CAR INSURANCE CLAIM PREDICTION

PROBLEM STATEMENT

In the auto insurance industry, accurately identifying policyholders who are likely to file a claim is essential for effective risk management, pricing optimization, and fraud detection. Misjudging risk can lead to financial losses and unfair premium allocation. To address this, an insurance company has tasked me with developing a predictive model that uses historical customer and vehicle data to estimate the likelihood of a policyholder filing a claim. The goal is to support data-driven decisions that enhance underwriting accuracy and improve overall business outcomes.

OBJECTIVES

The objective of this project is to:

- Explore and Apply various feature engineering techniques to improve model interpretability
- To build classification models that predict the likelihood of a policyholder filing a c/laim
- To improve the AUC-ROC score by around 10% through hyperparameter tuning of the best-performing models

DATA UNDERSTANDING

COLUMN DESCRIPTION

The dataset for this project is from Kaggle and it contains various information of determining whether a policyholder will file a claim or not

The column names and their description is as follows:

IMPORT THE NECESSARY LIBRARIES

```
# import the necessary libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
import warnings
warnings.filterwarnings("ignore")
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler, MinMaxScaler,
OneHotEncoder
from sklearn.metrics import roc_auc_score,roc_curve, auc,
```

```
classification_report, confusion_matrix
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier,
GradientBoostingClassifier
from scipy.stats import chi2_contingency
from sklearn.model_selection import cross_val_score
from sklearn.ensemble import RandomForestClassifier
from xgboost import XGBClassifier
```

LOAD THE DATASET

```
# Load dataset
df = pd.read_csv("./data/CarInsurance.csv").copy()
pd.set_option('display.max_columns', None)

# Display first 5 rows
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

# Display the summary
df.info()

<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
```

```python
#Display the number of rows and columns
display(df.shape)
```

```
(58592, 44)
```

```python
#Display summary Statistics
df.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
```

selecting the features

```
# Display the column names
display(df.columns)
```

```
Index(['policy_id', 'policy_tenure', 'age_of_car',
'age_of_policyholder',
       'area_cluster', 'population_density', 'make', 'segment',
'model',
       'fuel_type', 'max_torque', 'max_power', 'engine_type',
'airbags',
       'is_esc', 'is_adjustable_steering', 'is_tpms',
'is_parking_sensors',
       'is_parking_camera', 'rear_brakes_type', 'displacement',
'cylinder',
       'transmission_type', 'gear_box', 'steering_type',
'turning_radius',
       'length', 'width', 'height', 'gross_weight',
'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', 'ncap_rating', 'is_claim'],
      dtype='object')
```

Display the unique categories and their count for each column (cardinality)

This helps in to identifying features with high number of unique categories which are not useful for prediction and those that require preprocessing e.g., inconsistent strings,mixed datatypes, encoding, scaling, etc

```
for col in df.columns:
    #if df[col].dtype == 'object':
        print(f"column: {col}, Total unique categories:
{df[col].nunique()}, data type: {df[col].dtype}")
        print(df[col].value_counts())
        print("\n")
```

```
column: policy_id, Total unique categories: 58592, data type: object
ID51721    1
ID31908    1
ID48837    1
ID05788    1
ID45043    1
          ..
ID19188    1
ID19225    1
ID06075    1
ID06765    1
ID16274    1
Name: policy_id, Length: 58592, dtype: int64


column: policy_tenure, Total unique categories: 58592, data type:
float64
1.167538    1
0.083828    1
0.073493    1
0.135073    1
0.123339    1
           ..
0.666820    1
0.347605    1
0.441174    1
0.986366    1
1.215153    1
Name: policy_tenure, Length: 58592, dtype: int64


column: age_of_car, Total unique categories: 49, data type: float64
0.01    6362
0.00    5257
0.02    5189
0.03    4415
0.04    3763
0.05    3342
0.10    3123
0.06    3053
0.07    2888
0.08    2730
0.09    2643
0.12    2506
0.11    2442
0.13    2315
0.14    2151
0.15    1964
0.16    1291
0.17     931
```

```
0.18     738
0.19     458
0.20     287
0.21     172
0.22     148
0.23      90
0.24      65
0.25      46
0.30      32
0.27      29
0.31      26
0.28      25
0.26      24
0.29      21
0.32      13
0.33      12
0.36       8
0.34       6
0.39       5
0.38       4
0.37       3
1.00       3
0.49       2
0.44       2
0.46       2
0.81       1
0.42       1
0.45       1
0.62       1
0.82       1
0.35       1
Name: age_of_car, dtype: int64


column: age_of_policyholder, Total unique categories: 75, data type:
float64
0.375000    1779
0.365385    1766
0.346154    1733
0.355769    1724
0.394231    1715
            ...
0.961538       2
0.971154       1
1.000000       1
0.980769       1
0.990385       1
Name: age_of_policyholder, Length: 75, dtype: int64
```

```
column: area_cluster, Total unique categories: 22, data type: object
C8     13654
C2      7342
C5      6979
C3      6101
C14     3660
C13     3423
C10     3155
C9      2734
C7      2167
C12     1589
C1      1468
C11     1212
C19      952
C6       890
C15      771
C4       665
C17      492
C16      401
C21      379
C18      242
C22      207
C20      109
Name: area_cluster, dtype: int64


column: population_density, Total unique categories: 22, data type:
int64
8794     13654
27003     7342
34738     6979
4076      6101
7788      3660
5410      3423
73430     3155
17804     2734
6112      2167
34791     1589
4990      1468
6108      1212
27742      952
13051      890
290        771
21622      665
65567      492
16206      401
3264       379
35036      242
16733      207
20905      109
```

```
Name: population_density, dtype: int64


column: make, Total unique categories: 5, data type: int64
1    38126
3    14018
2     2373
5     2114
4     1961
Name: make, dtype: int64


column: segment, Total unique categories: 6, data type: object
B2         18314
A          17321
C2         14018
B1          4173
C1          3557
Utility     1209
Name: segment, dtype: int64


column: model, Total unique categories: 11, data type: object
M1     14948
M4     14018
M6     13776
M8      4173
M7      2940
M3      2373
M9      2114
M5      1598
M10     1209
M2      1080
M11      363
Name: model, dtype: int64


column: fuel_type, Total unique categories: 3, data type: object
Petrol    20532
CNG       20330
Diesel    17730
Name: fuel_type, dtype: int64


column: max_torque, Total unique categories: 9, data type: object
113Nm@4400rpm     17796
60Nm@3500rpm      14948
250Nm@2750rpm     14018
82.1Nm@3400rpm     4173
91Nm@4250rpm       2373
```

```
200Nm@1750rpm      2114
200Nm@3000rpm      1598
85Nm@3000rpm       1209
170Nm@4000rpm       363
Name: max_torque, dtype: int64


column: max_power, Total unique categories: 9, data type: object
88.50bhp@6000rpm     17796
40.36bhp@6000rpm     14948
113.45bhp@4000rpm    14018
55.92bhp@5300rpm      4173
67.06bhp@5500rpm      2373
97.89bhp@3600rpm      2114
88.77bhp@4000rpm      1598
61.68bhp@6000rpm      1209
118.36bhp@5500rpm      363
Name: max_power, dtype: int64


column: engine_type, Total unique categories: 11, data type: object
F8D Petrol Engine            14948
1.5 L U2 CRDi                14018
K Series Dual jet            13776
K10C                          4173
1.2 L K Series Engine         2940
1.0 SCe                       2373
i-DTEC                        2114
1.5 Turbocharged Revotorq     1598
G12B                          1209
1.2 L K12N Dualjet            1080
1.5 Turbocharged Revotron      363
Name: engine_type, dtype: int64


column: airbags, Total unique categories: 3, data type: int64
2    40425
6    16958
1     1209
Name: airbags, dtype: int64


column: is_esc, Total unique categories: 2, data type: object
No     40191
Yes    18401
Name: is_esc, dtype: int64


column: is_adjustable_steering, Total unique categories: 2, data type: 
object
Yes    35526
```

```
No     23066
Name: is_adjustable_steering, dtype: int64


column: is_tpms, Total unique categories: 2, data type: object
No     44574
Yes    14018
Name: is_tpms, dtype: int64


column: is_parking_sensors, Total unique categories: 2, data type:
object
Yes    56219
No      2373
Name: is_parking_sensors, dtype: int64


column: is_parking_camera, Total unique categories: 2, data type:
object
No     35704
Yes    22888
Name: is_parking_camera, dtype: int64


column: rear_brakes_type, Total unique categories: 2, data type:
object
Drum    44574
Disc    14018
Name: rear_brakes_type, dtype: int64


column: displacement, Total unique categories: 9, data type: int64
1197    17796
796     14948
1493    14018
998      4173
999      2373
1498     2114
1497     1598
1196     1209
1199      363
Name: displacement, dtype: int64


column: cylinder, Total unique categories: 2, data type: int64
4    36735
3    21857
Name: cylinder, dtype: int64


column: transmission_type, Total unique categories: 2, data type:
```

```
object
Manual       38181
Automatic    20411
Name: transmission_type, dtype: int64


column: gear_box, Total unique categories: 2, data type: int64
5    44211
6    14381
Name: gear_box, dtype: int64


column: steering_type, Total unique categories: 3, data type: object
Power       33502
Electric    23881
Manual       1209
Name: steering_type, dtype: int64


column: turning_radius, Total unique categories: 9, data type: float64
4.60    14948
4.80    14856
5.20    14018
4.70     4173
5.00     3971
4.85     2940
4.90     2114
4.50     1209
5.10      363
Name: turning_radius, dtype: int64


column: length, Total unique categories: 9, data type: int64
3445    14948
4300    14018
3845    13776
3990     4538
3655     4173
3995     3194
3731     2373
3675     1209
3993      363
Name: length, dtype: int64


column: width, Total unique categories: 10, data type: int64
1515    14948
1735    14856
1790    14018
1620     4173
1745     2940
```

```
1579     2373
1695     2114
1755     1598
1475     1209
1811      363
Name: width, dtype: int64


column: height, Total unique categories: 11, data type: int64
1475    14948
1635    14018
1530    13776
1675     4173
1500     2940
1490     2373
1501     2114
1523     1598
1825     1209
1515     1080
1606      363
Name: height, dtype: int64


column: gross_weight, Total unique categories: 10, data type: int64
1185    14948
1335    14856
1720    14018
1340     4173
1410     2940
1155     2373
1051     2114
1490     1598
1510     1209
1660      363
Name: gross_weight, dtype: int64


column: is_front_fog_lights, Total unique categories: 2, data type:
object
Yes    33928
No     24664
Name: is_front_fog_lights, dtype: int64


column: is_rear_window_wiper, Total unique categories: 2, data type:
object
No     41634
Yes    16958
Name: is_rear_window_wiper, dtype: int64
```

```
column: is_rear_window_washer, Total unique categories: 2, data type:
object
No     41634
Yes    16958
Name: is_rear_window_washer, dtype: int64


column: is_rear_window_defogger, Total unique categories: 2, data
type: object
No     38077
Yes    20515
Name: is_rear_window_defogger, dtype: int64


column: is_brake_assist, Total unique categories: 2, data type: object
Yes    32177
No     26415
Name: is_brake_assist, dtype: int64


column: is_power_door_locks, Total unique categories: 2, data type:
object
Yes    42435
No     16157
Name: is_power_door_locks, dtype: int64


column: is_central_locking, Total unique categories: 2, data type:
object
Yes    42435
No     16157
Name: is_central_locking, dtype: int64


column: is_power_steering, Total unique categories: 2, data type:
object
Yes    57383
No      1209
Name: is_power_steering, dtype: int64


column: is_driver_seat_height_adjustable, Total unique categories: 2,
data type: object
Yes    34291
No     24301
Name: is_driver_seat_height_adjustable, dtype: int64


column: is_day_night_rear_view_mirror, Total unique categories: 2,
data type: object
```

```
No     36309
Yes    22283
Name: is_day_night_rear_view_mirror, dtype: int64


column: is_ecw, Total unique categories: 2, data type: object
Yes    42435
No     16157
Name: is_ecw, dtype: int64


column: is_speed_alert, Total unique categories: 2, data type: object
Yes    58229
No       363
Name: is_speed_alert, dtype: int64


column: ncap_rating, Total unique categories: 5, data type: int64
2    21402
0    19097
3    14018
4     2114
5     1961
Name: ncap_rating, dtype: int64


column: is_claim, Total unique categories: 2, data type: int64
0    54844
1     3748
Name: is_claim, dtype: int64
```

DATA PREPARATION

DROP IDS

```
# drop useless column
df.drop(['policy_id'],axis=1, inplace=True)
df.head()

   policy_tenure  age_of_car  age_of_policyholder area_cluster  \
0       0.515874        0.05             0.644231           C1
1       0.672619        0.02             0.375000           C2
2       0.841110        0.02             0.384615           C3
3       0.900277        0.11             0.432692           C4
4       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
```

CHECK FOR FOR CLASS IMBALANCE

```
# check if the dataset is imbalanced in percentage
df['is_claim'].value_counts(normalize=True)

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

Insight: The dataset is heavily imbalanced with approximately **6.4%** positive claims and **93.6%** negative claims. To ensure both train and test sets preserve this distribution, **stratification** is performed

SPLIT INTO TEST AND TRAIN

This is done at this point to avoid data leakage later on when performing cleaing and preprocessing

```
# Split the data into X and y
y = df['is_claim']
X = df.drop(columns=['is_claim'])

# perform a train-test split using stratify
from sklearn.model_selection import StratifiedKFold
X_train, X_test, y_train, y_test = train_test_split(X, y, stratify=
y , test_size=0.2, random_state=42)

# confirm the distribution after the split
print("Train distribution:\n", y_train.value_counts(normalize=True))
print("Test distribution:\n", y_test.value_counts(normalize=True))
```

```
Train distribution:
 0    0.93604
1    0.06396
Name: is_claim, dtype: float64
Test distribution:
 0    0.936001
1    0.063999
Name: is_claim, dtype: float64
```

DATA CLEANING

1.Check for missing values

```
# display columns with missing values
missing_values_X_train = X_train.isnull().sum().sum()
missing_values_X_test= X_test.isnull().sum().sum()
print("Missing values in train:", missing_values_X_train)
print("Missing values in test:", missing_values_X_test)
```

```
Missing values in train: 0
Missing values in test: 0
```

2.Check for duplicates

```
# check for duplicates
duplicates_train = X_train.duplicated().sum()
```

```
duplicates_test = X_test.duplicated().sum()

print("Duplicate rows in train:", duplicates_train)
print("Duplicate rows in test:", duplicates_test)
```

```
Duplicate rows in train: 0
Duplicate rows in test: 0
```

3.Confirm correct string formatting

```
# check for correct string formatting
object_columns = X_train.select_dtypes(include='object').columns

for col in object_columns:
    print(f"Column: {col},  unique value count:
{X_train[col].nunique()} \n")
    print(f"Unique values: {X_train[col].unique()}\n\n")
```

```
Column: area_cluster,  unique value count: 22

Unique values: ['C5' 'C13' 'C8' 'C12' 'C3' 'C14' 'C6' 'C4' 'C1' 'C2'
'C9' 'C19' 'C10'
 'C15' 'C7' 'C16' 'C22' 'C11' 'C17' 'C21' 'C18' 'C20']


Column: segment,  unique value count: 6

Unique values: ['C1' 'B1' 'B2' 'A' 'C2' 'Utility']


Column: model,  unique value count: 11

Unique values: ['M2' 'M8' 'M6' 'M1' 'M4' 'M5' 'M7' 'M10' 'M3' 'M9'
'M11']


Column: fuel_type,  unique value count: 3

Unique values: ['Petrol' 'CNG' 'Diesel']


Column: max_torque,  unique value count: 9

Unique values: ['113Nm@4400rpm' '82.1Nm@3400rpm' '60Nm@3500rpm'
'250Nm@2750rpm'
 '200Nm@3000rpm' '85Nm@3000rpm' '91Nm@4250rpm' '200Nm@1750rpm'
 '170Nm@4000rpm']


Column: max_power,  unique value count: 9
```

```
Unique values: ['88.50bhp@6000rpm' '55.92bhp@5300rpm'
'40.36bhp@6000rpm'
 '113.45bhp@4000rpm' '88.77bhp@4000rpm' '61.68bhp@6000rpm'
 '67.06bhp@5500rpm' '97.89bhp@3600rpm' '118.36bhp@5500rpm']


Column: engine_type,  unique value count: 11

Unique values: ['1.2 L K12N Dualjet' 'K10C' 'K Series Dual jet' 'F8D
Petrol Engine'
 '1.5 L U2 CRDi' '1.5 Turbocharged Revotorq' '1.2 L K Series Engine'
 'G12B' '1.0 SCe' 'i-DTEC' '1.5 Turbocharged Revotron']


Column: is_esc,  unique value count: 2

Unique values: ['Yes' 'No']


Column: is_adjustable_steering,  unique value count: 2

Unique values: ['Yes' 'No']


Column: is_tpms,  unique value count: 2

Unique values: ['No' 'Yes']


Column: is_parking_sensors,  unique value count: 2

Unique values: ['Yes' 'No']


Column: is_parking_camera,  unique value count: 2

Unique values: ['Yes' 'No']


Column: rear_brakes_type,  unique value count: 2

Unique values: ['Drum' 'Disc']


Column: transmission_type,  unique value count: 2

Unique values: ['Automatic' 'Manual']


Column: steering_type,  unique value count: 3
```

```
Unique values: ['Electric' 'Power' 'Manual']

Column: is_front_fog_lights,  unique value count: 2

Unique values: ['Yes' 'No']

Column: is_rear_window_wiper,  unique value count: 2

Unique values: ['No' 'Yes']

Column: is_rear_window_washer,  unique value count: 2

Unique values: ['No' 'Yes']

Column: is_rear_window_defogger,  unique value count: 2

Unique values: ['Yes' 'No']

Column: is_brake_assist,  unique value count: 2

Unique values: ['Yes' 'No']

Column: is_power_door_locks,  unique value count: 2

Unique values: ['Yes' 'No']

Column: is_central_locking,  unique value count: 2

Unique values: ['Yes' 'No']

Column: is_power_steering,  unique value count: 2

Unique values: ['Yes' 'No']

Column: is_driver_seat_height_adjustable,  unique value count: 2

Unique values: ['Yes' 'No']

Column: is_day_night_rear_view_mirror,  unique value count: 2

Unique values: ['Yes' 'No']
```

```
Column: is_ecw,  unique value count: 2

Unique values: ['Yes' 'No']


Column: is_speed_alert,  unique value count: 2

Unique values: ['Yes' 'No']
```

4.Convert to correct data type

Check the datatype

Check for categorical features disguised as numeric features

```
print(X_train.dtypes)
```

```
policy_tenure                       float64
age_of_car                          float64
age_of_policyholder                 float64
area_cluster                         object
population_density                    int64
make                                  int64
segment                              object
model                                object
fuel_type                            object
max_torque                           object
max_power                            object
engine_type                          object
airbags                               int64
is_esc                               object
is_adjustable_steering               object
is_tpms                              object
is_parking_sensors                   object
is_parking_camera                    object
rear_brakes_type                     object
displacement                          int64
cylinder                              int64
transmission_type                    object
gear_box                              int64
steering_type                        object
turning_radius                      float64
length                                int64
width                                 int64
height                                int64
```

```
gross_weight                                int64
is_front_fog_lights                        object
is_rear_window_wiper                       object
is_rear_window_washer                      object
is_rear_window_defogger                    object
is_brake_assist                            object
is_power_door_locks                        object
is_central_locking                         object
is_power_steering                          object
is_driver_seat_height_adjustable           object
is_day_night_rear_view_mirror              object
is_ecw                                     object
is_speed_alert                             object
ncap_rating                                 int64
dtype: object
```

```
# Convert make from float to object
X_train['make'] = X_train['make'].astype(str)
X_test['make'] = X_test['make'].astype(str)

# confirm it is of type object
print(X_train['make'].dtype)
```

```
object
```

display summary statistics

```
X_train.describe()
```

```
       policy_tenure    age_of_car  age_of_policyholder
population_density  \
count   46873.000000  46873.000000         46873.000000
46873.000000
mean        0.612408      0.069343             0.469697
18829.491946
std         0.414739      0.056389             0.122799
17660.971421
min         0.002735      0.000000             0.288462
290.000000
25%         0.209692      0.020000             0.375000
6112.000000
50%         0.575494      0.060000             0.451923
8794.000000
75%         1.040034      0.110000             0.548077
27003.000000
max         1.396641      1.000000             1.000000
73430.000000
```

```
             airbags  displacement      cylinder      gear_box
turning_radius  \
count   46873.000000  46873.000000  46873.000000  46873.000000
46873.000000
mean        3.137862   1163.143345      3.628272      5.245536
4.853295
std         1.833305    266.068922      0.483271      0.430409
0.227930
min         1.000000    796.000000      3.000000      5.000000
4.500000
25%         2.000000    796.000000      3.000000      5.000000
4.600000
50%         2.000000   1197.000000      4.000000      5.000000
4.800000
75%         6.000000   1493.000000      4.000000      5.000000
5.000000
max         6.000000   1498.000000      4.000000      6.000000
5.200000

              length         width        height  gross_weight
ncap_rating
count   46873.000000  46873.000000  46873.000000  46873.000000
46873.000000
mean     3851.108143   1672.481983   1553.453203   1385.409788
1.763787
std       311.079047    111.985636     79.672626    212.480747
1.390179
min      3445.000000   1475.000000   1475.000000   1051.000000
0.000000
25%      3445.000000   1515.000000   1475.000000   1185.000000
0.000000
50%      3845.000000   1735.000000   1530.000000   1335.000000
2.000000
75%      3995.000000   1755.000000   1635.000000   1510.000000
3.000000
max      4300.000000   1811.000000   1825.000000   1720.000000
5.000000
```

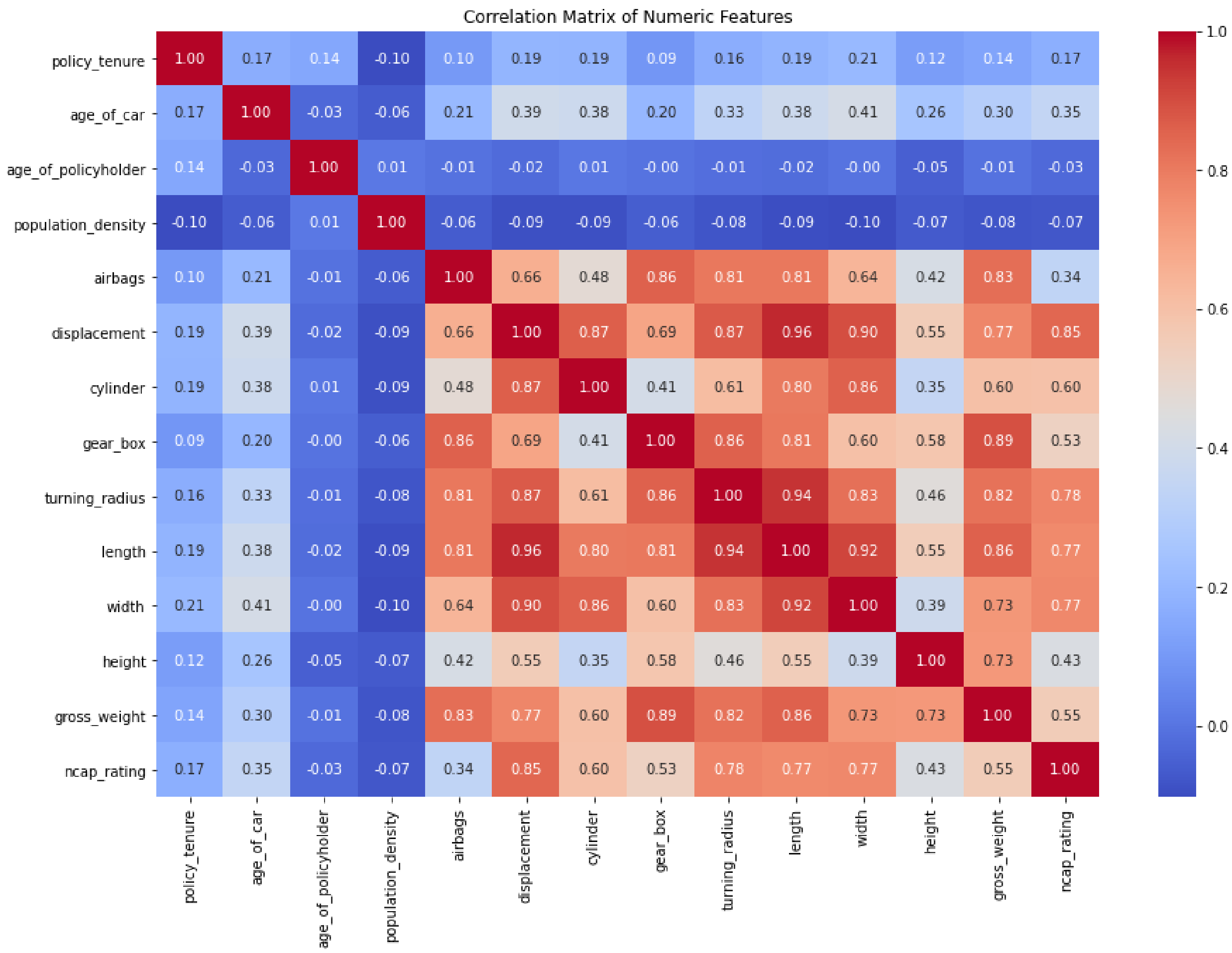
DATA PREPROCESSING

1.Check for highly correlated features

(I). High correlation in numeric features

```
# Correlation matrix for numeric features
numeric_cols = X_train.select_dtypes(include='number').columns
corr_matrix = X_train[numeric_cols].corr()

plt.figure(figsize=(15, 10))
```

```python
sns.heatmap(corr_matrix, annot=True, cmap='coolwarm', fmt=".2f")
plt.title("Correlation Matrix of Numeric Features")
plt.show()
```




```python
#print pairs with high correlation for easier selection
high_corr = []
threshold = 0.8
for i in range(len(corr_matrix.columns)):
    for j in range(i):
        if abs(corr_matrix.iloc[i, j]) > threshold:
            high_corr.append((corr_matrix.columns[i],
corr_matrix.columns[j], corr_matrix.iloc[i, j]))
print("Highly correlated pairs (>|0.8|):\n")
for pair in high_corr:
    print(f"{pair[0]} & {pair[1]}: correlation = {pair[2]:.2f}")
```

```
Highly correlated pairs (>|0.8|):
```

```
cylinder & displacement: correlation = 0.87
gear_box & airbags: correlation = 0.86
turning_radius & airbags: correlation = 0.81
turning_radius & displacement: correlation = 0.87
turning_radius & gear_box: correlation = 0.86
length & airbags: correlation = 0.81
length & displacement: correlation = 0.96
length & cylinder: correlation = 0.80
length & gear_box: correlation = 0.81
length & turning_radius: correlation = 0.94
width & displacement: correlation = 0.90
width & cylinder: correlation = 0.86
width & turning_radius: correlation = 0.83
width & length: correlation = 0.92
gross_weight & airbags: correlation = 0.83
gross_weight & gear_box: correlation = 0.89
gross_weight & turning_radius: correlation = 0.82
gross_weight & length: correlation = 0.86
ncap_rating & displacement: correlation = 0.85
```

Insight - From the correlation matrix features with correlation coefficient grater tha 0.80 are identified as highly correlated. For example: `displacement` and `length` have `0.96`, `gear_box` and `gross_weight` have `0.89`.

The decision of which feature to keep was based on domain knowledge, which feature has a direct explainable association with the likelihood of a claim being filed.

The features that were kept were:

- `Airbags` - They are directly linked to passenger safety and injury severity in accidents which can significantly infuence injury claims
- `ncap_rating` - This is a standardized safety rating provided by the **NCAP** based on crash tests done. This makes it a reliable feature to include in the model

Drop all highly correlated numeric features

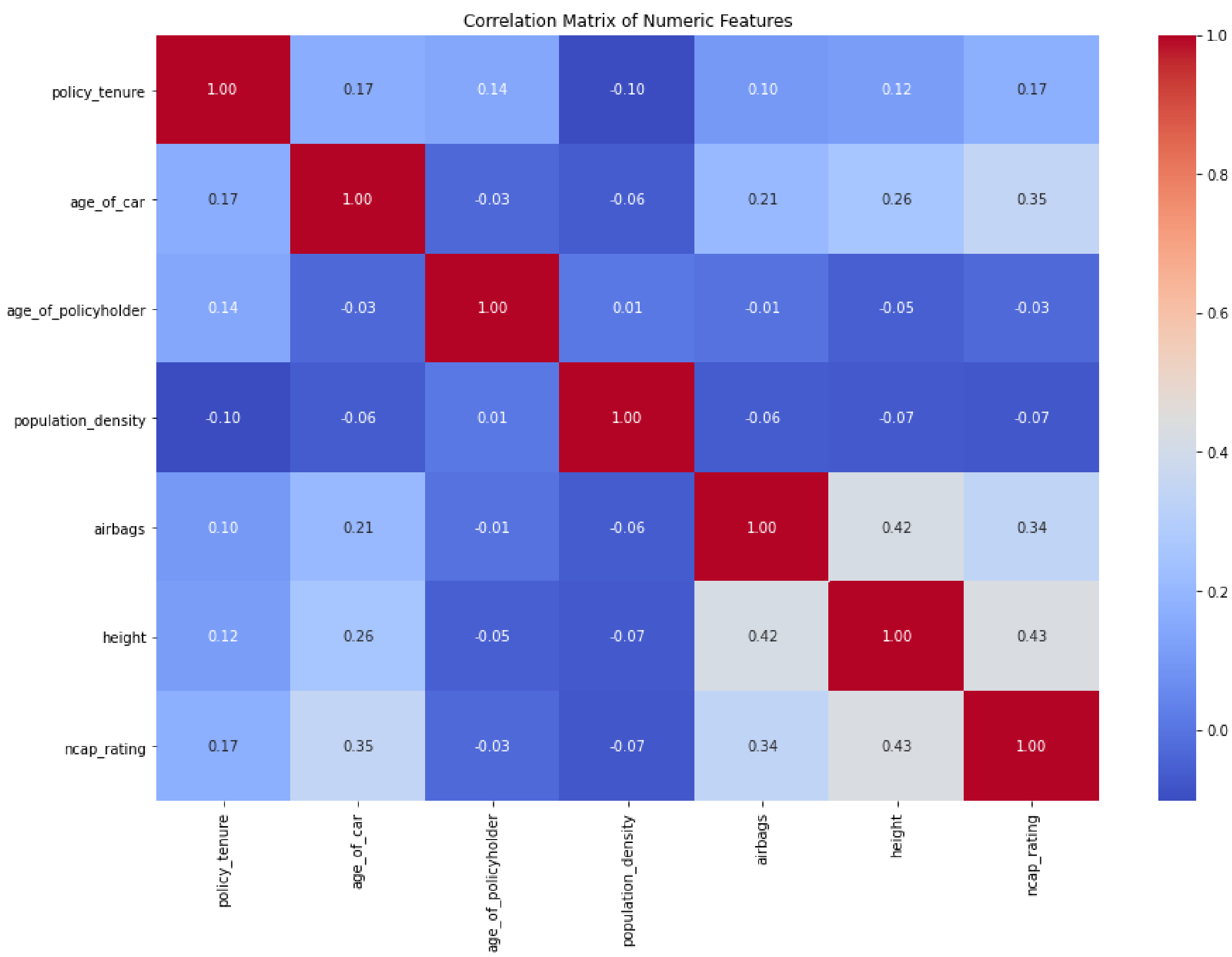
```
# drop the highly correleatad columns


drop_columns = ['gear_box', 'gross_weight', 'length', 'width',
'cylinder', 'displacement', 'turning_radius', 'displacement', ]

#drop the features
X_train = X_train.drop(columns=drop_columns)
X_test = X_test.drop(columns=drop_columns)

# Get numeric columns
numeric_cols1 = X_train.select_dtypes(include='number').columns

# Get the number of numeric columns
num_numeric_cols1= len(numeric_cols1)
```

```
print("Number of numeric columns:", num_numeric_cols1)
numeric_cols1
```

```
Number of numeric columns: 7

Index(['policy_tenure', 'age_of_car', 'age_of_policyholder',
       'population_density', 'airbags', 'height', 'ncap_rating'],
      dtype='object')
```

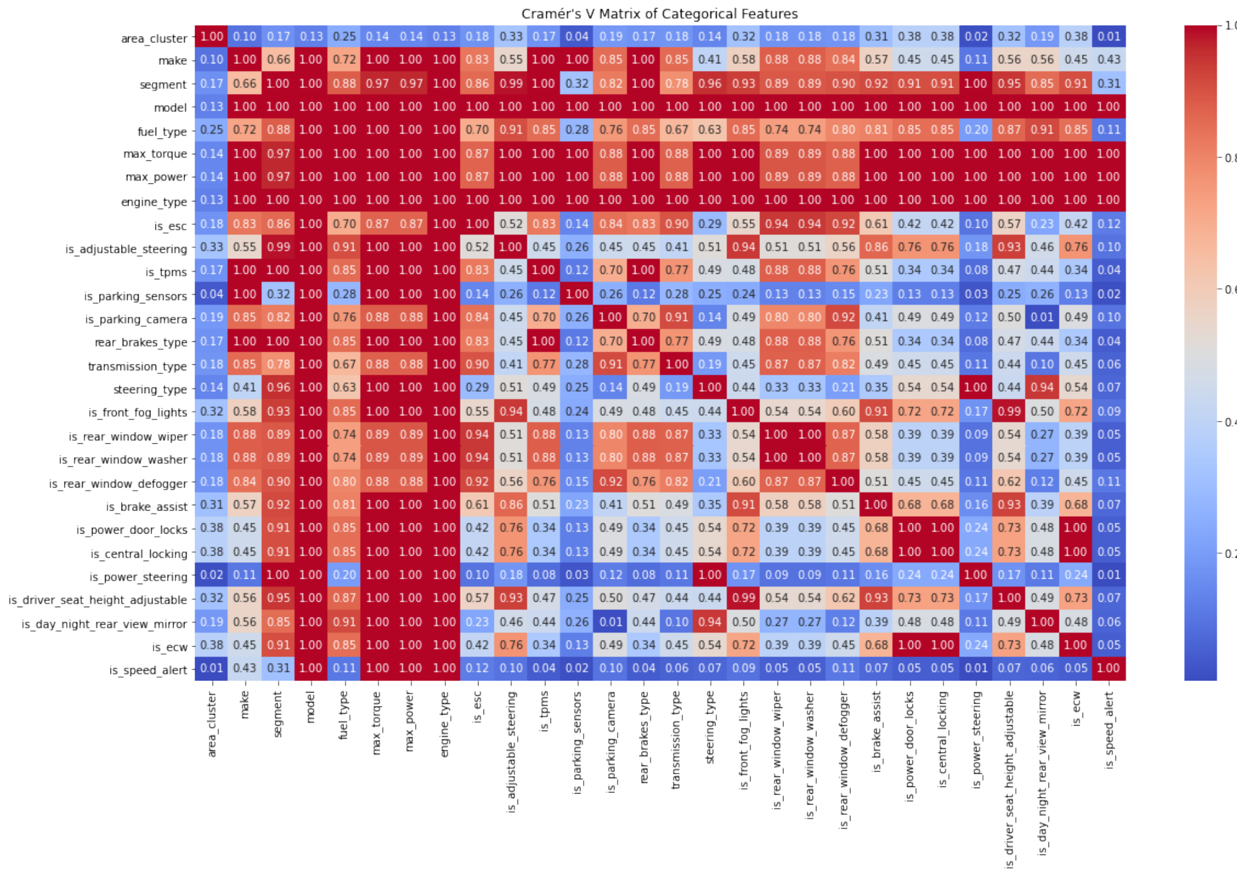
Confirm there is no highly correlated features

```
#print pairs with high correlation for easier selection

numeric_cols = X_train.select_dtypes(include='number').columns
corr_matrix = X_train[numeric_cols].corr()

plt.figure(figsize=(15, 10))
sns.heatmap(corr_matrix, annot=True, cmap='coolwarm', fmt=".2f")
plt.title("Correlation Matrix of Numeric Features")
plt.show()
```



(II). Checking for high correlation in categorical features

```
# check using the Cramer's V
def cramers_v(x, y):
    confusion_matrix = pd.crosstab(x, y)
    chi2 = chi2_contingency(confusion_matrix)[0]
    n = confusion_matrix.sum().sum()
    phi2 = chi2 / n
    r, k = confusion_matrix.shape
    phi2corr = max(0, phi2 - ((k-1)*(r-1))/(n-1))
    rcorr = r - ((r-1)**2)/(n-1)
    kcorr = k - ((k-1)**2)/(n-1)
    denom = min((kcorr-1), (rcorr-1))
    if denom <= 0:
        return np.nan
    return np.sqrt(phi2corr / denom)

cat_cols = X_train.select_dtypes(include='object').columns
cramers_results = pd.DataFrame(index=cat_cols, columns=cat_cols)

for col1 in cat_cols:
    for col2 in cat_cols:
        if col1 != col2:
            cramers_results.loc[col1, col2] = cramers_v(X_train[col1],
X_train[col2])
        else:
            cramers_results.loc[col1, col2] = 1.00

# Display the heatmap of Cramér's V matrix
cramers_results_float = cramers_results.astype(float)
plt.figure(figsize=(19, 11))
sns.heatmap(cramers_results_float, annot=True, cmap='coolwarm',
fmt=".2f")
plt.title("Cramér's V Matrix of Categorical Features")
plt.show()
```




```
# Pint pairs of categorical features with high Cramér's V for easier selection
high_cramers = []
threshold = 0.8
cat_cols = cramers_results.columns

for i in range(len(cat_cols)):
    for j in range(i):
        value = float(cramers_results.iloc[i, j])
        if value > threshold:
            high_cramers.append((cat_cols[i], cat_cols[j], value))

print("Highly associated categorical pairs (Cramér's V > 0.8):\n")
for pair in high_cramers:
    print(f"{pair[0]} & {pair[1]}: Cramér's V = {pair[2]:.2f}")
```

```
Highly associated categorical pairs (Cramér's V > 0.8):

model & make: Cramér's V = 1.00
model & segment: Cramér's V = 1.00
fuel_type & segment: Cramér's V = 0.88
fuel_type & model: Cramér's V = 1.00
max_torque & make: Cramér's V = 1.00
```

```
max_torque & segment: Cramér's V = 0.97
max_torque & model: Cramér's V = 1.00
max_torque & fuel_type: Cramér's V = 1.00
max_power & make: Cramér's V = 1.00
max_power & segment: Cramér's V = 0.97
max_power & model: Cramér's V = 1.00
max_power & fuel_type: Cramér's V = 1.00
max_power & max_torque: Cramér's V = 1.00
engine_type & make: Cramér's V = 1.00
engine_type & segment: Cramér's V = 1.00
engine_type & model: Cramér's V = 1.00
engine_type & fuel_type: Cramér's V = 1.00
engine_type & max_torque: Cramér's V = 1.00
engine_type & max_power: Cramér's V = 1.00
is_esc & make: Cramér's V = 0.83
is_esc & segment: Cramér's V = 0.86
is_esc & model: Cramér's V = 1.00
is_esc & max_torque: Cramér's V = 0.87
is_esc & max_power: Cramér's V = 0.87
is_esc & engine_type: Cramér's V = 1.00
is_adjustable_steering & segment: Cramér's V = 0.99
is_adjustable_steering & model: Cramér's V = 1.00
is_adjustable_steering & fuel_type: Cramér's V = 0.91
is_adjustable_steering & max_torque: Cramér's V = 1.00
is_adjustable_steering & max_power: Cramér's V = 1.00
is_adjustable_steering & engine_type: Cramér's V = 1.00
is_tpms & make: Cramér's V = 1.00
is_tpms & segment: Cramér's V = 1.00
is_tpms & model: Cramér's V = 1.00
is_tpms & fuel_type: Cramér's V = 0.85
is_tpms & max_torque: Cramér's V = 1.00
is_tpms & max_power: Cramér's V = 1.00
is_tpms & engine_type: Cramér's V = 1.00
is_tpms & is_esc: Cramér's V = 0.83
is_parking_sensors & make: Cramér's V = 1.00
is_parking_sensors & model: Cramér's V = 1.00
is_parking_sensors & max_torque: Cramér's V = 1.00
is_parking_sensors & max_power: Cramér's V = 1.00
is_parking_sensors & engine_type: Cramér's V = 1.00
is_parking_camera & make: Cramér's V = 0.85
is_parking_camera & segment: Cramér's V = 0.82
is_parking_camera & model: Cramér's V = 1.00
is_parking_camera & max_torque: Cramér's V = 0.88
is_parking_camera & max_power: Cramér's V = 0.88
is_parking_camera & engine_type: Cramér's V = 1.00
is_parking_camera & is_esc: Cramér's V = 0.84
rear_brakes_type & make: Cramér's V = 1.00
rear_brakes_type & segment: Cramér's V = 1.00
rear_brakes_type & model: Cramér's V = 1.00
```

```
rear_brakes_type & fuel_type: Cramér's V = 0.85
rear_brakes_type & max_torque: Cramér's V = 1.00
rear_brakes_type & max_power: Cramér's V = 1.00
rear_brakes_type & engine_type: Cramér's V = 1.00
rear_brakes_type & is_esc: Cramér's V = 0.83
rear_brakes_type & is_tpms: Cramér's V = 1.00
transmission_type & make: Cramér's V = 0.85
transmission_type & model: Cramér's V = 1.00
transmission_type & max_torque: Cramér's V = 0.88
transmission_type & max_power: Cramér's V = 0.88
transmission_type & engine_type: Cramér's V = 1.00
transmission_type & is_esc: Cramér's V = 0.90
transmission_type & is_parking_camera: Cramér's V = 0.91
steering_type & segment: Cramér's V = 0.96
steering_type & model: Cramér's V = 1.00
steering_type & max_torque: Cramér's V = 1.00
steering_type & max_power: Cramér's V = 1.00
steering_type & engine_type: Cramér's V = 1.00
is_front_fog_lights & segment: Cramér's V = 0.93
is_front_fog_lights & model: Cramér's V = 1.00
is_front_fog_lights & fuel_type: Cramér's V = 0.85
is_front_fog_lights & max_torque: Cramér's V = 1.00
is_front_fog_lights & max_power: Cramér's V = 1.00
is_front_fog_lights & engine_type: Cramér's V = 1.00
is_front_fog_lights & is_adjustable_steering: Cramér's V = 0.94
is_rear_window_wiper & make: Cramér's V = 0.88
is_rear_window_wiper & segment: Cramér's V = 0.89
is_rear_window_wiper & model: Cramér's V = 1.00
is_rear_window_wiper & max_torque: Cramér's V = 0.89
is_rear_window_wiper & max_power: Cramér's V = 0.89
is_rear_window_wiper & engine_type: Cramér's V = 1.00
is_rear_window_wiper & is_esc: Cramér's V = 0.94
is_rear_window_wiper & is_tpms: Cramér's V = 0.88
is_rear_window_wiper & rear_brakes_type: Cramér's V = 0.88
is_rear_window_wiper & transmission_type: Cramér's V = 0.87
is_rear_window_washer & make: Cramér's V = 0.88
is_rear_window_washer & segment: Cramér's V = 0.89
is_rear_window_washer & model: Cramér's V = 1.00
is_rear_window_washer & max_torque: Cramér's V = 0.89
is_rear_window_washer & max_power: Cramér's V = 0.89
is_rear_window_washer & engine_type: Cramér's V = 1.00
is_rear_window_washer & is_esc: Cramér's V = 0.94
is_rear_window_washer & is_tpms: Cramér's V = 0.88
is_rear_window_washer & rear_brakes_type: Cramér's V = 0.88
is_rear_window_washer & transmission_type: Cramér's V = 0.87
is_rear_window_washer & is_rear_window_wiper: Cramér's V = 1.00
is_rear_window_defogger & make: Cramér's V = 0.84
is_rear_window_defogger & segment: Cramér's V = 0.90
is_rear_window_defogger & model: Cramér's V = 1.00
```

```
is_rear_window_defogger & max_torque: Cramér's V = 0.88
is_rear_window_defogger & max_power: Cramér's V = 0.88
is_rear_window_defogger & engine_type: Cramér's V = 1.00
is_rear_window_defogger & is_esc: Cramér's V = 0.92
is_rear_window_defogger & is_parking_camera: Cramér's V = 0.92
is_rear_window_defogger & transmission_type: Cramér's V = 0.82
is_rear_window_defogger & is_rear_window_wiper: Cramér's V = 0.87
is_rear_window_defogger & is_rear_window_washer: Cramér's V = 0.87
is_brake_assist & segment: Cramér's V = 0.92
is_brake_assist & model: Cramér's V = 1.00
is_brake_assist & fuel_type: Cramér's V = 0.81
is_brake_assist & max_torque: Cramér's V = 1.00
is_brake_assist & max_power: Cramér's V = 1.00
is_brake_assist & engine_type: Cramér's V = 1.00
is_brake_assist & is_adjustable_steering: Cramér's V = 0.86
is_brake_assist & is_front_fog_lights: Cramér's V = 0.91
is_power_door_locks & segment: Cramér's V = 0.91
is_power_door_locks & model: Cramér's V = 1.00
is_power_door_locks & fuel_type: Cramér's V = 0.85
is_power_door_locks & max_torque: Cramér's V = 1.00
is_power_door_locks & max_power: Cramér's V = 1.00
is_power_door_locks & engine_type: Cramér's V = 1.00
is_central_locking & segment: Cramér's V = 0.91
is_central_locking & model: Cramér's V = 1.00
is_central_locking & fuel_type: Cramér's V = 0.85
is_central_locking & max_torque: Cramér's V = 1.00
is_central_locking & max_power: Cramér's V = 1.00
is_central_locking & engine_type: Cramér's V = 1.00
is_central_locking & is_power_door_locks: Cramér's V = 1.00
is_power_steering & segment: Cramér's V = 1.00
is_power_steering & model: Cramér's V = 1.00
is_power_steering & max_torque: Cramér's V = 1.00
is_power_steering & max_power: Cramér's V = 1.00
is_power_steering & engine_type: Cramér's V = 1.00
is_power_steering & steering_type: Cramér's V = 1.00
is_driver_seat_height_adjustable & segment: Cramér's V = 0.95
is_driver_seat_height_adjustable & model: Cramér's V = 1.00
is_driver_seat_height_adjustable & fuel_type: Cramér's V = 0.87
is_driver_seat_height_adjustable & max_torque: Cramér's V = 1.00
is_driver_seat_height_adjustable & max_power: Cramér's V = 1.00
is_driver_seat_height_adjustable & engine_type: Cramér's V = 1.00
is_driver_seat_height_adjustable & is_adjustable_steering: Cramér's V
= 0.93
is_driver_seat_height_adjustable & is_front_fog_lights: Cramér's V =
0.99
is_driver_seat_height_adjustable & is_brake_assist: Cramér's V = 0.93
is_day_night_rear_view_mirror & segment: Cramér's V = 0.85
is_day_night_rear_view_mirror & model: Cramér's V = 1.00
is_day_night_rear_view_mirror & fuel_type: Cramér's V = 0.91
```

```
is_day_night_rear_view_mirror & max_torque: Cramér's V = 1.00
is_day_night_rear_view_mirror & max_power: Cramér's V = 1.00
is_day_night_rear_view_mirror & engine_type: Cramér's V = 1.00
is_day_night_rear_view_mirror & steering_type: Cramér's V = 0.94
is_ecw & segment: Cramér's V = 0.91
is_ecw & model: Cramér's V = 1.00
is_ecw & fuel_type: Cramér's V = 0.85
is_ecw & max_torque: Cramér's V = 1.00
is_ecw & max_power: Cramér's V = 1.00
is_ecw & engine_type: Cramér's V = 1.00
is_ecw & is_power_door_locks: Cramér's V = 1.00
is_ecw & is_central_locking: Cramér's V = 1.00
is_speed_alert & model: Cramér's V = 1.00
is_speed_alert & max_torque: Cramér's V = 1.00
is_speed_alert & max_power: Cramér's V = 1.00
is_speed_alert & engine_type: Cramér's V = 1.00
```

Insight

From the Cramer's V matrix, there are several categorical features showed a strong associations (0.8 and above), with some even reaching perfect correlation of 1.00. These highly indicate redundancy, which could negatively impact model performance.

Examples are:

- `model` and `is_speed_alert` with a correlation of `1.00`
- `max_power` and `transmission_type` with a correlation of `0.88`.

As with numeric numeric features, the decision of which categorical feature to keep was based on domain knowledge -specifically, which feature has a direct explainable assosication with the likelihood of a claim being filed.

Each of the attributes have a high relationship with one another and thus only one is choosen from the lot. The feature retained was: Model as it summarizes several other attributes like power , safety feature, transimssion,... And others can be derived from it.

Drop all highly correlated categorical features

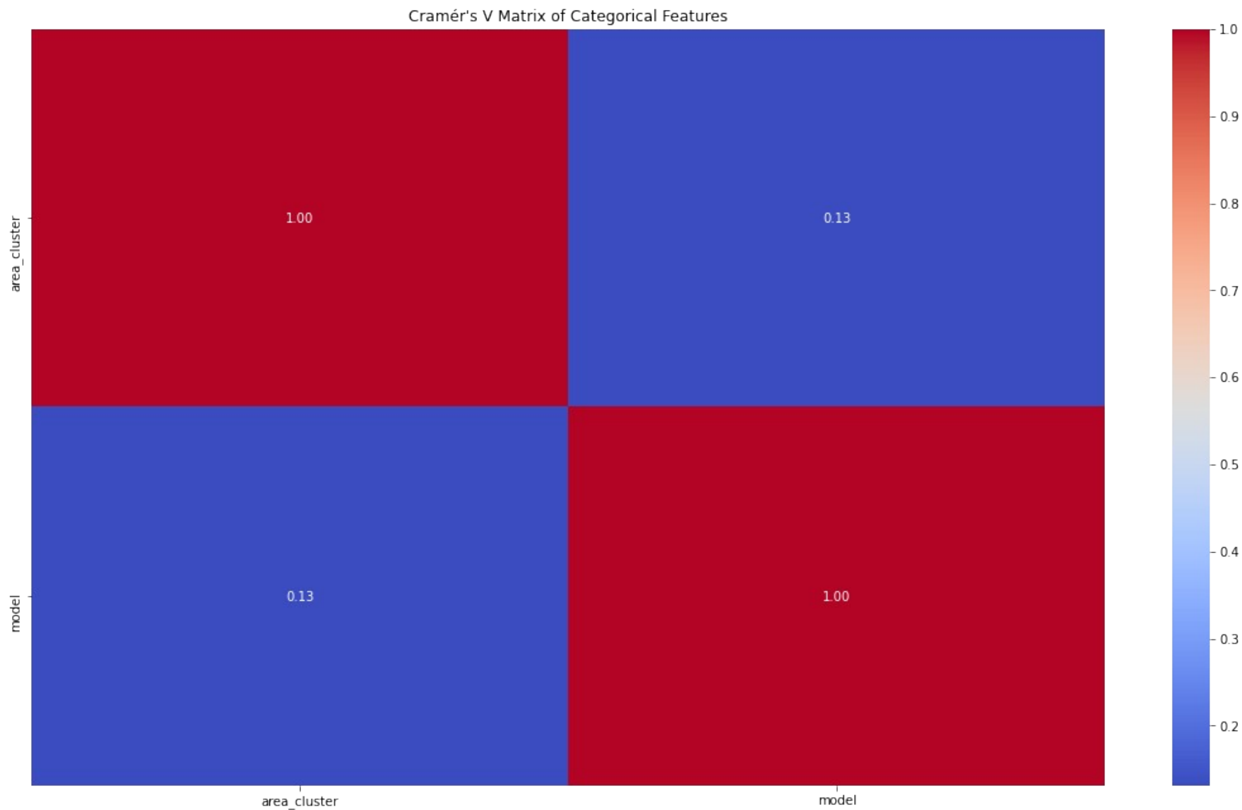
```
cat_col_drop = [
     'segment', 'fuel_type', 'max_torque', 'make',
    'max_power', 'transmission_type','engine_type',
'is_adjustable_steering',
    'is_tpms', 'is_parking_sensors', 'rear_brakes_type',
     'steering_type', 'is_front_fog_lights', 'is_rear_window_wiper',
    'is_rear_window_washer',
    'is_central_locking',  'is_driver_seat_height_adjustable',
'is_day_night_rear_view_mirror',
    'is_ecw', 'is_esc', 'is_parking_camera', 'is_brake_assist',
'is_speed_alert',
    'is_power_door_locks', 'is_power_steering',
'is_rear_window_defogger'
```

```
]


categorical_cols = X_train.select_dtypes(include='object').columns
X_train = X_train.drop(columns=cat_col_drop, axis=1)
X_test = X_test.drop(columns=cat_col_drop, axis=1)


#confirm only the two are present
X_train.select_dtypes(include='object').columns
# X_train.drop(columns=num_cols_keep, inplace=True)
X_train.columns


Index(['policy_tenure', 'age_of_car', 'age_of_policyholder',
'area_cluster',
       'population_density', 'model', 'airbags', 'height',
'ncap_rating'],
      dtype='object')
```

Verify the remaining columns have no high correlation

```
# Verify the remaining columns have no strong correlation


def cramers_v(x, y):
    confusion_matrix = pd.crosstab(x, y)
    chi2 = chi2_contingency(confusion_matrix)[0]
    n = confusion_matrix.sum().sum()
    phi2 = chi2 / n
    r, k = confusion_matrix.shape
    phi2corr = max(0, phi2 - ((k-1)*(r-1))/(n-1))
    rcorr = r - ((r-1)**2)/(n-1)
    kcorr = k - ((k-1)**2)/(n-1)
    return np.sqrt(phi2corr / min((kcorr-1), (rcorr-1)))

cat_cols = X_train.select_dtypes(include='object').columns
cramers_results = pd.DataFrame(index=cat_cols, columns=cat_cols)

for col1 in cat_cols:
    for col2 in cat_cols:
        if col1 != col2:
            cramers_results.loc[col1, col2] = cramers_v(X_train[col1],
X_train[col2])
        else:
            cramers_results.loc[col1, col2] = 1.00

# Display the heatmap of Cramér's V matrix
cramers_results_float = cramers_results.astype(float)
plt.figure(figsize=(19, 11))
```

```
sns.heatmap(cramers_results_float, annot=True, cmap='coolwarm',
fmt=".2f")
plt.title("Cramér's V Matrix of Categorical Features")
plt.show()
```




```
# Total number of Categorical columns
print(X_train.select_dtypes(include='object').columns)

Index(['area_cluster', 'model'], dtype='object')

# Total number of columns left
print(X_train.columns)
len(X_train.columns)

Index(['policy_tenure', 'age_of_car', 'age_of_policyholder',
'area_cluster',
       'population_density', 'model', 'airbags', 'height',
'ncap_rating'],
      dtype='object')

9
```

The original dataset had `44` columns but after performing correlation analysis including `Pearson correlation` for numerical features and`Cramer's V` for categorical features, the highly redundant columns were identified and removed. This reduced the dataset to 9 non-redundant features, indicating there was significant **multicollinearity**.

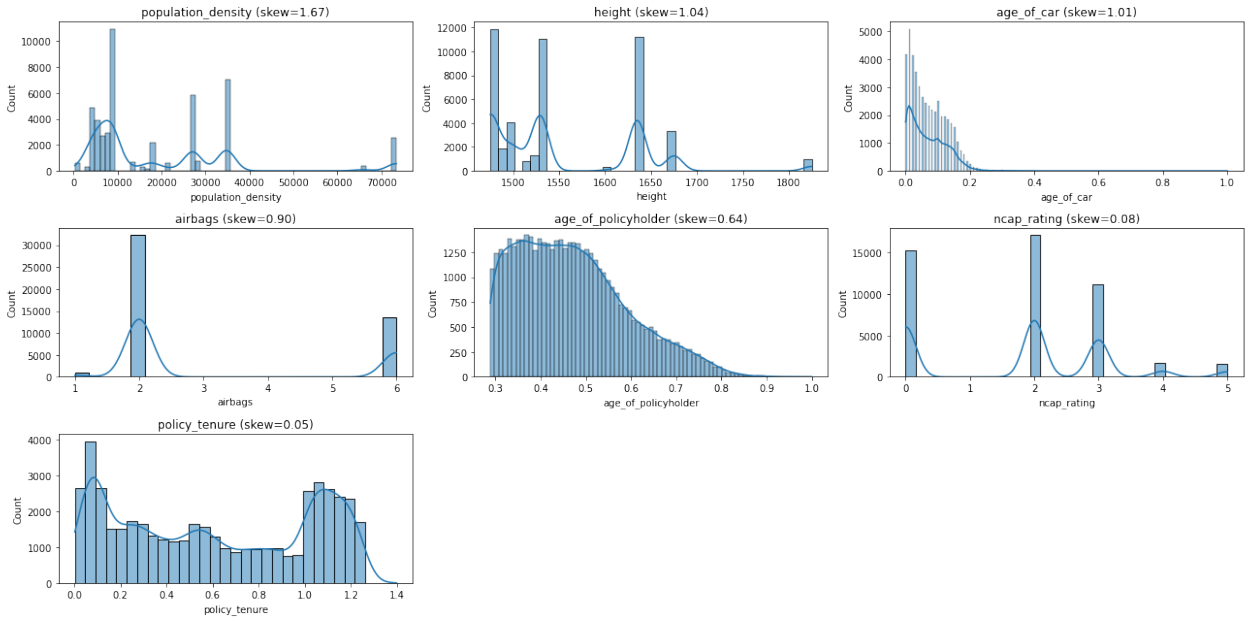
With a cleaner feature set, the next step of preprocessing can be carried out

2. Check for skewness in data

This is done on all numeric columns

```
import math

numeric_cols = X_train.select_dtypes(include='number').columns
skewness = X_train[numeric_cols].skew().sort_values(ascending=False)
print("Skewness of numerical features:\n", skewness)

# Set up the subplot grid
n_cols = 3  # Number of columns in the grid
n_rows = math.ceil(len(skewness) / n_cols)
fig, axes = plt.subplots(n_rows, n_cols, figsize=(6 * n_cols, 3 *
n_rows))

# Flatten axes for easy iteration
axes = axes.flatten()

for i, col in enumerate(skewness.index):
    sns.histplot(X_train[col], kde=True, ax=axes[i])
    axes[i].set_title(f"{col} (skew={skewness[col]:.2f})")

# Remove any unused subplots
for j in range(i + 1, len(axes)):
    fig.delaxes(axes[j])

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

```
Skewness of numerical features:
 population_density     1.673469
height                 1.038330
age_of_car             1.010484
airbags                0.904408
age_of_policyholder    0.644099
ncap_rating            0.083777
policy_tenure          0.047993
dtype: float64
```



Insight: The plot reveals that several features, like `population_density`, `height`, `age_of_car`, and `airbags`, are right-skewed, showing that most values are concentrated at the lower end. From data understanding this suggests, that most cars are relatively new, have fewer airbags, and are of average height, while only a small number have much higher values. The `age_of_policyholder` feature is also right-skewed, meaning most policyholders are younger.

However, features like `ncap_rating` and `policy_tenure` are nearly symmetric, showing a balanced distribution across their ranges. Highly skewed features may benefit from transformation (log transformation) to reduce skewness, which can help improve the performance and stability of machine learning models.

3. Perform transformation

```
# transform the highly skewed features and the moderately skewed
features

from sklearn.preprocessing import FunctionTransformer
skewed_features = ['population_density', 'height', 'age_of_car',
'airbags', 'age_of_policyholder']

# Log1p transformer
log_transformer = FunctionTransformer(np.log1p, validate=True)

# Apply to skewed features
X_train[skewed_features] =
log_transformer.fit_transform(X_train[skewed_features])
X_test[skewed_features] =
log_transformer.transform(X_test[skewed_features])
```

```python
# confirm the skewness of the features has been handled
numeric_cols = X_train.select_dtypes(include='number').columns
skewness = X_train[numeric_cols].skew().sort_values(ascending=False)
print("Skewness of numerical features:\n", skewness)
```

```
Skewness of numerical features:
 height                  0.924394
airbags                 0.836341
age_of_car              0.752415
age_of_policyholder     0.474758
ncap_rating             0.083777
policy_tenure           0.047993
population_density     -0.450551
dtype: float64
```

Insight from confirmation

The features that had an improvement after skewing were `population_density`(from 1.673469 to -0.450551) and `age_of_policyholder` (from 0.644099 to 0.474758). A meaningful reduction in skewness generally in this case reducing from over 0.8 to under 0.5. Make, height and airbags are still highly skewed with over 0.83. Possibility of why some features didn't resopond well to is if data has small integers, was already normalized

Undoing transformation for some features

The reason for undoing the transformation is to reduce unnecessary complexity. The features that remain skewed(> 0.5) are reverted back, as the transformation reduced skewness but not significantly enough to make a strong impact on model performance

```python
# Unding transformation of these features
X_train['height'] = np.expm1(X_train['height'])
X_train['age_of_car'] = np.expm1(X_train['age_of_car'])
X_train['airbags'] = np.expm1(X_train['airbags'])

X_test['height'] = np.expm1(X_test['height'])
X_test['age_of_car'] = np.expm1(X_test['age_of_car'])
X_test['airbags'] = np.expm1(X_test['airbags'])

X_train['age_of_car'][:10]
```

```
47135    0.18
58128    0.09
35000    0.03
6078     0.08
34780    0.01
19269    0.07
45356    0.17
48359    0.19
48178    0.06
```

```
36991    0.05
Name: age_of_car, dtype: float64
```

4. Feature encoding

Encode categorical features which converts them to numeric format that the models can understand

```
# list the categorical features
print(X_train.select_dtypes('object').columns)
```

```
Index(['area_cluster', 'model'], dtype='object')
```

```
# One-hot encode both test and train
X_train = pd.get_dummies(X_train, columns=['area_cluster', 'model'],
drop_first=True)
X_test = pd.get_dummies(X_test, columns=['area_cluster', 'model'],
drop_first=True)

# ensure the test and train have same columns
X_train_encoded, X_test_encoded = X_train.align(X_test, join='left',
axis=1, fill_value=0)

# preview the result of one hot encoding
X_train.head()
```

```
       policy_tenure  age_of_car  age_of_policyholder
population_density  \
47135       0.293321        0.18             0.386047
10.455618
58128       0.393585        0.09             0.290083
8.596189
35000       1.068827        0.03             0.473603
9.081939
6078        0.603159        0.08             0.497273
10.455618
34780       0.830327        0.01             0.424513
8.596189

       airbags  height  ncap_rating  area_cluster_C10
area_cluster_C11  \
47135      2.0  1515.0            2                 0
0
58128      2.0  1675.0            2                 0
0
35000      2.0  1530.0            2                 0
0
6078       2.0  1530.0            2                 0
0
34780      2.0  1475.0            0                 0
```

```
0

       area_cluster_C12  area_cluster_C13  area_cluster_C14
area_cluster_C15  \
47135                 0                 0                 0
0
58128                 0                 1                 0
0
35000                 0                 0                 0
0
6078                  0                 0                 0
0
34780                 0                 1                 0
0

       area_cluster_C16  area_cluster_C17  area_cluster_C18
area_cluster_C19  \
47135                 0                 0                 0
0
58128                 0                 0                 0
0
35000                 0                 0                 0
0
6078                  0                 0                 0
0
34780                 0                 0                 0
0

       area_cluster_C2  area_cluster_C20  area_cluster_C21
area_cluster_C22  \
47135                0                 0                 0
0
58128                0                 0                 0
0
35000                0                 0                 0
0
6078                 0                 0                 0
0
34780                0                 0                 0
0

       area_cluster_C3  area_cluster_C4  area_cluster_C5
area_cluster_C6  \
47135                0                0                1
0
58128                0                0                0
0
35000                0                0                0
0
6078                 0                0                1
```

```
0
34780                0                0                0
0

       area_cluster_C7  area_cluster_C8  area_cluster_C9  model_M10  \
47135                0                0                0          0
58128                0                0                0          0
35000                0                1                0          0
6078                 0                0                0          0
34780                0                0                0          0

       model_M11  model_M2  model_M3  model_M4  model_M5  model_M6
model_M7  \
47135          0         1         0         0         0         0
0
58128          0         0         0         0         0         0
0
35000          0         0         0         0         0         1
0
6078           0         0         0         0         0         1
0
34780          0         0         0         0         0         0
0

       model_M8  model_M9
47135         0         0
58128         1         0
35000         0         0
6078          0         0
34780         0         0
```

```
#view all columns
X_train.columns
```

```
Index(['policy_tenure', 'age_of_car', 'age_of_policyholder',
       'population_density', 'airbags', 'height', 'ncap_rating',
       'area_cluster_C10', 'area_cluster_C11', 'area_cluster_C12',
       'area_cluster_C13', 'area_cluster_C14', 'area_cluster_C15',
       'area_cluster_C16', 'area_cluster_C17', 'area_cluster_C18',
       'area_cluster_C19', 'area_cluster_C2', 'area_cluster_C20',
       'area_cluster_C21', 'area_cluster_C22', 'area_cluster_C3',
       'area_cluster_C4', 'area_cluster_C5', 'area_cluster_C6',
       'area_cluster_C7', 'area_cluster_C8', 'area_cluster_C9',
'model_M10',
       'model_M11', 'model_M2', 'model_M3', 'model_M4', 'model_M5',
'model_M6',
       'model_M7', 'model_M8', 'model_M9'],
      dtype='object')
```

5. Feature Scaling

```
numeric_features = X_train.select_dtypes(include=['float64', 'int64'])
numeric_features.head()
```

```
       policy_tenure  age_of_car  age_of_policyholder
population_density  \
47135       0.293321        0.18             0.386047
10.455618
58128       0.393585        0.09             0.290083
8.596189
35000       1.068827        0.03             0.473603
9.081939
6078        0.603159        0.08             0.497273
10.455618
34780       0.830327        0.01             0.424513
8.596189

       airbags  height  ncap_rating
47135      2.0  1515.0            2
58128      2.0  1675.0            2
35000      2.0  1530.0            2
6078       2.0  1530.0            2
34780      2.0  1475.0            0
```

```
# Store numeric columns in a variable
numeric_features = X_train.select_dtypes(include=['float64',
'int64']).columns

#Initialize scaler
scaler = StandardScaler()

# Fit on training data and transform both train and te  st
X_train[numeric_features] =
scaler.fit_transform(X_train[numeric_features])
X_test[numeric_features] = scaler.transform(X_test[numeric_features])

# check the scaled and the whole dataframe to ensure everything is ok
X_train.head()
```

```
       policy_tenure  age_of_car  age_of_policyholder
population_density  \
47135      -0.769378    1.962404             0.053567
1.072532
58128      -0.527624    0.366329            -1.118040           -
0.879110
35000       1.100508   -0.697721             1.122521           -
0.369271
6078       -0.022301    0.188987             1.411501
1.072532
34780       0.525442   -1.052405             0.523195           -
```

```
0.879110

        airbags    height  ncap_rating  area_cluster_C10
area_cluster_C11  \
47135 -0.620668 -0.482645     0.169917                 0
0
58128 -0.620668  1.525594     0.169917                 0
0
35000 -0.620668 -0.294373     0.169917                 0
0
6078  -0.620668 -0.294373     0.169917                 0
0
34780 -0.620668 -0.984705    -1.268762                 0
0

       area_cluster_C12  area_cluster_C13  area_cluster_C14
area_cluster_C15  \
47135                 0                 0                 0
0
58128                 0                 1                 0
0
35000                 0                 0                 0
0
6078                  0                 0                 0
0
34780                 0                 1                 0
0

       area_cluster_C16  area_cluster_C17  area_cluster_C18
area_cluster_C19  \
47135                 0                 0                 0
0
58128                 0                 0                 0
0
35000                 0                 0                 0
0
6078                  0                 0                 0
0
34780                 0                 0                 0
0

       area_cluster_C2  area_cluster_C20  area_cluster_C21
area_cluster_C22  \
47135                0                 0                 0
0
58128                0                 0                 0
0
35000                0                 0                 0
0
6078                 0                 0                 0
```

```
0
34780                0                 0                 0
0

       area_cluster_C3  area_cluster_C4  area_cluster_C5
area_cluster_C6  \
47135                0                0                1
0
58128                0                0                0
0
35000                0                0                0
0
6078                 0                0                1
0
34780                0                0                0
0

       area_cluster_C7  area_cluster_C8  area_cluster_C9  model_M10  \
47135                0                0                0          0
58128                0                0                0          0
35000                0                1                0          0
6078                 0                0                0          0
34780                0                0                0          0

       model_M11  model_M2  model_M3  model_M4  model_M5  model_M6
model_M7  \
47135          0         1         0         0         0         0
0
58128          0         0         0         0         0         0
0
35000          0         0         0         0         0         1
0
6078           0         0         0         0         0         1
0
34780          0         0         0         0         0         0
0

       model_M8  model_M9
47135         0         0
58128         1         0
35000         0         0
6078          0         0
34780         0         0
```

Check for class imbalance

Check for imbalance in the target variable To determine if rebalancing is needed either via smote or undersampling the major class

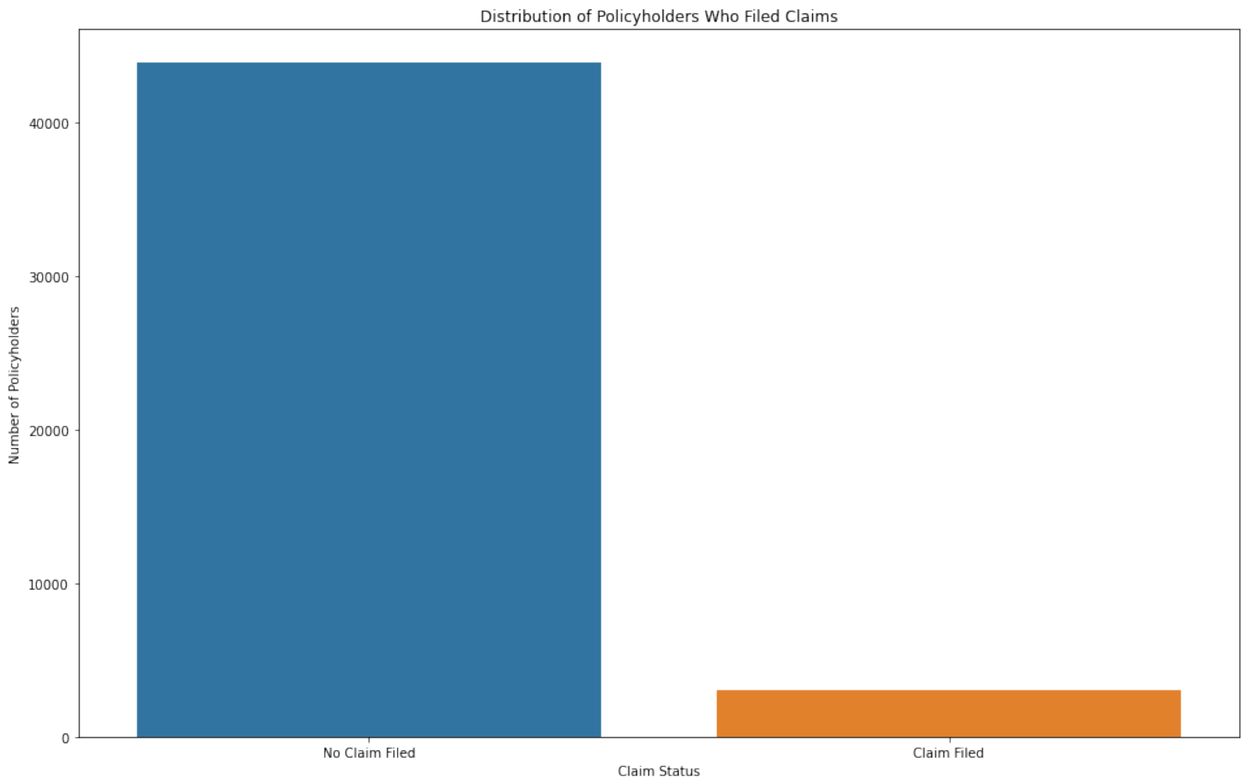
```
# check the distribution to confirm imbalance
print("Train distribution:\n", y_train.value_counts(normalize=True))
```

```
Train distribution:
 0    0.93604
1    0.06396
Name: is_claim, dtype: float64
```

Observation: The dataset is heavily imbalanced with approximately **6.4%** positive claims and **93.6%** negative claims.

`SMOTE`was performed however it was later seen to reduce the model performance by some points thus the alternative of using the parameter `class_weight='balanced'` worked well

```
# ...existing code...
import matplotlib.pyplot as plt
import seaborn as sns

# Map 0 and 1 to descriptive labels
y_train_named = y_train.map({0: "No Claim Filed", 1: "Claim Filed"})

plt.figure(figsize=(16, 10))
sns.countplot(x=y_train_named)
plt.title('Distribution of Policyholders Who Filed Claims')
plt.xlabel('Claim Status')
plt.ylabel('Number of Policyholders')
plt.show()
# ...existing code...
```



Insight: As you can see, the dataset is heavily imbalanced. The vast majority of policyholders do not file a claim (class 0) while only a small fraction filed a claim (class 1).

BUILDING BASELINE MODELS

1. Logistic Regression Model

```
# create a function to call multiple times to evaluate performance
after each change


 # Initialize models
log_reg = LogisticRegression(max_iter=1000, random_state=42,
class_weight='balanced')

 # Perform 5-fold cross-validation
log_reg_scores = cross_val_score(log_reg, X_train, y_train, cv=5,
scoring='roc_auc')

 # Display results
print("Logistic Regression ROC-AUC Scores:", log_reg_scores)
print("Logistic Regression Average ROC-AUC:", np.mean(log_reg_scores))
```

```
Logistic Regression ROC-AUC Scores: [0.59627483 0.6282944  0.60060361
0.61287578 0.61544607]
Logistic Regression Average ROC-AUC: 0.6106989372918143
```

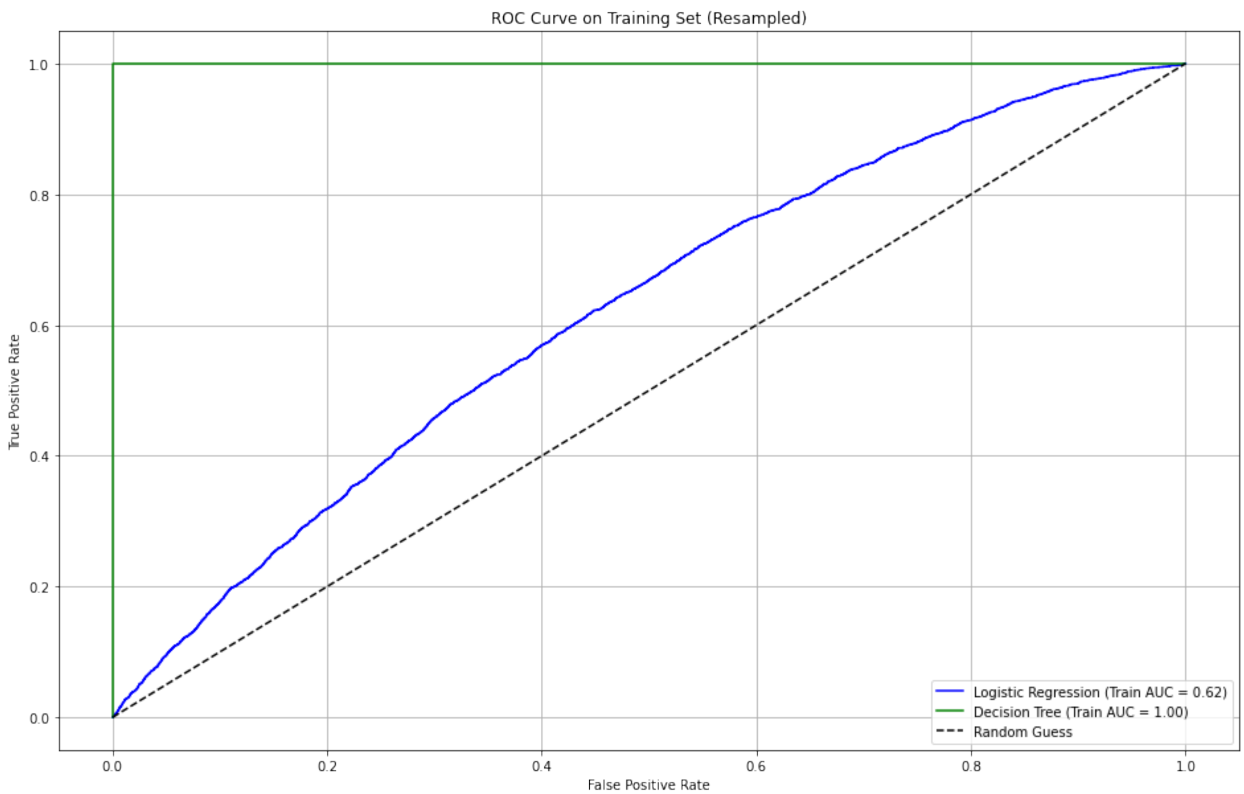
2.Decision Tree

```
#Initialize models
decision_tree = DecisionTreeClassifier(random_state=42)

# Perform 5-fold cross-validation
tree_scores = cross_val_score(decision_tree, X_train, y_train, cv=5,
scoring= 'roc_auc')

# Display results
print("Decision Tree ROC-AUC Scores:", tree_scores)
print("Decision Tree Average ROC-AUC:", np.mean(tree_scores))

Decision Tree ROC-AUC Scores: [0.49507835 0.51211538 0.50345442
0.50323474 0.50443132]
Decision Tree Average ROC-AUC: 0.503662840251321
```

Visualizing the performance of both models using the ROC-AUC curve on the train data

```
from sklearn.metrics import roc_curve, auc
import matplotlib.pyplot as plt

# Fit on resampled training set
log_reg.fit(X_train, y_train)
decision_tree.fit(X_train, y_train)

#call predict_proba
log_reg_train_probs = log_reg.predict_proba(X_train)[:, 1]
tree_train_probs = decision_tree.predict_proba(X_train)[:, 1]

#Predict on train
log_reg_train_probs = log_reg.predict_proba(X_train)[:, 1]
tree_train_probs = decision_tree.predict_proba(X_train)[:, 1]

#ROC curve
fpr_log_train, tpr_log_train, _ = roc_curve(y_train,
log_reg_train_probs)
fpr_tree_train, tpr_tree_train, _ = roc_curve(y_train,
tree_train_probs)

# calculate AUC score
auc_log_train = auc(fpr_log_train, tpr_log_train)
auc_tree_train = auc(fpr_tree_train, tpr_tree_train)

#Plot
plt.figure(figsize=(16, 10))
plt.plot(fpr_log_train, tpr_log_train, label=f'Logistic Regression
(Train AUC = {auc_log_train:.2f})', color='blue')
plt.plot(fpr_tree_train, tpr_tree_train, label=f'Decision Tree (Train
```

```
AUC = {auc_tree_train:.2f})', color='green')
plt.plot([0, 1], [0, 1], 'k--', label='Random Guess')

plt.title('ROC Curve on Training Set (Resampled)')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.legend(loc='lower right')
plt.grid(True)
plt.show()
```



Obervation: From the ROC curve visualization on the training data, Logistic Regression achieved an auc of 0.62, indicating the models ability to distinquish between classes. In contrast the decision tree showed an auc of 1.00 which is a high sign of overfitting, suggesting decision tree has memorized the train set and may not generalize well on unseen data.

Testing both models on the test set is necessary to evaluate their real-world performance

Evaluate the performance of the models on the test set

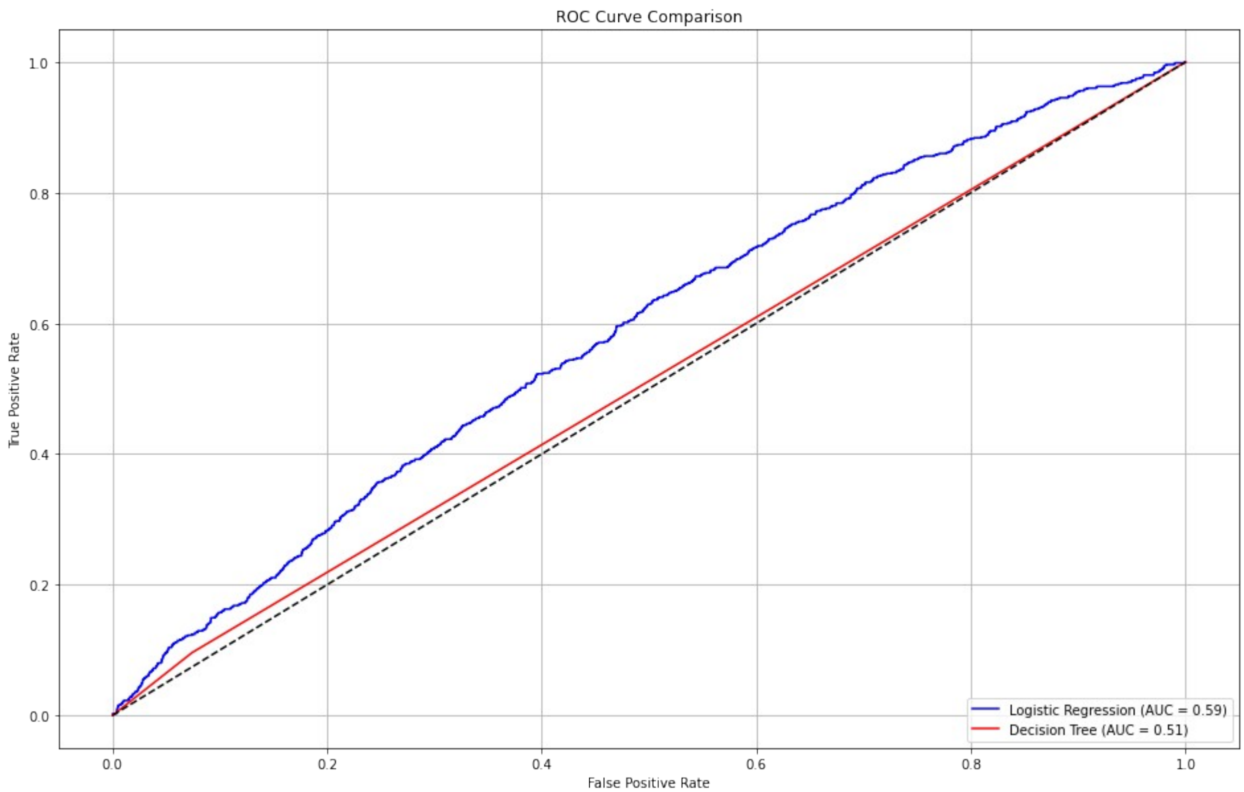
```
# Fit on resampled training set
log_reg.fit(X_train, y_train)
decision_tree.fit(X_train, y_train)

#call predict_proba
log_reg_probs = log_reg.predict_proba(X_test)[:, 1]
tree_probs = decision_tree.predict_proba(X_test)[:, 1]
```

```
#Predict on train
log_reg_auc = roc_auc_score(y_test, log_reg_probs)
tree_auc = roc_auc_score(y_test, tree_probs)

print("Logistic Regression ROC-AUC on Test Set:", log_reg_auc)
print("Decision Tree ROC-AUC on Test Set:", tree_auc)
```

```
Logistic Regression ROC-AUC on Test Set: 0.5860898896891238
Decision Tree ROC-AUC on Test Set: 0.5109410155893883
```

Visualizing the performance of both models using the ROC-AUC curve on the `test` data

```
#Get FPR, TPR for both models
fpr_log, tpr_log, _ = roc_curve(y_test, log_reg_probs)
fpr_tree, tpr_tree, _ = roc_curve(y_test, tree_probs)

# Calculate AUC
roc_auc_log = auc(fpr_log, tpr_log)
roc_auc_tree = auc(fpr_tree, tpr_tree)

# Plot the ROC curves
plt.figure(figsize=(16, 10))
plt.plot(fpr_log, tpr_log, color='blue', label=f'Logistic Regression
(AUC = {roc_auc_log:.2f})')
plt.plot(fpr_tree, tpr_tree, color='red', label=f'Decision Tree (AUC =
{roc_auc_tree:.2f})')
plt.plot([0, 1], [0, 1], color='black', linestyle='--')  # Diagonal
line for random guess
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve Comparison')
plt.legend(loc='lower right')
plt.grid(True)
plt.show()
```



Observation: When evaluated on the unseen test data, the AUC score drops significantly in both:

- Logistic Regression: The AUC score decreased from 0.62 to 0.59, indicating moderate overfitting and limited generalization to new data
- Decision Tree: The AUC score dropped from 1.00 to 0.51. This suggests the model memorized the training data but failed to generalize. Its test performance is no better than random guessing

This result shows that neither model generalizes well to unseen data, with Decision Tree clearly overfitting and Logistic Regression performing slightly better.

Selecting a model to improve

Despite its limitations. Logistic Regression shows more stable and generalizable behavior compared to Decision Tree. The drop in AUC in test data suggests room for improvement but it mainains a performance above 0.5 and avoids extreme overfitting which is seen in the decision tree. Based on this reason logistic regression is selected as the model to proceed with for further refinement including hyperparameter tuning

```
# create a function to call multiple times to evaluate performance
after each change

def evaluate_log_reg(X, y):

 # Initialize models
```

```
 log_reg = LogisticRegression(max_iter=1000, random_state=42,
class_weight='balanced')

 # Perform 5-fold cross-validation
 log_reg_scores = cross_val_score(log_reg, X, y, cv=5,
scoring='roc_auc')

 # Display results
 print("Logistic Regression ROC-AUC Scores:", log_reg_scores)
 print("Logistic Regression Average ROC-AUC:",
np.mean(log_reg_scores))

evaluate_log_reg(X_train, y_train)

Logistic Regression ROC-AUC Scores: [0.59627483 0.6282944  0.60060361
0.61287578 0.61544607]
Logistic Regression Average ROC-AUC: 0.6106989372918143
```

More Feature Engineering

The aim of this section is to engineer features that will be able to reveal underlying patterns in the data, enabling the Logistic Regression model to learn more effectively and improve its predictive performance

```
#Display the dataset to have an overview
X_train.head()

       policy_tenure  age_of_car  age_of_policyholder
population_density  \
47135      -0.769378    1.962404             0.053567
1.072532
58128      -0.527624    0.366329            -1.118040           -
0.879110
35000       1.100508   -0.697721             1.122521           -
0.369271
6078       -0.022301    0.188987             1.411501
1.072532
34780       0.525442   -1.052405             0.523195           -
0.879110

        airbags    height  ncap_rating  area_cluster_C10
area_cluster_C11  \
47135 -0.620668 -0.482645     0.169917                 0
0
58128 -0.620668  1.525594     0.169917                 0
0
35000 -0.620668 -0.294373     0.169917                 0
0
6078  -0.620668 -0.294373     0.169917                 0
```

```
0
34780 -0.620668 -0.984705    -1.268762                 0
0

       area_cluster_C12  area_cluster_C13  area_cluster_C14
area_cluster_C15  \
47135                 0                 0                 0
0
58128                 0                 1                 0
0
35000                 0                 0                 0
0
6078                  0                 0                 0
0
34780                 0                 1                 0
0

       area_cluster_C16  area_cluster_C17  area_cluster_C18
area_cluster_C19  \
47135                 0                 0                 0
0
58128                 0                 0                 0
0
35000                 0                 0                 0
0
6078                  0                 0                 0
0
34780                 0                 0                 0
0

       area_cluster_C2  area_cluster_C20  area_cluster_C21
area_cluster_C22  \
47135                0                 0                 0
0
58128                0                 0                 0
0
35000                0                 0                 0
0
6078                 0                 0                 0
0
34780                0                 0                 0
0

       area_cluster_C3  area_cluster_C4  area_cluster_C5
area_cluster_C6  \
47135                0                0                1
0
58128                0                0                0
0
35000                0                0                0
```

```
0
6078                    0                 0                 1
0
34780                   0                 0                 0
0

       area_cluster_C7  area_cluster_C8  area_cluster_C9  model_M10  \
47135                0                0                0          0
58128                0                0                0          0
35000                0                1                0          0
6078                 0                0                0          0
34780                0                0                0          0

       model_M11  model_M2  model_M3  model_M4  model_M5  model_M6
model_M7  \
47135          0         1         0         0         0         0
0
58128          0         0         0         0         0         0
0
35000          0         0         0         0         0         1
0
6078           0         0         0         0         0         1
0
34780          0         0         0         0         0         0
0

       model_M8  model_M9
47135         0         0
58128         1         0
35000         0         0
6078          0         0
34780         0         0
```

Polynormial Transformation

Polynormial Transformation is performed to created new features by squaring existing numerical variables (`age_of_car` and `age_of_policyholder`) to help the logistic regression model capture non-linear relationships that the original linear features might miss.

```
# Add polynomial terms
X_train['age_of_car_squared'] = X_train['age_of_car'] ** 2
X_train['age_of_policyholder_squared'] =
X_train['age_of_policyholder'] ** 2

X_test['age_of_car_squared'] = X_test['age_of_car'] ** 2
X_test['age_of_policyholder_squared'] = X_test['age_of_policyholder']
** 2

X_train.head()
```

```
       policy_tenure  age_of_car  age_of_policyholder
population_density  \
47135      -0.769378    1.962404             0.053567
1.072532
58128      -0.527624    0.366329            -1.118040           -
0.879110
35000       1.100508   -0.697721             1.122521           -
0.369271
6078       -0.022301    0.188987             1.411501
1.072532
34780       0.525442   -1.052405             0.523195           -
0.879110

        airbags    height  ncap_rating  area_cluster_C10
area_cluster_C11  \
47135 -0.620668 -0.482645     0.169917                 0
0
58128 -0.620668  1.525594     0.169917                 0
0
35000 -0.620668 -0.294373     0.169917                 0
0
6078  -0.620668 -0.294373     0.169917                 0
0
34780 -0.620668 -0.984705    -1.268762                 0
0

       area_cluster_C12  area_cluster_C13  area_cluster_C14
area_cluster_C15  \
47135                 0                 0                 0
0
58128                 0                 1                 0
0
35000                 0                 0                 0
0
6078                  0                 0                 0
0
34780                 0                 1                 0
0

       area_cluster_C16  area_cluster_C17  area_cluster_C18
area_cluster_C19  \
47135                 0                 0                 0
0
58128                 0                 0                 0
0
35000                 0                 0                 0
0
6078                  0                 0                 0
0
34780                 0                 0                 0
```

```
0

       area_cluster_C2  area_cluster_C20  area_cluster_C21
area_cluster_C22  \
47135                0                 0                 0
0
58128                0                 0                 0
0
35000                0                 0                 0
0
6078                 0                 0                 0
0
34780                0                 0                 0
0

       area_cluster_C3  area_cluster_C4  area_cluster_C5
area_cluster_C6  \
47135                0                0                1
0
58128                0                0                0
0
35000                0                0                0
0
6078                 0                0                1
0
34780                0                0                0
0

       area_cluster_C7  area_cluster_C8  area_cluster_C9  model_M10  \
47135                0                0                0          0
58128                0                0                0          0
35000                0                1                0          0
6078                 0                0                0          0
34780                0                0                0          0

       model_M11  model_M2  model_M3  model_M4  model_M5  model_M6
model_M7  \
47135          0         1         0         0         0         0
0
58128          0         0         0         0         0         0
0
35000          0         0         0         0         0         1
0
6078           0         0         0         0         0         1
0
34780          0         0         0         0         0         0
0

       model_M8  model_M9  age_of_car_squared
age_of_policyholder_squared
```

```
47135          0         0            3.851030
0.002869
58128          1         0            0.134197
1.250013
35000          0         0            0.486815
1.260054
6078           0         0            0.035716
1.992335
34780          0         0            1.107556
0.273733
```

This can help capture non-linear patterns for logistic regression which it can't learn easily

Tuning Logistic Regression model

```
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import GridSearchCV
# Define model
log_reg = LogisticRegression(max_iter=1000, class_weight='balanced',
random_state=42)

# hyperparameter grid
param_grid = {
    'C': [0.01, 0.1, 1, 10, 100],
    'penalty': ['l1', 'l2'],
    'solver': ['liblinear']  #supports l1 and l2
}

# Setup GridSearchCV with 5-fold CV
grid_search = GridSearchCV(log_reg, param_grid, cv=5,
scoring='roc_auc', n_jobs=-1)

# Fit on training data
grid_search.fit(X_train, y_train)

# Best params and score
print("Best parameters:", grid_search.best_params_)
print("Best ROC-AUC score:", grid_search.best_score_)

Best parameters: {'C': 0.01, 'penalty': 'l2', 'solver': 'liblinear'}
Best ROC-AUC score: 0.6112356411049121

# Retrain the model with the best hyperparameters
log_reg = LogisticRegression(
    max_iter=1000,
    random_state=42,
    class_weight='balanced',
    C=0.01,
    penalty='l2',
```

```
    solver='liblinear'
)

# Fit the model on the full training data
log_reg.fit(X_train, y_train)
```

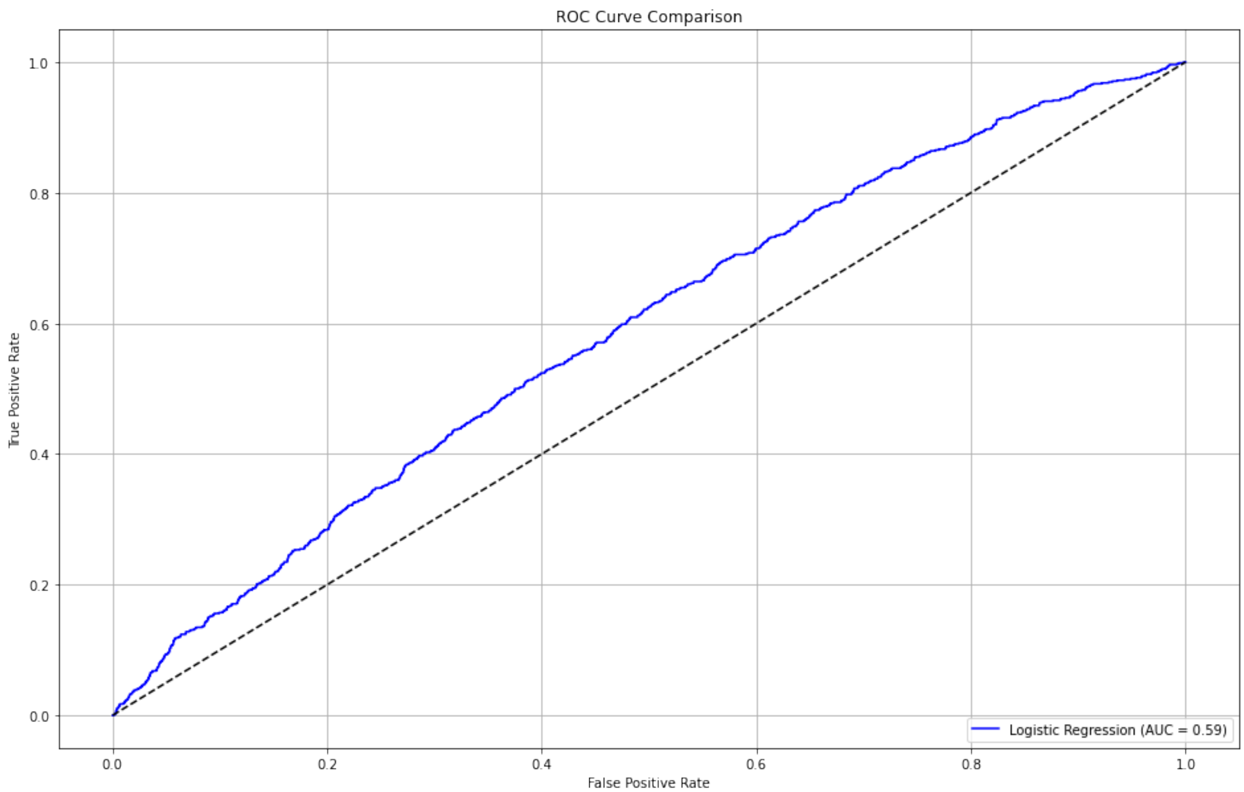
```
LogisticRegression(C=0.01, class_weight='balanced', max_iter=1000,
                   random_state=42, solver='liblinear')
```

```
#Evaluate model performance on test data
log_reg_probs = log_reg.predict_proba(X_test)[:, 1]

# Calculate AUC score on test data
test_auc = roc_auc_score(y_test, log_reg_probs)

print("Test ROC-AUC:", test_auc)
```

```
Test ROC-AUC: 0.5882912450238551
```

Visualizing Logistic Regression performance after tuning

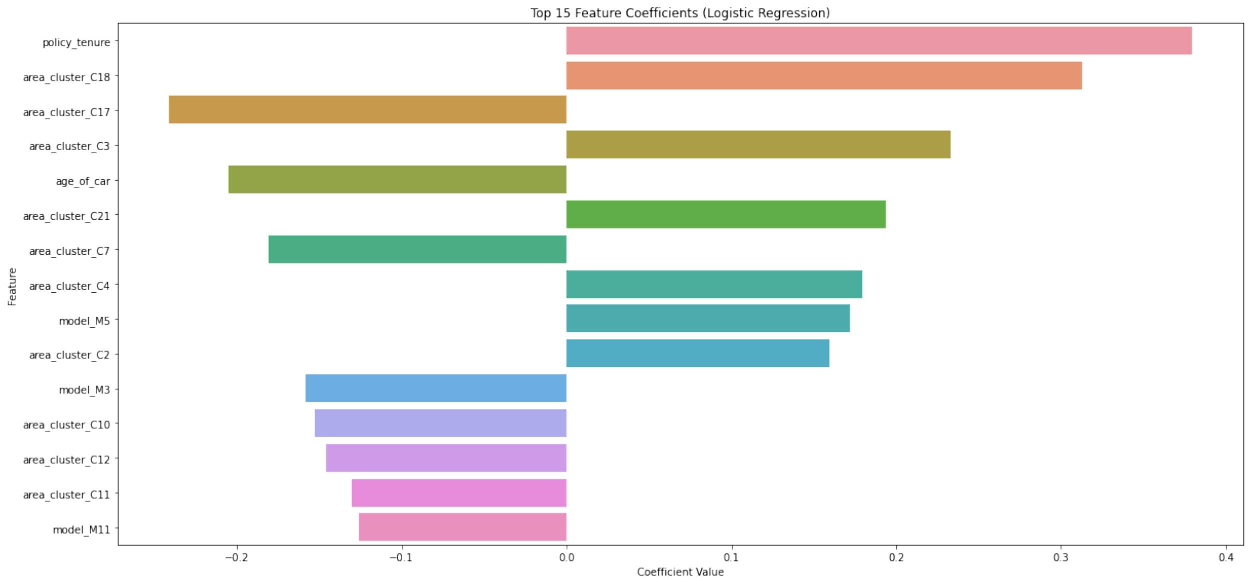
```
#Get FPR, TPR for both models
fpr_log, tpr_log, _ = roc_curve(y_test, log_reg_probs)

# Calculate AUC
roc_auc_log = auc(fpr_log, tpr_log)

# Plot the ROC curves
plt.figure(figsize=(16, 10))
plt.plot(fpr_log, tpr_log, color='blue', label=f'Logistic Regression
(AUC = {roc_auc_log:.2f})')
plt.plot([0, 1], [0, 1], color='black', linestyle='--')  # Diagonal
line for random guess
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve Comparison')
plt.legend(loc='lower right')
plt.grid(True)
plt.show()
```



Insight

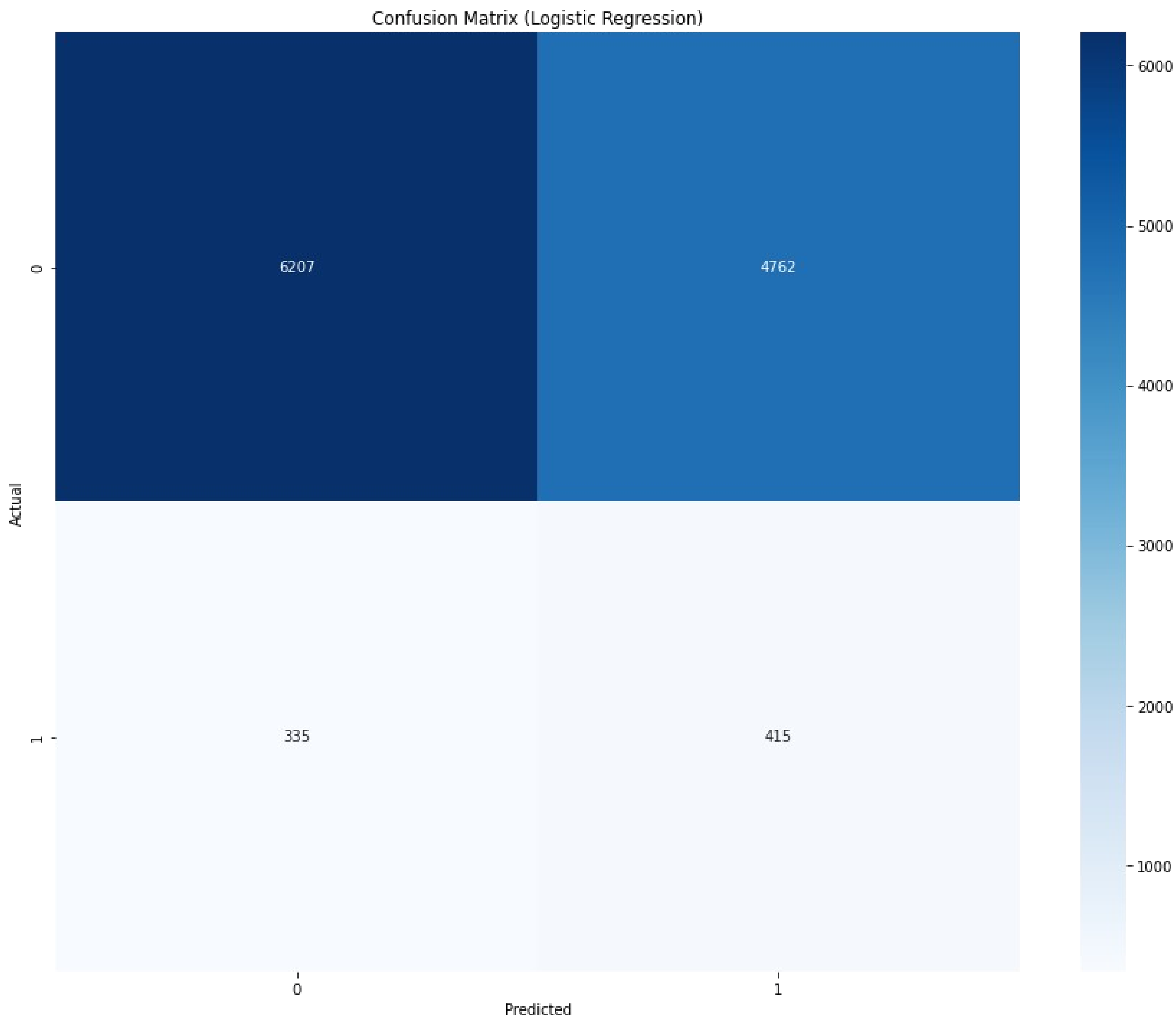
After tuning and feature selection, logistic regression consistently achieved an AUC score around 0.59, with only marginal improvements observed. For further gains, incorporating more sophisticated models can increase the AUC score.

```
# Get feature names and coefficients
features = X_train.columns
coefficients = log_reg.coef_[0]

# Get indices of top 15 features by absolute coefficient value
indices = np.argsort(np.abs(coefficients))[::-1][:15]

plt.figure(figsize=(17,8))
sns.barplot(x=coefficients[indices], y=features[indices])
plt.title("Top 15 Feature Coefficients (Logistic Regression)")
plt.xlabel("Coefficient Value")
plt.ylabel("Feature")
plt.tight_layout()
plt.show()
```



Insight The bar plot shows the top 15 features (by absolute coefficient value) from the Logistic Regression model. Features like policy_tenure, several area_cluster categories, and age_of_car have the largest influence on the model's predictions. The direction (positive or negative) of each bar indicates whether the feature increases or decreases the likelihood of a claim

```
from sklearn.metrics import confusion_matrix

cm = confusion_matrix(y_test, log_reg.predict(X_test))
plt.figure(figsize=(15, 12))  # Set the figure size here
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix (Logistic Regression)')
plt.show()
```



Insight: The confusion matrix for the Logistic Regression model shows that while most non-claim cases (class 0) are correctly identified, a large number of them are incorrectly predicted as claims (false positives). For actual claims (class 1), the model correctly identifies some but misses many (false negatives). This highlights the challenge of predicting rare events in imbalanced datasets, where the model struggles to accurately capture the minority class.

4. RANDOM FOREST

Training basic Random Forest model

```
def evaluate_random_forest(X, y):
    # Initialize the Random Forest model with a fixed random state for reproducibility
    rf = RandomForestClassifier(random_state=42, class_weight='balanced', n_jobs=-1)

    # Perform 5-fold cross-validation and get ROC-AUC scores
```

```
    rf_scores = cross_val_score(rf, X, y, cv=5, scoring='roc_auc',
n_jobs=-1)

    # Print the ROC-AUC scores for each fold and their average
    print("Random Forest ROC-AUC Scores:", rf_scores)
    print("Random Forest Average ROC-AUC:", np.mean(rf_scores))

# Call the function with your training data
evaluate_random_forest(X_train, y_train)

Random Forest ROC-AUC Scores: [0.5666886  0.56445185 0.54970266
0.5652864  0.57218841]
Random Forest Average ROC-AUC: 0.5636635837189872
```

Tuning the Random Forest Model to see if its performance increases

```
from sklearn.model_selection import GridSearchCV
from sklearn.ensemble import RandomForestClassifier

# Perform tuning
rf = RandomForestClassifier(random_state=42, class_weight='balanced',
n_jobs=-1)

param_grid = {
    'n_estimators': [100, 200],
    'max_depth': [5, 10, None],
    'min_samples_split': [2, 5],
    'min_samples_leaf': [1, 2]
}

grid_search = GridSearchCV(rf, param_grid, cv=5, scoring='roc_auc',
n_jobs=-1)
grid_search.fit(X_train, y_train)

print("Best parameters:", grid_search.best_params_)
print("Best ROC-AUC score:", grid_search.best_score_)

Best parameters: {'max_depth': 5, 'min_samples_leaf': 1,
'min_samples_split': 2, 'n_estimators': 100}
Best ROC-AUC score: 0.647088681832811
```

Testing the tuned Random Forest Model on the test data to see its performance on unseen data

```
#Adding the best hyperparameters

# Initialize Random Forest with tuned parameters
rf_par = RandomForestClassifier(
    max_depth=5,
    min_samples_leaf=1,
    min_samples_split=2,
```

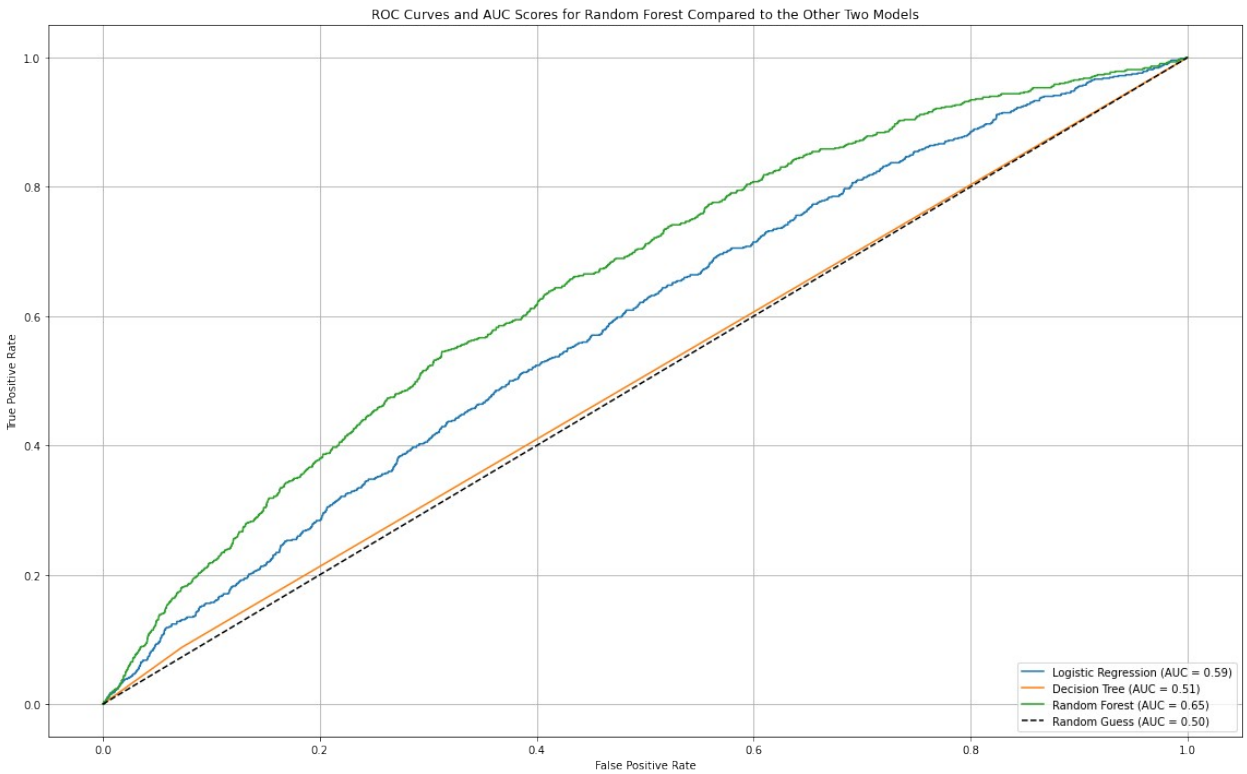
```
    n_estimators=100,
    random_state=42,
    class_weight='balanced'
)

# 3. Fit the model on the full training data
rf_par.fit(X_train, y_train)

# 4. Predict probabilities on test set (for positive class)
rf_test_probs = rf_par.predict_proba(X_test)[:, 1]

# 5. Calculate ROC-AUC on test set
test_auc = roc_auc_score(y_test, rf_test_probs)
print(f"Random Forest Test ROC-AUC: {test_auc: }")
```

```
Random Forest Test ROC-AUC:  0.6549892727991005
```

Visualizing its performance compared with other models

```
decision_tree = DecisionTreeClassifier(random_state=42)
decision_tree.fit(X_train, y_train)  # Refit after all feature
engineering
tree_probs = decision_tree.predict_proba(X_test)[:, 1]

#Get predicted probabilities for each model
log_reg_probs = log_reg.predict_proba(X_test)[:, 1]
tree_probs = decision_tree.predict_proba(X_test)[:, 1]
rf_probs = rf_par.predict_proba(X_test)[:, 1]

#Compute ROC curves and AUCs
fpr_log, tpr_log, _ = roc_curve(y_test, log_reg_probs)
fpr_tree, tpr_tree, _ = roc_curve(y_test, tree_probs)
fpr_rf, tpr_rf, _ = roc_curve(y_test, rf_probs)

auc_log = auc(fpr_log, tpr_log)
auc_tree = auc(fpr_tree, tpr_tree)
auc_rf = auc(fpr_rf, tpr_rf)

# Plot the figures
plt.figure(figsize=(16, 10))
plt.plot(fpr_log, tpr_log, label=f"Logistic Regression (AUC =
{auc_log:.2f})")
plt.plot(fpr_tree, tpr_tree, label=f"Decision Tree (AUC =
{auc_tree:.2f})")
plt.plot(fpr_rf, tpr_rf, label=f"Random Forest (AUC = {auc_rf:.2f})")

# Chance line
plt.plot([0, 1], [0, 1], 'k--', label='Random Guess (AUC = 0.50)')

# labels and formatting
plt.xlabel("False Positive Rate")
```

```
plt.ylabel("True Positive Rate")
plt.title("ROC Curves and AUC Scores for Random Forest Compared to the Other Two Models")
plt.legend(loc="lower right")
plt.grid(True)
plt.tight_layout()
plt.show()
```



Insight: This ROC curve shows that the Random Forest model (AUC = 0.65) outperforms both Logistic Regression (AUC = 0.59) and Decision Tree (AUC = 0.51) in distinguishing between claim and non-claim cases.

4. XGBOOST

Training basic basic XGBoost model

```
# Initialize XGBoost model
xgb = XGBClassifier(eval_metric='logloss', random_state=42)

# 5-fold cross-validation with ROC-AUC scoring
xgb_scores = cross_val_score(xgb, X_train, y_train, cv=5, scoring='roc_auc')

# Display results
print("XGBoost ROC-AUC Scores:", xgb_scores)
print("XGBoost Average ROC-AUC:", np.mean(xgb_scores))
```

```
XGBoost ROC-AUC Scores: [0.60996828 0.61497388 0.59971491 0.62664146
0.6213211 ]
XGBoost Average ROC-AUC: 0.6145239267408327
```

Tuning the XGBoost Model to see if its performance increases

```
# get best parameters
xgb = XGBClassifier(random_state=42,eval_metric='logloss')

# hyperparameter grid
param_grid = {
    'n_estimators': [100, 200],
    'max_depth': [3, 5, 7],
    'learning_rate': [0.01, 0.1, 0.2],
    'subsample': [0.8, 1.0],
    'colsample_bytree': [0.8, 1.0]
}

# GridSearchCV
grid_search = GridSearchCV(estimator=xgb, param_grid=param_grid,
scoring='roc_auc', cv=5, n_jobs=-1,
    verbose=1
)

#Fit the model
grid_search.fit(X_train, y_train)

#Print best parameters and score
print("Best Parameters:", grid_search.best_params_)
print("Best ROC-AUC Score (CV):", grid_search.best_score_)
```

```
Fitting 5 folds for each of 72 candidates, totalling 360 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 8 concurrent
workers.
[Parallel(n_jobs=-1)]: Done  34 tasks      | elapsed:   59.0s
[Parallel(n_jobs=-1)]: Done 184 tasks      | elapsed:  6.0min
[Parallel(n_jobs=-1)]: Done 360 out of 360 | elapsed: 13.6min finished

Best Parameters: {'colsample_bytree': 0.8, 'learning_rate': 0.01,
'max_depth': 5, 'n_estimators': 200, 'subsample': 0.8}
Best ROC-AUC Score (CV): 0.6521241153426016
```

Testing the tuned XGBoost Model on the test data to see its performance on unseen data

```
# Initialize XGBoost with best parameters
xgb_par = XGBClassifier(
    n_estimators=200,
    max_depth=5,
    learning_rate=0.01,
```

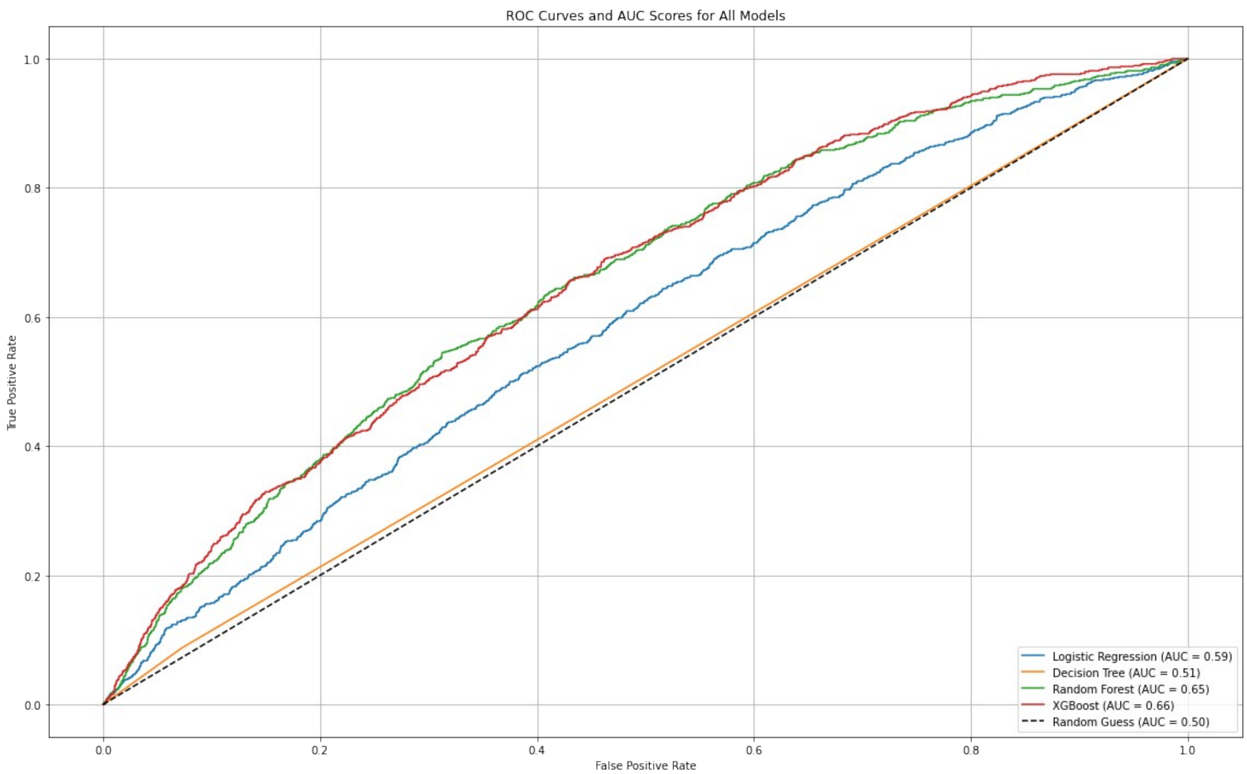
```
    subsample=0.8,
    colsample_bytree=0.8,
    eval_metric='logloss',
    random_state=42
)

# Fit the model on full training data
xgb_par.fit(X_train, y_train)

# Predict probabilities on the test set
xgb_test_probs = xgb_par.predict_proba(X_test)[:, 1]

# Evaluate using ROC-AUC on test set
xgb_test_auc = roc_auc_score(y_test, xgb_test_probs)
print(f"XGBoost Test ROC-AUC: {xgb_test_auc:.4f}")
```

```
XGBoost Test ROC-AUC: 0.6583
```

Visualizing its performance compared with other models

```
from sklearn.metrics import roc_curve, auc
import matplotlib.pyplot as plt

# 1. Get predicted probabilities for each model
log_reg_probs = log_reg.predict_proba(X_test)[:, 1]
tree_probs = decision_tree.predict_proba(X_test)[:, 1]
rf_probs = rf_par.predict_proba(X_test)[:, 1]
xgb_probs = xgb_par.predict_proba(X_test)[:, 1]

# 2. Compute ROC curves and AUCs
fpr_log, tpr_log, _ = roc_curve(y_test, log_reg_probs)
fpr_tree, tpr_tree, _ = roc_curve(y_test, tree_probs)
fpr_rf, tpr_rf, _ = roc_curve(y_test, rf_probs)
fpr_xgb, tpr_xgb, _ = roc_curve(y_test, xgb_probs)

auc_log = auc(fpr_log, tpr_log)
auc_tree = auc(fpr_tree, tpr_tree)
auc_rf = auc(fpr_rf, tpr_rf)
auc_xgb = auc(fpr_xgb, tpr_xgb)

# 3. Plot
plt.figure(figsize=(16, 10))
plt.plot(fpr_log, tpr_log, label=f"Logistic Regression (AUC =
{auc_log:.2f})")
plt.plot(fpr_tree, tpr_tree, label=f"Decision Tree (AUC =
{auc_tree:.2f})")
plt.plot(fpr_rf, tpr_rf, label=f"Random Forest (AUC = {auc_rf:.2f})")
plt.plot(fpr_xgb, tpr_xgb, label=f"XGBoost (AUC = {auc_xgb:.2f})")

# Chance line
```

```
plt.plot([0, 1], [0, 1], 'k--', label='Random Guess (AUC = 0.50)')

# Plot formatting
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title("ROC Curves and AUC Scores for All Models")
plt.legend(loc="lower right")
plt.grid(True)
plt.tight_layout()
plt.show()
```

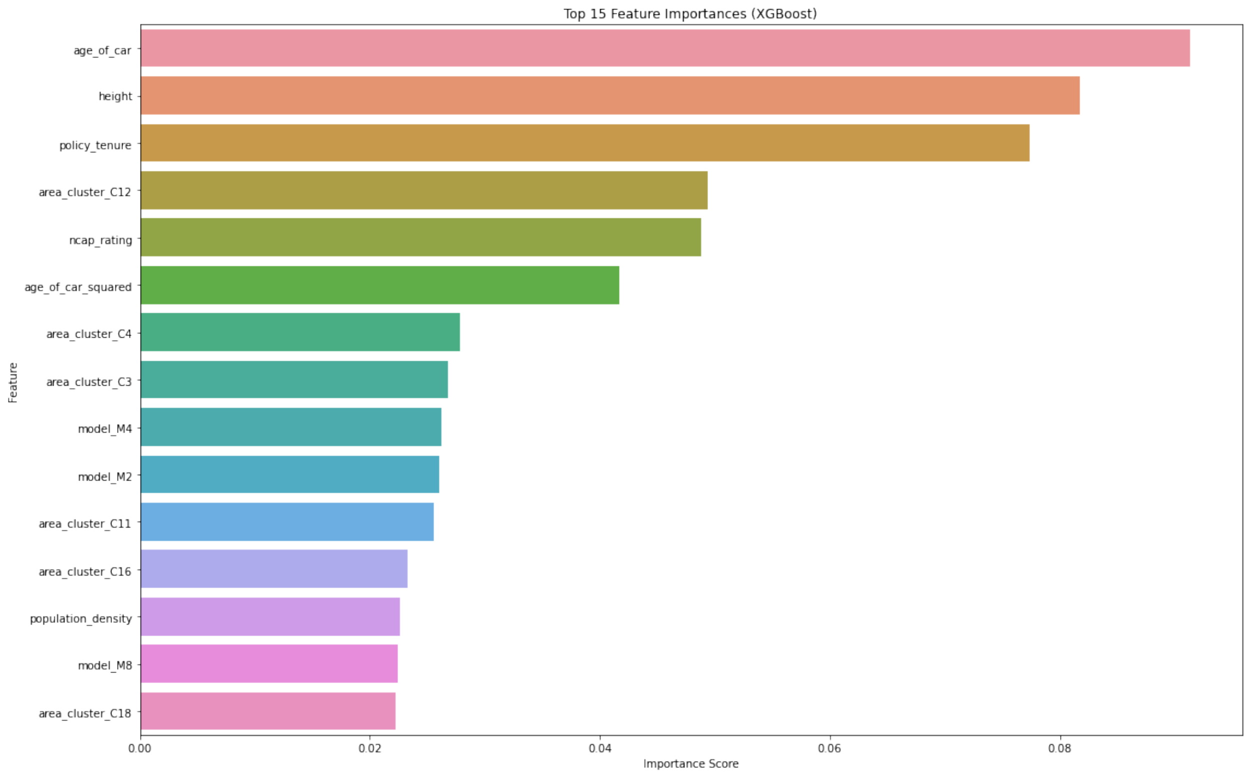


Insight: The ROC curve comparison plot shows that among all the models tested, XGBoost achieves the highest AUC score (0.66), indicating it is the best at distinguishing between policyholders who will and will not file a claim. Random Forest also performs well with an AUC of 0.65, showing strong predictive power. In contrast, Logistic Regression (AUC = 0.59) and especially the Decision Tree (AUC = 0.51) perform worse, with the Decision Tree barely outperforming random guessing

Visualize the top 15 important features for XGBoost

```
importances = xgb_par.feature_importances_
features = X_train.columns
indices = np.argsort(importances)[::-1]

plt.figure(figsize=(16, 10))
sns.barplot(x=importances[indices][:15], y=features[indices][:15])
```

```
plt.title("Top 15 Feature Importances (XGBoost)")
plt.xlabel("Importance Score")
plt.ylabel("Feature")
plt.tight_layout()
plt.show()
```



Insight: The above plot shows that age_of_car, policy_tenture, height and ncap_rating have the strongest influence on whether a claim is predicted correctly

FINAL MODEL

Several classification models were built when trying to identify the best in generalizing which policyholder is most likely to file a claim. The dataset was highly imbalanced with about 94% of policyholders unlikely to file a claim and only 6% were likely to do so. Careful model selection and evaluation were essential

The ROC-AUC metric was chosen as the evaluation measure because this is a binary classification task with imbalanced classes. Unlike accuracy, which can be misleading when one class dominates.; AUC works by evaluating the model's ability to rank positive cases higher than negative ones which is crucial in insurance settings where identifying potential climants(true positives) is more crucial than minimizing false alarms.

The process began by building simple baseline models. A Logistic Regression moedl which had an ROC-AUC score of 0.58 ,a modest improvement over random guessing (0.5).Decision Tree followed and the two models were compared visually. Decision Tree, severely overfit the training data, scoring 1.00 in training but only 0.51 on the test set. Decided to go with the

Logistic Regression for tuning to see if performance will improve. Despite tuning Logistic Regression, further gains were very minimal, with the AUC improving by only small margins mostly less than 0.01. This plateau justified exploring more complex models like the Random Forest as the AUC score was still low (0.586).

Next, a Random Forest model was implemented and tuned, which improved performance to a ROC-AUC of 0.6490. That was a significant gain over the earlier models. However, tuning improvements also began to stagnate. Therefore, the decision was made to test XGBoost, a model well known for handling imbalanced data well. After tuning, XGBoost achieved the highest ROC-AUC score of 0.66, demonstrating the strongest balance between generalization and predictive power among the four models.

In colclusion XGBoost was selected as the final model due to its superior performance of better handling of class imbalance and reduced overfitting. Its ability to improve the AUC from 0.58 to 0.66 makes it a valid model for identifying high-risk policyholders in an imbalanced insurance dataset.

Suggestions for Improvement

1. More robust feature engineering techniques could help extract more signal from the data
2. Trying more advanced Gradient Boosting Models - E.G., LightGBM or CatBoost which sometimes outperform XGBoost
3. Collect More Data - Increasing the dataset size (features) to help model learn more patterns and improve generalization.