defaulters | Non-Defaulters | | | |
|---|---------------------|------------|----------------|--|--|--|
| | Defaulters | 173 | 826 | | | |
| \ | Non - Defaulters | 218 | 14753 | | | |

| CART MODEL 2 | Defaulters | Non-Defaulters |
|---------------------|------------|----------------|
| Defaulters | 0 | 999 |
| Non - Defaulters | 0 | 14971 |

| Naïve Bayes | Defaulters | Non-Defaulters |
|---------------------|------------|----------------|
| Defaulters | 0 | 3 |
| Non - Defaulters | 999 | 14968 |

| Logistic Regression | Defaulters | Non-Defaulters |
|------------------------|------------------|----------------|
| Defaulters | <mark>122</mark> | 96 |
| Non - Defaulters | 877 | 14875 |

| KNN | Defaulters | Non-Defaulters |
|---------------------|------------|----------------|
| Defaulters | 98 | 901 |
| Non - Defaulters | 103 | 14868 |

| Gradient Boosting | | Defaulters | Non-Defaulteเ |
|----------------------|---------------------|------------------|--------------------|
| | Defaulters | <mark>147</mark> | 852 |
| | Non - Defaulters | 126 | <mark>14845</mark> |

| Random Forest 1 | Defaulters | Non-Defaulters | |
|---------------------|------------------|----------------|--|
| Defaulters | <mark>159</mark> | 840 | |
| Non - Defaulters | 154 | 14817 | |

| Random Forest 1 | Defaulters | Non-Defaulters |
|---------------------|------------|----------------|
| Defaulters | 2 | 997 |
| Non - Defaulters | 0 | 14971 |

| XG Boost | Defaulters | Non-Defaulters |
|---------------------|------------------|----------------|
| Defaulters | <mark>113</mark> | 886 |
| Non - Defaulters | 81 | 14890 |

Overview: Models Analysis

| Models | Accuracy | Sensitivity | Specificity | Precision | KS | AUC | Gini | Concordance |
|---------------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|-------------|
| Cart Model 1 | 0.93 | 0.92 | 0.01 | 0.92 | 0.5 | 0.80 | 0.03 | 0.17 |
| Cart Model 2 | 9.374452e-01 | 9.374452e-01 | 0.00 | 9.374452e-01 | 0.00 | 5.0 | -2.27 | 0.00 |
| Random Forest 1 | 0.93 | 0.92 | .009 | 47.33 | 0.50 | 0.81 | 0.05 | NaN |
| Random Forest 2 | 9.375704e-01 | 9.375704e-01 | 1.252348e-04 | 7.48 | 5.111567e-01 | 8.177137e-01 | 1.159270e-02 | NaN |
| Logistic Regression | 0.93 | 0.93 | 0.007 | 0.93 | 0.5 | NA | 0.03 | NaN |
| Naïve Bayes | 0.93 | 0.93 | 0.00 | 0.93 | 0.51 | NA | 0.0001 | NaN |
| KNN | 0.93 | 0.93 | 0.006 | 73.97 | 0.39 | 0.72 | 0.043 | NaN |
| Gradient Boost | 0.93 | 0.92 | 0.009 | 0.92 | NA | 0.82 | NA | NaN |
| X G Boost | 0.93 | 0.93 | 0.007 | 0.93 | 0.51 | 0.82 | 0.02 | NaN |

Most Important & Influencer variables

Important
Influencing
Variable to deep dive

Late in Payment of Premiums

- · Late by 3 to 6 Months
- · Late by 6 to 12 months
- Late by more than 12 months

Paying Premiums in Cash Credit

Cash in hand to pay Premium is a major attribute for paying Premiums

Risk Score

High Income = High Risk -Score = Low Defaulters

Income

High Income = Low Defaulters

Late in Payment of Premiums Paying Premium in Cash

Risk Score



Key Findings

- Looking at customers who are late in paying premiums in all 3 categories. They seem to follow a common pattern. Also, the risk score is a good indicator here as low risk score customer tend to have defaulted on the payments.
- Paying Premiums in Cash Credit seems like a stumbling block for some customers. Look at solutions to manage this issue by creating options towards offering insurance types and subsequent premiums.
- Income seems an influencing factor. We comparatively see lesser defaulters amidst the higher income bracket
- 1 Interactive Engaging Incentive based options
- 05 Flexible, customized, tailored payment options for eligible customers

Recommendation

You can download professional PowerPoint diagrams for free





Short term vs Long Term Options

Rather providing a long term offering, what needs to be offered would be a solution which addresses the current issue in hand and something that will rightly fit in their scheme of things.

A comprehensive but simple product which is easy to issue and pick needs to be developed.



Is capability to make Payment the only reason to Default?

Convenience, simplified product, easier issuance of insurance could at times solve the lethargy of not prioritizing the payments towards your premiums.

Options for cashless service, credit service, EMI offerings, deferring options (case basis), etc. can be offered to pay premiums timely



Solution bases customized offering (Sachet, Bouquet, etc.)

Relevant and simpler options could at times be easier to pick up especially during the challenging times like the pandemic when work, business, jobs and earnings are a challenge.



Interactive – Engaging – Incentive based options

Coming up with easy to adapt and engage programs for the customers by which one can achieve solutions for the insurer and the insured.

We need to keep in mind the current economic fallout due to the pandemic and the impact it has had on jobs/ business/income when we come our with solutions for the payments of the premiums.

Changing the Customer Mindset

outlook towards priority for health – insurance – paying premium

Incentivize customers for having health priorities



· Regular incentives on milestones which offers discounts, freebies, add-ons for encouraging fitness on a

Easy to adopt solutions (like loading app on customer's handset) and interactive options for easy

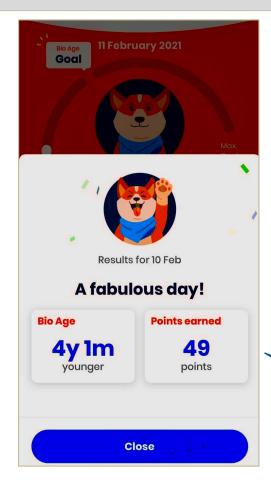
participation to keep customers interested, engaged and encouraged.

daily basis.

Recommendation Example

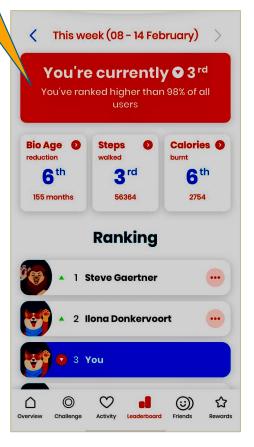


A Vitality
Fitness App to
keep the user
engaged with
regards to
his/her physical
activities like
walk, jog, sleep,
etc.



the rewards and incentives on a regular basis is a significant gain plus staying in great shape keeps you positive to manage life

Incentivize the user with a lesser premium amount by basis of their bio age fitness level



Recommendation Example

Variety of benefits ranging from daily refreshments, daily rides, vouchers for eshopping

Benefits * Incentives * Rewards * Recognition *
Discounts * Deferred payment options

- Deferred period options for payment of premium**
- More active and healthy = more attractive offerings on premiums**
- a healthier customer = benefits from other financial & professional service**
- **All stakeholders together create a 'value prop" with customer at the center**







Thankyou

... end of presentation