```
cd /content/drive/MyDrive/Assignt CS_Doc_AAIC/Analytics_Vidhya/AV-
Dataverse-Hackthon_NOV
```

```
/content/drive/MyDrive/Assignt CS_Doc_AAIC/Analytics_Vidhya/AV-
Dataverse-Hackthon_NOV
```

```
# installing catboost since it is not readily available in Google
Colab
!pip3 install catboost
```

```
Looking in indexes: https://pypi.org/simple, https://us-
python.pkg.dev/colab-wheels/public/simple/
Collecting catboost
  Downloading catboost-1.1.1-cp37-none-manylinux1_x86_64.whl (76.6 MB)
ent already satisfied: plotly in /usr/local/lib/python3.7/dist-
packages (from catboost) (5.5.0)
Requirement already satisfied: pandas>=0.24.0 in
/usr/local/lib/python3.7/dist-packages (from catboost) (1.3.5)
Requirement already satisfied: scipy in /usr/local/lib/python3.7/dist-
packages (from catboost) (1.7.3)
Requirement already satisfied: numpy>=1.16.0 in
/usr/local/lib/python3.7/dist-packages (from catboost) (1.21.6)
Requirement already satisfied: six in /usr/local/lib/python3.7/dist-
packages (from catboost) (1.15.0)
Requirement already satisfied: matplotlib in
/usr/local/lib/python3.7/dist-packages (from catboost) (3.2.2)
Requirement already satisfied: graphviz in
/usr/local/lib/python3.7/dist-packages (from catboost) (0.10.1)
Requirement already satisfied: pytz>=2017.3 in
/usr/local/lib/python3.7/dist-packages (from pandas>=0.24.0->catboost)
(2022.6)
Requirement already satisfied: python-dateutil>=2.7.3 in
/usr/local/lib/python3.7/dist-packages (from pandas>=0.24.0->catboost)
(2.8.2)
Requirement already satisfied: cycler>=0.10 in
/usr/local/lib/python3.7/dist-packages (from matplotlib->catboost)
(0.11.0)
Requirement already satisfied: pyparsing!=2.0.4,!=2.1.2,!
=2.1.6,>=2.0.1 in /usr/local/lib/python3.7/dist-packages (from
matplotlib->catboost) (3.0.9)
Requirement already satisfied: kiwisolver>=1.0.1 in
/usr/local/lib/python3.7/dist-packages (from matplotlib->catboost)
(1.4.4)
Requirement already satisfied: typing-extensions in
/usr/local/lib/python3.7/dist-packages (from kiwisolver>=1.0.1-
>matplotlib->catboost) (4.1.1)
Requirement already satisfied: tenacity>=6.2.0 in
/usr/local/lib/python3.7/dist-packages (from plotly->catboost) (8.1.0)
Installing collected packages: catboost
Successfully installed catboost-1.1.1
```

```
! pip install xverse
! pip install --upgrade category_encoders
```

```
Looking in indexes: https://pypi.org/simple, https://us-
python.pkg.dev/colab-wheels/public/simple/
Collecting xverse
  Downloading xverse-1.0.5-py3-none-any.whl (21 kB)
Requirement already satisfied: scikit-learn>=0.19.0 in
/usr/local/lib/python3.7/dist-packages (from xverse) (1.0.2)
Requirement already satisfied: matplotlib>=3.0.3 in
/usr/local/lib/python3.7/dist-packages (from xverse) (3.2.2)
Requirement already satisfied: numpy>=1.11.3 in
/usr/local/lib/python3.7/dist-packages (from xverse) (1.21.6)
Requirement already satisfied: statsmodels>=0.6.1 in
/usr/local/lib/python3.7/dist-packages (from xverse) (0.12.2)
Requirement already satisfied: scipy>=0.19.0 in
/usr/local/lib/python3.7/dist-packages (from xverse) (1.7.3)
Requirement already satisfied: pandas>=0.21.1 in
/usr/local/lib/python3.7/dist-packages (from xverse) (1.3.5)
Requirement already satisfied: python-dateutil>=2.1 in
/usr/local/lib/python3.7/dist-packages (from matplotlib>=3.0.3-
>xverse) (2.8.2)
Requirement already satisfied: pyparsing!=2.0.4,!=2.1.2,!
=2.1.6,>=2.0.1 in /usr/local/lib/python3.7/dist-packages (from
matplotlib>=3.0.3->xverse) (3.0.9)
Requirement already satisfied: kiwisolver>=1.0.1 in
/usr/local/lib/python3.7/dist-packages (from matplotlib>=3.0.3-
>xverse) (1.4.4)
Requirement already satisfied: cycler>=0.10 in
/usr/local/lib/python3.7/dist-packages (from matplotlib>=3.0.3-
>xverse) (0.11.0)
Requirement already satisfied: typing-extensions in
/usr/local/lib/python3.7/dist-packages (from kiwisolver>=1.0.1-
>matplotlib>=3.0.3->xverse) (4.1.1)
Requirement already satisfied: pytz>=2017.3 in
/usr/local/lib/python3.7/dist-packages (from pandas>=0.21.1->xverse)
(2022.6)
Requirement already satisfied: six>=1.5 in
/usr/local/lib/python3.7/dist-packages (from python-dateutil>=2.1-
>matplotlib>=3.0.3->xverse) (1.15.0)
Requirement already satisfied: threadpoolctl>=2.0.0 in
/usr/local/lib/python3.7/dist-packages (from scikit-learn>=0.19.0-
>xverse) (3.1.0)
Requirement already satisfied: joblib>=0.11 in
/usr/local/lib/python3.7/dist-packages (from scikit-learn>=0.19.0-
>xverse) (1.2.0)
Requirement already satisfied: patsy>=0.5 in
/usr/local/lib/python3.7/dist-packages (from statsmodels>=0.6.1-
>xverse) (0.5.3)
Installing collected packages: xverse
```

```
Successfully installed xverse-1.0.5
Looking in indexes: https://pypi.org/simple, https://us-
python.pkg.dev/colab-wheels/public/simple/
Collecting category_encoders
  Downloading category_encoders-2.5.1.post0-py2.py3-none-any.whl (72
kB)
ent already satisfied: patsy>=0.5.1 in /usr/local/lib/python3.7/dist-
packages (from category_encoders) (0.5.3)
Requirement already satisfied: scipy>=1.0.0 in
/usr/local/lib/python3.7/dist-packages (from category_encoders)
(1.7.3)
Requirement already satisfied: statsmodels>=0.9.0 in
/usr/local/lib/python3.7/dist-packages (from category_encoders)
(0.12.2)
Requirement already satisfied: scikit-learn>=0.20.0 in
/usr/local/lib/python3.7/dist-packages (from category_encoders)
(1.0.2)
Requirement already satisfied: pandas>=1.0.5 in
/usr/local/lib/python3.7/dist-packages (from category_encoders)
(1.3.5)
Requirement already satisfied: numpy>=1.14.0 in
/usr/local/lib/python3.7/dist-packages (from category_encoders)
(1.21.6)
Requirement already satisfied: pytz>=2017.3 in
/usr/local/lib/python3.7/dist-packages (from pandas>=1.0.5-
>category_encoders) (2022.6)
Requirement already satisfied: python-dateutil>=2.7.3 in
/usr/local/lib/python3.7/dist-packages (from pandas>=1.0.5-
>category_encoders) (2.8.2)
Requirement already satisfied: six in /usr/local/lib/python3.7/dist-
packages (from patsy>=0.5.1->category_encoders) (1.15.0)
Requirement already satisfied: joblib>=0.11 in
/usr/local/lib/python3.7/dist-packages (from scikit-learn>=0.20.0-
>category_encoders) (1.2.0)
Requirement already satisfied: threadpoolctl>=2.0.0 in
/usr/local/lib/python3.7/dist-packages (from scikit-learn>=0.20.0-
>category_encoders) (3.1.0)
Installing collected packages: category-encoders
Successfully installed category-encoders-2.5.1.post0
```

```
# to show the time taken by each cell
!pip install ipython-autotime
%load_ext autotime
```

```
Looking in indexes: https://pypi.org/simple, https://us-
python.pkg.dev/colab-wheels/public/simple/
Collecting ipython-autotime
  Downloading ipython_autotime-0.3.1-py2.py3-none-any.whl (6.8 kB)
Requirement already satisfied: ipython in
/usr/local/lib/python3.7/dist-packages (from ipython-autotime) (7.9.0)
Requirement already satisfied: pygments in
```

```
/usr/local/lib/python3.7/dist-packages (from ipython->ipython-
autotime) (2.6.1)
Requirement already satisfied: traitlets>=4.2 in
/usr/local/lib/python3.7/dist-packages (from ipython->ipython-
autotime) (5.1.1)
Requirement already satisfied: decorator in
/usr/local/lib/python3.7/dist-packages (from ipython->ipython-
autotime) (4.4.2)
Collecting jedi>=0.10
  Downloading jedi-0.18.2-py2.py3-none-any.whl (1.6 MB)
ent already satisfied: prompt-toolkit<2.1.0,>=2.0.0 in
/usr/local/lib/python3.7/dist-packages (from ipython->ipython-
autotime) (2.0.10)
Requirement already satisfied: setuptools>=18.5 in
/usr/local/lib/python3.7/dist-packages (from ipython->ipython-
autotime) (57.4.0)
Requirement already satisfied: pickleshare in
/usr/local/lib/python3.7/dist-packages (from ipython->ipython-
autotime) (0.7.5)
Requirement already satisfied: pexpect in
/usr/local/lib/python3.7/dist-packages (from ipython->ipython-
autotime) (4.8.0)
Requirement already satisfied: backcall in
/usr/local/lib/python3.7/dist-packages (from ipython->ipython-
autotime) (0.2.0)
Requirement already satisfied: parso<0.9.0,>=0.8.0 in
/usr/local/lib/python3.7/dist-packages (from jedi>=0.10->ipython-
>ipython-autotime) (0.8.3)
Requirement already satisfied: wcwidth in
/usr/local/lib/python3.7/dist-packages (from prompt-
toolkit<2.1.0,>=2.0.0->ipython->ipython-autotime) (0.2.5)
Requirement already satisfied: six>=1.9.0 in
/usr/local/lib/python3.7/dist-packages (from prompt-
toolkit<2.1.0,>=2.0.0->ipython->ipython-autotime) (1.15.0)
Requirement already satisfied: ptyprocess>=0.5 in
/usr/local/lib/python3.7/dist-packages (from pexpect->ipython-
>ipython-autotime) (0.7.0)
Installing collected packages: jedi, ipython-autotime
Successfully installed ipython-autotime-0.3.1 jedi-0.18.2
time: 485 µs (started: 2022-11-23 16:27:14 +00:00)
```

```python
import numpy as np
import pandas as pd

pd.set_option('display.max_rows', None)
pd.set_option('display.max_columns', None)

import matplotlib.pyplot as plt
import seaborn as sns
```

```
from xverse.transformer import WOE
from category_encoders.cat_boost import CatBoostEncoder
from category_encoders.woe import WOEEncoder

from sklearn.model_selection import train_test_split
from sklearn.pipeline import Pipeline
from catboost import CatBoostClassifier

from sklearn.ensemble import RandomForestClassifier
from xgboost import XGBClassifier
from lightgbm import LGBMClassifier
from sklearn.model_selection import RandomizedSearchCV, GridSearchCV
from sklearn.metrics import classification_report, f1_score,
confusion_matrix, ConfusionMatrixDisplay
from statsmodels.stats.outliers_influence import
variance_inflation_factor

from scipy.stats import randint as sp_randint
from scipy.stats import uniform as sp_uniform
from sklearn.feature_selection import RFE
```

```
time: 1.89 s (started: 2022-11-23 16:27:14 +00:00)
```

```
# importing required libraries

%matplotlib inline

import pandas as pd
from catboost import CatBoostClassifier
import numpy as np
import matplotlib.pyplot as plt

from sklearn.metrics import confusion_matrix, roc_curve, auc,
ConfusionMatrixDisplay, f1_score, RocCurveDisplay, roc_auc_score,
accuracy_score, classification_report, recall_score
from sklearn.model_selection import train_test_split
```

```
time: 4.89 ms (started: 2022-11-23 16:28:08 +00:00)
```

# # About the Dataset

## ## Insurance Claim Prediction

1. An insurance policy is an agreement between a company and a customer by which a company undertakes to provide a guarantee of compensation for specified loss, damage or illness in return for the payment of a specified premium. A premium is a sum of money that the customer needs to pay regularly to an insurance company for this guarantee.

2. For example, you pay a premium of Rs. 3000/- each year for car insurance with a coverage of Rs. 100,000/-. Unfortunately, in case of an accident, the car is severely damaged. In that case, the insurance provider company will bear the cost of damage etc. for up to Rs. 100,000.

3. Now if you are wondering how can a company bear such a high cost when it charges a premium of only Rs. 3000/- per year only i.e. where the concept of probability comes into the picture. For example, there might be thousands of customers who would be paying a premium of Rs. 3000 every year just like you, but only a few of them (say 2-3) would have had an accident that year and not everyone. This way everyone shares the risk of everyone else.

4. Our client is an Insurance company that provides insurance for cars to its customers. In this hackathon, you will be closely working with the insurer in understanding the behaviour of the policyholders.

```
# to display all the rows and columns
pd.set_option('display.max_rows', 100)
pd.set_option('display.max_columns', 100)
```

```
time: 1.07 ms (started: 2022-11-23 16:28:08 +00:00)
```

```
df = pd.read_csv('train_qWM28Yl.csv')
oot = pd.read_csv('test_zo1G9sv.csv')
```

```
time: 557 ms (started: 2022-11-23 16:45:04 +00:00)
```

```
# checking for any duplicate policy IDs
df['policy_id'].duplicated().sum()
```

```
0

time: 16.6 ms (started: 2022-11-23 16:28:08 +00:00)
```

```
df.head()
```

```
  policy_id  policy_tenure  age_of_car  age_of_policyholder 
area_cluster  \
0   ID00001       0.515874        0.05             0.644231 
C1
1   ID00002       0.672619        0.02             0.375000 
C2
2   ID00003       0.841110        0.02             0.384615 
C3
3   ID00004       0.900277        0.11             0.432692 
C4
4   ID00005       0.596403        0.11             0.634615 
C5

   population_density  make segment model fuel_type     max_torque  \
0                4990     1       A    M1       CNG   60Nm@3500rpm
```

```
1               27003     1       A    M1       CNG   60Nm@3500rpm
2                4076     1       A    M1       CNG   60Nm@3500rpm
3               21622     1      C1    M2    Petrol  113Nm@4400rpm
4               34738     2       A    M3    Petrol   91Nm@4250rpm

          max_power         engine_type  airbags is_esc  \
0  40.36bhp@6000rpm   F8D Petrol Engine        2     No
1  40.36bhp@6000rpm   F8D Petrol Engine        2     No
2  40.36bhp@6000rpm   F8D Petrol Engine        2     No
3  88.50bhp@6000rpm  1.2 L K12N Dualjet        2    Yes
4  67.06bhp@5500rpm             1.0 SCe        2     No

  is_adjustable_steering is_tpms is_parking_sensors is_parking_camera
\
0                     No      No                Yes                No

1                     No      No                Yes                No

2                     No      No                Yes                No

3                    Yes      No                Yes               Yes

4                     No      No                 No               Yes


  rear_brakes_type  displacement  cylinder transmission_type  gear_box
\
0             Drum           796         3            Manual         5

1             Drum           796         3            Manual         5

2             Drum           796         3            Manual         5

3             Drum          1197         4         Automatic         5

4             Drum           999         3         Automatic         5


  steering_type  turning_radius  length  width  height
gross_weight  \
0         Power             4.6    3445   1515    1475          1185

1         Power             4.6    3445   1515    1475          1185

2         Power             4.6    3445   1515    1475          1185

3      Electric             4.8    3995   1735    1515          1335
```

```
4      Electric             5.0    3731   1579    1490          1155


  is_front_fog_lights is_rear_window_wiper is_rear_window_washer  \
0                  No                   No                    No
1                  No                   No                    No
2                  No                   No                    No
3                 Yes                   No                    No
4                  No                   No                    No

  is_rear_window_defogger is_brake_assist is_power_door_locks  \
0                      No              No                  No
1                      No              No                  No
2                      No              No                  No
3                     Yes             Yes                 Yes
4                      No              No                 Yes

  is_central_locking is_power_steering
is_driver_seat_height_adjustable  \
0                 No               Yes
No
1                 No               Yes
No
2                 No               Yes
No
3                Yes               Yes
Yes
4                Yes               Yes
No

  is_day_night_rear_view_mirror is_ecw is_speed_alert  ncap_rating
is_claim
0                            No     No            Yes            0
0
1                            No     No            Yes            0
0
2                            No     No            Yes            0
0
3                           Yes    Yes            Yes            2
0
4                           Yes    Yes            Yes            2
0

time: 45.6 ms (started: 2022-11-23 16:28:08 +00:00)
```

## ## Description of each column:

| Variable | Description |
|---:|---|
| policy_id | Unique identifier of the policyholder |
| policy_tenure | Time period of the policy |

| | |
|---|---|
| age_of_car | Normalized age of the car in years |
| age_of_policyholder | Normalized age of policyholder in years |
| area_cluster | Area cluster of the policyholder\| |
| population | Population density of the city (Policyholder City) |
| make | Encoded Manufacturer/company of the car |
| segment | Segment of the car (A/ B1/ B2/ C1/ C2) |
| model | Encoded name of the car |
| fuel_type | Type of fuel used by the car |
| max_torque | Maximum Torque generated by the car (Nm@rpm) |
| max_power | Maximum Power generated by the car (bhp@rpm) |
| engine_type | Type of engine used in the car |
| engine_type | Type of engine used in the car |
| airbags | Number of airbags installed in the car |
| is_esc | Boolean flag indicating whether Electronic Stability Control (ESC) is present in the car or not. |
| is_adjustable_steering | Boolean flag indicating whether the steering wheel of the car is adjustable or not. |
| 'is_tpms' | Boolean flag indicating whether Tyre Pressure Monitoring System (TPMS) is present in the car or not. |
| is_parking_sensors | Boolean flag indicating whether parking sensors are present in the car or not. |
| is_parking_camera | Boolean flag indicating whether the parking camera is present in the car or not. |
| rear_brakes_type | Type of brakes used in the rear of the car\| |
| displacement | Engine displacement of the car (cc) |
| cylinder | Number of cylinders present in the engine of the car |
| transmission_type | Transmission type of the car |
| gear_box | Number of gears in the car |
| steering_type | Type of the power steering present in the car |
| turning_radius | The space a vehicle needs to make a certain turn (Meters) |

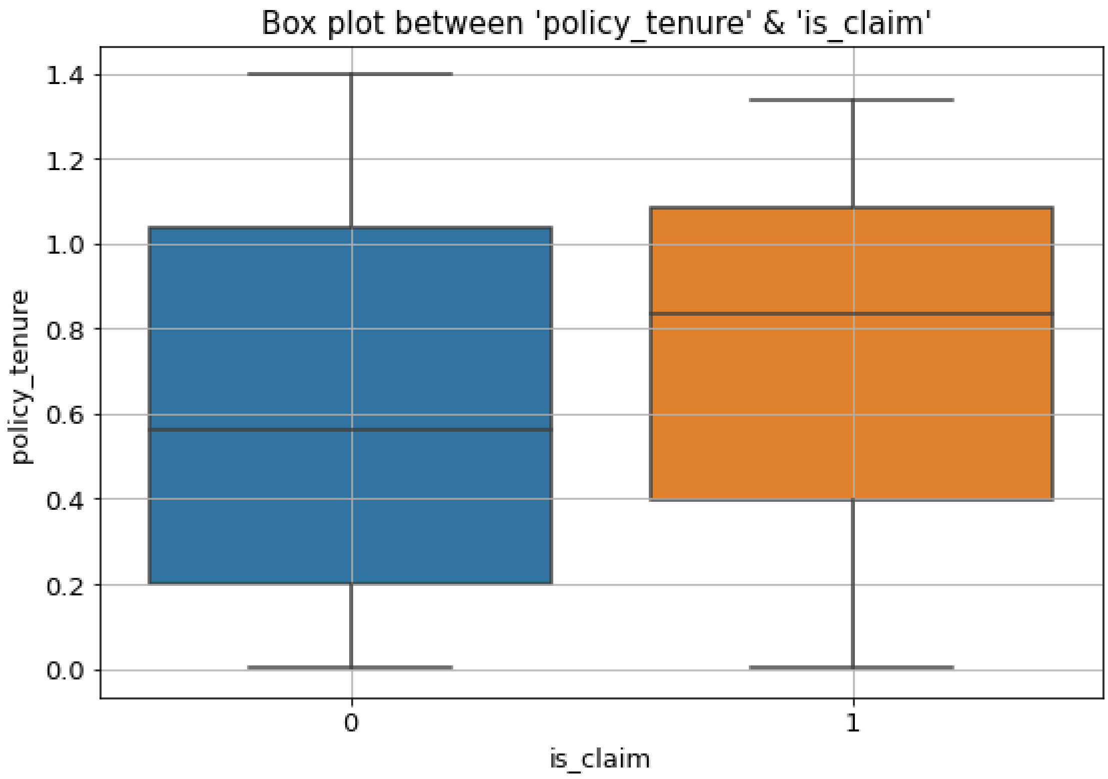
| | |
|---|---|
| lemgth | Length of the car (Millimetre) |
| width | Width of the car (Millimetre)\| |
| height | Height of the car (Millimetre) |
| gross_weight | The maximum allowable weight of the fully-loaded car, including passengers, cargo and equipment (Kg) |
| is_front_fog_lights | Boolean flag indicating whether front fog lights are available in the car or not. |
| is_rear_window_wiper | Boolean flag indicating whether the rear window wiper is available in the car or not. |
| is_rear_window_washer | Boolean flag indicating whether the rear window washer is available in the car or not. |
| is_rear_window_defogger | Boolean flag indicating whether rear window defogger is available in the car or not. |
| is_brake_assist | Boolean flag indicating whether the brake assistance feature is available in the car or not. |
| is_power_door_lock | Boolean flag indicating whether a power door lock is available in the car or not. |
| is_central_locking | Boolean flag indicating whether the central locking feature is available in the car or not. |
| is_power_steering | Boolean flag indicating whether power steering is available in the car or not. |
| is_driver_seat_height_adjustable | Boolean flag indicating whether the height of the driver seat is adjustable or not. |
| is_day_night_rear_view_mirror | Boolean flag indicating whether day & night rearview mirror is present in the car or not.\| |
| is_ecw | Boolean flag indicating whether Engine Check Warning (ECW) is available in the car or not. |
| is_speed_alert | Boolean flag indicating whether the speed alert system is available in the car or not. |
| ncap_rating | Safety rating given by NCAP (out of 5) |
| is_claim | Outcome: Boolean flag indicating whether the policyholder file a claim in the next 6 months or not.\| |

is_claim: 0 -- not claimed & 1 -- claimed

## # Exploratory Data Analysis (EDA)

## Plot between 'policy_tenure' & 'is_claim'

```
plt.figure(figsize=(9, 6))
ax = sns.boxplot(x = 'is_claim', y = 'policy_tenure', data = df)

#plt.legend(fontsize = 13)

# y-axis
plt.ylabel("policy_tenure ", fontdict = {'fontsize': 13})
plt.yticks(size=13)

#x-axis
plt.xlabel("is_claim", fontdict = {'fontsize': 13})
plt.xticks(size=13)

# title
plt.title("Box plot between 'policy_tenure' & 'is_claim' ", fontdict =
{'fontsize': 15})

#plotting the graph
plt.grid()
plt.show()
```



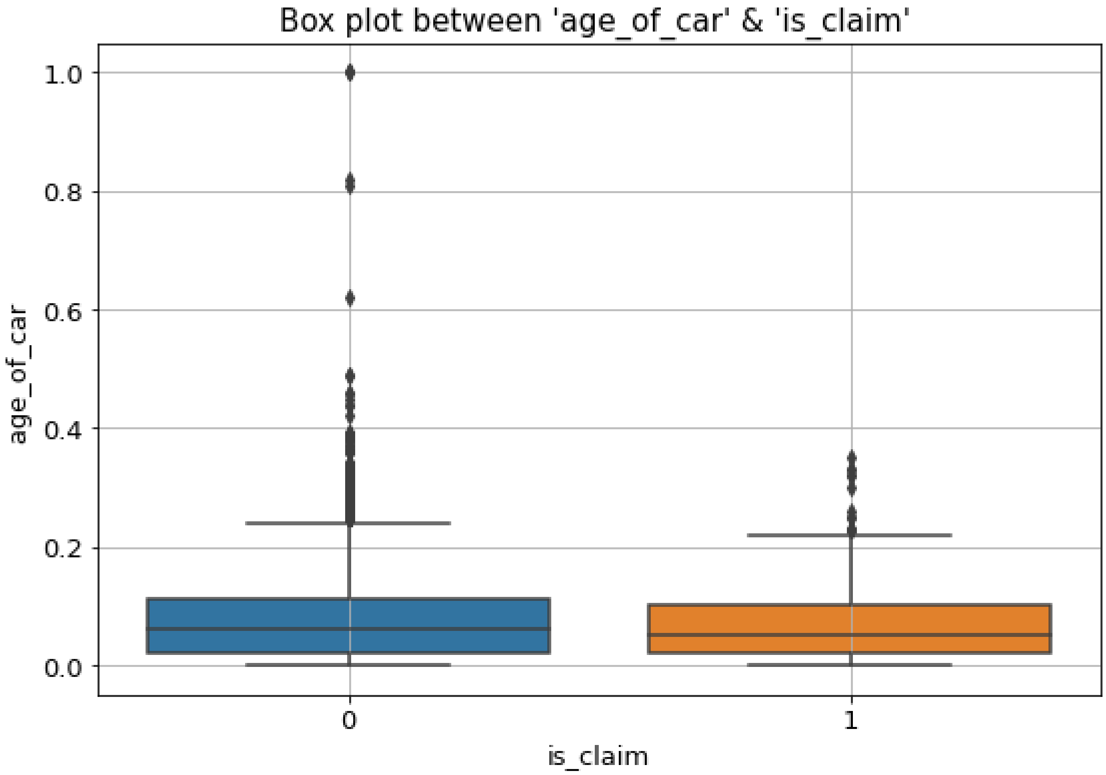
```
time: 172 ms (started: 2022-11-23 16:28:09 +00:00)
```

## Observations:

1. Customers who has claimed the insurance are having more policty tenure when compared to the ones who didnot claim.
2. Nearly 50% of the customers who has claimed the insurance are having policy tenure = 0.8 which is only 0.55 for customers who has not claimed.

## Box plot between 'age_of_car' & 'is_claim'

```
plt.figure(figsize=(9, 6))

# specifying x and y axis for our graph
ax = sns.boxplot(x = 'is_claim', y = 'age_of_car', data = df);

#plt.legend(fontsize = 13)

# y-axis
plt.ylabel("age_of_car ", fontdict = {'fontsize': 13})
plt.yticks(size=13)

# x-axis
plt.xlabel("is_claim", fontdict = {'fontsize': 13})
plt.xticks(size=13)

# title
plt.title("Box plot between 'age_of_car' & 'is_claim' ", fontdict =
{'fontsize': 15})

# plotting the graph
plt.grid()
plt.show()
```



```
time: 157 ms (started: 2022-11-23 16:28:09 +00:00)
```

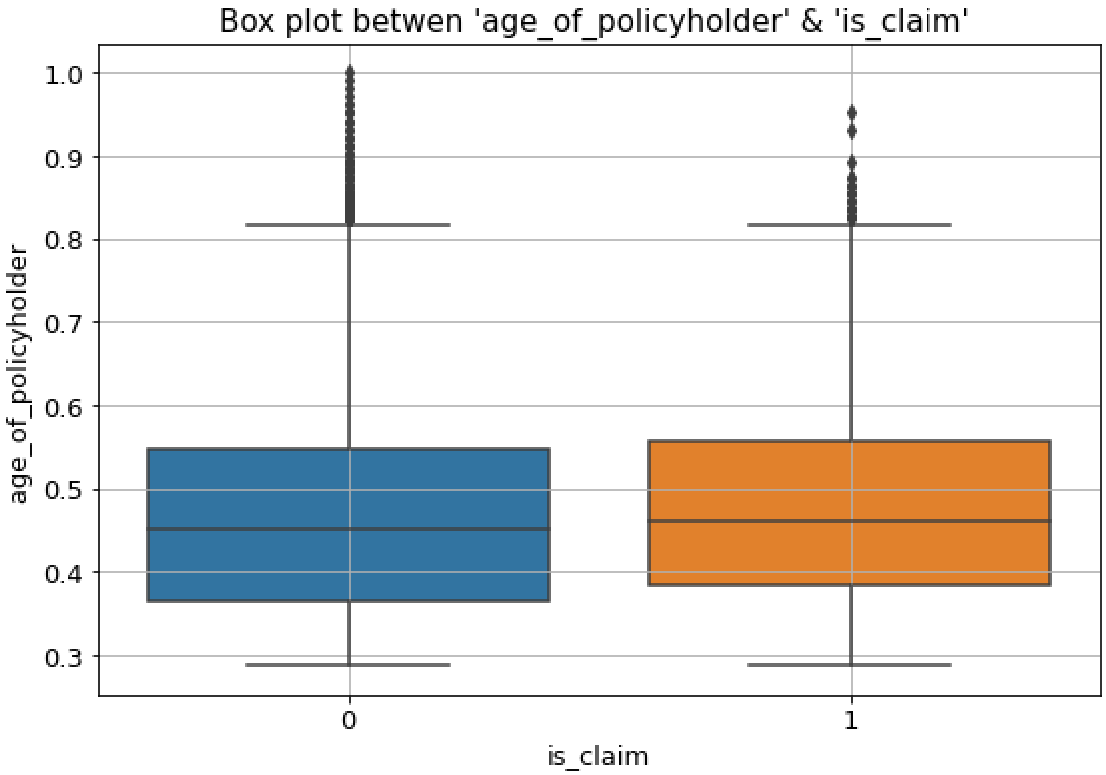
### Observations:

1. age of the cars is very much high for the customers who has not claimed.

### Box plot betwen 'age_of_policyholder' & 'is_claim'

```
plt.figure(figsize=(9, 6))

# specifying x and y axis for our graph
ax = sns.boxplot(x = 'is_claim', y = 'age_of_policyholder', data = df)

#plt.legend(fontsize = 13)

# y-axis
plt.ylabel("age_of_policyholder ", fontdict = {'fontsize': 13})
plt.yticks(size=13)

# x-axis
plt.xlabel("is_claim", fontdict = {'fontsize': 13})
plt.xticks(size=13)

# title
plt.title("Box plot betwen 'age_of_policyholder' & 'is_claim' ",
fontdict = {'fontsize': 15})
```

```
# plotting the graph
plt.grid()
plt.show()
```



```
time: 195 ms (started: 2022-11-23 16:28:09 +00:00)
```

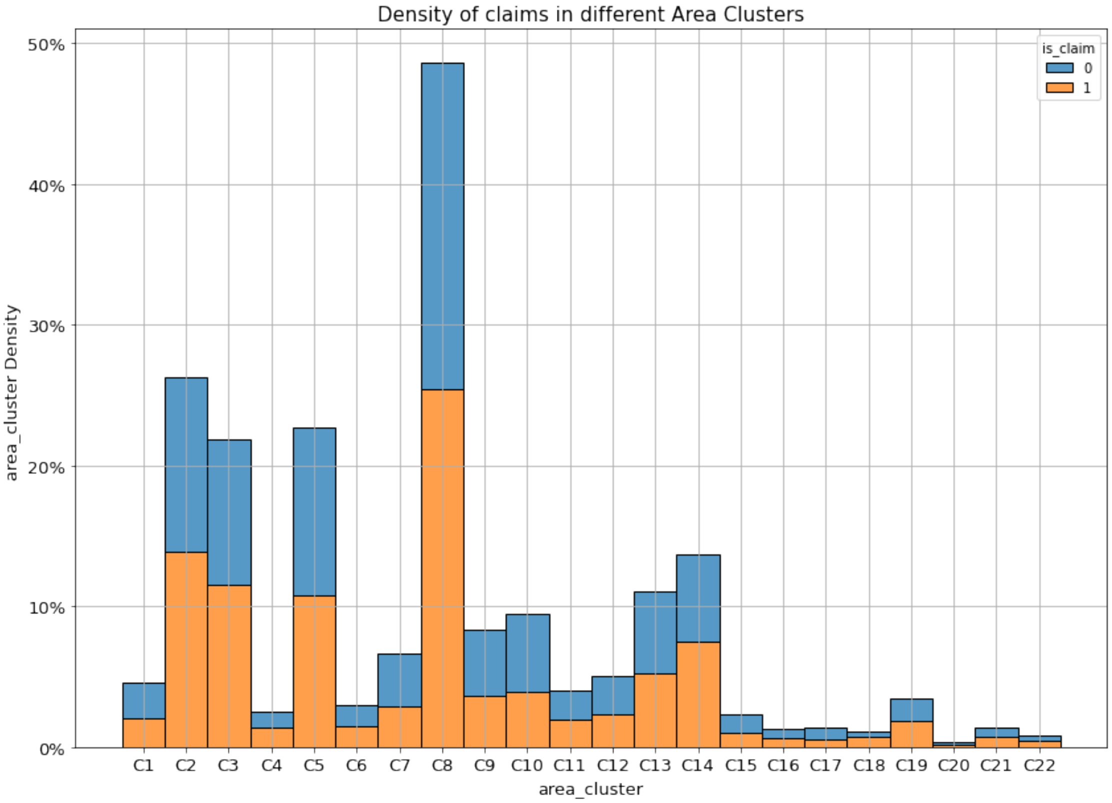
## Observations:

1. Age of policy holders who not claimed is little high when compared to the customers who has claimed.

## Density of claims in different Area Clusters

```
plt.figure(figsize=(14, 10))

# specifying x and y axis for our graph
ax = sns.histplot(x = 'area_cluster', hue = 'is_claim', data = df,
multiple = 'stack', stat = 'density', common_norm = False);

# y-axis
plt.ylabel("area_cluster Density ", fontdict = {'fontsize': 13})
plt.yticks(size=13)

# x-axis
plt.xlabel("area_cluster", fontdict = {'fontsize': 13})
plt.xticks(size=13)

# title
```

```
plt.title("Density of claims in different Area Clusters", fontdict =
{'fontsize': 15})
from matplotlib.ticker import PercentFormatter
plt.gca().yaxis.set_major_formatter(PercentFormatter(1))

# plotting the graph
plt.grid()
plt.show()
```



```
time: 429 ms (started: 2022-11-23 16:28:09 +00:00)
```

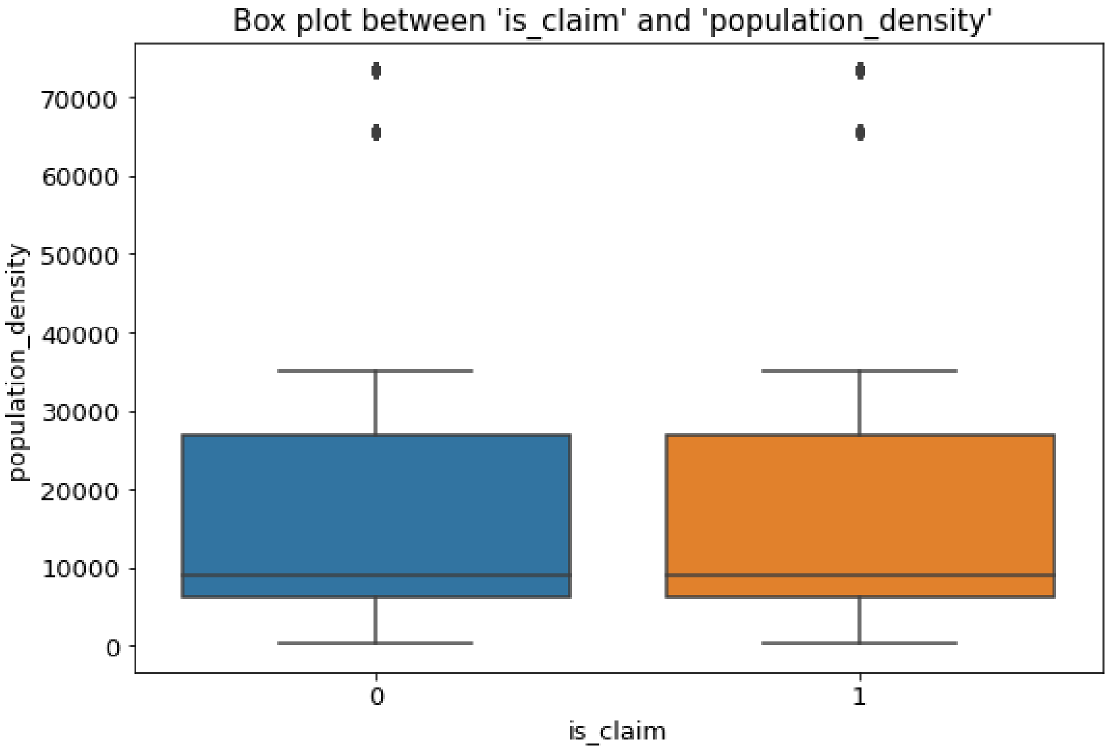
### Observation:

1. We can observer that most of the policy holders are the area_cluster C8 and least are from C20 area cluster.

### Box plot between 'is_claim' and 'population_density'

```
plt.figure(figsize=(9, 6))

# specifying x and y axis for our graph
ax = sns.boxplot(x = 'is_claim', y = 'population_density', data = df);


# y-axis
plt.ylabel("population_density ", fontdict = {'fontsize': 13})
plt.yticks(size=13)
```

```
# x-axis
plt.xlabel("is_claim", fontdict = {'fontsize': 13})
plt.xticks(size=13)

# title
plt.title("Box plot between 'is_claim' and 'population_density' ",
fontdict = {'fontsize': 15})

# plotting the graph
plt.show()
```



```
time: 165 ms (started: 2022-11-23 16:28:10 +00:00)
```

## Observation:

1. population density is almost same in both the categories.

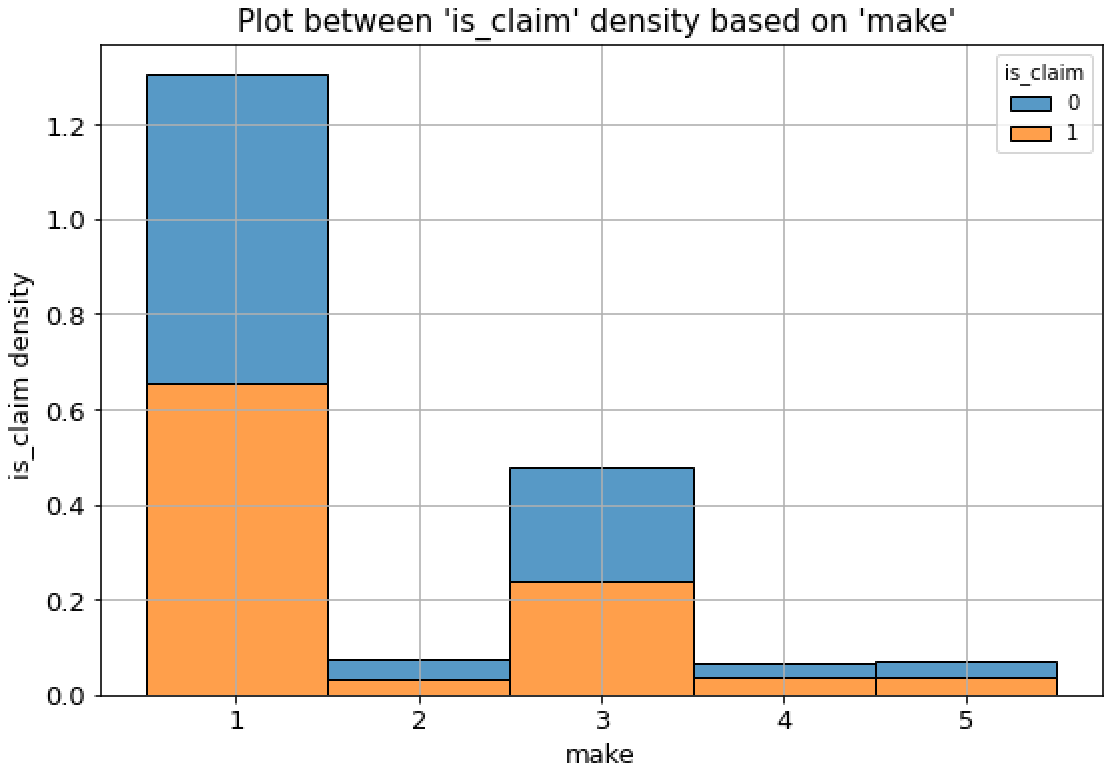
```
df.make.value_counts().sort_values(ascending = False)
```

```
1    38126
3    14018
2     2373
5     2114
4     1961
Name: make, dtype: int64
```

```
time: 9.51 ms (started: 2022-11-23 16:28:10 +00:00)
```

### Plot between 'is_claim' density based on 'make'

```
df['make'] = df['make'].astype('category')

plt.figure(figsize=(9, 6))

# specifying x and y axis for our graph
ax = sns.histplot(x = 'make', hue = 'is_claim', data = df, multiple =
'stack', stat = 'density', common_norm=False);

# y-axis
plt.ylabel("is_claim density ", fontdict = {'fontsize': 13})
plt.yticks(size=13)

# x-axis
plt.xlabel("make", fontdict = {'fontsize': 13})
plt.xticks(size=13)

# title
plt.title("Plot between 'is_claim' density based on 'make' ", fontdict
= {'fontsize': 15})

# plotting the graph
plt.grid()
plt.show()
```



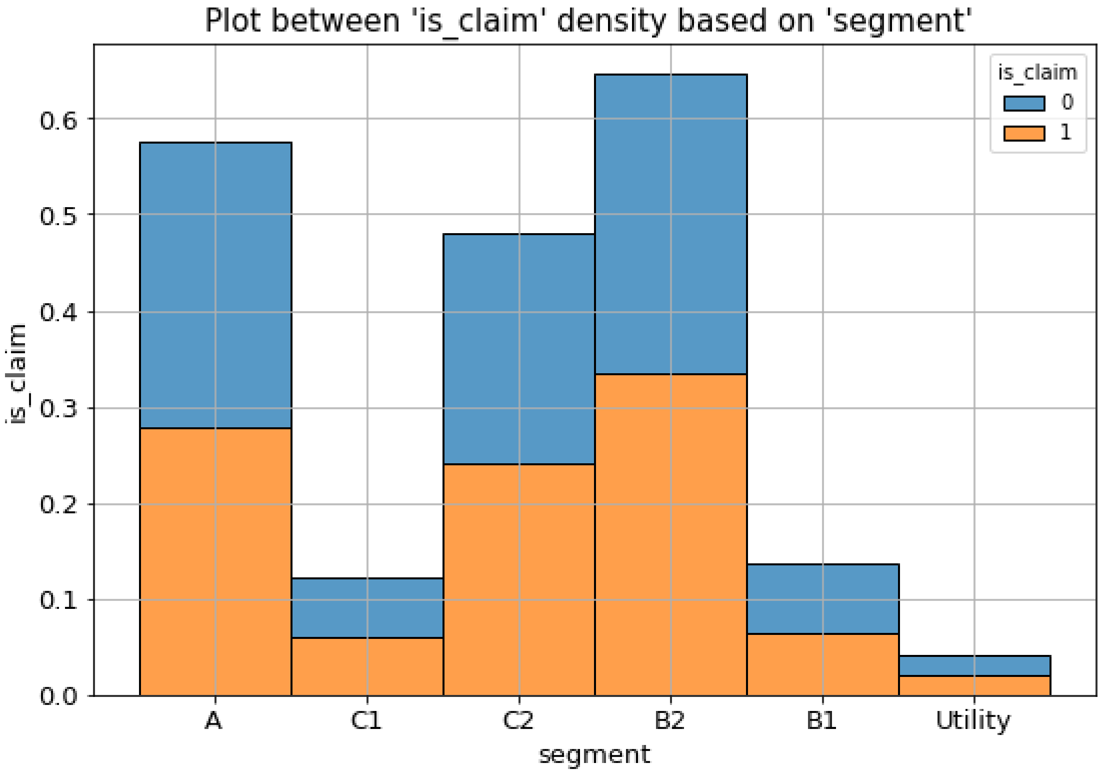
```
time: 422 ms (started: 2022-11-23 16:28:10 +00:00)
```

## Observation:

1. We can observe that most of the policy holders are from make = 1 cateogory and claimed, not claimed ration is alomost same in the same type.

## Plot between 'is_claim' density based on 'segment'

```
plt.figure(figsize=(9, 6))

# specifying x and y axis for our graph
ax = sns.histplot(x = 'segment', hue = 'is_claim', data = df, multiple
= 'stack', stat = 'density', common_norm=False) ;

# y-axis
plt.ylabel("is_claim", fontdict = {'fontsize': 13})
plt.yticks(size=13)

# x-axis
plt.xlabel("segment", fontdict = {'fontsize': 13})
plt.xticks(size=13)

# title
plt.title("Plot between 'is_claim' density based on 'segment' ",
fontdict = {'fontsize': 15})

# plotting the graph
plt.grid()
plt.show()
```



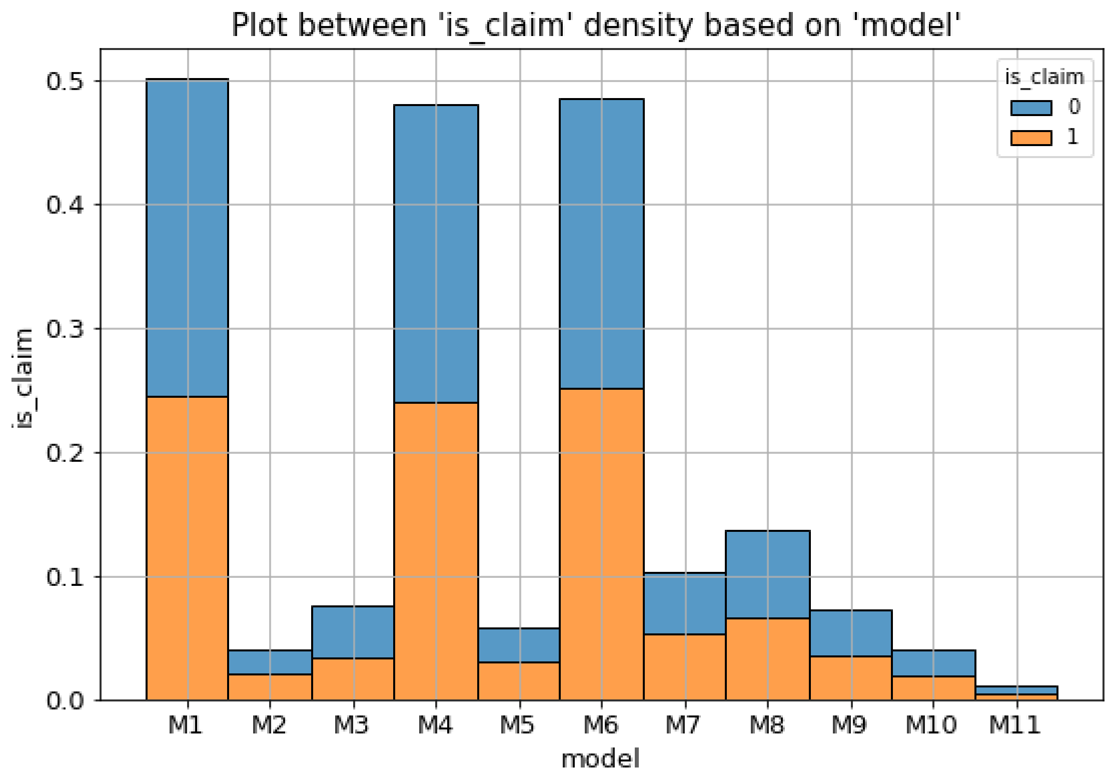
```
time: 273 ms (started: 2022-11-23 16:28:10 +00:00)
```

### Plot between 'is_claim' density based on 'model' of the Car

```
a = df.groupby(['is_claim']).model.value_counts(normalize = False)
print(a)
```

```
is_claim  model
0         M1       14030
          M4       13117
          M6       12837
          M8        3929
          M7        2739
          M3        2245
          M9        1981
          M5        1482
          M10       1136
          M2        1000
          M11        348
1         M6         939
          M1         918
          M4         901
          M8         244
          M7         201
          M9         133
          M3         128
          M5         116
          M2          80
          M10         73
          M11         15
Name: model, dtype: int64
time: 19.2 ms (started: 2022-11-23 16:28:10 +00:00)
```

```
plt.figure(figsize=(9, 6))

# specifying x and y axis for our graph
ax = sns.histplot(x = 'model', hue = 'is_claim', data = df, multiple =
'stack', stat = 'density', common_norm=False);

# y-axis
plt.ylabel("is_claim", fontdict = {'fontsize': 13})
plt.yticks(size=13)

# x-axis
plt.xlabel("model", fontdict = {'fontsize': 13})
plt.xticks(size=13)

# title
plt.title("Plot between 'is_claim' density based on 'model' ",
fontdict = {'fontsize': 15})

# plotting the graph
plt.grid()
plt.show()
```



```
time: 315 ms (started: 2022-11-23 16:28:10 +00:00)
```

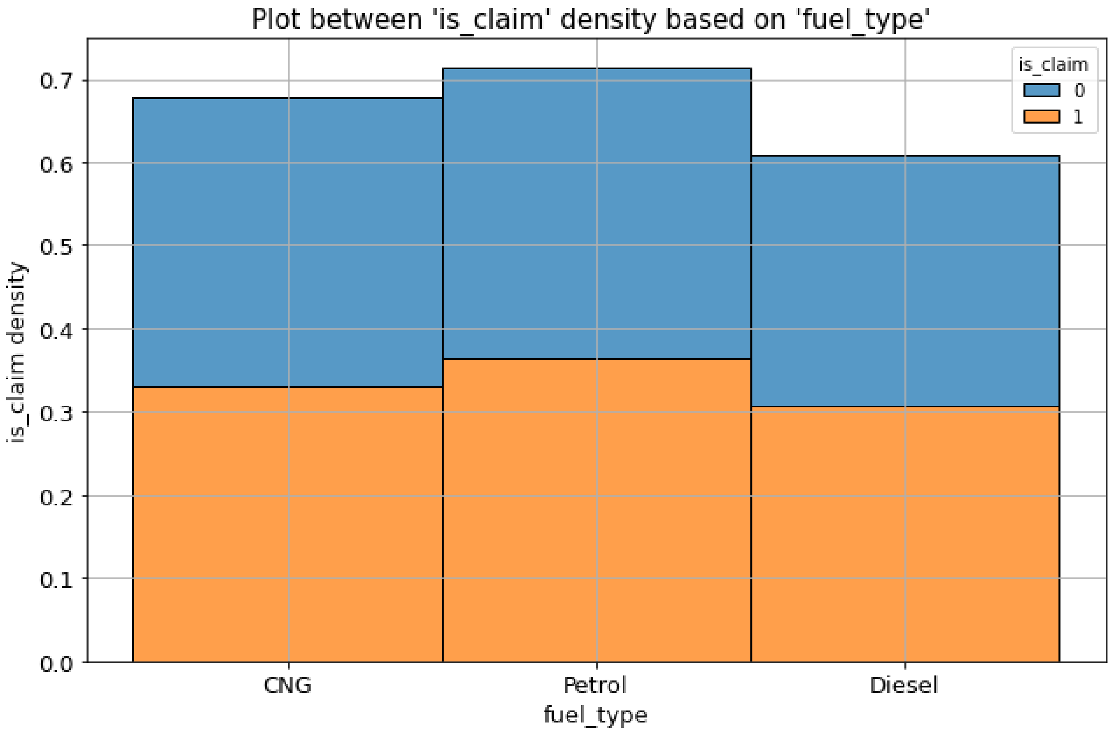
### Observations:

1. We can observe that most of the claims are done by the model M6 which is around 939 and least number of claims i.e, 15 are made by M11 model.

### Plot between 'is_claim' density based on 'fuel_type'

```
plt.figure(figsize=(9, 6))

# specifying x and y axis for our graph
ax = sns.histplot(x = 'fuel_type', hue = 'is_claim', data = df,
multiple = 'stack', stat = 'density', common_norm=False);

# y-axis
plt.ylabel("is_claim density", fontdict = {'fontsize': 13})
plt.yticks(size=13)

# x-axis
plt.xlabel("fuel_type", fontdict = {'fontsize': 13})
plt.xticks(size=13)

# title
plt.title("Plot between 'is_claim' density based on 'fuel_type' ",
fontdict = {'fontsize': 15})
```

```
# plotting the graph
plt.grid()
plt.tight_layout()
plt.show()
```



```
time: 317 ms (started: 2022-11-23 16:28:11 +00:00)
```

### Observation:

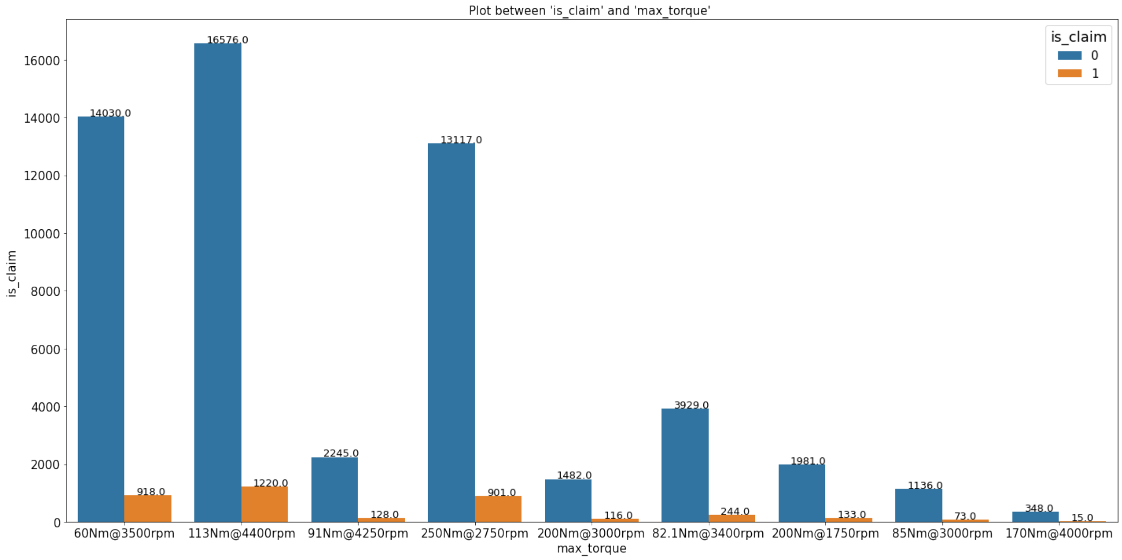
1. Most of the Claims are made by the cars which are having fuel_type as Petrol and next to this almost equal number of claims are made by the cars which are having fuel type of Diesel and CNG.

```
a = df.groupby(['is_claim']).max_torque.value_counts(normalize = True)
print(a)
```

```
is_claim  max_torque
0         113Nm@4400rpm     0.302239
          60Nm@3500rpm      0.255816
          250Nm@2750rpm     0.239169
          82.1Nm@3400rpm    0.071640
          91Nm@4250rpm      0.040934
          200Nm@1750rpm     0.036121
          200Nm@3000rpm     0.027022
          85Nm@3000rpm      0.020713
          170Nm@4000rpm     0.006345
1         113Nm@4400rpm     0.325507
          60Nm@3500rpm      0.244931
          250Nm@2750rpm     0.240395
          82.1Nm@3400rpm    0.065101
          200Nm@1750rpm     0.035486
          91Nm@4250rpm      0.034152
          200Nm@3000rpm     0.030950
          85Nm@3000rpm      0.019477
          170Nm@4000rpm     0.004002
Name: max_torque, dtype: float64
time: 19.7 ms (started: 2022-11-23 16:28:11 +00:00)
```

### Plot between 'is_claim' density based on 'max_torque'

```
plt.figure(figsize=(20, 10))
ax = sns.countplot(data = df, x='max_torque', hue='is_claim')

# adding legend with title
plt.legend(title = 'is_claim', title_fontsize = 18, fontsize = 15)

# x-axis
plt.xlabel("max_torque", fontdict = {'fontsize': 15})
plt.xticks(size = 15)

# y-axis
plt.ylabel("is_claim ", fontdict = {'fontsize': 15})
plt.yticks(size = 15)

# adding title
plt.title("Plot between 'is_claim' and 'max_torque' ", fontdict =
{'fontsize': 15})

# annotating the bars
for p in ax.patches:
        ax.annotate('{:.1f}'.format(p.get_height()), (p.get_x()+0.1,
p.get_height()+25), ha='left', va='baseline', fontsize = 13)

# plotting the graph
#plt.grid()
plt.tight_layout()
plt.show()
```



```
time: 508 ms (started: 2022-11-23 16:28:11 +00:00)
```

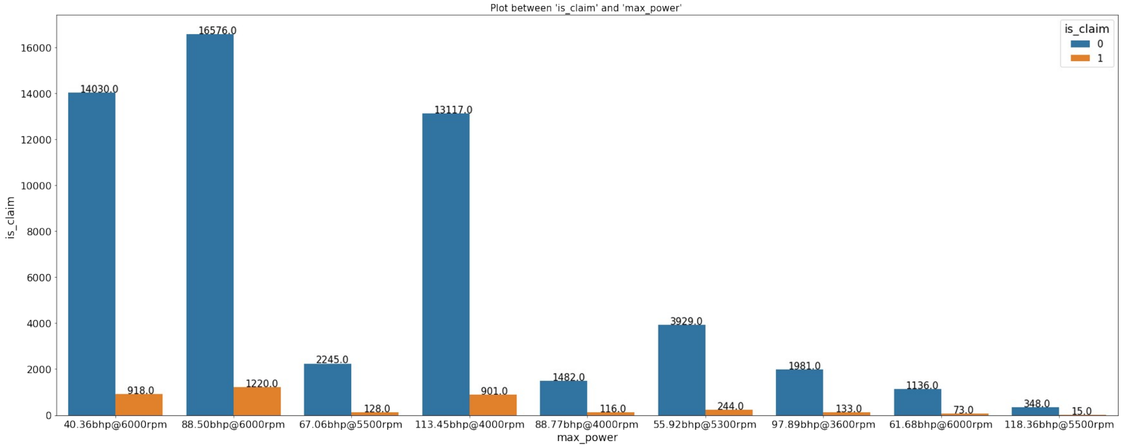
## Observation:

1. 1220 claims are made by the cars which are having max_torque as 113Nm@440rpm and least of them which is 15 claims were made by cars having max_torque as 170Nm@4000 rpm.

## Plot between 'is_claim' and 'max_power'

```
plt.figure(figsize=(25, 10))
ax = sns.countplot(data = df, x='max_power', hue='is_claim')

# adding legend with title
plt.legend(title = 'is_claim', title_fontsize = 18, fontsize = 15)

# x-axis
plt.xlabel("max_power", fontdict = {'fontsize': 17})
plt.xticks(size = 16)

# y-axis
plt.ylabel("is_claim ", fontdict = {'fontsize': 17})
plt.yticks(size = 16)

# adding title
plt.title("Plot between 'is_claim' and 'max_power' ", fontdict =
{'fontsize': 15})

# annotating the bars
for p in ax.patches:
        ax.annotate('{:.1f}'.format(p.get_height()), (p.get_x()+0.1,
p.get_height()+25), ha='left', va='baseline', fontsize = 15)

# plotting the graph
```

```
#plt.grid()
plt.tight_layout()
plt.show()
```



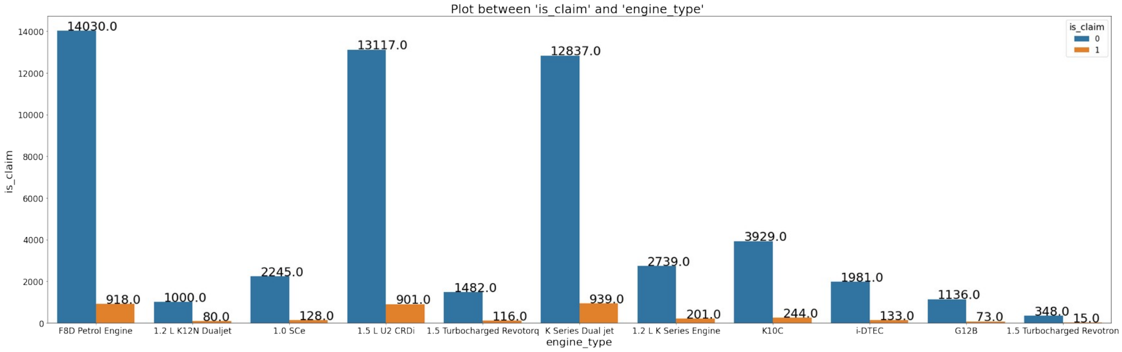
## Observation:

1. We can observe that the cars which are having max_power of 88.50bhp@6000rpm has made as highest of 1220 claims and least numbers of claims are made by the cars that have max_power of 118.36bhp@5500rpm which is 15 claims.

## Plot between 'is_claim' and 'engine_type'

```
plt.figure(figsize=(32, 10))
ax = sns.countplot(data = df, x='engine_type', hue='is_claim')

# adding legend with title
plt.legend(title = 'is_claim', title_fontsize = 18, fontsize = 15)

# x-axis
plt.xlabel("engine_type", fontdict = {'fontsize': 22})
plt.xticks(size = 17)

# y-axis
plt.ylabel("is_claim ", fontdict = {'fontsize': 22})
plt.yticks(size = 17)

# adding title
plt.title("Plot between 'is_claim' and 'engine_type' ", fontdict =
{'fontsize': 25})

# annotating the bars
for p in ax.patches:
        ax.annotate('{:.1f}'.format(p.get_height()), (p.get_x()+0.1,
p.get_height()+25), ha='left', va='baseline', fontsize = 25)

# plotting the graph
# plt.grid()
```

```
plt.tight_layout()
plt.show()
```



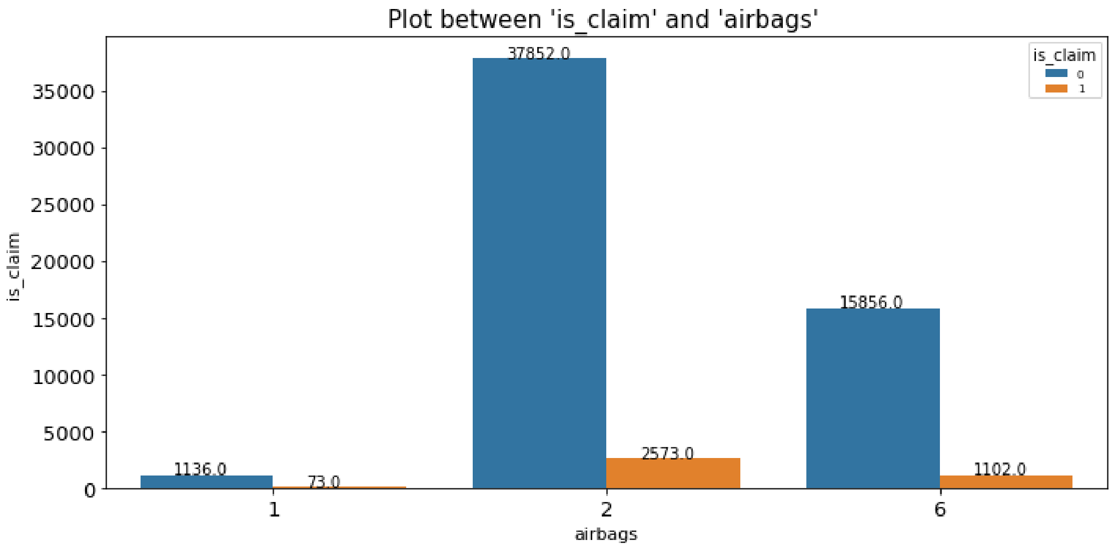
```
time: 1.21 s (started: 2022-11-23 16:29:32 +00:00)
```

## Observation:

1. Most number of claims are made by the cars that have engine type as F&D Petrol engine and least number by the ones which have engine type as 1.5 Turbocharged Revotron

## Plot between 'is_claim' and 'airbags'

```
plt.figure(figsize=(10, 5))
ax = sns.countplot(data = df, x='airbags', hue='is_claim')

# adding legend with title
plt.legend(title = 'is_claim', title_fontsize = 10, fontsize = 7)

# x-axis
plt.xlabel("airbags", fontdict = {'fontsize': 11})
plt.xticks(size = 13)

# y-axis
plt.ylabel("is_claim ", fontdict = {'fontsize': 11})
plt.yticks(size = 13)

# adding title
plt.title("Plot between 'is_claim' and 'airbags' ", fontdict = 
{'fontsize': 15})

# annotating the bars
for p in ax.patches:
        ax.annotate('{:.1f}'.format(p.get_height()), (p.get_x()+0.1, 
p.get_height()+25), ha='left', va='baseline', fontsize = 10)

# plotting the graph
#plt.grid()
plt.tight_layout()
plt.show()
```



```
time: 264 ms (started: 2022-11-23 16:28:13 +00:00)
```

### Observations:

1. Cars that have only 2 air bags have claimed more times when compared to the ones have 1 and 6 air bags .

```
cols = ['is_esc', 'is_adjustable_steering', 'is_tpms',
'is_parking_sensors', 'is_parking_camera',
        'is_front_fog_lights', 'is_rear_window_wiper',
'is_rear_window_washer',
        'is_rear_window_defogger', 'is_brake_assist',
'is_power_door_locks', 'is_central_locking', 'is_power_steering',
        'is_driver_seat_height_adjustable',
'is_day_night_rear_view_mirror', 'is_ecw', 'is_speed_alert']

for col in cols:
    df[col] = np.where(df[col] == 'Yes', 1, 0)

for col in cols:
    oot[col] = np.where(oot[col] == 'Yes', 1, 0)
```

```
time: 357 ms (started: 2022-11-23 16:45:20 +00:00)
```

## # Modelling - LGBM

### Train and Validation Split

```
X = df.drop(columns = ['policy_id', 'is_claim'])
y = df['is_claim']
```

```
time: 22.9 ms (started: 2022-11-23 16:45:26 +00:00)
```

```
# using 10% of the given data in testing
x_train, x_test, y_train, y_test = train_test_split(X, y, test_size =
0.1, stratify = y, random_state = 1)
```

```
time: 44.6 ms (started: 2022-11-23 16:45:28 +00:00)
```

```
print("Number of points available in Training data for each claim type
are:")
y_train.value_counts()
```

```
Number of points available in Training data for each claim type are:

0    49359
1     3373
Name: is_claim, dtype: int64

time: 8.87 ms (started: 2022-11-23 16:45:31 +00:00)
```

```
val = (y_train.value_counts(normalize = True)) * 100
print("Percentage of points available in Training data for each claim
type are:")
print(val)
# we can observe that nearly 93% percent of the values are having
is_claim status as '0' and other 6% have as status '1'
```

```
Percentage of points available in Training data for each claim type
are:
0    93.603505
1     6.396495
Name: is_claim, dtype: float64
time: 3.89 ms (started: 2022-11-23 16:45:33 +00:00)
```

```
print("Number of points available in Test data for each claim type
are:")
y_test.value_counts()
```

```
Number of points available in Test data for each claim type are:

0    5485
1     375
Name: is_claim, dtype: int64

time: 8.43 ms (started: 2022-11-23 16:45:37 +00:00)
```

```
val = (y_test.value_counts(normalize = True)) * 100
print("Percentage of points available in Test data for each claim type
are:")
print(val)
```

```
Percentage of points available in Test data for each claim type are:
0    93.600683
1     6.399317
Name: is_claim, dtype: float64
time: 5.68 ms (started: 2022-11-23 16:45:39 +00:00)
```

## References for WOEEncoder( Weight of Evidence):

1. https://www.listendata.com/2015/03/weight-of-evidence-woe-and-information.html
2. https://towardsdatascience.com/an-easier-way-to-encode-categorical-features-d840ff6b3900
3. https://www.analyticsvidhya.com/blog/2021/06/understand-weight-of-evidence-and-information-value/

```
# implementing Weight of Evidence Encoding
woe = WOEEncoder()
```

```
time: 723 µs (started: 2022-11-23 16:45:44 +00:00)
```

```
# listing down all the categorical features in our Data
feature_list = ['area_cluster', 'make', 'segment', 'model',
'fuel_type', 'max_torque', 'max_power', 'engine_type',
                 'rear_brakes_type', 'transmission_type',
'steering_type']
```

```
time: 976 µs (started: 2022-11-23 16:45:46 +00:00)
```

```
# applying WOEEncoder on Train and Test data sets
train_woe = woe.fit_transform(x_train[feature_list], y_train)
test_woe = woe.transform(x_test[feature_list])
oot_woe = woe.transform(oot[feature_list])
```

```
time: 1.01 s (started: 2022-11-23 16:45:48 +00:00)
```

```
train_woe.shape
```

```
(52732, 11)
```

```
time: 3.89 ms (started: 2022-11-23 16:45:54 +00:00)
```

```
train_woe.head()
```

```
       area_cluster  make   segment     model   fuel_type  
max_torque  \
42769      0.104014     1  0.090258  0.076777   0.043882    0.083521

35051      0.104014     1 -0.060953 -0.037514  -0.053764   -0.037514

12127      0.116440     1 -0.060953 -0.037514  -0.053764   -0.037514

17456      0.127955     1  0.090258  0.076777   0.043882    0.083521

17734     -0.087772     3 -0.007887 -0.007887   0.009051   -0.007887


       max_power  engine_type  rear_brakes_type  transmission_type  \
42769   0.083521     0.076777          0.002479           0.003574
```

```
35051  -0.037514    -0.037514          0.002479           0.003574
12127  -0.037514    -0.037514          0.002479           0.003574
17456   0.083521     0.076777          0.002479           0.003574
17734  -0.007887    -0.007887         -0.007887          -0.006683

       steering_type
42769       0.054712
35051      -0.040718
12127      -0.040718
17456       0.054712
17734      -0.040718

time: 18.2 ms (started: 2022-11-23 16:45:55 +00:00)
```

```
x_train.drop(columns = feature_list, inplace = True)
x_test.drop(columns = feature_list, inplace = True)
oot.drop(columns = feature_list, inplace = True)
```

```
time: 19.5 ms (started: 2022-11-23 16:46:01 +00:00)
```

```
x_train_final = pd.concat([x_train, train_woe], axis = 1)
x_test_final = pd.concat([x_test, test_woe], axis = 1)
oot_final = pd.concat([oot, oot_woe], axis = 1)
```

```
time: 21.2 ms (started: 2022-11-23 16:46:07 +00:00)
```

```
x_train_final.head()
```

```
       policy_tenure  age_of_car  age_of_policyholder
population_density  \
42769       0.868744        0.08             0.346154
8794
35051       0.383458        0.00             0.509615
8794
12127       0.869126        0.00             0.423077
4076
17456       0.766596        0.01             0.307692
27742
17734       0.031597        0.06             0.298077
5410

       airbags  is_esc  is_adjustable_steering  is_tpms
is_parking_sensors  \
42769        2       0                       1        0
1
35051        2       0                       0        0
1
12127        2       0                       0        0
1
17456        2       0                       1        0
1
```

```
17734       6       1                       1        1
1

       is_parking_camera  displacement  cylinder  gear_box
turning_radius  \
42769                  0          1197         4         5
4.8
35051                  0           796         3         5
4.6
12127                  0           796         3         5
4.6
17456                  0          1197         4         5
4.8
17734                  1          1493         4         6
5.2

       length  width  height  gross_weight  is_front_fog_lights  \
42769    3845   1735    1530          1335                    1
35051    3445   1515    1475          1185                    0
12127    3445   1515    1475          1185                    0
17456    3845   1735    1530          1335                    1
17734    4300   1790    1635          1720                    1

       is_rear_window_wiper  is_rear_window_washer
is_rear_window_defogger  \
42769                    0                      0
0
35051                    0                      0
0
12127                    0                      0
0
17456                    0                      0
0
17734                    1                      1
1

       is_brake_assist  is_power_door_locks  is_central_locking  \
42769                1                    1                   1
35051                0                    0                   0
12127                0                    0                   0
17456                1                    1                   1
17734                1                    1                   1

       is_power_steering  is_driver_seat_height_adjustable  \
42769                  1                                 1
35051                  1                                 0
12127                  1                                 0
17456                  1                                 1
17734                  1                                 1
```

```
       is_day_night_rear_view_mirror  is_ecw  is_speed_alert  
ncap_rating  \
42769                              1       1               1   
2  
35051                              0       0               1   
0  
12127                              0       0               1   
0  
17456                              1       1               1   
2  
17734                              0       1               1   
3  

       area_cluster  make   segment     model  fuel_type  
max_torque  \
42769      0.104014     1  0.090258  0.076777   0.043882    0.083521   

35051      0.104014     1 -0.060953 -0.037514  -0.053764   -0.037514   

12127      0.116440     1 -0.060953 -0.037514  -0.053764   -0.037514   

17456      0.127955     1  0.090258  0.076777   0.043882    0.083521   

17734     -0.087772     3 -0.007887 -0.007887   0.009051   -0.007887   


       max_power  engine_type  rear_brakes_type  transmission_type  \
42769   0.083521     0.076777          0.002479           0.003574   
35051  -0.037514    -0.037514          0.002479           0.003574   
12127  -0.037514    -0.037514          0.002479           0.003574   
17456   0.083521     0.076777          0.002479           0.003574   
17734  -0.007887    -0.007887         -0.007887          -0.006683   

       steering_type  
42769       0.054712  
35051      -0.040718  
12127      -0.040718  
17456       0.054712  
17734      -0.040718  
```

```
time: 31 ms (started: 2022-11-23 16:46:07 +00:00)
```

```
x_test_final.head()
```

```
       policy_tenure  age_of_car  age_of_policyholder  
population_density  \
24307       0.867852        0.02             0.653846   
4076   
57327       1.090563        0.17             0.451923   
8794   
```

```
24703       1.088634        0.18             0.423077
8794
40585       0.913375        0.01             0.605769
4076
17527       0.745566        0.04             0.576923
6108

       airbags  is_esc  is_adjustable_steering  is_tpms
is_parking_sensors  \
24307        2       0                       0        0
1
57327        2       0                       1        0
1
24703        2       0                       1        0
1
40585        6       1                       1        1
1
17527        2       0                       0        0
1

       is_parking_camera  displacement  cylinder  gear_box
turning_radius  \
24307                  0           796         3         5
4.6
57327                  1          1498         4         5
4.9
24703                  0          1197         4         5
4.8
40585                  1          1493         4         6
5.2
17527                  0           796         3         5
4.6

       length  width  height  gross_weight  is_front_fog_lights  \
24307    3445   1515    1475          1185                    0
57327    3995   1695    1501          1051                    1
24703    3845   1735    1530          1335                    1
40585    4300   1790    1635          1720                    1
17527    3445   1515    1475          1185                    0

       is_rear_window_wiper  is_rear_window_washer
is_rear_window_defogger  \
24307                     0                      0
0
57327                     0                      0
1
24703                     0                      0
0
40585                     1                      1
1
```

```
17527                     0                       0
0

       is_brake_assist  is_power_door_locks  is_central_locking  \
24307                0                    0                   0
57327                0                    1                   1
24703                1                    1                   1
40585                1                    1                   1
17527                0                    0                   0

       is_power_steering  is_driver_seat_height_adjustable  \
24307                  1                                 0
57327                  1                                 1
24703                  1                                 1
40585                  1                                 1
17527                  1                                 0

       is_day_night_rear_view_mirror  is_ecw  is_speed_alert
ncap_rating  \
24307                              0       0               1
0
57327                              1       1               1
4
24703                              1       1               1
2
40585                              0       1               1
3
17527                              0       0               1
0

       area_cluster  make   segment     model  fuel_type
max_torque  \
24307      0.116440     1 -0.060953 -0.037514  -0.053764   -0.037514

57327      0.104014     5 -0.010470 -0.029199   0.009051   -0.029199

24703      0.104014     1  0.090258  0.076777   0.043882    0.083521

40585      0.116440     3 -0.007887 -0.007887   0.009051   -0.007887

17527     -0.105572     1 -0.060953 -0.037514  -0.053764   -0.037514


       max_power  engine_type  rear_brakes_type  transmission_type  \
24307  -0.037514    -0.037514          0.002479           0.003574
57327  -0.029199    -0.029199          0.002479           0.003574
24703   0.083521     0.076777          0.002479           0.003574
40585  -0.007887    -0.007887         -0.007887          -0.006683
17527  -0.037514    -0.037514          0.002479           0.003574
```

```
       steering_type
24307      -0.040718
57327       0.054712
24703       0.054712
40585      -0.040718
17527      -0.040718
```

```
time: 32.1 ms (started: 2022-11-23 16:46:18 +00:00)
```

```
oot_final.head()
```

```
  policy_id  policy_tenure  age_of_car  age_of_policyholder  \
0   ID58593       0.341732        0.00             0.586538   
1   ID58594       0.307241        0.13             0.442308   
2   ID58595       0.327924        0.12             0.451923   
3   ID58596       0.782654        0.01             0.461538   
4   ID58597       1.233404        0.02             0.634615   

   population_density  airbags  is_esc  is_adjustable_steering 
is_tpms  \
0                4076        2       0                       0 
0   
1                8794        2       0                       1 
0   
2                8794        2       0                       0 
0   
3               34738        2       0                       0 
0   
4               34738        2       0                       0 
0   

   is_parking_sensors  is_parking_camera  displacement  cylinder 
gear_box  \
0                   1                  0           796         3 
5   
1                   1                  0          1197         4 
5   
2                   0                  1           999         3 
5   
3                   1                  0           796         3 
5   
4                   1                  0           796         3 
5   

   turning_radius  length  width  height  gross_weight 
is_front_fog_lights  \
0             4.6    3445   1515    1475          1185 
0   
1             4.8    3845   1735    1530          1335 
```

```
1
2             5.0    3731   1579    1490          1155
0
3             4.6    3445   1515    1475          1185
0
4             4.6    3445   1515    1475          1185
0

   is_rear_window_wiper  is_rear_window_washer
is_rear_window_defogger  \
0                     0                      0
0
1                     0                      0
0
2                     0                      0
0
3                     0                      0
0
4                     0                      0
0

   is_brake_assist  is_power_door_locks  is_central_locking  \
0                0                    0                   0
1                1                    1                   1
2                0                    1                   1
3                0                    0                   0
4                0                    0                   0

   is_power_steering  is_driver_seat_height_adjustable  \
0                  1                                 0
1                  1                                 1
2                  1                                 0
3                  1                                 0
4                  1                                 0

   is_day_night_rear_view_mirror  is_ecw  is_speed_alert  ncap_rating
\
0                              0       0               1            0

1                              1       1               1            2

2                              1       1               1            2

3                              0       0               1            0

4                              0       0               1            0


   area_cluster  make   segment     model  fuel_type  max_torque
```

```
max_power  \
0      0.116440     1 -0.060953 -0.037514  -0.053764   -0.037514  -
0.037514
1      0.104014     1  0.090258  0.076777   0.043882    0.083521   
0.083521
2      0.104014     2 -0.060953 -0.212061   0.043882   -0.212061  -
0.212061
3     -0.095075     1 -0.060953 -0.037514  -0.053764   -0.037514  -
0.037514
4     -0.095075     1 -0.060953 -0.037514  -0.053764   -0.037514  -
0.037514

   engine_type  rear_brakes_type  transmission_type  steering_type
0    -0.037514          0.002479           0.003574      -0.040718
1     0.076777          0.002479           0.003574       0.054712
2    -0.212061          0.002479          -0.006683       0.054712
3    -0.037514          0.002479           0.003574      -0.040718
4    -0.037514          0.002479           0.003574      -0.040718
```

```
time: 29 ms (started: 2022-11-23 16:46:23 +00:00)
```

### Hyperparameter tuning

```
# parameters that will be used for Random Seacrh CV
params  = {'num_leaves': [8, 12, 16, 20, 25],
           'subsample': [0.5, 0.7, 0.9],
           'colsample_bytree': [0.4, 0.5, 0.6, 0.7, 0.8],
           'reg_alpha': [0, 1e-1, 1, 5, 7, 10, 50],
           'reg_lambda': [0, 1e-1, 1, 5, 10, 50],
           'learning_rate': [0.015, 0.02, 0.03, 0.05, 0.07, 0.1, 0.2,
0.3],
           'n_estimators': [100, 120, 140, 150]}
```

```
time: 1.95 ms (started: 2022-11-23 16:46:28 +00:00)
```

```
lgbm = LGBMClassifier(objective = 'binary', is_unbalance = True,
random_state = 1)
```

```
time: 1.04 ms (started: 2022-11-23 16:46:32 +00:00)
```

```
# performing Random Search on the above mentioned hyperparameters with
'f1' score as a metric
model_lgbm = RandomizedSearchCV(estimator = lgbm,
                                param_distributions = params,
                                n_iter = 30,
                                scoring ='f1',
                                cv = 3,
                                random_state = 1,
                                verbose = 1)

model_lgbm.fit(x_train_final, y_train)
```

```
Fitting 3 folds for each of 30 candidates, totalling 90 fits
```

```
RandomizedSearchCV(cv=3,
                   estimator=LGBMClassifier(is_unbalance=True,
                                            objective='binary',
                                            random_state=1),
                   n_iter=30,
                   param_distributions={'colsample_bytree': [0.4, 0.5,
0.6, 0.7,
                                                             0.8],
                                        'learning_rate': [0.015, 0.02,
0.03,

                                                          0.05, 0.07,
0.1, 0.2,

                                                          0.3],
                                        'n_estimators': [100, 120,
140, 150],
                                        'num_leaves': [8, 12, 16, 20,
25],
                                        'reg_alpha': [0, 0.1, 1, 5, 7,
10, 50],
                                        'reg_lambda': [0, 0.1, 1, 5,
10, 50],
                                        'subsample': [0.5, 0.7, 0.9]},
                   random_state=1, scoring='f1', verbose=1)
```

```
time: 1min 14s (started: 2022-11-23 16:46:32 +00:00)
```

```
# best score using our LGBM Model
model_lgbm.best_score_
```

```
0.1696347022813929
```

```
time: 4.18 ms (started: 2022-11-23 16:48:12 +00:00)
```

```
# best Parameteres for our LGBM Model
model_lgbm.best_params_
```

```
{'subsample': 0.9,
 'reg_lambda': 0,
 'reg_alpha': 0.1,
 'num_leaves': 8,
 'n_estimators': 140,
 'learning_rate': 0.015,
 'colsample_bytree': 0.5}
```

```
time: 3.81 ms (started: 2022-11-23 16:48:15 +00:00)
```

```
# defining LGBM Model based on Best parameters
lgbm_best = LGBMClassifier(objective = 'binary',
                           colsample_bytree = 0.5,
                           subsample = 0.9,
                           is_unbalance = True,
                           learning_rate = 0.015,
                           num_leaves = 8,
                           max_depth = 5,
                           reg_lambda = 0,
                           reg_alpha = 0.1,
                           n_estimators = 140,
                           random_state = 1)
```

```
time: 1.51 ms (started: 2022-11-23 16:48:38 +00:00)
```

```
# fitting on Train data
y_pred_train_lgbm = lgbm_best.fit(x_train_final, y_train)
```

```
time: 1.16 s (started: 2022-11-23 16:48:41 +00:00)
```

```
# predicting on the Test data
y_pred_test_lgbm = lgbm_best.predict(x_test_final)
```

```
time: 37.5 ms (started: 2022-11-23 16:48:48 +00:00)
```

```
''' function to evaluate our model using different metrics '''

# values to be passed :
# model_name = Our Model name, model = classifier used used to
predict, y_train_pred, y_test_pred, x_train, x_test
def evaluate_model(model_name, model, y_train_pred, y_test_pred,
x_train, x_test):

    print('Printing various Evaluation metrics for our
'+str(model_name)+' model...........')
    print('\n')


#*********************************************************************
**************************************#

    # Printing Train & Test Accuracy scores
    print("Train Accuracy :", accuracy_score(y_train,
model.predict(x_train)))
    print("Test Accuracy :", accuracy_score(y_test,
model.predict(x_test)))

    print('\n')
    print("="*60)
    print('\n')


#*********************************************************************
**************************************#
```

```
    # Printing Confusion Matrix for Train & Test data
    print("Train Confusion Matrix:")
    print(confusion_matrix(y_train, model.predict(x_train)))
    print("Test Confusion Matrix:")
    print(confusion_matrix(y_test, model.predict(x_test)))

    print('\n')
    print("="*60)
    print('\n')


#*********************************************************************
***************************************#
    # Printing classification reports

    # For Train Data
    print("Classification report for our Model's Training data:")
    print("-"*52)
    print(classification_report(y_train, model.predict(x_train)))

    print('\n')
    print("="*60)
    print('\n')

    # For Train Data
    print("Classification report for our Model's Test data:")
    print("-"*52)
    print(classification_report(y_test, model.predict(x_test)))

    print('\n')
    print("="*60)
    print('\n')


#*********************************************************************
*****************************************#

    # Calculating AUC ROC scores
    auc_train_data = roc_auc_score(y_train, model.predict(x_train))
    auc_test_data = roc_auc_score(y_test, model.predict(x_test))
    print("AUC scores for \nTrain data is :", auc_train_data," & \
nTest data is :", auc_test_data)

    print('\n')
    print("="*60)
    print('\n')

    # Plotting AUC ROC scores for Train & Test data
    # ROC Curve using predict_proba method
    print("Plotting AUC ROC curves for Train and Test Data")
    tr_fpr, tr_tpr, tr_thresh = roc_curve(y_train,
model.predict(x_train))
    te_fpr, te_tpr, te_thresh = roc_curve(y_test,
model.predict(x_test))

    plt.style.use('seaborn')

    # plot roc curves
    plt.plot(tr_fpr, tr_tpr, linestyle='--', color='orange',
label='Train AUC ='+str(auc(tr_fpr, tr_tpr).round(3)))
    plt.plot(te_fpr, te_tpr, linestyle='--', color='green',
label='Test AUC ='+str(auc(te_fpr, te_tpr).round(3)))

    # title
    plt.title('ROC curve using '+str(model_name)+' model')
    # x label
    plt.xlabel('False Positive Rate')
    # y label
    plt.ylabel('True Positive rate')

    plt.legend(loc='best')

    plt.show();
    print('\n')


#*********************************************************************
*********************************************#

    # https://www.quantinsti.com/blog/creating-heatmap-using-python-
seaborn

    # Plotting Train & Test Confusion matrices
    print("Plotting Train and Test Confusion matrices")
    sns.set()

    con_m_train = confusion_matrix(y_train, model.predict(x_train))
    con_m_test = confusion_matrix(y_test, model.predict(x_test))

    key = (np.asarray([['TN','FP'], ['FN', 'TP']]))
    fig, ax = plt.subplots(1,2, figsize=(12,5))

    labels_train = (np.asarray(["{0} = {1:.2f}" .format(key, value)
for key, value in zip(key.flatten(),
con_m_train.flatten())])).reshape(2,2)
    labels_test = (np.asarray(["{0} = {1:.2f}" .format(key, value) for
key, value in zip(key.flatten(), con_m_test.flatten())])).reshape(2,2)
```

```
    sns.heatmap(con_m_train, linewidths=.5, xticklabels=['PREDICTED :
0', 'PREDICTED : 1'], yticklabels=['ACTUAL : 0', 'ACTUAL : 1'], annot
= labels_train, fmt = '', ax=ax[0], cmap='Blues')
    sns.heatmap(con_m_test, linewidths=.5, xticklabels=['PREDICTED :
0', 'PREDICTED : 1'], yticklabels=['ACTUAL : 0', 'ACTUAL : 1'], annot
= labels_test, fmt = '', ax=ax[1], cmap='Blues')

    ax[0].set_title('Train Data')
    ax[1].set_title('Test Data')

    plt.show()
    print('\n')


#*********************************************************************
********************#

    # printing F1-score for Train and Test Datasets
    print('Printing F1-scores for our '+str(model_name)+' model')
    print("="*60)
    print('\n')

    # for Train Data
    f1_score_train = f1_score(y_train, model.predict(x_train))
    print('For Train data: \n ', f1_score_train )

    # for test data
    f1_score_test = f1_score(y_test, model.predict(x_test))
    print('For Test data: \n ', f1_score_test )
    print('\n')


#*********************************************************************
********************#
```

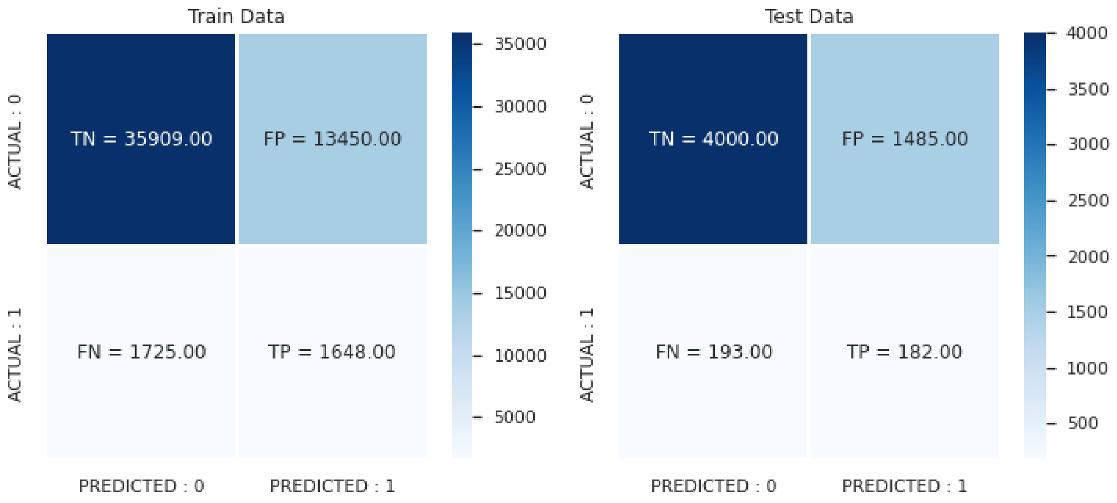
```
time: 44.3 ms (started: 2022-11-23 17:36:32 +00:00)
```

## Evaluation Metrics

```
# function to evaluate our model using different metrics

# values to be passed :
# model_name = Our Model name, model = classifier used used to
predict, y_train_pred, y_test_pred, x_train, x_test

model_name = 'LGBM'
evaluate_model(model_name, lgbm_best, y_pred_train_lgbm,
y_pred_test_lgbm, x_train_final, x_test_final);
```

```
Printing various Evaluation metrics for our LGBM model...........


Train Accuracy : 0.7122240764621103
Test Accuracy : 0.7136518771331058


============================================================


Train Confusion Matrix:
[[35909 13450]
 [ 1725  1648]]
Test Confusion Matrix:
[[4000 1485]
 [ 193  182]]


============================================================


Classification report for our Model's Training data:
----------------------------------------------------
              precision    recall  f1-score   support

           0       0.95      0.73      0.83     49359
           1       0.11      0.49      0.18      3373

    accuracy                           0.71     52732
   macro avg       0.53      0.61      0.50     52732
weighted avg       0.90      0.71      0.78     52732



============================================================


Classification report for our Model's Test data:
----------------------------------------------------
              precision    recall  f1-score   support

           0       0.95      0.73      0.83      5485
           1       0.11      0.49      0.18       375

    accuracy                           0.71      5860
   macro avg       0.53      0.61      0.50      5860
weighted avg       0.90      0.71      0.79      5860
```

```
============================================================

Plotting Train and Test Confusion matrices
```



```
Printing F1-scores for our LGBM model
============================================================


For Train data:
  0.17844188186887555
For Test data:
  0.178256611165524


time: 2.1 s (started: 2022-11-23 16:53:32 +00:00)
```

```
# storing f1 scores of Train and Test data in another variable to
tabulate them at a larger stage
f1_Score_train_LGBM = 0.17844188186887555
f1_Score_test_LGBM = 0.178256611165524
```

```
time: 621 µs (started: 2022-11-23 17:37:24 +00:00)
```

```
print("F1-score of Train data using LGBM is : ", f1_Score_train_LGBM)
print("F1-score of Test data using LGBM is : ", f1_Score_test_LGBM)
```

```
F1-score of Train data using LGBM is :  0.17844188186887555
F1-score of Test data using LGBM is :  0.178256611165524
time: 1.66 ms (started: 2022-11-23 17:52:37 +00:00)
```

# # Modelling - Catboost

```
# loading train data
df_train = pd.read_csv('train_qWM28Yl.csv')
df_train.head(2)
```

```
  policy_id  policy_tenure  age_of_car  age_of_policyholder
area_cluster  \
0   ID00001       0.515874        0.05             0.644231
C1
1   ID00002       0.672619        0.02             0.375000
C2

   population_density  make segment model fuel_type    max_torque  \
0                4990     1       A    M1       CNG  60Nm@3500rpm
1               27003     1       A    M1       CNG  60Nm@3500rpm

          max_power        engine_type  airbags is_esc
is_adjustable_steering  \
0  40.36bhp@6000rpm  F8D Petrol Engine        2     No
No
1  40.36bhp@6000rpm  F8D Petrol Engine        2     No
No

  is_tpms is_parking_sensors is_parking_camera rear_brakes_type
displacement  \
0      No                Yes                No             Drum
796
1      No                Yes                No             Drum
796

   cylinder transmission_type  gear_box steering_type  turning_radius
length  \
0         3            Manual         5         Power             4.6
3445
1         3            Manual         5         Power             4.6
3445

   width  height  gross_weight is_front_fog_lights
is_rear_window_wiper  \
0   1515    1475          1185                  No
No
1   1515    1475          1185                  No
No

  is_rear_window_washer is_rear_window_defogger is_brake_assist  \
0                    No                      No              No
1                    No                      No              No

  is_power_door_locks is_central_locking is_power_steering  \
0                  No                 No                Yes
1                  No                 No                Yes

  is_driver_seat_height_adjustable is_day_night_rear_view_mirror
is_ecw  \
0                                No                             No
No
1                                No                             No
No

  is_speed_alert  ncap_rating  is_claim
0            Yes            0         0
1            Yes            0         0

time: 332 ms (started: 2022-11-23 16:58:23 +00:00)
```

## References for Catboost classifier algorithm:

1. https://dataaspirant.com/catboost-algorithm/#t-1609567161984
2. https://catboost.ai/en/docs/
3. https://stackoverflow.com/questions/59746304/catboost-classifier-for-class-imbalance

```
# we have a total of 58k observations in our Train data
df_train.shape
```

```
(58592, 44)

time: 7.54 ms (started: 2022-11-23 17:00:35 +00:00)
```

```
df_train.info()
# all the columns are not-null and this will help us a lot
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 58592 entries, 0 to 58591
Data columns (total 44 columns):
 #   Column                            Non-Null Count  Dtype
---  ------                            --------------  -----
 0   policy_id                         58592 non-null  object
 1   policy_tenure                     58592 non-null  float64
 2   age_of_car                        58592 non-null  float64
 3   age_of_policyholder               58592 non-null  float64
 4   area_cluster                      58592 non-null  object
 5   population_density                58592 non-null  int64
 6   make                              58592 non-null  int64
 7   segment                           58592 non-null  object
 8   model                             58592 non-null  object
 9   fuel_type                         58592 non-null  object
 10  max_torque                        58592 non-null  object
 11  max_power                         58592 non-null  object
 12  engine_type                       58592 non-null  object
 13  airbags                           58592 non-null  int64
 14  is_esc                            58592 non-null  object
 15  is_adjustable_steering            58592 non-null  object
 16  is_tpms                           58592 non-null  object
 17  is_parking_sensors                58592 non-null  object
 18  is_parking_camera                 58592 non-null  object
 19  rear_brakes_type                  58592 non-null  object
 20  displacement                      58592 non-null  int64
 21  cylinder                          58592 non-null  int64
 22  transmission_type                 58592 non-null  object
 23  gear_box                          58592 non-null  int64
 24  steering_type                     58592 non-null  object
 25  turning_radius                    58592 non-null  float64
 26  length                            58592 non-null  int64
 27  width                             58592 non-null  int64
 28  height                            58592 non-null  int64
 29  gross_weight                      58592 non-null  int64
 30  is_front_fog_lights               58592 non-null  object
 31  is_rear_window_wiper              58592 non-null  object
 32  is_rear_window_washer             58592 non-null  object
 33  is_rear_window_defogger           58592 non-null  object
 34  is_brake_assist                   58592 non-null  object
 35  is_power_door_locks               58592 non-null  object
 36  is_central_locking                58592 non-null  object
 37  is_power_steering                 58592 non-null  object
 38  is_driver_seat_height_adjustable  58592 non-null  object
 39  is_day_night_rear_view_mirror     58592 non-null  object
 40  is_ecw                            58592 non-null  object
 41  is_speed_alert                    58592 non-null  object
 42  ncap_rating                       58592 non-null  int64
 43  is_claim                          58592 non-null  int64
dtypes: float64(4), int64(12), object(28)
memory usage: 19.7+ MB
time: 94.7 ms (started: 2022-11-23 17:00:39 +00:00)
```

```
df_train.describe()
```

```
       policy_tenure    age_of_car  age_of_policyholder
population_density  \
count   58592.000000  58592.000000         58592.000000
58592.000000
mean        0.611246      0.069424             0.469420
18826.858667
std         0.414156      0.056721             0.122886
17660.174792
min         0.002735      0.000000             0.288462
290.000000
25%         0.210250      0.020000             0.365385
6112.000000
50%         0.573792      0.060000             0.451923
8794.000000
75%         1.039104      0.110000             0.548077
```

```
27003.000000
max         1.396641      1.000000             1.000000
73430.000000

               make       airbags  displacement      cylinder
gear_box  \
count  58592.000000  58592.000000  58592.000000  58592.000000
58592.000000
mean       1.763722      3.137066   1162.355851      3.626963
5.245443
std        1.136988      1.832641    266.304786      0.483616
0.430353
min        1.000000      1.000000    796.000000      3.000000
5.000000
25%        1.000000      2.000000    796.000000      3.000000
5.000000
50%        1.000000      2.000000   1197.000000      4.000000
5.000000
75%        3.000000      6.000000   1493.000000      4.000000
5.000000
max        5.000000      6.000000   1498.000000      4.000000
6.000000

       turning_radius        length         width        height
gross_weight  \
count    58592.000000  58592.000000  58592.000000  58592.00000
58592.000000
mean         4.852893   3850.476891   1672.233667   1553.33537
1385.276813
std          0.228061    311.457119    112.089135     79.62227
212.423085
min          4.500000   3445.000000   1475.000000   1475.00000
1051.000000
25%          4.600000   3445.000000   1515.000000   1475.00000
1185.000000
50%          4.800000   3845.000000   1735.000000   1530.00000
1335.000000
75%          5.000000   3995.000000   1755.000000   1635.00000
1510.000000
max          5.200000   4300.000000   1811.000000   1825.00000
1720.000000

        ncap_rating      is_claim
count  58592.000000  58592.000000
mean       1.759950      0.063968
std        1.389576      0.244698
min        0.000000      0.000000
25%        0.000000      0.000000
50%        2.000000      0.000000
```

```
75%        3.000000      0.000000
max        5.000000      1.000000
```

```
time: 92 ms (started: 2022-11-23 17:00:43 +00:00)
```

```
# train.select_dtypes(include = ['int64']) This gives you a filtered
dataframe where the dataframe is entirely NUMERIC dedicated.
# Similarly, when you perform train_df.dscribe(include = ['O']) it
pulls out the objects dtypes attributes and shows their
count/frequency/max/quartiles.
```

```
time: 567 µs (started: 2022-11-23 17:59:57 +00:00)
```

```
df_train.describe(include=['O'])
```

```
       policy_id area_cluster segment  model fuel_type     max_torque
\
count      58592        58592   58592  58592      58592          58592

unique     58592           22       6     11         3              9

top      ID00001           C8      B2     M1    Petrol  113Nm@4400rpm

freq           1        13654   18314  14948      20532          17796


               max_power        engine_type is_esc
is_adjustable_steering  \
count              58592              58592  58592
58592
unique                 9                 11      2
2
top     88.50bhp@6000rpm  F8D Petrol Engine     No
Yes
freq               17796              14948  40191
35526

       is_tpms is_parking_sensors is_parking_camera
rear_brakes_type  \
count    58592              58592             58592             58592

unique       2                  2                 2                 2

top         No                Yes                No              Drum

freq     44574              56219             35704             44574


       transmission_type steering_type is_front_fog_lights  \
count              58592         58592               58592
```

```
unique                 2             3                   2
top               Manual         Power                 Yes
freq               38181         33502               33928

       is_rear_window_wiper is_rear_window_washer
is_rear_window_defogger  \
count                 58592                 58592
58592
unique                    2                     2
2
top                      No                    No
No
freq                  41634                 41634
38077

       is_brake_assist is_power_door_locks is_central_locking  \
count            58592               58592              58592
unique               2                   2                  2
top                Yes                 Yes                Yes
freq             32177               42435              42435

       is_power_steering is_driver_seat_height_adjustable  \
count              58592                            58592
unique                 2                                2
top                  Yes                              Yes
freq               57383                            34291

       is_day_night_rear_view_mirror is_ecw is_speed_alert
count                          58592  58592          58592
unique                             2      2              2
top                               No    Yes            Yes
freq                           36309  42435          58229

time: 271 ms (started: 2022-11-23 17:00:47 +00:00)
```

```
# loading Test data
df_test = pd.read_csv('test_zo1G9sv.csv')
df_test.head(2)
```

```
  policy_id  policy_tenure  age_of_car  age_of_policyholder
area_cluster  \
0   ID58593       0.341732        0.00             0.586538
C3
1   ID58594       0.307241        0.13             0.442308
C8

   population_density  make segment model fuel_type     max_torque  \
0                4076     1       A    M1       CNG   60Nm@3500rpm
1                8794     1      B2    M6    Petrol  113Nm@4400rpm
```

```
          max_power        engine_type  airbags is_esc
is_adjustable_steering  \
0  40.36bhp@6000rpm  F8D Petrol Engine        2     No
No
1  88.50bhp@6000rpm  K Series Dual jet        2     No
Yes

  is_tpms is_parking_sensors is_parking_camera rear_brakes_type
displacement  \
0      No                Yes                No             Drum
796
1      No                Yes                No             Drum
1197

   cylinder transmission_type  gear_box steering_type  turning_radius
length  \
0         3            Manual         5         Power             4.6
3445
1         4            Manual         5      Electric             4.8
3845

   width  height  gross_weight is_front_fog_lights
is_rear_window_wiper  \
0   1515    1475          1185                  No
No
1   1735    1530          1335                 Yes
No

  is_rear_window_washer is_rear_window_defogger is_brake_assist  \
0                    No                      No              No
1                    No                      No             Yes

  is_power_door_locks is_central_locking is_power_steering  \
0                  No                 No               Yes
1                 Yes                Yes               Yes

  is_driver_seat_height_adjustable is_day_night_rear_view_mirror
is_ecw  \
0                               No                             No
No
1                              Yes                            Yes
Yes

  is_speed_alert  ncap_rating
0            Yes            0
1            Yes            2

time: 230 ms (started: 2022-11-23 17:00:55 +00:00)
```

```python
df_test.shape
# we have a total of 39k observations in our Test data
```

```
(39063, 43)
```

```
time: 3.58 ms (started: 2022-11-23 17:00:55 +00:00)
```

```python
# copying Train and Test data into new DataFrames
df_train_take = df_train.copy()
df_test_take = df_test.copy()
```

```
time: 20.5 ms (started: 2022-11-23 17:00:56 +00:00)
```

```python
# removing policy id columns from the new DataFrames
df_train_take.drop(['policy_id'], axis = 1, inplace = True)
df_test_take.drop(['policy_id'], axis =1, inplace = True)
```

```
time: 30.5 ms (started: 2022-11-23 17:01:00 +00:00)
```

```python
df_train['is_claim'].value_counts()
# this data is very much imbalanced
```

```
0    54844
1     3748
Name: is_claim, dtype: int64
```

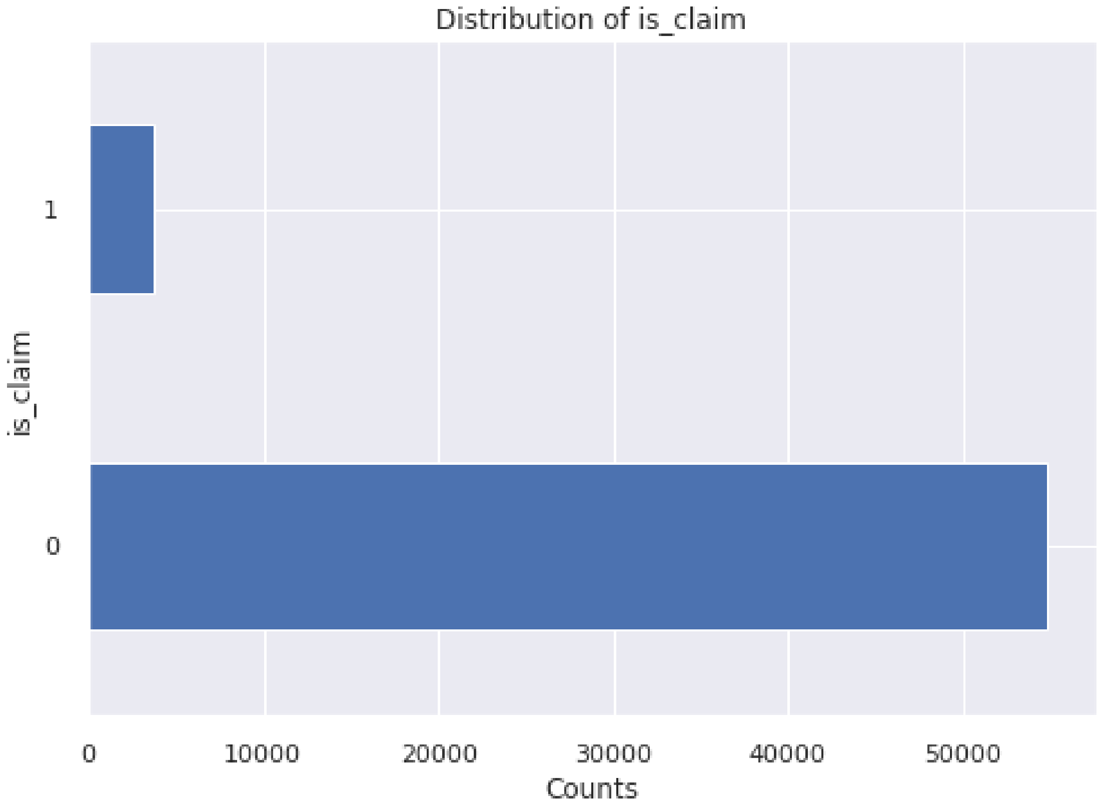
```
time: 6.84 ms (started: 2022-11-23 17:01:00 +00:00)
```

```python
df_train['is_claim'].value_counts( normalize = True)
# this data is very much imbalanced
```

```
0    0.936032
1    0.063968
Name: is_claim, dtype: float64
```

```
time: 9.63 ms (started: 2022-11-23 17:01:03 +00:00)
```

```python
df_train['is_claim'].value_counts().plot(kind='barh')
plt.xlabel('Counts')
plt.ylabel('is_claim')
plt.title('Distribution of is_claim')
plt.show()

# from the plot we can clearly see that Data is imbalanced
```



```
time: 319 ms (started: 2022-11-23 17:26:09 +00:00)
```

```
df_train_take.shape
```

```
(58592, 43)
```

```
time: 4.13 ms (started: 2022-11-23 17:26:14 +00:00)
```

```
# dropping the column 'is_claim' from X and storing it in y
X = df_train_take.drop(['is_claim'], axis=1)
y = df_train_take['is_claim']
X_test = df_test_take.copy()
```

```
time: 27 ms (started: 2022-11-23 17:26:18 +00:00)
```

### Giving category as indexs to Catboost classifier

```
# storing all the categorical columns in a variable
categorical_features_indices = np.where((df_train_take.dtypes ==
object).values.astype(int) == 1)[0]
```

```
time: 2.76 ms (started: 2022-11-23 17:26:25 +00:00)
```

```
X.shape
```

```
(58592, 42)
```

```
time: 4.62 ms (started: 2022-11-23 17:26:26 +00:00)
```

```
# splitting data into train and validation with 30% of validation data
X_train, X_val, y_train, y_val = train_test_split(X, y, test_size =
0.3, random_state = 42)
```

```
time: 43.9 ms (started: 2022-11-23 17:34:48 +00:00)
```

```
# shape of training and testing data sets
X_train.shape, X_val.shape
```

```
((41014, 42), (17578, 42))
```

```
time: 4.08 ms (started: 2022-11-23 17:34:54 +00:00)
```

```
# implementing Catboost with default parameters and scale_pos_weight =
10
catboost_base = CatBoostClassifier( random_state = 1, scale_pos_weight
= 10, verbose = False)
catboost_base.fit(X_train, y_train, cat_features =
categorical_features_indices, eval_set = (X_val, y_val))
print('\n')
```

```
time: 1min 54s (started: 2022-11-23 17:32:54 +00:00)
```

```
# predicting on the Train data
y_train_pred_CB = catboost_base.predict(X_train)

# predicting on the Validaiton data
y_test_pred_CB = catboost_base.predict(X_val)

# predicting on the actual given Test data
y_pred = catboost_base.predict(X_test)
```

```
time: 655 ms (started: 2022-11-23 17:35:07 +00:00)
```

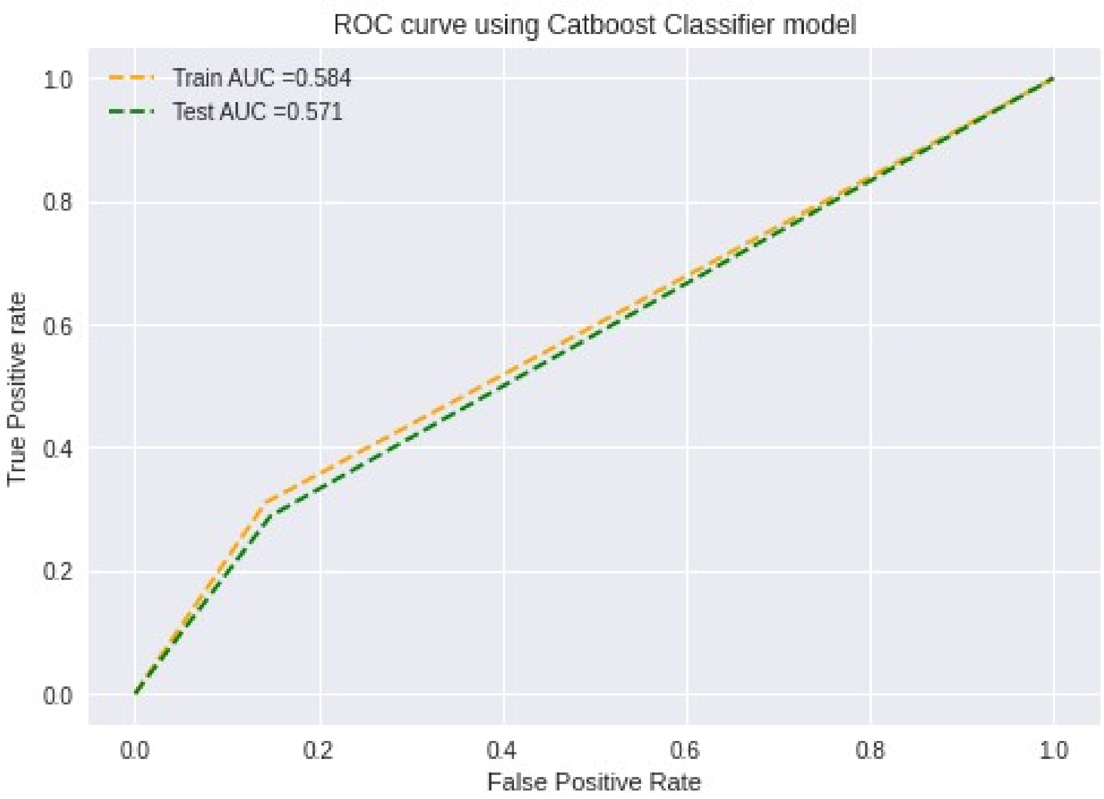
## Evaluation Metrics

```
# function to evaluate our model using different metrics

# values to be passed :
# model_name = Our Model name, model = classifier used used to
predict, y_train_pred, y_test_pred, x_train, x_test

y_test = y_val
model_name = 'Catboost Classifier'
evaluate_model(model_name, catboost_base, y_train_pred_CB,
y_test_pred_CB, X_train, X_val);
```

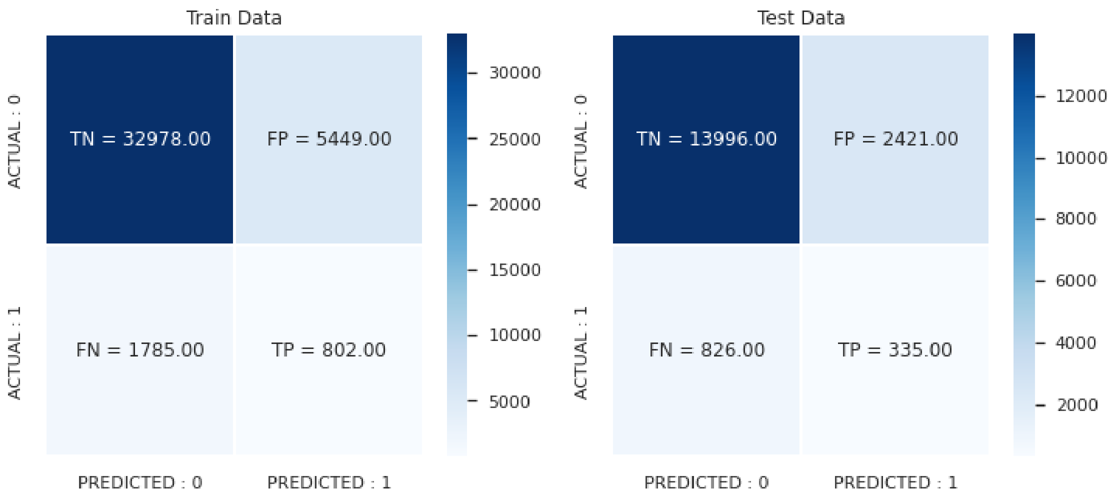
```
Printing various Evaluation metrics for our Catboost Classifier
model..........
```

```
Train Accuracy : 0.823621202516214
Test Accuracy : 0.8152804642166345


============================================================


Train Confusion Matrix:
[[32978  5449]
 [ 1785   802]]
Test Confusion Matrix:
[[13996  2421]
 [  826   335]]


============================================================


Classification report for our Model's Training data:
----------------------------------------------------
              precision    recall  f1-score   support

           0       0.95      0.86      0.90     38427
           1       0.13      0.31      0.18      2587

    accuracy                           0.82     41014
   macro avg       0.54      0.58      0.54     41014
weighted avg       0.90      0.82      0.86     41014



============================================================


Classification report for our Model's Test data:
----------------------------------------------------
              precision    recall  f1-score   support

           0       0.94      0.85      0.90     16417
           1       0.12      0.29      0.17      1161

    accuracy                           0.82     17578
   macro avg       0.53      0.57      0.53     17578
weighted avg       0.89      0.82      0.85     17578
```

```
============================================================


AUC scores for
Train data is : 0.5841051294212958  &
Test data is : 0.5705376356948536


============================================================


Plotting AUC ROC curves for Train and Test Data
```



```
Plotting Train and Test Confusion matrices
```



```
Printing F1-scores for our Catboost Classifier model
============================================================


For Train data:
  0.18148902466621408
For Test data:
  0.17104927240234874


time: 3.92 s (started: 2022-11-23 17:36:39 +00:00)
```

```
# storing f1 scores of Train and Test data in another variable to
tabulate them at a larger stage
f1_Score_train_CB = 0.18148902466621408
f1_Score_test_CB = 0.17104927240234874
```

```
time: 10.3 ms (started: 2022-11-23 17:38:19 +00:00)
```

```
print("F1-score of Train data using Catboost Classifier is : ",
f1_Score_train_CB)
print("F1-score of Test data using Catboost Classifier is : ",
f1_Score_test_CB)
```

```
F1-score of Train data using Catboost Classifier is :
0.18148902466621408
F1-score of Test data using Catboost Classifier is :
0.17104927240234874
time: 3.09 ms (started: 2022-11-23 17:53:18 +00:00)
```

```
# predicting the given test data with our model
y_pred = catboost_base.predict(X_test)
```

```
time: 269 ms (started: 2022-11-23 17:38:46 +00:00)
```

```
# loading the sample submission file given to us
submission_df = pd.read_csv('sample_submission_KvRh9Sx.csv')
submission_df.head(2)
```

```
  policy_id  is_claim
0   ID58593         1
1   ID58594         1
```

```
time: 605 ms (started: 2022-11-23 17:38:50 +00:00)
```

```
# taking the 'policy_id' given in our test data to our submission
DataFrame
submission_df['policy_id'] = df_test['policy_id']
```

```
time: 4.47 ms (started: 2022-11-23 17:38:54 +00:00)
```

```
# storing the predicted value in 'is_claim' column of our submission
DataFrame
submission_df['is_claim'] = y_pred
```

```
time: 1.44 ms (started: 2022-11-23 17:38:57 +00:00)
```

```
print("Percentage of each status present in our column 'is_claim'")
(submission_df['is_claim'].value_counts(normalize = True) ) * 100
```

```
Percentage of each status present in our column 'is_claim'

0    84.3714
1    15.6286
Name: is_claim, dtype: float64
```

```
time: 18.7 ms (started: 2022-11-23 17:47:59 +00:00)
```

```
print("Occurrences of each status present in our column 'is_claim'")
submission_df['is_claim'].value_counts()
```

```
Occurrences of each status present in our column 'is_claim'

0    32958
1     6105
Name: is_claim, dtype: int64
```

```
time: 14.8 ms (started: 2022-11-23 17:48:21 +00:00)
```

```
# storing our submission results into a csv file
submission_df.to_csv('submission_catboost_best.csv', index = False) #
index = False to avoid row index values in our CSV
```

```
time: 695 ms (started: 2022-11-23 17:39:05 +00:00)
```

```
# Tabulating our results
from prettytable import PrettyTable

# initializing a table
table = PrettyTable()

# adding title
table.title = "Peformance of Insurance Claim Prediction modelling
overview"
# adding fields
table.field_names = ["Model", "Test F1-score"]


# adding rows to our table
table.add_row(['LGBM', f1_Score_test_LGBM])
table.add_row(['Catboost Classifier', f1_Score_test_CB])

# printing the table
print(table)

+-------------------------------------------------------------+
| Peformance of Insurance Claim Prediction modelling overview |
+------------------------------+------------------------------+
|            Model             |        Test F1-score         |
+------------------------------+------------------------------+
|             LGBM             |      0.178256611165524       |
|     Catboost Classifier      |     0.17104927240234874      |
+------------------------------+------------------------------+
time: 3.51 ms (started: 2022-11-23 17:49:10 +00:00)
```