



CUSTOMER LIFETIME VALUE

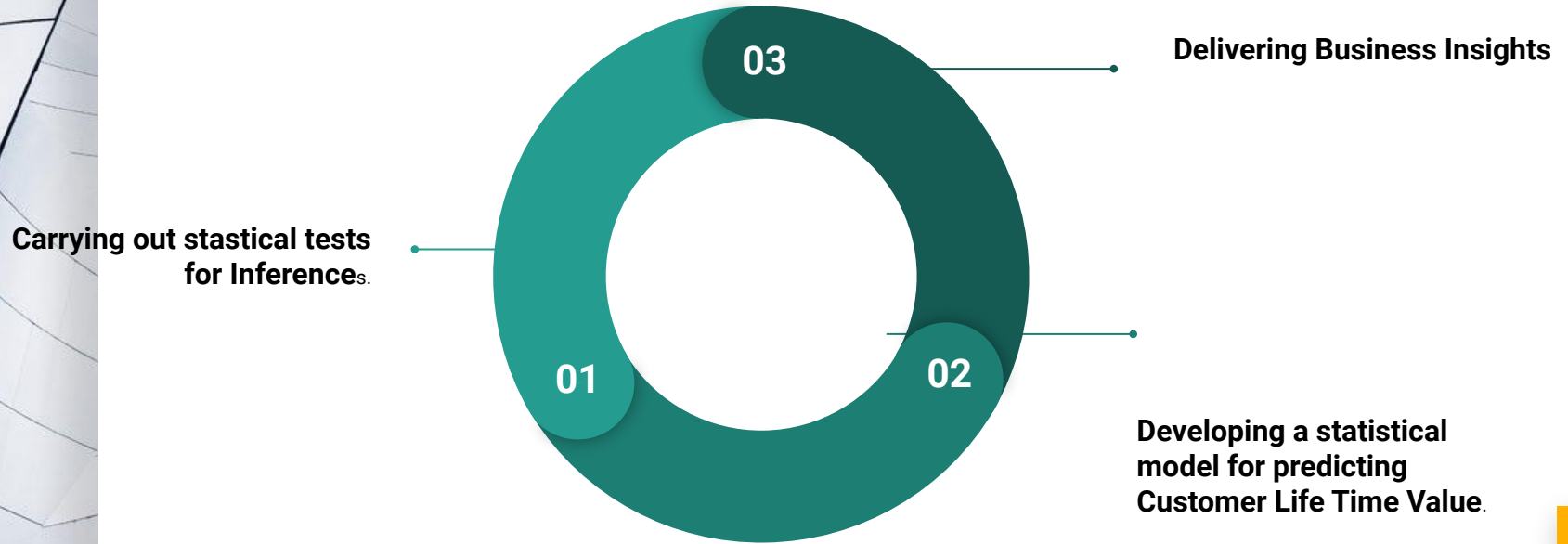
The present value of the future cash flows attributed to the customer during his/her entire relationship with the company

-CLV is the unit of measurement that creates customer equity , which in turn creates greater firm value

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SOLUTION APPROACH



WHY is CLVT IMPORTANT ?



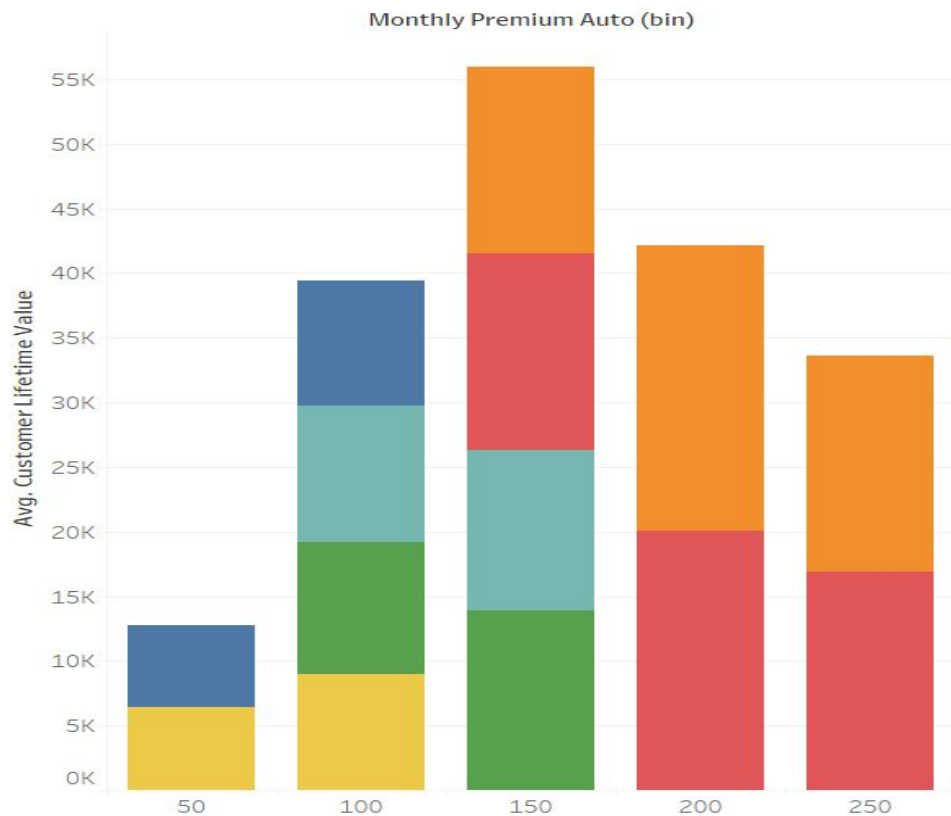
Because it represents an upper limit on spending to acquire new customers



WORKFLOW



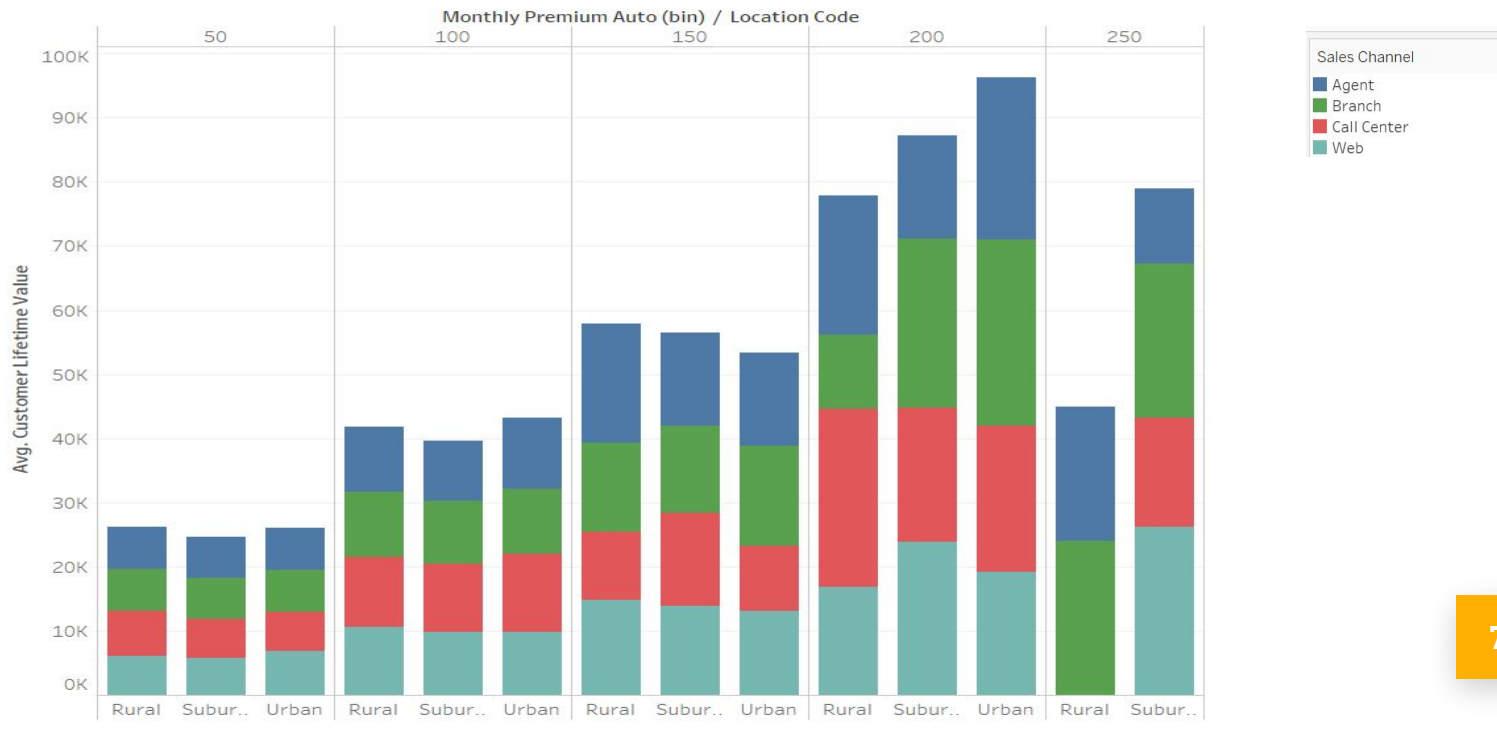
EXPLORATORY ANALYSIS



Vehicle Class

- Four-Door Car
- Luxury Car
- Luxury SUV
- Sports Car
- SUV
- Two-Door Car

EXPLORATORY ANALYSIS



EXPLORATORY ANALYSIS



Sheet 4



Policy Type

- Corporate Auto
- Personal Auto
- Special Auto

FEATURE CORRELATION



- ★ Monthly premium auto - Total claim amount : 0.63
- ★ Income - Employment status : -0.73
- ★ Policy type - Policy : 0.88

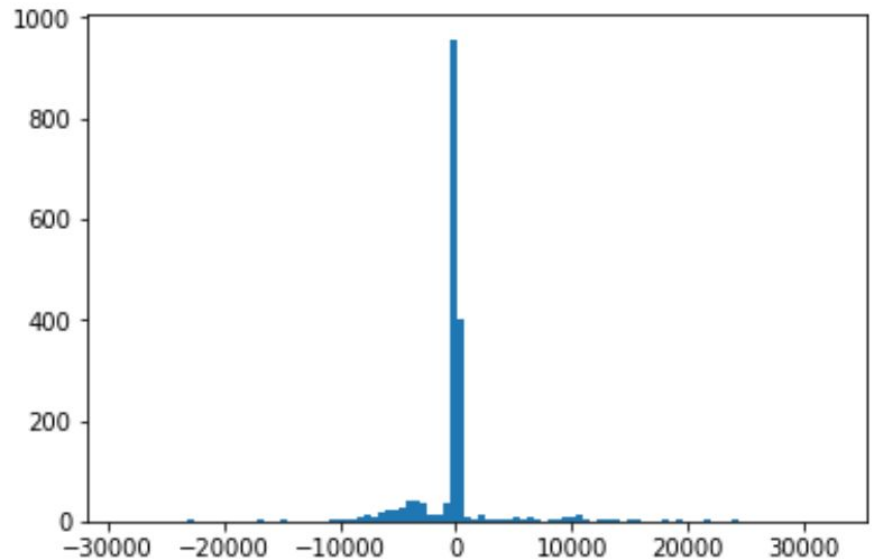
On the basis of these data we decided to drop these features in our model



SCEDASTICITY

Distribution of error terms is not Gaussian hence the data is heteroscedastic.

Therefore an advanced technique of tree based model is being used



Random Forest Regressor



Parameters :

(Using Grid Search) :-

1. N_estimators = 2500
2. Max_features = 6
3. Min_samples_split = 4
4. Random_state = 42

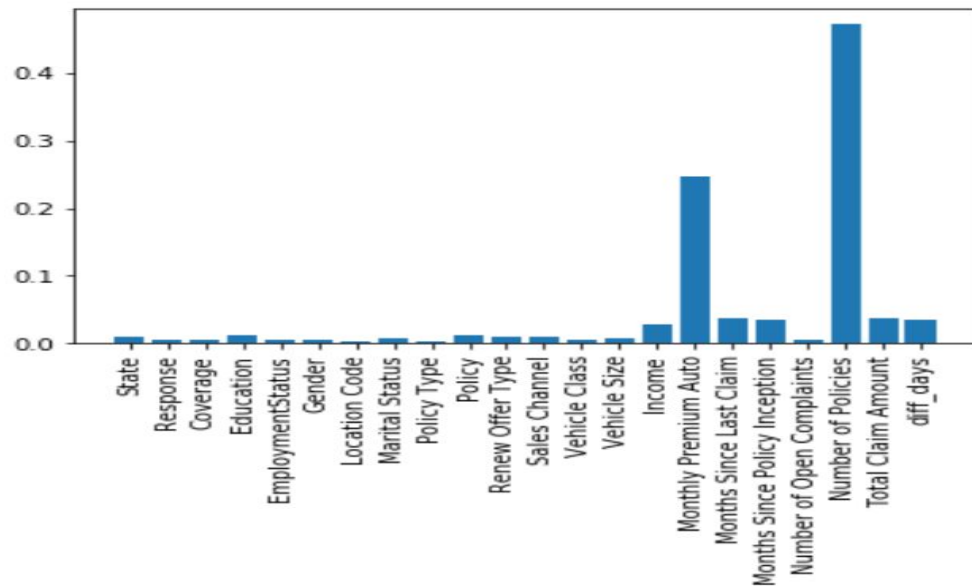
Model Performance:

Adjusted r^2 - 70.54

MAPE -17.54

Important Features :

1. Number of policies
2. Monthly premium auto.
3. Months since last claim
4. Total claim amount
5. Month since policy inception



FEATURE SELECTION(Random Forest Regressor with Boruta)

❖ Important Features :

1. Monthly premium auto
2. Months since last claim
3. Number of policies.
4. Total claim amount
5. Months since policy inception

Recursive Feature Elimination (RFE) :

❖ Important Features :(using random forest)

1. Monthly premium auto
2. Months since last claim
3. Number of policies.
4. Total claim amount
5. Months since policy inception

XGBoost



Parameters :

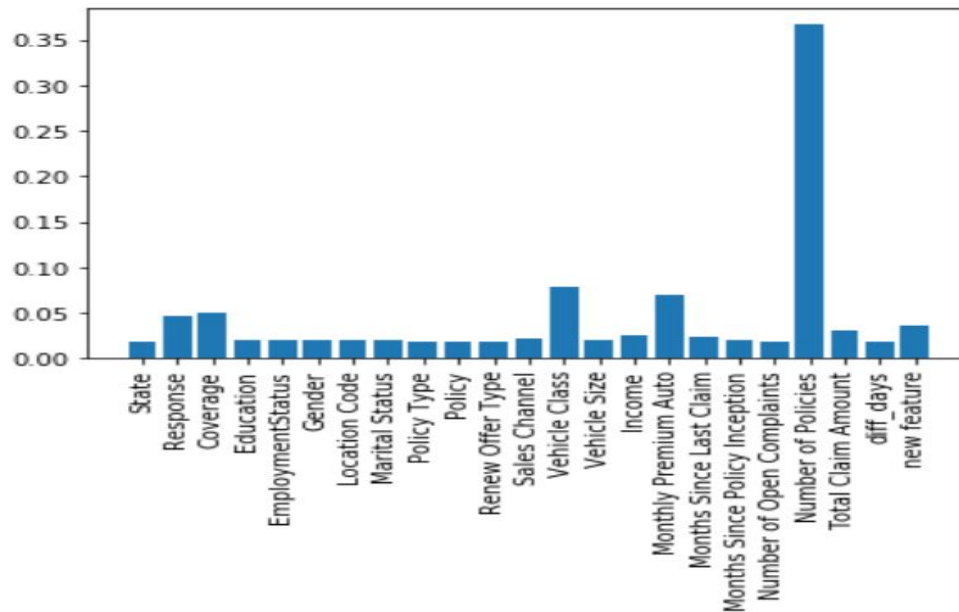
1. colsample_bytree=0.4,
2. learning_rate=0.07,
3. max_depth=3,
4. min_child_weight=1.5,
5. n_estimators=10000,

Accuracy :

r^2 value - 65.22
Adjusted r^2 - 70.81
MAPE - 29.42

Important Features :

1. Number of policies
2. Vehicle class
3. Monthly premium auto
4. Coverage
5. Response



BUSINESS INSIGHTS



NUMBER OF POLICIES

NUMBER OF
POLICIES=2

NUMBER OF
CUSTOMER=2294

AVG. CLTV
VALUE=15723

NUMBER OF
POLICIES!=2

NUMBER OF
CUSTOMER=6840

AVG. CLTV
VALUE=
5416.39

H_0 : Mean CLTV (#policies=2) = Mean CLTV (#policies!=2)

H_1 : Mean CLTV (#policies=2) > Mean CLTV (#policies!=2)

Through Student's t-test we have rejected the null hypothesis.

Hence, No. of policies = 2 is a strong evidence for high CLTV value.

Hence It is advisable for the company to target the aforementioned customer segment

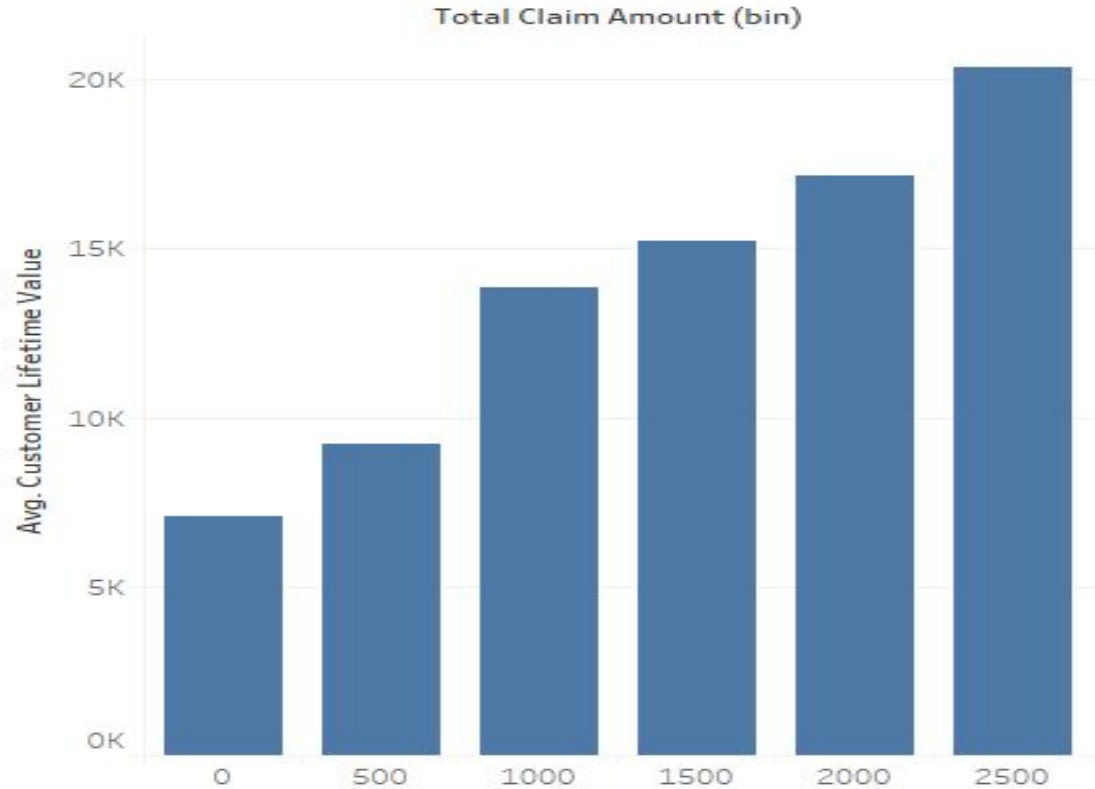
BUSINESS INSIGHTS

MONTHLY PREMIUM AUTO

- ❖ The average CLTV value of customers who pay Monthly premium auto between 50 - 100 rupees is less than customers with monthly premium auto greater than 100 ,also number of later customers are less in number .
- ❖ So it advisable that company should focus more on customer with Monthly premium auto greater than 100.

BUSINESS INSIGHT

With the increase in Total Claim Amount the average Customer Lifetime Value increases





72.04%

Whoa! That's a big number, aren't you proud?

- ❖ Five fold cross validation was performed
- ❖ By using Random Forest Regressor



ANNEXURE

1. Highest VIF values
2. Existing Features
3. Engineered Features
4. Resources

HIGHEST VIF VALUES :

The **VIF** measures how much the variance of an estimated regression coefficient increases if your predictors are correlated. More variation is bad news

It is a measure of multicollinearity

On the basis of VIF ,we have excluded the top four values in our model i.e Difference in days ,Feature_2 ,Employment status and Policy

VIF	Features
61.4	diff_days
6.8	feature2
5.5	Employment Status
4.4	Policy
4.4	Policy Type
3.5	new_feature
3.4	Monthly Premium Auto
2.7	Total Claim Amount
2.3	Income
2.2	Months Since Policy Inception
1.7	Number of Policies
1.3	Coverage

EXISTING FEATURES

- ★ Number of Policies : Number of insurance policy taken by an individual provided the company.
- ★ Monthly Premium Auto : It is the amount which is paid to the insurance company by the customer every month as premium of its insurance policy
- ★ Total Claim Amount : Amount claimed by a person against its policy on the insurance company.
- ★ Months Since Last Claim : Duration (in months) since when customer has not claimed its policy
- ★ Months Since Policy Inception : Duration (in months) since insurance policy began

EXISTING FEATURES

- ★ Number of Open Complaints : Complaints made by customer against its insurance policy.
- ★ Policy Type : Type of policy taken by a customer among the available ones.
- ★ Vehicle Class : It describes the type of vehicle ; e.g two door , four door vehicles.
- ★ Employment Status : It defines the current working status of the customer.
- ★ Income : It is the amount earned by customer in the period of a month.

ENGINEERED FEATURES

- ★ **Fraction_income_auto** = (monthly premium auto/income)
- ★ **Net_value_per_policy** = (((months since policy inception+months since last claim)*monthly premium auto)-total claim amount)/no of policy)
- ★ **Inverse_net_difference** = $1 - (1 / (\text{monthly premium auto} - \text{total claim amount}))$

RESOURCES

<https://youtu.be/-FtIH4svqx4>

https://en.wikipedia.org/wiki/Vehicle_insurance

<https://youtu.be/5Z90IYA8He8>

<https://medium.com/@vinaysays/how-to-calculate-the-customer-lifetime-value-cltv-ecfe2b1d046f>

<https://medium.com/usf-msds/choosing-the-right-metric-for-machine-learning-models-part-1-a99d7d7414e4>

https://www.datascience.com/blog/intro-to-predictive-modeling-for-customer-lifetime-value?hs_amp=true

<https://www.intechopen.com/books/data-mining/estimating-customer-lifetime-value-using-machine-learning-techniques>

<https://thoughtnerve.com/machine-learning/predict-customer-lifetime-value/>

<https://towardsdatascience.com/data-driven-growth-with-python-part-3-customer-lifetime-value-prediction-6017802f2e0f>

<https://www.kaggle.com/dhimananubhav/customer-lifetime-value>

<https://www.datacamp.com/community/tutorials/customer-life-time-value>

<https://www.sciencedirect.com/science/article/pii/S1026309812000107>