



# CUSTOMER LIFETIME VALUE

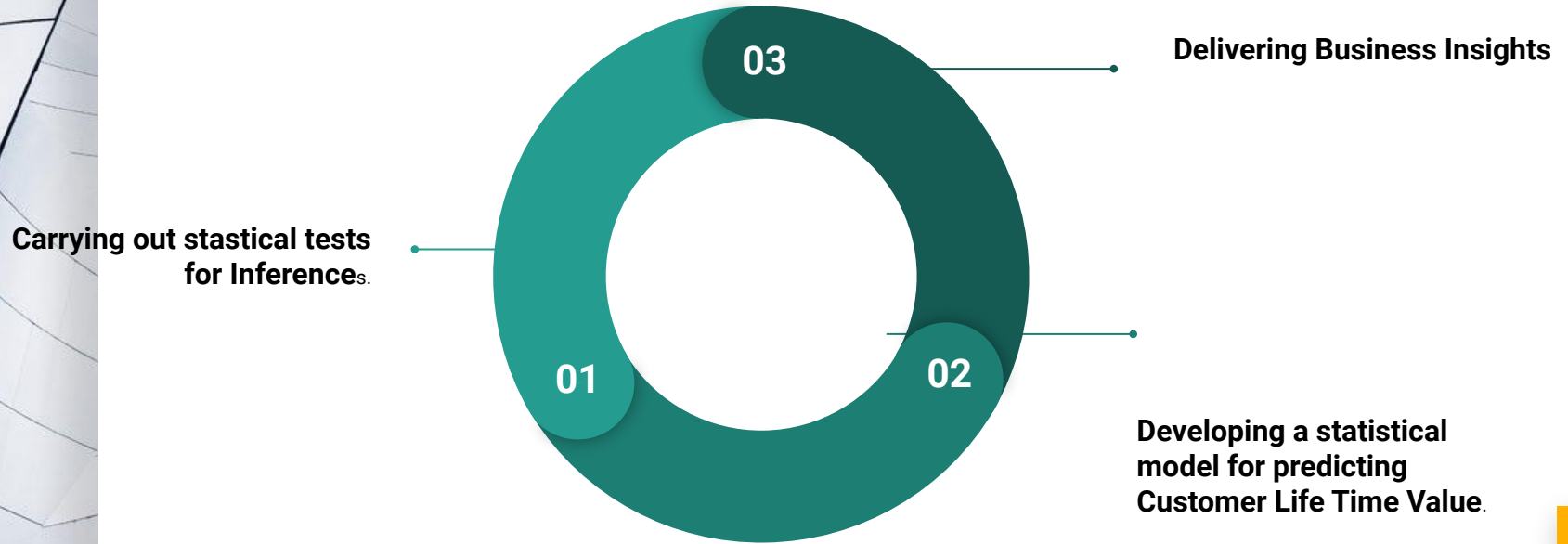
**The present value of the future cash flows attributed to the customer during his/her entire relationship with the company**

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

# INDEX

1. Solution Approach
2. Why is CLVT Important ?
3. Workflow
4. Exploratory Analysis
5. Feature Correlation
6. Scedasticity
7. Random Forest Regressor
8. Feature Selection ( Random Forest Regressor with Boruta)
9. XGBoost
10. Business Insight
11. Maximum Accuracy Achieved
12. Annexure

# SOLUTION APPROACH



# WHY is CLVT IMPORTANT ?



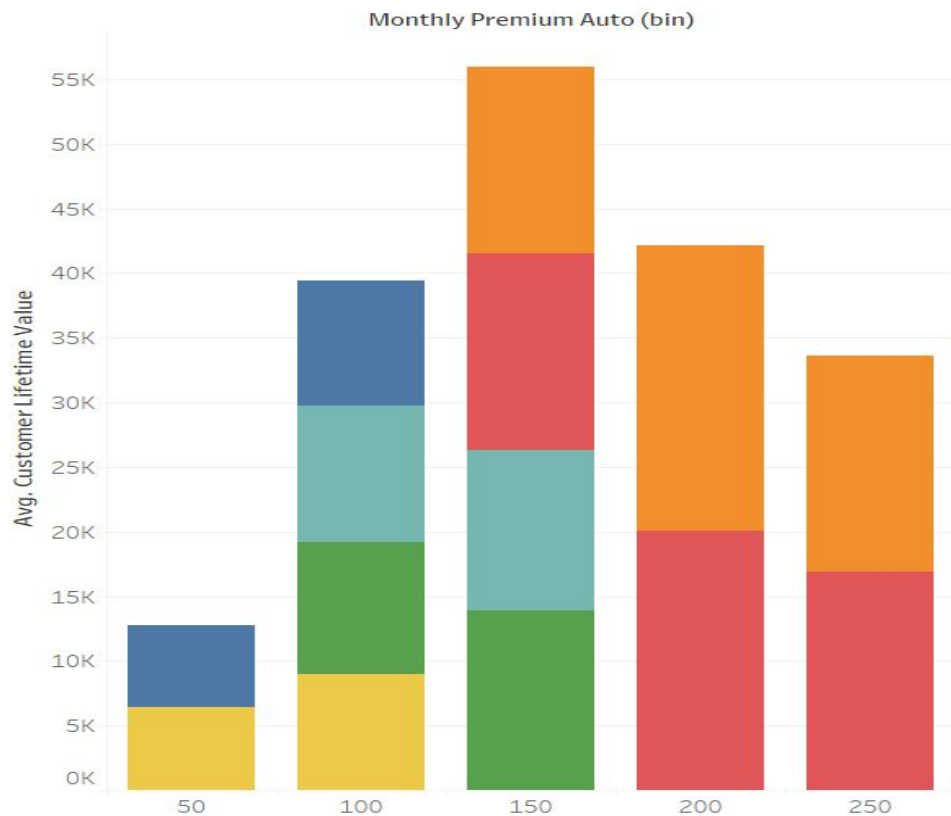
Because it represents an upper limit on spending to acquire new customers



# WORKFLOW



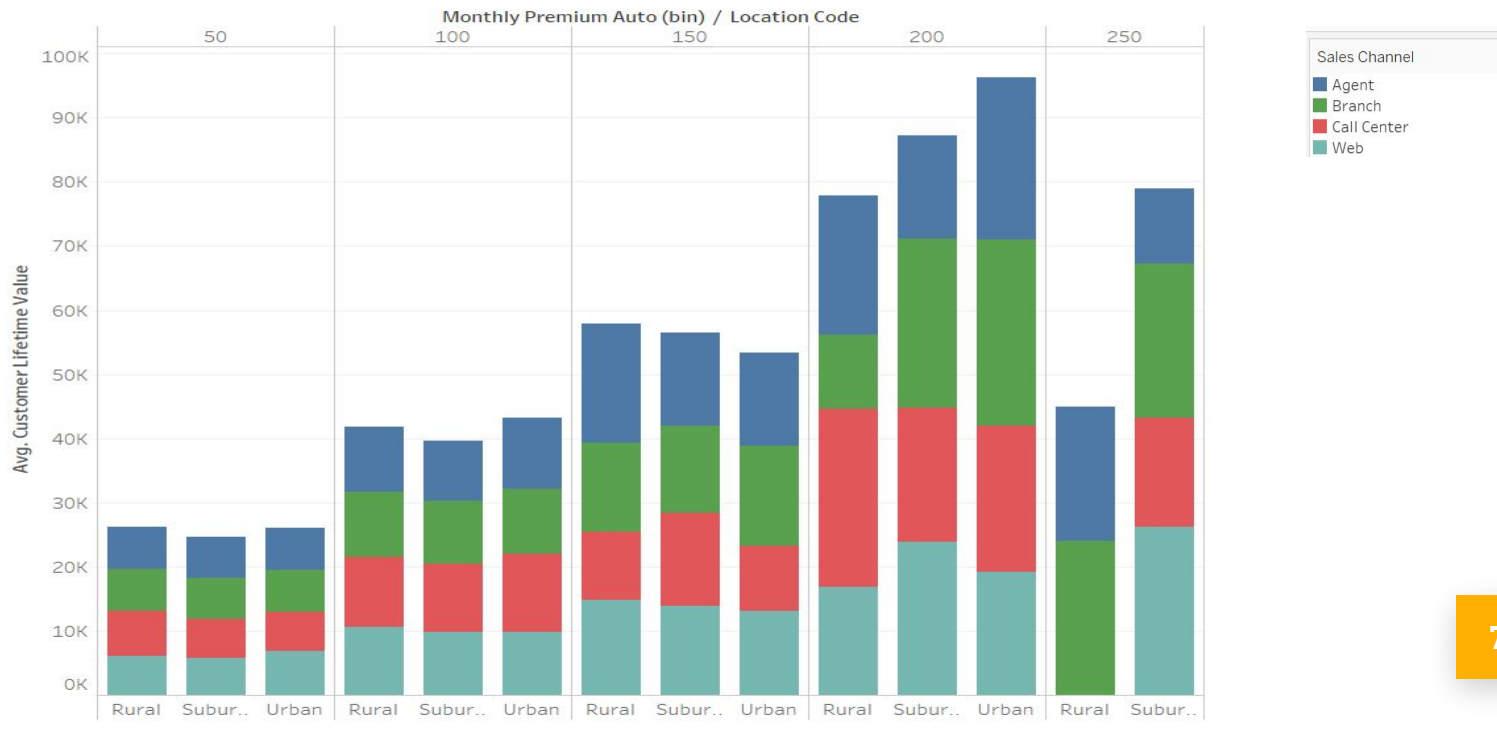
# EXPLORATORY ANALYSIS



## 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

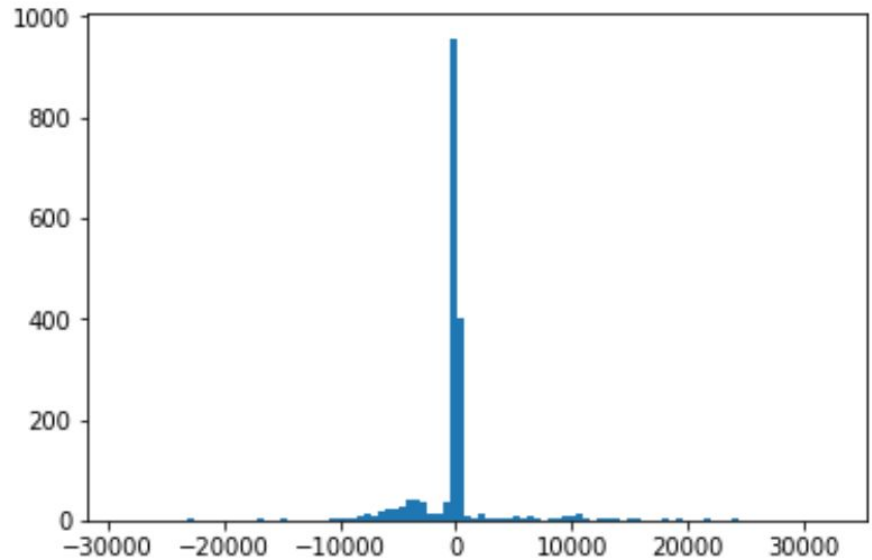


On the basis of these data we decided to drop these features in our model

# 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

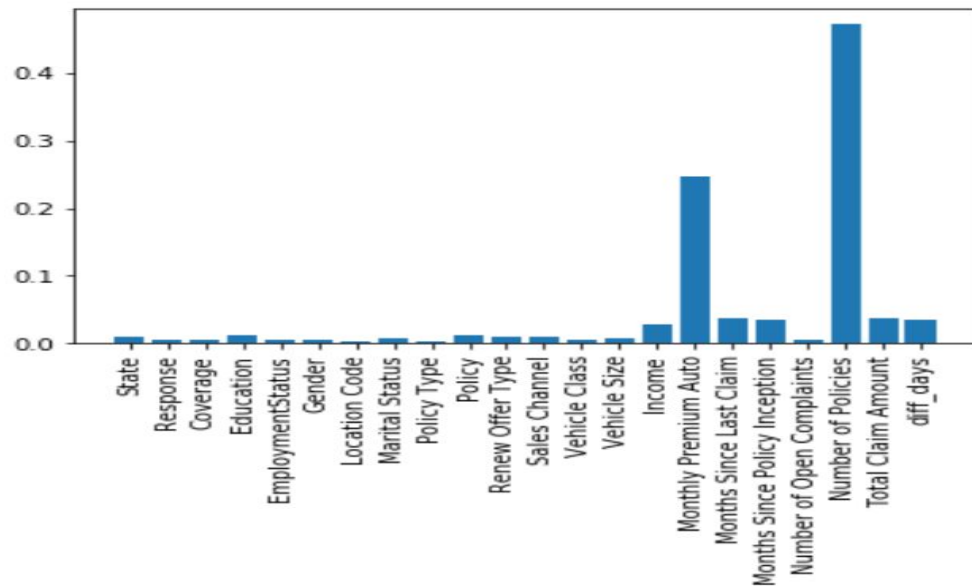
## Model Performance:

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 :

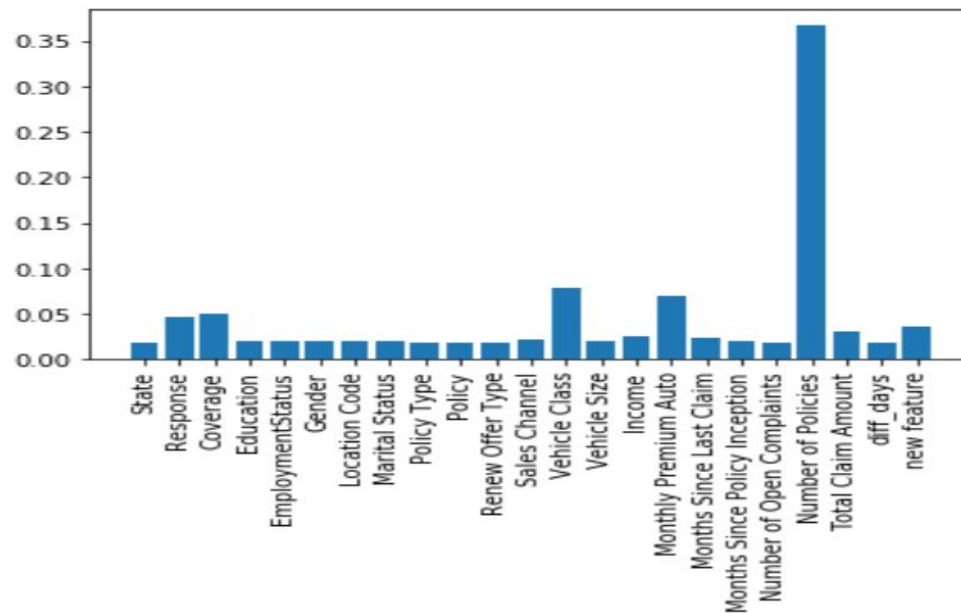
1. `colsample_bytree=0.4`,
2. `learning_rate=0.07`,
3. `max_depth=3`,
4. `min_child_weight=1.5`,
5. `n_estimators=10000`,

## 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

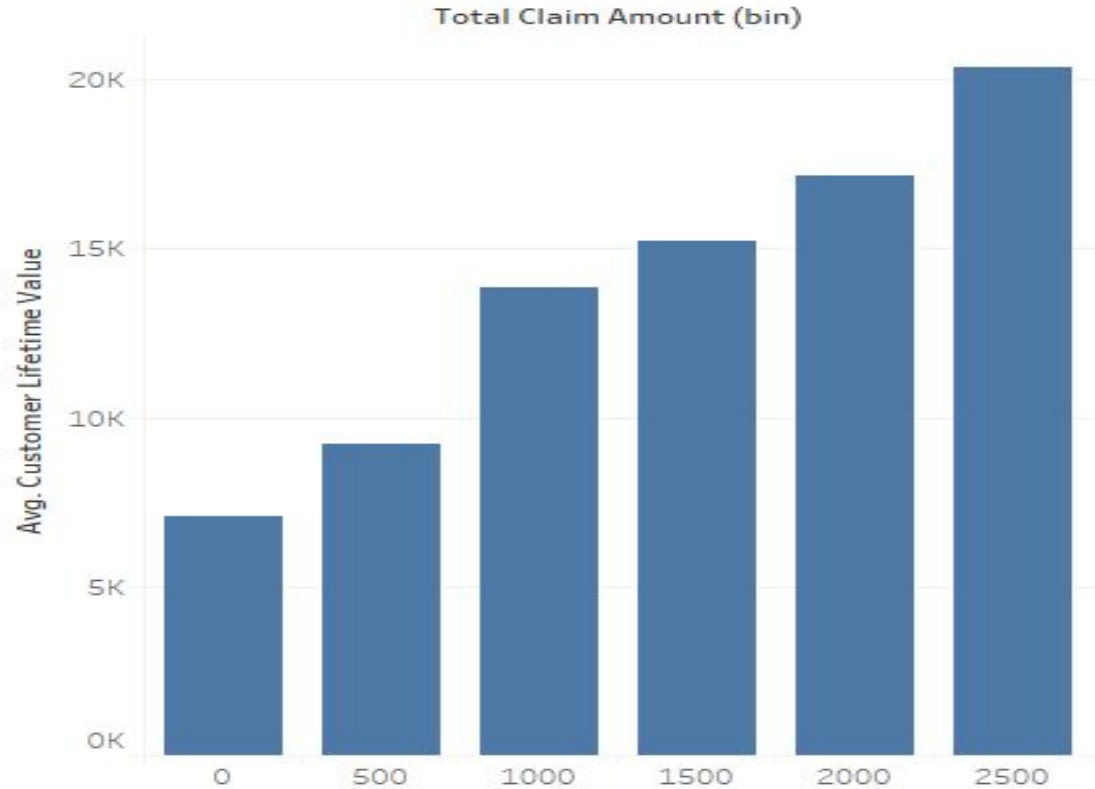
# BUSINESS INSIGHTS

## 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/(monthly premium auto-total claim amount))

# RESOURCES

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

[https://en.wikipedia.org/wiki/Vehicle\\_insurance](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.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>

A decorative orange bar at the top of the slide, with a lighter orange segment on the right. The background features a vertical strip on the left showing a curved architectural structure, possibly a stadium roof, and the rest of the slide is white.

# **THANK YOU**

**Submitted by  
TECNOTUNERS**