# 2022 Travelers Modeling Competition

## Project Description

You work for Peace of Mind Insurance Company in their personal automotive insurance department as a modeler. For personal auto, anyone that asks for an estimated price for a policy from your company (also known as a quote) will receive one. However, of those quoted, only a fraction will choose your company as their insurer (versus other companies they also received quotes from). Your team has been asked to build what's known as a conversion model, with the goal of understanding the population of policies Peace of Mind Insurance Company is most likely to write (a.k.a. issue or convert). In other words, what types of customers is your company writing over its competitors?

**Your goals in this competition are as follows:**

- Identify quoted policies that your company will convert (a.k.a. issue)
- Understand key characteristics of policies your company tends to write, as well as those they tend not to write (e.g. understand quoted policies with both high and low conversion rates)
- Provide a recommendation on how this information could be leveraged at Peace of Mind Insurance

## Data Description

The data provided to you and your team consists of variables describing customers that asked for quotes. There are three datasets: at the policy, driver, and vehicle levels. Each row of the policy dataset corresponds to a single policy, which may be associated with multiple drivers and vehicles. Likewise, each row of the driver dataset represents a single driver, and each row of the vehicle dataset represents a single vehicle. It's easy to check that each driver and each vehicle are associated with just one policy. You may assume that all members on a policy live at the same address.

Your company was only able to convert a fraction of the policies found in this sample. The policy dataset also has a training and test split variable called split. Note that the conversion indicator (the response variable) is missing for policies in the test split. Your task is to build a model on the training data and apply your model to predict the conversion indicator for each policy in test data.

**Policies.csv**

policy_id: Unique customer identifier

Quote_dt: Date the quote was submitted

quoted_amt: Quote amount (US dollars)

Prior_carrier_grp: Prior carrier group

Cov_package_type: Level of coverage needed

discount: Whether or not a discount was applied to the quote amount

number_drivers: Number of drivers

credit_score: Credit score of primary policy holder

num_loaned_veh: Number of vehicles on policy that have a loan associated with them

num_owned_veh: Number of owned vehicles on the policy

num_leased_veh: Number of leased vehicles on the policy

total_number_veh: Total number vehicles on the policy

primary_parking: Where car(s) are primarily parked

CAT_zone: Catastrophe risk zone

Home_policy_ind: Does customer has existing home insurance policy with Peace of Mind

zip: US zip code of policy holder

state_id: State of policy holder

county_name: County of policy holder

Agent_cd: Unique agent code (8 digits)

split: Train/Test split

convert_ind: Conversion indicator (0=no, 1=yes). This is the response variable

**Drivers.csv:**

policy_id: Unique customer identifier

gender: Gender of driver

age: Age of driver

high_education_ind: Higher education indicator

safty_rating: Safety rating index of driver

living_status: Driver's living status (levels = 'own', 'rent', 'neither')

**Vehicles.csv:**

policy_id: Unique customer identifier

car_no: Unique car identifier (per policy)

ownership_type: Whether the car is loaned, owned or leased

color: Vehicle color

age: Vehicle age

make_model: Make and model of the vehicle

NOTE Training and Test sets are combined across the files, and need to be separated manually by your group!

In [1]:
```
# Importing basic libraries
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import datetime as dt
```

# Importing Data

In [2]:
```
data = pd.read_csv("policies_train.csv")
```

In [3]:
```
vehicles = pd.read_csv("vehicles.csv")
```

In [4]:
```
drivers = pd.read_csv("drivers.csv")
```

In [5]:
```
test = pd.read_csv("policies_test.csv")
```

In [6]:
```
test1 = pd.read_csv("policies_test.csv") #????????????
```

In [7]:
```
pd.options.display.max_columns = None
pd.options.display.max_rows = 150
```

Checking the number of rows and columns in the given datasets

In [8]:
```
data.shape
```

Out[8]:
```
(36871, 22)
```

In [9]:
```
vehicles.shape
```

Out[9]:
```
(169237, 7)
```

In [10]:
```
drivers.shape
```

Out[10]:
```
(106294, 7)
```

In [11]:
```
test.shape
```

Out[11]:
```
(12291, 22)
```

In [12]:
```
# Checking first few rows of policies train dataset
data.head()
```

Out[12]:

| | Unnamed: 0 | Quote_dt | discount | Home_policy_ind | zip | state_id | county_name | Agent_cd | quoted_amt | Pri |
|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 1 | 28-01-2015 | Yes | Y | 10465.0 | NY | Bronx | 15973623.0 | $5,153 | |
| **1** | 3 | 03-09-2018 | No | N | 11548.0 | NY | Nassau | 32759856.0 | $3,090 | |
| **2** | 5 | 18-05-2016 | No | N | 14622.0 | NY | Monroe | 15675431.0 | $14,917 | |
| **3** | 6 | 17-11- | No | N | 32811.0 | FL | Orange | 91762319.0 | $4,620 | |

| | | 2016 | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| **4** | 7 | 04-07-2017 | No | N | 10306.0 | NY | Richmond | 97388179.0 | $11,470 |

In [13]:
```
# Checking the columns and their data types of policies train dataset
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 36871 entries, 0 to 36870
Data columns (total 22 columns):
 #   Column              Non-Null Count  Dtype  
---  ------              --------------  -----  
 0   Unnamed: 0          36871 non-null  int64  
 1   Quote_dt            36871 non-null  object 
 2   discount            36871 non-null  object 
 3   Home_policy_ind     36871 non-null  object 
 4   zip                 36519 non-null  float64
 5   state_id            36871 non-null  object 
 6   county_name         36871 non-null  object 
 7   Agent_cd            32799 non-null  float64
 8   quoted_amt          36784 non-null  object 
 9   Prior_carrier_grp   33133 non-null  object 
 10  credit_score        36647 non-null  float64
 11  Cov_package_type    36278 non-null  object 
 12  CAT_zone            36690 non-null  float64
 13  policy_id           36871 non-null  object 
 14  number_drivers      36871 non-null  int64  
 15  num_loaned_veh      36871 non-null  int64  
 16  num_owned_veh       36871 non-null  int64  
 17  num_leased_veh      36871 non-null  int64  
 18  total_number_veh    36871 non-null  int64  
 19  convert_ind         36871 non-null  int64  
 20  split               36871 non-null  object 
 21  primary_parking     36871 non-null  object 
dtypes: float64(4), int64(7), object(11)
memory usage: 6.2+ MB
```

In [14]:
```
# Checking first few rows of vehciles dataset
vehicles.head()
```

Out[14]:

| | Unnamed: 0 | policy_id | car_no | ownership_type | color | age | make_model |
|---|---|---|---|---|---|---|---|
| **0** | 6 | policy_74571 | 1 | leased | other | 4.0 | BMW : R1200CL |
| **1** | 7 | policy_74571 | 2 | owned | blue | 3.0 | ACURA : TL |
| **2** | 15 | policy_1998 | 1 | owned | gray | 7.0 | BMW : 750LI |
| **3** | 29 | policy_28085 | 1 | owned | gray | 4.0 | MERCEDES-BENZ : G55 AMG |
| **4** | 34 | policy_64282 | 1 | owned | black | 4.0 | BMW : 550I GT |

In [15]:
```
# Checking the columns and their data types of vehicles dataset
vehicles.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 169237 entries, 0 to 169236
Data columns (total 7 columns):
 #   Column          Non-Null Count   Dtype  
---  ------          --------------   -----  
 0   Unnamed: 0      169237 non-null  int64  
 1   policy_id       169237 non-null  object 
 2   car_no          169237 non-null  int64  
 3   ownership_type  169237 non-null  object 
```

```
 4   color             168165 non-null  object
 5   age               168701 non-null  float64
 6   make_model        169237 non-null  object
dtypes: float64(1), int64(2), object(4)
memory usage: 9.0+ MB
```

In [16]:

```
# Checking first few rows of drivers dataset
drivers.head()
```

Out[16]:

| | Unnamed: 0 | policy_id | gender | living_status | age | safty_rating | high_education_ind |
|---|---|---|---|---|---|---|---|
| **0** | 2 | policy_2 | M | own | 44 | 85.0 | 0.0 |
| **1** | 3 | policy_2 | M | own | 44 | 63.0 | 1.0 |
| **2** | 4 | policy_3 | M | own | 65 | 56.0 | 1.0 |
| **3** | 7 | policy_5 | M | rent | 60 | 74.0 | 1.0 |
| **4** | 8 | policy_5 | F | dependent | 20 | 30.0 | 0.0 |

In [17]:

```
# Checking the columns and their data types of drivers dataset
drivers.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 106294 entries, 0 to 106293
Data columns (total 7 columns):
 #   Column              Non-Null Count   Dtype
---  ------              --------------   -----
 0   Unnamed: 0          106294 non-null  int64
 1   policy_id           106294 non-null  object
 2   gender              106294 non-null  object
 3   living_status       106244 non-null  object
 4   age                 106294 non-null  int64
 5   safty_rating        106217 non-null  float64
 6   high_education_ind  105751 non-null  float64
dtypes: float64(2), int64(2), object(3)
memory usage: 5.7+ MB
```

In [18]:

```
# Creating a copy of policy train dataset
vdata = vehicles
```

---

# Merging vehicles with policy

---

In [19]:

```
vdata.head()
```

Out[19]:

| | Unnamed: 0 | policy_id | car_no | ownership_type | color | age | make_model |
|---|---|---|---|---|---|---|---|
| **0** | 6 | policy_74571 | 1 | leased | other | 4.0 | BMW : R1200CL |
| **1** | 7 | policy_74571 | 2 | owned | blue | 3.0 | ACURA : TL |
| **2** | 15 | policy_1998 | 1 | owned | gray | 7.0 | BMW : 750LI |
| **3** | 29 | policy_28085 | 1 | owned | gray | 4.0 | MERCEDES-BENZ : G55 AMG |
| **4** | 34 | policy_64282 | 1 | owned | black | 4.0 | BMW : 550I GT |

In [20]:

```
vdata['make_model'].value_counts().shape
```

```
(1049,)
```

Out[20]:

**We can see that the policy dataset has a column named 'make_model'. Keeping this column as it is in our analysis of the policies would make it very difficult to generate meaningful predictions as it has more than 1000 unique values. So we just keep the make of the cars and remove the model as the make could give us some insights on the policies that the company converts.**

In [21]:
```
vdata['make'] = vdata['make_model'].str.split(':', 0).str[0]
vdata.head()
```

Out[21]:

| | Unnamed: 0 | policy_id | car_no | ownership_type | color | age | make_model | make |
|---|---|---|---|---|---|---|---|---|
| **0** | 6 | policy_74571 | 1 | leased | other | 4.0 | BMW : R1200CL | BMW |
| **1** | 7 | policy_74571 | 2 | owned | blue | 3.0 | ACURA : TL | ACURA |
| **2** | 15 | policy_1998 | 1 | owned | gray | 7.0 | BMW : 750LI | BMW |
| **3** | 29 | policy_28085 | 1 | owned | gray | 4.0 | MERCEDES-BENZ : G55 AMG | MERCEDES-BENZ |
| **4** | 34 | policy_64282 | 1 | owned | black | 4.0 | BMW : 550I GT | BMW |

In [22]:
```
vdata.drop(['make_model'], axis = 1, inplace = True)
vdata.head()
```

Out[22]:

| | Unnamed: 0 | policy_id | car_no | ownership_type | color | age | make |
|---|---|---|---|---|---|---|---|
| **0** | 6 | policy_74571 | 1 | leased | other | 4.0 | BMW |
| **1** | 7 | policy_74571 | 2 | owned | blue | 3.0 | ACURA |
| **2** | 15 | policy_1998 | 1 | owned | gray | 7.0 | BMW |
| **3** | 29 | policy_28085 | 1 | owned | gray | 4.0 | MERCEDES-BENZ |
| **4** | 34 | policy_64282 | 1 | owned | black | 4.0 | BMW |

In [23]:
```
vdata['make'].unique()
```

Out[23]:
```
array(['BMW ', 'ACURA ', 'MERCEDES-BENZ ', 'AUDI ', 'CADILLAC ', 'HONDA ',
       'CHEVROLET ', 'FORD ', 'GMC ', 'CHRYSLER ', 'NISSAN ', 'TOYOTA ',
       'MAZDA ', 'BUICK ', 'SATURN ', 'SUBARU ', 'DODGE ', 'RAM ',
       'SMART '], dtype=object)
```

In [24]:
```
vdata['make'].value_counts().shape
```

Out[24]:
```
(19,)
```

**We can see that now the 'make' column has 19 unique values and we can analyse this column more effectively.**

## Transforming categorical variables

In [25]:
```
vdata = pd.get_dummies(vdata, columns = ['ownership_type', 'color', 'make' ])
vdata.head()
```

Out[25]:

| | Unnamed: 0 | policy_id | car_no | age | ownership_type_leased | ownership_type_loaned | ownership_type_owned | c |
|---|---|---|---|---|---|---|---|---|
| **0** | 6 | policy_74571 | 1 | 4.0 | 1 | 0 | 0 | |
| **1** | 7 | policy_74571 | 2 | 3.0 | 0 | 0 | 1 | |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| **2** | 15 | policy_1998 | 1 | 7.0 | 0 | 0 | 1 |
| **3** | 29 | policy_28085 | 1 | 4.0 | 0 | 0 | 1 |
| **4** | 34 | policy_64282 | 1 | 4.0 | 0 | 0 | 1 |

## Grouping by Policy Number

**- For attribute age -> mean, min, max is tabulated in seperate columns**

**- For attribute car_no, only the max value from the column is taken for each policy, as that gives total cars in that policy**

**- For all binary columns that we just transformed, the sum is taken to aggregate data for each policy**

In [26]:

```
bool_cols = [col for col in vdata
             if np.isin(vdata[col].dropna().unique(), [0, 1]).all()]
bool_cols
```

Out[26]:

```
['ownership_type_leased',
 'ownership_type_loaned',
 'ownership_type_owned',
 'color_black',
 'color_blue',
 'color_gray',
 'color_other',
 'color_red',
 'color_silver',
 'color_white',
 'make_ACURA ',
 'make_AUDI ',
 'make_BMW ',
 'make_BUICK ',
 'make_CADILLAC ',
 'make_CHEVROLET ',
 'make_CHRYSLER ',
 'make_DODGE ',
 'make_FORD ',
 'make_GMC ',
 'make_HONDA ',
 'make_MAZDA ',
 'make_MERCEDES-BENZ ',
 'make_NISSAN ',
 'make_RAM ',
 'make_SATURN ',
 'make_SMART ',
 'make_SUBARU ',
 'make_TOYOTA ']
```

In [27]:

```
vdata['age_min'] = vdata['age']
vdata['age_max'] = vdata['age']
d1 = {'car_no':'max'}
d2 = {'age':'mean'}
d3 = {'age_min':'min'}
d4 = {'age_max':'max'}
d5 = dict.fromkeys(bool_cols, 'sum')

d = {**d1, **d2, **d3, **d4, **d5}
vvdata = vdata.groupby('policy_id', as_index=False).agg(d)
vvdata.head()
```

Out[27]:

| | policy_id | car_no | age | age_min | age_max | ownership_type_leased | ownership_type_loaned | ownership_t |
|---|---|---|---|---|---|---|---|---|

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| **0** | policy_100 | 6 | 7.333333 | 4.0 | 9.0 | 0 | 3 |
| **1** | policy_1000 | 2 | 5.500000 | 3.0 | 8.0 | 0 | 1 |
| **2** | policy_10001 | 2 | 5.000000 | 2.0 | 8.0 | 0 | 0 |
| **3** | policy_10002 | 5 | 7.200000 | 5.0 | 10.0 | 2 | 0 |
| **4** | policy_10004 | 2 | 5.000000 | 1.0 | 9.0 | 0 | 1 |

## Inner Join

In [28]:
```
data_veh = pd.merge(left = data, right = vvdata, how = 'inner', on = 'policy_id')
data_veh.head()
```

Out[28]:

| | Unnamed: 0 | Quote_dt | discount | Home_policy_ind | zip | state_id | county_name | Agent_cd | quoted_amt | Pri |
|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 1 | 28-01-2015 | Yes | Y | 10465.0 | NY | Bronx | 15973623.0 | $5,153 | |
| **1** | 3 | 03-09-2018 | No | N | 11548.0 | NY | Nassau | 32759856.0 | $3,090 | |
| **2** | 5 | 18-05-2016 | No | N | 14622.0 | NY | Monroe | 15675431.0 | $14,917 | |
| **3** | 6 | 17-11-2016 | No | N | 32811.0 | FL | Orange | 91762319.0 | $4,620 | |
| **4** | 7 | 04-07-2017 | No | N | 10306.0 | NY | Richmond | 97388179.0 | $11,470 | |

---

# Merging drivers to the previously merged dataset

---

In [29]:
```
# Creating a copy of drivers dataset
ddata = drivers
```

In [30]:
```
ddata.head()
```

Out[30]:

| | Unnamed: 0 | policy_id | gender | living_status | age | safty_rating | high_education_ind |
|---|---|---|---|---|---|---|---|
| **0** | 2 | policy_2 | M | own | 44 | 85.0 | 0.0 |
| **1** | 3 | policy_2 | M | own | 44 | 63.0 | 1.0 |
| **2** | 4 | policy_3 | M | own | 65 | 56.0 | 1.0 |
| **3** | 7 | policy_5 | M | rent | 60 | 74.0 | 1.0 |
| **4** | 8 | policy_5 | F | dependent | 20 | 30.0 | 0.0 |

In [31]:
```
ddata.describe()
```

Out[31]:

| | Unnamed: 0 | age | safty_rating | high_education_ind |
|---|---|---|---|---|
| **count** | 106294.000000 | 106294.000000 | 106217.000000 | 105751.000000 |

| | | | | |
|---|---|---|---|---|
| **mean** | 101689.784108 | 38.477318 | 69.411092 | 0.404488 |
| **std** | 60406.123405 | 18.432746 | 16.760435 | 0.490795 |
| **min** | 2.000000 | 16.000000 | -28.000000 | 0.000000 |
| **25%** | 49453.750000 | 18.000000 | 60.000000 | 0.000000 |
| **50%** | 99647.500000 | 40.000000 | 72.000000 | 0.000000 |
| **75%** | 154169.750000 | 53.000000 | 82.000000 | 1.000000 |
| **max** | 206110.000000 | 147.000000 | 100.000000 | 1.000000 |

In [32]:
```
ddata[ddata['age']>100].describe()
```

Out[32]:

| | Unnamed: 0 | age | safty_rating | high_education_ind |
|---|---|---|---|---|
| **count** | 63.000000 | 63.000000 | 63.000000 | 63.000000 |
| **mean** | 95065.793651 | 109.317460 | 72.968254 | 0.571429 |
| **std** | 56555.864579 | 8.774643 | 16.966730 | 0.498847 |
| **min** | 4911.000000 | 101.000000 | 26.000000 | 0.000000 |
| **25%** | 58387.500000 | 103.000000 | 64.000000 | 0.000000 |
| **50%** | 83515.000000 | 107.000000 | 76.000000 | 1.000000 |
| **75%** | 143051.000000 | 113.500000 | 85.000000 | 1.000000 |
| **max** | 199618.000000 | 147.000000 | 97.000000 | 1.000000 |

**We can see that the age in a number of policies is greater than 100. This data is mostly inaccurate and since there is only a small number of data points with this inaccuracy, these can be removed.**

In [33]:
```
ddata = ddata.drop(ddata[ddata['age'] > 100].index)
```

In [34]:
```
ddata['age'].describe()
```

Out[34]:
```
count    106231.000000
mean         38.435306
std          18.356055
min          16.000000
25%          18.000000
50%          40.000000
75%          53.000000
max         100.000000
Name: age, dtype: float64
```

## Transforming categorical variables

**We can group the age into bins to make it a categorical variable**

In [35]:
```
bins = [0,25,35,45,55,65,101]
labels = ['15-25','26-35','36-45','46-55','56-65','65+']
ddata['Age Group'] = pd.cut(ddata['age'], bins = bins, labels = labels)
ddata.head()
```

Out[35]:

| | Unnamed: 0 | policy_id | gender | living_status | age | safty_rating | high_education_ind | Age Group |
|---|---|---|---|---|---|---|---|---|
| **0** | 2 | policy_2 | M | own | 44 | 85.0 | 0.0 | 36-45 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| **1** | 3 | policy_2 | M | own | 44 | 63.0 | 1.0 | 36-45 |
| **2** | 4 | policy_3 | M | own | 65 | 56.0 | 1.0 | 56-65 |
| **3** | 7 | policy_5 | M | rent | 60 | 74.0 | 1.0 | 56-65 |
| **4** | 8 | policy_5 | F | dependent | 20 | 30.0 | 0.0 | 15-25 |

In [36]:
```
ddata = pd.get_dummies(ddata, columns = ['gender', 'living_status', 'Age Group' ,'high_e
ddata.head()
```

Out[36]:

| | Unnamed: 0 | policy_id | age | safty_rating | gender_F | gender_M | living_status_dependent | living_status_own | living |
|---|---|---|---|---|---|---|---|---|---|
| **0** | 2 | policy_2 | 44 | 85.0 | 0 | 1 | 0 | 1 | |
| **1** | 3 | policy_2 | 44 | 63.0 | 0 | 1 | 0 | 1 | |
| **2** | 4 | policy_3 | 65 | 56.0 | 0 | 1 | 0 | 1 | |
| **3** | 7 | policy_5 | 60 | 74.0 | 0 | 1 | 0 | 0 | |
| **4** | 8 | policy_5 | 20 | 30.0 | 1 | 0 | 1 | 0 | |

In [37]:
```
ddata.head()
```

Out[37]:

| | Unnamed: 0 | policy_id | age | safty_rating | gender_F | gender_M | living_status_dependent | living_status_own | living |
|---|---|---|---|---|---|---|---|---|---|
| **0** | 2 | policy_2 | 44 | 85.0 | 0 | 1 | 0 | 1 | |
| **1** | 3 | policy_2 | 44 | 63.0 | 0 | 1 | 0 | 1 | |
| **2** | 4 | policy_3 | 65 | 56.0 | 0 | 1 | 0 | 1 | |
| **3** | 7 | policy_5 | 60 | 74.0 | 0 | 1 | 0 | 0 | |
| **4** | 8 | policy_5 | 20 | 30.0 | 1 | 0 | 1 | 0 | |

## Grouping by Policy Number

**- For attribute safety rating -> mean, min, max is tabulated in seperate columns**

**- For all binary columns that we just transformed, the sum is taken to aggregate data for each policy**

In [38]:
```
bool_cols1 = [col for col in ddata
              if np.isin(ddata[col].dropna().unique(), [0, 1]).all()]
bool_cols1
```

Out[38]:
```
['gender_F',
 'gender_M',
 'living_status_dependent',
 'living_status_own',
 'living_status_rent',
 'Age Group_15-25',
 'Age Group_26-35',
 'Age Group_36-45',
 'Age Group_46-55',
 'Age Group_56-65',
 'Age Group_65+',
 'high_education_ind_0.0',
 'high_education_ind_1.0']
```

In [39]:
```
ddata['safety_min'] = ddata['safty_rating']
ddata['safety_max'] = ddata['safty_rating']
d1 = {'safty_rating':'mean'}
d2 = {'safety_min':'min'}
d3 = {'safety_max':'max'}
d4 = dict.fromkeys(bool_cols1, 'sum')

d = {**d1, **d2, **d3, **d4}
dddata = ddata.groupby('policy_id', as_index=False).agg(d)
dddata.head()
```

Out[39]:

| | policy_id | safty_rating | safety_min | safety_max | gender_F | gender_M | living_status_dependent | living_status_( |
|---|---|---|---|---|---|---|---|---|
| 0 | policy_100 | 75.500000 | 75.0 | 76.0 | 1 | 1 | 1 | |
| 1 | policy_1000 | 50.000000 | 50.0 | 50.0 | 0 | 1 | 0 | |
| 2 | policy_10001 | 59.333333 | 45.0 | 71.0 | 2 | 1 | 2 | |
| 3 | policy_10002 | 76.000000 | 64.0 | 90.0 | 1 | 4 | 4 | |
| 4 | policy_10004 | 72.000000 | 29.0 | 86.0 | 2 | 3 | 3 | |

## Inner Join

In [40]:
```
df_policy = pd.merge(left = data_veh, right = dddata, how = 'inner', on = 'policy_id')
df_policy.head()
```

Out[40]:

| | Unnamed: 0 | Quote_dt | discount | Home_policy_ind | zip | state_id | county_name | Agent_cd | quoted_amt | Pri |
|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 1 | 28-01-2015 | Yes | Y | 10465.0 | NY | Bronx | 15973623.0 | $5,153 | |
| 1 | 3 | 03-09-2018 | No | N | 11548.0 | NY | Nassau | 32759856.0 | $3,090 | |
| 2 | 5 | 18-05-2016 | No | N | 14622.0 | NY | Monroe | 15675431.0 | $14,917 | |
| 3 | 6 | 17-11-2016 | No | N | 32811.0 | FL | Orange | 91762319.0 | $4,620 | |
| 4 | 7 | 04-07-2017 | No | N | 10306.0 | NY | Richmond | 97388179.0 | $11,470 | |

In [41]:
```
# df_policy.to_csv('policy_merged.csv')
```

# Data cleaning on merged dataset

In [42]:
```
df_policy['county_name'].value_counts().shape
```

Out[42]:
```
(112,)
```

**After running the XGBoost model, we observed from the feature importance plots that only the counties New York and Kings have coniderably high importance amongst all the counties, and there are more than 100 counties. So, only these counties are kept, while others are made zero.**

In [43]:
```
df_policy['county_name'] = np.where((df_policy['county_name'] == 'New York')|(df_policy[
```

In [44]:
```
df_policy['county_name'].value_counts()
```

Out[44]:
```
0           34985
New York      953
Kings         924
Name: county_name, dtype: int64
```

**Similary for Prior Carrier Group, only the carriers 3, 7, and 8 have coniderably high importance amongst all the carriers. So, only these carriers are kept, while others are made zero.**

In [45]:
```
df_policy['Prior_carrier_grp'] = np.where((df_policy['Prior_carrier_grp'] == 'Carrier_3'
```

In [46]:
```
df_policy['Prior_carrier_grp'].value_counts()
```

Out[46]:
```
0            26636
Carrier_3     3763
Carrier_8     3319
Carrier_7     3144
Name: Prior_carrier_grp, dtype: int64
```

In [47]:
```
df_policy.columns
```

Out[47]:
```
Index(['Unnamed: 0', 'Quote_dt', 'discount', 'Home_policy_ind', 'zip',
       'state_id', 'county_name', 'Agent_cd', 'quoted_amt',
       'Prior_carrier_grp', 'credit_score', 'Cov_package_type', 'CAT_zone',
       'policy_id', 'number_drivers', 'num_loaned_veh', 'num_owned_veh',
       'num_leased_veh', 'total_number_veh', 'convert_ind', 'split',
       'primary_parking', 'car_no', 'age', 'age_min', 'age_max',
       'ownership_type_leased', 'ownership_type_loaned',
       'ownership_type_owned', 'color_black', 'color_blue', 'color_gray',
       'color_other', 'color_red', 'color_silver', 'color_white',
       'make_ACURA ', 'make_AUDI ', 'make_BMW ', 'make_BUICK ',
       'make_CADILLAC ', 'make_CHEVROLET ', 'make_CHRYSLER ', 'make_DODGE ',
       'make_FORD ', 'make_GMC ', 'make_HONDA ', 'make_MAZDA ',
       'make_MERCEDES-BENZ ', 'make_NISSAN ', 'make_RAM ', 'make_SATURN ',
       'make_SMART ', 'make_SUBARU ', 'make_TOYOTA ', 'safty_rating',
       'safety_min', 'safety_max', 'gender_F', 'gender_M',
       'living_status_dependent', 'living_status_own', 'living_status_rent',
       'Age Group_15-25', 'Age Group_26-35', 'Age Group_36-45',
       'Age Group_46-55', 'Age Group_56-65', 'Age Group_65+',
       'high_education_ind_0.0', 'high_education_ind_1.0'],
      dtype='object')
```

**Only the top 5 'make' according to feature importance plots from XGBoost are kept while others are removed**

In [48]:
```
df_policy.drop(['make_ACURA ', 'make_BUICK ', 'make_CADILLAC ', 'make_CHRYSLER ', 'make_
                'make_NISSAN ','make_RAM ','make_SATURN ','make_SMART ','make_SUBARU ','
```

In [49]:
```
df_policy.columns
```

Out[49]:
```
Index(['Unnamed: 0', 'Quote_dt', 'discount', 'Home_policy_ind', 'zip',
       'state_id', 'county_name', 'Agent_cd', 'quoted_amt',
       'Prior_carrier_grp', 'credit_score', 'Cov_package_type', 'CAT_zone',
       'policy_id', 'number_drivers', 'num_loaned_veh', 'num_owned_veh',
       'num_leased_veh', 'total_number_veh', 'convert_ind', 'split',
       'primary_parking', 'car_no', 'age', 'age_min', 'age_max',
       'ownership_type_leased', 'ownership_type_loaned',
       'ownership_type_owned', 'color_black', 'color_blue', 'color_gray',
       'color_other', 'color_red', 'color_silver', 'color_white', 'make_AUDI ',
       'make_BMW ', 'make_CHEVROLET ', 'make_HONDA ', 'make_MERCEDES-BENZ ',
```

```
       'safty_rating', 'safety_min', 'safety_max', 'gender_F', 'gender_M',
       'living_status_dependent', 'living_status_own', 'living_status_rent',
       'Age Group_15-25', 'Age Group_26-35', 'Age Group_36-45',
       'Age Group_46-55', 'Age Group_56-65', 'Age Group_65+',
       'high_education_ind_0.0', 'high_education_ind_1.0'],
      dtype='object')
```

In [50]:
```python
# Checking the data in numerical columns
df_policy.describe()
```

Out[50]:

| | Unnamed: 0 | zip | Agent_cd | credit_score | CAT_zone | number_drivers | num_loaned_veh | r |
|---|---|---|---|---|---|---|---|---|
| **count** | 36862.000000 | 36510.000000 | 3.279100e+04 | 36638.000000 | 36681.000000 | 36862.000000 | 36862.000000 | |
| **mean** | 24522.768488 | 22448.670857 | 5.461499e+07 | 641.515339 | 2.872195 | 2.159568 | 1.305545 | |
| **std** | 14202.438688 | 15691.373190 | 2.524748e+07 | 78.801623 | 1.439576 | 1.236384 | 0.901570 | |
| **min** | 1.000000 | 6051.000000 | 1.278836e+07 | 369.000000 | 1.000000 | 1.000000 | 0.000000 | |
| **25%** | 12212.250000 | 10004.000000 | 3.275986e+07 | 583.000000 | 2.000000 | 1.000000 | 1.000000 | |
| **50%** | 24478.500000 | 12801.000000 | 5.332332e+07 | 642.000000 | 3.000000 | 2.000000 | 1.000000 | |
| **75%** | 36855.750000 | 33313.000000 | 7.644067e+07 | 697.000000 | 4.000000 | 3.000000 | 2.000000 | |
| **max** | 49162.000000 | 56075.000000 | 9.957344e+07 | 850.000000 | 5.000000 | 6.000000 | 3.000000 | |

**Safety rating has negative values and that most probably will have to be cleaned.**

In [51]:
```python
df_policy.isna().sum()
```

Out[51]:
```
Unnamed: 0                   0
Quote_dt                     0
discount                     0
Home_policy_ind              0
zip                        352
state_id                     0
county_name                  0
Agent_cd                  4071
quoted_amt                  87
Prior_carrier_grp            0
credit_score               224
Cov_package_type           593
CAT_zone                   181
policy_id                    0
number_drivers               0
num_loaned_veh               0
num_owned_veh                0
num_leased_veh               0
total_number_veh             0
convert_ind                  0
split                        0
primary_parking              0
car_no                       0
age                         10
age_min                     10
age_max                     10
ownership_type_leased        0
ownership_type_loaned        0
ownership_type_owned         0
color_black                  0
color_blue                   0
color_gray                   0
color_other                  0
```

```
color_red                   0
color_silver                0
color_white                 0
make_AUDI                   0
make_BMW                    0
make_CHEVROLET              0
make_HONDA                  0
make_MERCEDES-BENZ          0
safty_rating               13
safety_min                 13
safety_max                 13
gender_F                    0
gender_M                    0
living_status_dependent     0
living_status_own           0
living_status_rent          0
Age Group_15-25             0
Age Group_26-35             0
Age Group_36-45             0
Age Group_46-55             0
Age Group_56-65             0
Age Group_65+               0
high_education_ind_0.0      0
high_education_ind_1.0      0
dtype: int64
```

In [52]:
```
#Checking unique values of state id
df_policy['state_id'].unique()
```

Out[52]:
```
array(['NY', 'FL', 'MN', 'NJ', 'WI', 'CT', 'GA', 'AL'], dtype=object)
```

**Checking data consistency for 'zip' column**

In [53]:
```
df_policy['zip'].max()
```

Out[53]:
```
56075.0
```

In [54]:
```
df_policy['zip'].min()
```

Out[54]:
```
6051.0
```

In [55]:
```
# Checking no. of unique agents
len(df_policy['Agent_cd'].unique())
```

Out[55]:
```
1629
```

In [56]:
```
# Checking the ratio of the predictions
df_policy['convert_ind'].value_counts(normalize = True)
```

Out[56]:
```
0    0.888286
1    0.111714
Name: convert_ind, dtype: float64
```

**We can see that the predictions in our dataset are highly imbalanced.**

In [57]:
```
df_policy['quoted_amt'].head()
```

Out[57]:
```
0     $5,153
1     $3,090
2    $14,917
3     $4,620
4    $11,470
Name: quoted_amt, dtype: object
```

**The 'quoted_amt' column needs to be cleaned.**

In [58]:
```
# Removing $ and , from 'quoted_amt' and changing its datatype
df_policy['quote'] = df_policy['quoted_amt'].str.replace(',','')
df_policy['quote'] = df_policy['quote'].str.replace('$','')
df_policy['quote'] = pd.to_numeric(df_policy['quote'], errors='coerce')
df_policy['quote'].dtype
```

```
C:\Users\DELL\AppData\Local\Temp\ipykernel_24876\2232332588.py:3: FutureWarning: The def
ault value of regex will change from True to False in a future version. In addition, sin
gle character regular expressions will *not* be treated as literal strings when regex=Tr
ue.
  df_policy['quote'] = df_policy['quote'].str.replace('$','')
```

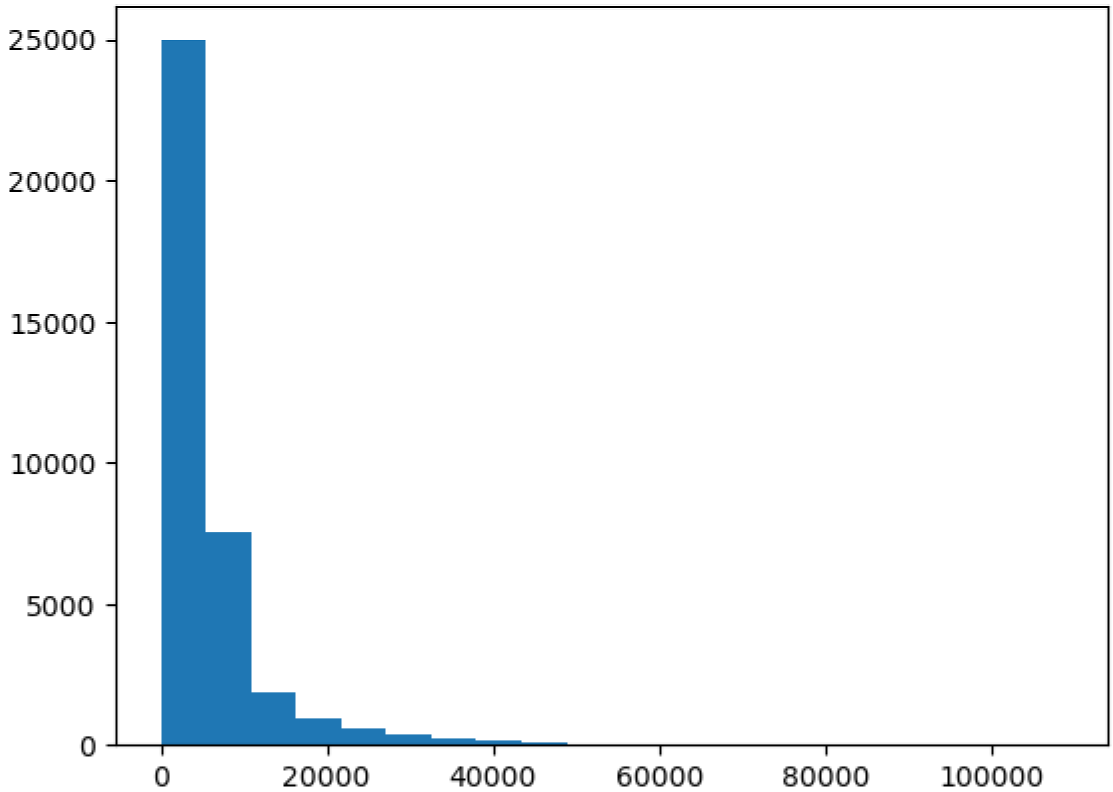
Out[58]:
```
dtype('float64')
```

In [59]:
```
df_policy['quote'].describe()
```

Out[59]:
```
count     36775.000000
mean       5849.299850
std        6808.005388
min          15.000000
25%        2246.000000
50%        3744.000000
75%        6523.500000
max      108608.000000
Name: quote, dtype: float64
```

In [60]:
```
plt.hist(df_policy['quote'], bins = 20)
```

Out[60]:
```
(array([2.4954e+04, 7.5440e+03, 1.8930e+03, 9.6400e+02, 5.6200e+02,
        3.4000e+02, 2.0000e+02, 1.3800e+02, 7.7000e+01, 5.0000e+01,
        1.9000e+01, 1.4000e+01, 1.1000e+01, 6.0000e+00, 1.0000e+00,
        0.0000e+00, 0.0000e+00, 1.0000e+00, 0.0000e+00, 1.0000e+00]),
 array([1.5000000e+01, 5.4446500e+03, 1.0874300e+04, 1.6303950e+04,
        2.1733600e+04, 2.7163250e+04, 3.2592900e+04, 3.8022550e+04,
        4.3452200e+04, 4.8881850e+04, 5.4311500e+04, 5.9741150e+04,
        6.5170800e+04, 7.0600450e+04, 7.6030100e+04, 8.1459750e+04,
        8.6889400e+04, 9.2319050e+04, 9.7748700e+04, 1.0317835e+05,
        1.0860800e+05]),
 <BarContainer object of 20 artists>)
```




**It can be seen that the quotes are highly skewed towards the right. We'll perform binning to convert quotes into categories.**

In [61]:
```
df_policy['quote'].quantile(np.linspace(.1,1,9,0))
```

Out[61]:
```
0.1     1378.0
0.2     1983.0
0.3     2509.2
0.4     3083.0
0.5     3744.0
0.6     4570.0
0.7     5736.8
0.8     7543.2
0.9    12123.4
Name: quote, dtype: float64
```

In [62]:
```
bins = [0,2500,5000,7500,10000,200000]
labels = ['Very Low','Low','Medium','High','Very High']
df_policy['quote_range'] = pd.cut(df_policy['quote'], bins = bins, labels = labels)
df_policy.head(10)
```

Out[62]:

| | Unnamed: 0 | Quote_dt | discount | Home_policy_ind | zip | state_id | county_name | Agent_cd | quoted_amt | Pri |
|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 1 | 28-01-2015 | Yes | Y | 10465.0 | NY | 0 | 15973623.0 | $5,153 | |
| **1** | 3 | 03-09-2018 | No | N | 11548.0 | NY | 0 | 32759856.0 | $3,090 | |
| **2** | 5 | 18-05-2016 | No | N | 14622.0 | NY | 0 | 15675431.0 | $14,917 | |
| **3** | 6 | 17-11-2016 | No | N | 32811.0 | FL | 0 | 91762319.0 | $4,620 | |
| **4** | 7 | 04-07-2017 | No | N | 10306.0 | NY | 0 | 97388179.0 | $11,470 | |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| **5** | 11 | 25-12-2017 | No | N | 55125.0 | MN | 0 | 59705446.0 | $2,566 |
| **6** | 12 | 22-11-2018 | No | N | 33136.0 | FL | 0 | 37520067.0 | $1,779 |
| **7** | 13 | 30-03-2015 | Yes | Y | 7666.0 | NJ | 0 | 84058252.0 | $4,597 |
| **8** | 14 | 11-11-2016 | No | N | 33143.0 | FL | 0 | 19952087.0 | $2,196 |
| **9** | 16 | 07-10-2018 | No | N | 7676.0 | NJ | 0 | 53860167.0 | $1,636 |

In [63]:

```
# CHecking the distribution of data into quote categories
df_policy['quote_range'].value_counts()
```

Out[63]:

```
Low          12690
Very Low     10975
Medium        5685
Very High     4809
High          2616
Name: quote_range, dtype: int64
```

In [64]:

```
# Checking conversion percentage in the quote categories
pd.crosstab(df_policy['quote_range'], df_policy['convert_ind'], normalize='index') * 100
```

Out[64]:

| **convert_ind** | **0** | **1** |
|---|---|---|
| **quote_range** | | |
| **Very Low** | 86.150342 | 13.849658 |
| **Low** | 88.045705 | 11.954295 |
| **Medium** | 89.709763 | 10.290237 |
| **High** | 91.896024 | 8.103976 |
| **Very High** | 94.198378 | 5.801622 |

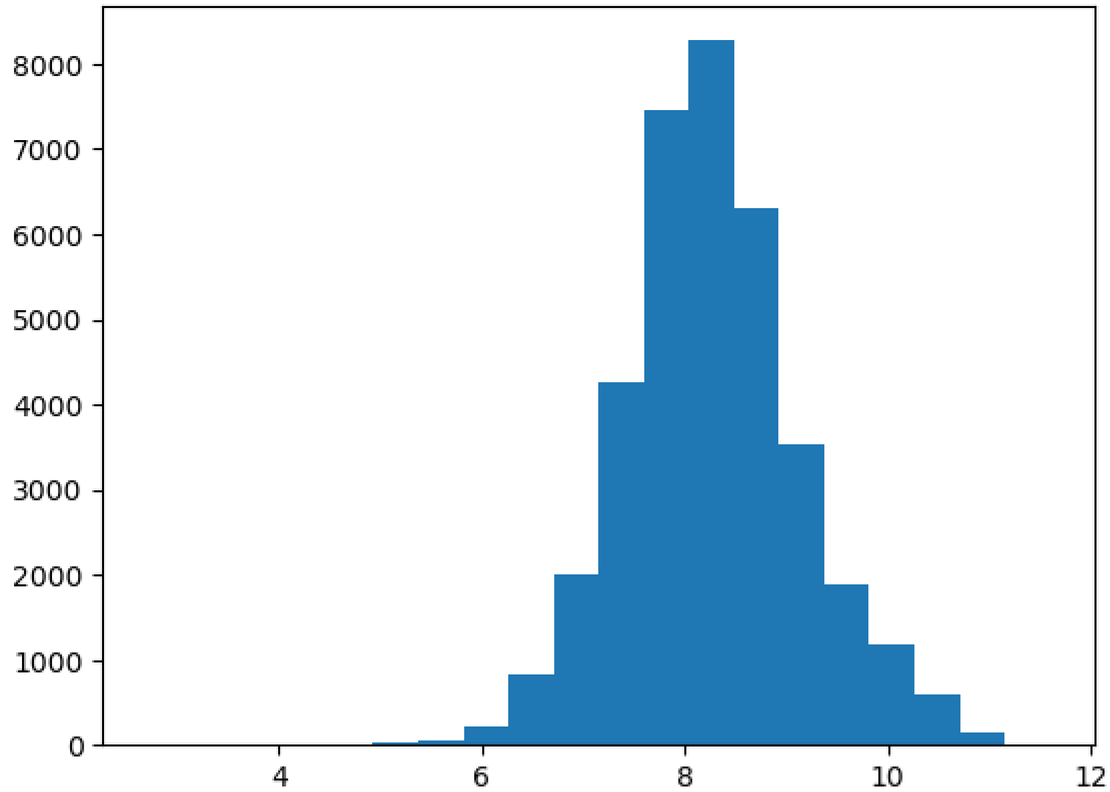
**We can see that higher quotes have higher conversion rates.**

In [65]:

```
# Skewness can also be removed by creating a log quote column
plt.hist(np.log(df_policy['quote']), bins = 20)
```

Out[65]:

```
(array([1.000e+00, 1.000e+00, 4.000e+00, 4.000e+00, 1.500e+01, 1.900e+01,
        4.500e+01, 2.190e+02, 8.280e+02, 1.994e+03, 4.269e+03, 7.449e+03,
        8.274e+03, 6.305e+03, 3.523e+03, 1.881e+03, 1.187e+03, 6.010e+02,
        1.450e+02, 1.100e+01]),
 array([ 2.7080502 ,  3.15242271,  3.59679522,  4.04116772,  4.48554023,
         4.92991274,  5.37428525,  5.81865775,  6.26303026,  6.70740277,
         7.15177527,  7.59614778,  8.04052029,  8.4848928 ,  8.9292653 ,
         9.37363781,  9.81801032, 10.26238283, 10.70675533, 11.15112784,
        11.59550035]),
 <BarContainer object of 20 artists>)
```




In [66]:
```
df_policy['log_quote'] = np.log(df_policy['quote'])
```

In [67]:
```
# Checking data distribution across Carrier Groups
df_policy['Prior_carrier_grp'].value_counts()
```

Out[67]:
```
0            26636
Carrier_3     3763
Carrier_8     3319
Carrier_7     3144
Name: Prior_carrier_grp, dtype: int64
```

In [68]:
```
# Checking data distribution for different coverage types
df_policy['Cov_package_type'].value_counts()
```

Out[68]:
```
Medium    13964
High      12282
Low       10023
Name: Cov_package_type, dtype: int64
```

In [69]:
```
# Checking data distribution across CAT zones
df_policy['CAT_zone'].value_counts()
```

Out[69]:
```
2.0    8778
1.0    8212
5.0    7237
3.0    6414
4.0    6040
Name: CAT_zone, dtype: int64
```

In [70]:
```
# Checking data distribution across parking types
df_policy['primary_parking'].value_counts()
```

Out[70]:
```
unknown           25828
home/driveway      5544
parking garage     3600
street             1890
Name: primary_parking, dtype: int64
```

**Checking data consistency for number of drivers across the two datasets provided.**

In [71]:
```
df_policy['total_drivers'] = df_policy['gender_F']+df_policy['gender_M']
```

In [72]:
```
len(df_policy)
```

Out[72]:
```
36862
```

In [73]:
```
len(df_policy[df_policy['number_drivers'] == df_policy['total_drivers']])
```

Out[73]:
```
36825
```

In [74]:
```
# Checking no. of males that have received policy quotes
df_policy['gender_F'].sum()
```

Out[74]:
```
39006
```

In [75]:
```
# Checking no. of females that have received policy quotes
df_policy['gender_M'].sum()
```

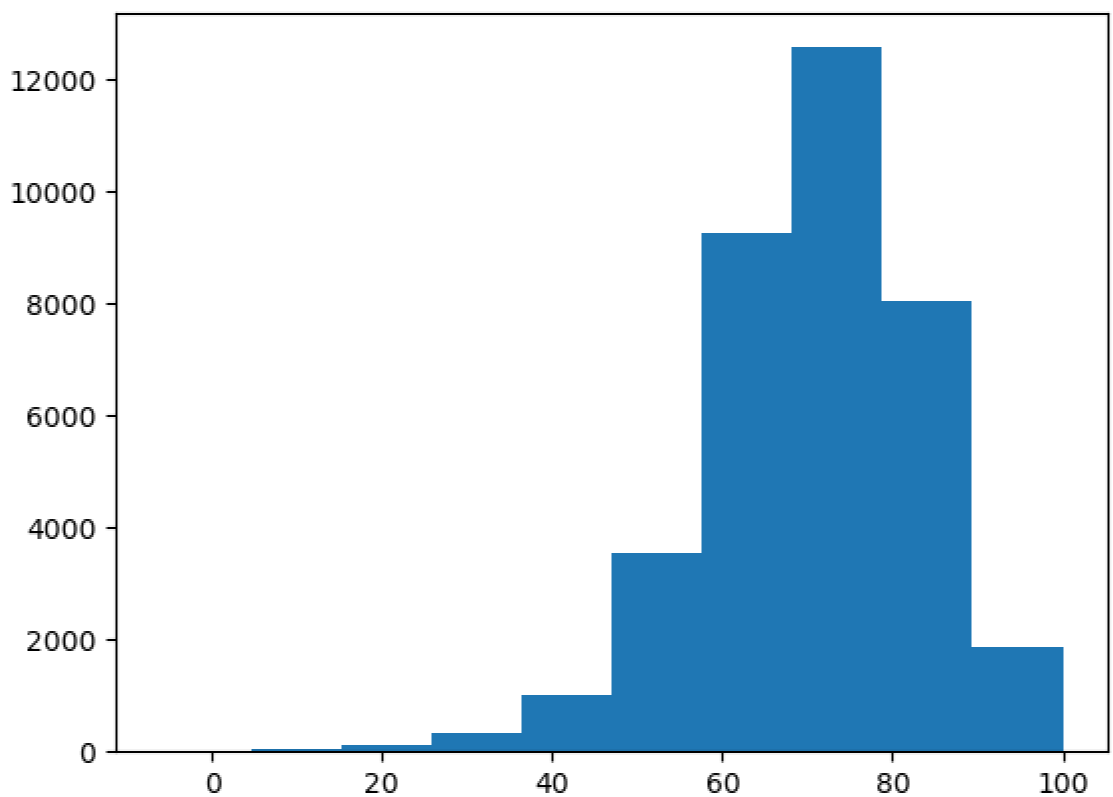
Out[75]:
```
40563
```

In [76]:
```
# Checking consistency for max credit score
df_policy['credit_score'].max()
```

Out[76]:
```
850.0
```

In [77]:
```
# Checking distribtuion of data by safety_rating
plt.hist(df_policy['safty_rating'],bins=10)
```

Out[77]:
```
(array([   19.,    59.,   103.,   344.,  1009.,  3545.,  9257., 12579.,
         8055.,  1879.]),
 array([ -6. ,   4.6,  15.2,  25.8,  36.4,  47. ,  57.6,  68.2,  78.8,
         89.4, 100. ]),
 <BarContainer object of 10 artists>)
```




In [78]:
```
df_policy['safty_rating'].quantile(np.linspace(.2,1,4,0))
```

Out[78]:
```
0.2    61.000000
0.4    68.520000
0.6    74.500000
0.8    81.333333
Name: safty_rating, dtype: float64
```

**Safety rating attribute is divided into 5 categories approximated from the distribution of safety ratings.**

In [79]:
```
bins = [0,59,69,79,89,100]
labels = ['Very Low','Low','Medium','High','Very High']
df_policy['safety_rating'] = pd.cut(df_policy['safty_rating'], bins = bins, labels = lab
df_policy.head(10)
```

Out[79]:

| | Unnamed: 0 | Quote_dt | discount | Home_policy_ind | zip | state_id | county_name | Agent_cd | quoted_amt | Pri |
|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 1 | 28-01-2015 | Yes | Y | 10465.0 | NY | 0 | 15973623.0 | $5,153 | |
| **1** | 3 | 03-09-2018 | No | N | 11548.0 | NY | 0 | 32759856.0 | $3,090 | |
| **2** | 5 | 18-05-2016 | No | N | 14622.0 | NY | 0 | 15675431.0 | $14,917 | |
| **3** | 6 | 17-11-2016 | No | N | 32811.0 | FL | 0 | 91762319.0 | $4,620 | |
| **4** | 7 | 04-07-2017 | No | N | 10306.0 | NY | 0 | 97388179.0 | $11,470 | |
| **5** | 11 | 25-12-2017 | No | N | 55125.0 | MN | 0 | 59705446.0 | $2,566 | |
| **6** | 12 | 22-11-2018 | No | N | 33136.0 | FL | 0 | 37520067.0 | $1,779 | |
| **7** | 13 | 30-03-2015 | Yes | Y | 7666.0 | NJ | 0 | 84058252.0 | $4,597 | |
| **8** | 14 | 11-11-2016 | No | N | 33143.0 | FL | 0 | 19952087.0 | $2,196 | |
| **9** | 16 | 07-10-2018 | No | N | 7676.0 | NJ | 0 | 53860167.0 | $1,636 | |

In [80]:
```
df_policy['safety_rating'].value_counts()
```

Out[80]:
```
Medium       12004
Low           9471
High          7415
Very Low      6076
Very High     1880
Name: safety_rating, dtype: int64
```

---

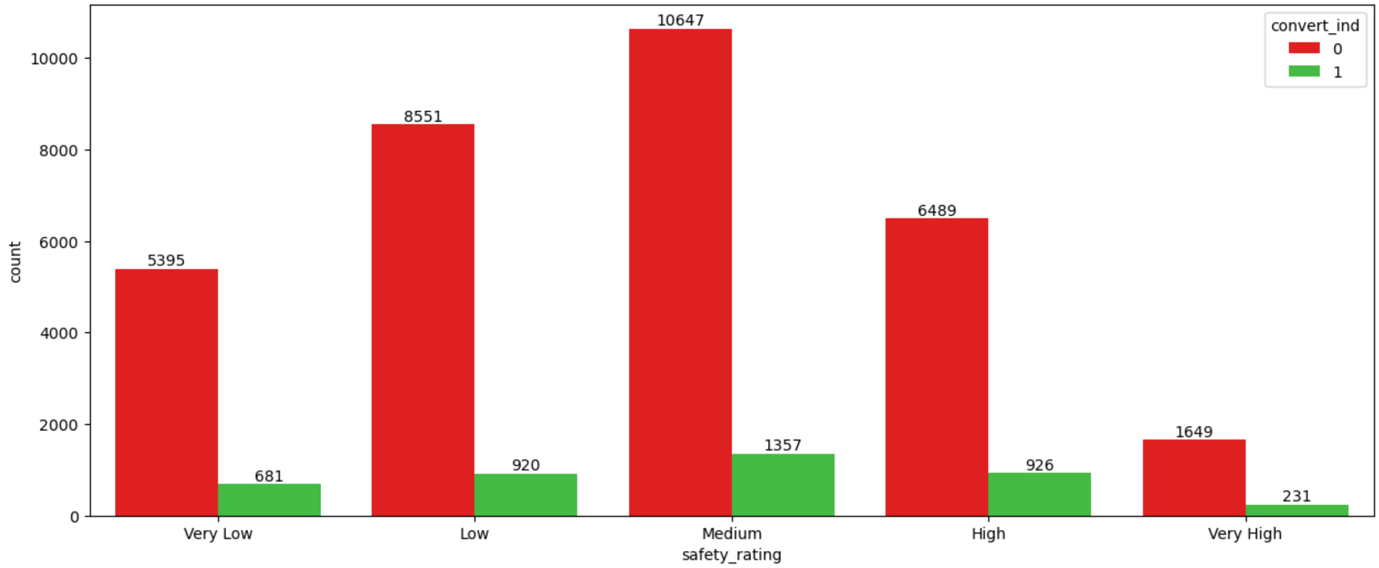
# EDA

---

**First, we check for bivariate analysis and look how the features affect the target variable independently.**

In [81]:
```
# Plotting safety rating categories vs conversion indicator
fig, ax = plt.subplots(figsize = (15,6))
sns.countplot(x='safety_rating', hue='convert_ind', data=df_policy, palette = ['Red','li
ax.bar_label(container=ax.containers[0])
ax.bar_label(container=ax.containers[1])
```

Out[81]:
```
[Text(0, 0, '681'),
 Text(0, 0, '920'),
 Text(0, 0, '1357'),
 Text(0, 0, '926'),
 Text(0, 0, '231')]
```




In [82]:
```
# Tabulating percentage conversions by safety rating categories
pd.crosstab(df_policy['safety_rating'], df_policy['convert_ind'], normalize='index') * 1
```

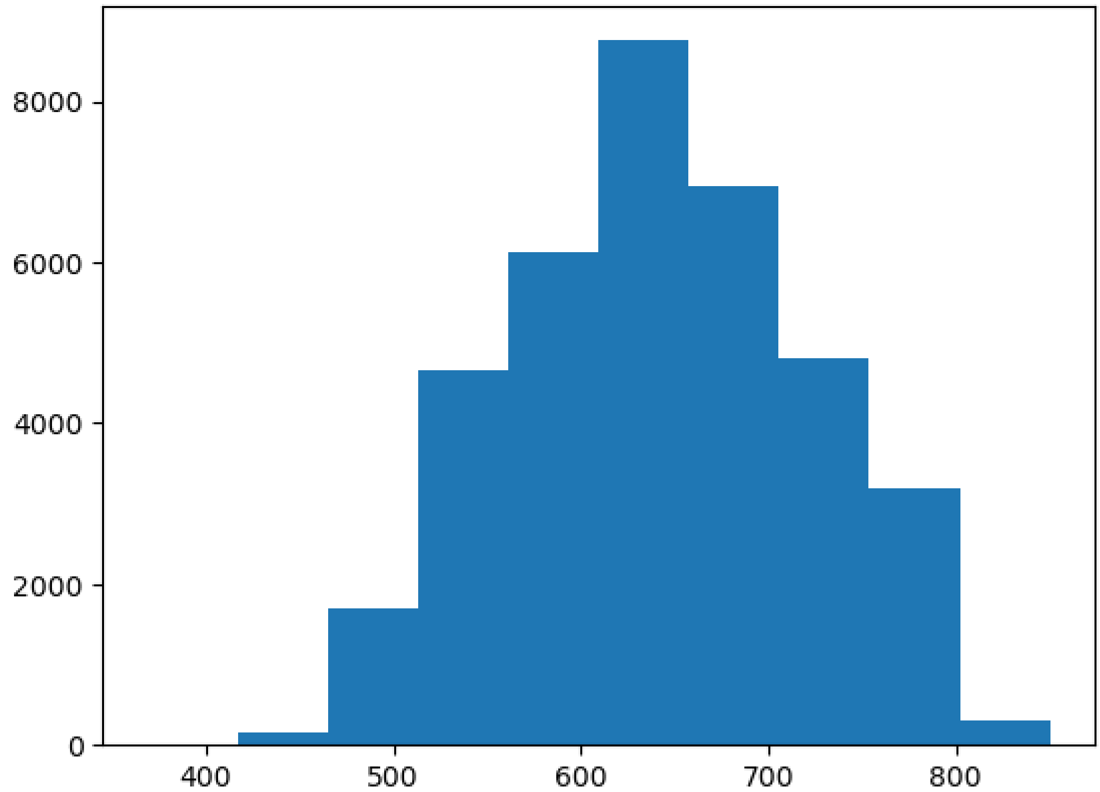
Out[82]:

| convert_ind | 0 | 1 |
|---|---|---|
| **safety_rating** | | |
| **Very Low** | 88.791968 | 11.208032 |
| **Low** | 90.286137 | 9.713863 |
| **Medium** | 88.695435 | 11.304565 |
| **High** | 87.511800 | 12.488200 |
| **Very High** | 87.712766 | 12.287234 |

**The conversion rate is highest for people with High and Very High safety rating, while maximum policies are sold to people in Medium safety rating category. The company sells extremely low number of policies to people with very high safety ratings.**

In [83]:
```
plt.hist(df_policy['credit_score'],bins=10)
```

Out[83]:
```
(array([  10.,  158., 1708., 4646., 6114., 8753., 6943., 4814., 3197.,
         295.]),
 array([369. , 417.1, 465.2, 513.3, 561.4, 609.5, 657.6, 705.7, 753.8,
        801.9, 850. ]),
 <BarContainer object of 10 artists>)
```




In [84]:
```
df_policy['credit_score'].quantile(np.linspace(.33,1,2,0))
```

Out[84]:
```
0.330    606.0
0.665    675.0
Name: credit_score, dtype: float64
```

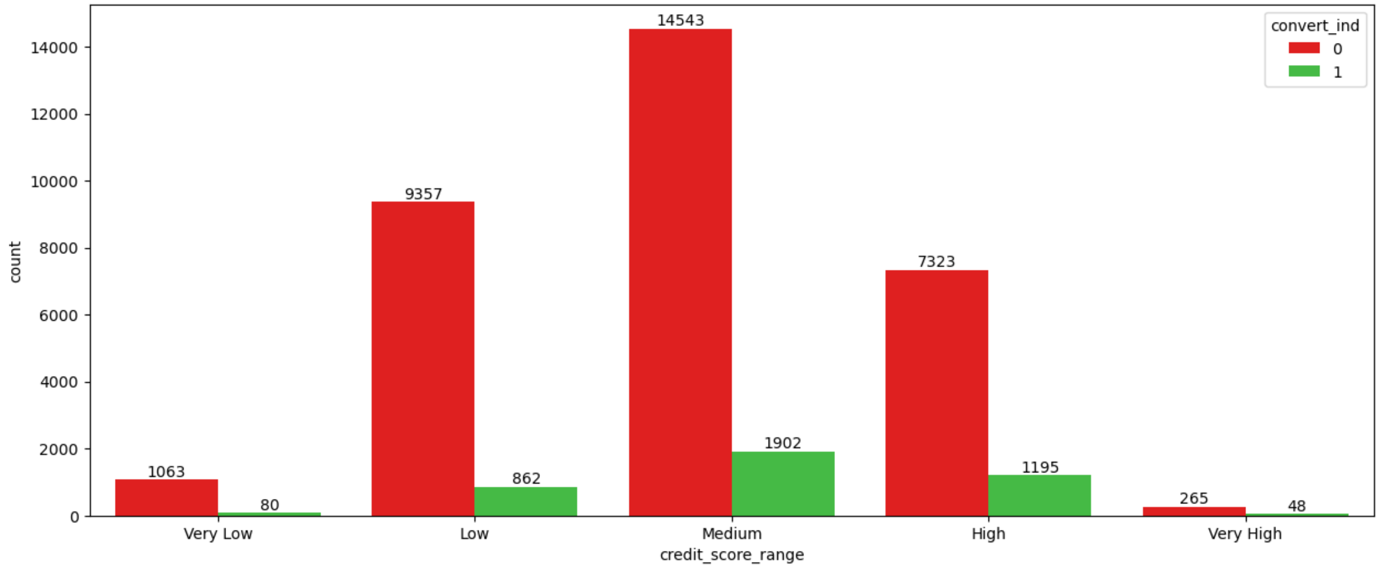
In [85]:
```
bins = [0,500,600,700,800,850]
labels = ['Very Low','Low','Medium','High','Very High']
df_policy['credit_score_range'] = pd.cut(df_policy['credit_score'], bins = bins, labels =
```

In [86]:
```
df_policy['credit_score_range'].value_counts()
```

Out[86]:
```
Medium       16445
Low          10219
High          8518
Very Low      1143
Very High      313
Name: credit_score_range, dtype: int64
```

In [87]:
```
# Plotting credit score categories vs conversion indicator
fig, ax = plt.subplots(figsize = (15,6))
sns.countplot(x='credit_score_range', hue='convert_ind', data=df_policy, palette = ['Red
ax.bar_label(container=ax.containers[0])
ax.bar_label(container=ax.containers[1])
```

Out[87]:
```
[Text(0, 0, '80'),
 Text(0, 0, '862'),
 Text(0, 0, '1902'),
 Text(0, 0, '1195'),
 Text(0, 0, '48')]
```




In [88]:
```
# Tabulating percentage conversions by credit score categories
pd.crosstab(df_policy['credit_score_range'], df_policy['convert_ind'], normalize='index'
```

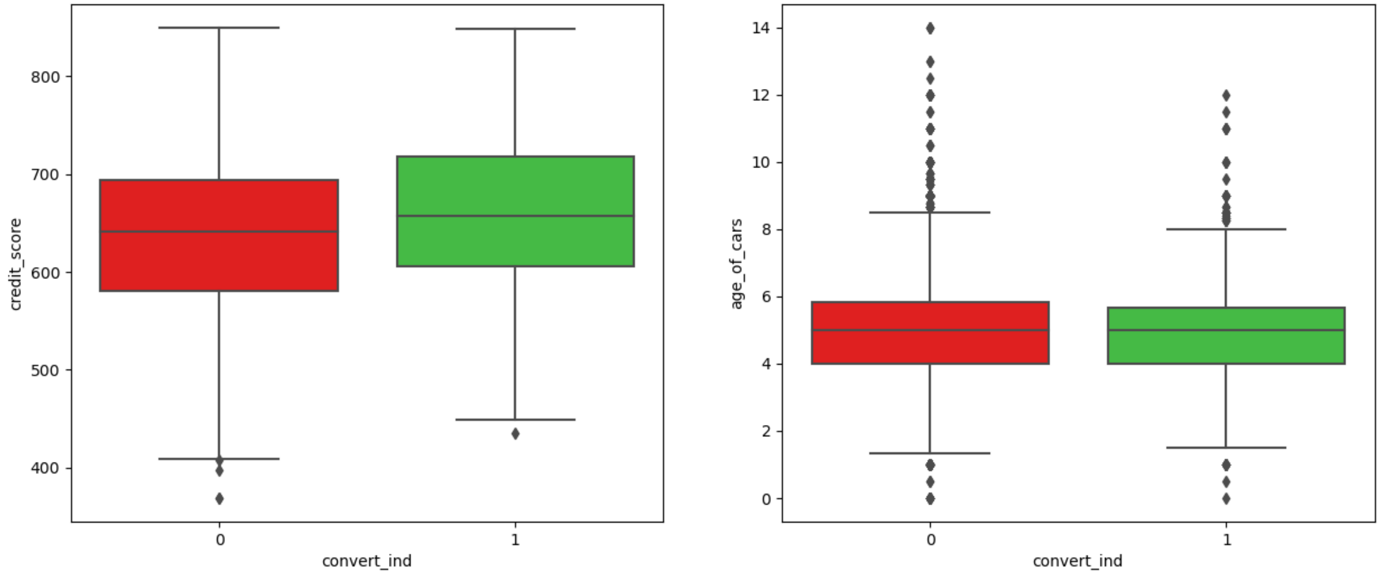
Out[88]:

| convert_ind<br>credit_score_range | 0 | 1 |
|---|---|---|
| **Very Low** | 93.000875 | 6.999125 |
| **Low** | 91.564732 | 8.435268 |
| **Medium** | 88.434175 | 11.565825 |
| **High** | 85.970885 | 14.029115 |
| **Very High** | 84.664537 | 15.335463 |

**The conversion rate is highest for people with High and Very High credit scores, while maximum policies are sold to people in Medium credit score category. The company sells extremely low number of policies to people with very high credit scores.**

In [89]:
```
# Plotting box plots of credit score and car age vs conversion indicator

fig, (ax1,ax2) = plt.subplots(1,2, figsize = (15,6))

sns.boxplot(x='convert_ind', y='credit_score', data=df_policy, palette = ['Red','limegre
sns.boxplot(x='convert_ind', y='age', data=df_policy, palette = ['Red','limegreen'], ax
ax2.set_ylabel('age_of_cars')
```

Out[89]:
```
Text(0, 0.5, 'age_of_cars')
```




**Car age doesn't seems to differ much, while credit scores seem to be higher for those that convert.**

In [90]:
```
pd.crosstab(df_policy['age'], df_policy['convert_ind'])
```

Out[90]:

| convert_ind | 0 | 1 |
|---|---|---|
| **age** | | |
| **0.000000** | 17 | 1 |
| **0.500000** | 2 | 1 |
| **1.000000** | 86 | 10 |
| **1.333333** | 8 | 0 |
| **1.500000** | 51 | 2 |
| **1.666667** | 18 | 2 |
| **1.750000** | 4 | 0 |
| **1.800000** | 2 | 0 |
| **2.000000** | 379 | 50 |
| **2.200000** | 10 | 1 |
| **2.250000** | 27 | 3 |
| **2.333333** | 82 | 15 |
| **2.400000** | 11 | 1 |
| **2.500000** | 258 | 51 |
| **2.600000** | 20 | 0 |
| **2.666667** | 195 | 22 |
| **2.750000** | 82 | 5 |
| **2.800000** | 40 | 5 |
| **2.833333** | 13 | 1 |
| **2.857143** | 1 | 1 |
| **3.000000** | 1181 | 159 |
| **3.142857** | 1 | 0 |

| | | |
|---|---|---|
| **3.166667** | 19 | 0 |
| **3.200000** | 86 | 17 |
| **3.250000** | 205 | 35 |
| **3.285714** | 5 | 1 |
| **3.333333** | 474 | 58 |
| **3.400000** | 103 | 13 |
| **3.428571** | 2 | 0 |
| **3.500000** | 899 | 127 |
| **3.571429** | 3 | 0 |
| **3.600000** | 167 | 16 |
| **3.666667** | 658 | 73 |
| **3.714286** | 15 | 0 |
| **3.750000** | 406 | 56 |
| **3.800000** | 206 | 9 |
| **3.833333** | 70 | 12 |
| **3.857143** | 9 | 3 |
| **3.875000** | 1 | 0 |
| **4.000000** | 2746 | 349 |
| **4.125000** | 1 | 0 |
| **4.142857** | 21 | 2 |
| **4.166667** | 94 | 11 |
| **4.200000** | 300 | 30 |
| **4.250000** | 607 | 72 |
| **4.285714** | 22 | 4 |
| **4.333333** | 983 | 131 |
| **4.375000** | 3 | 0 |
| **4.400000** | 321 | 54 |
| **4.428571** | 34 | 2 |
| **4.500000** | 1618 | 215 |
| **4.571429** | 28 | 3 |
| **4.600000** | 358 | 45 |
| **4.625000** | 3 | 0 |
| **4.666667** | 1093 | 138 |
| **4.714286** | 34 | 4 |
| **4.750000** | 706 | 82 |
| **4.800000** | 358 | 46 |
| **4.833333** | 148 | 15 |

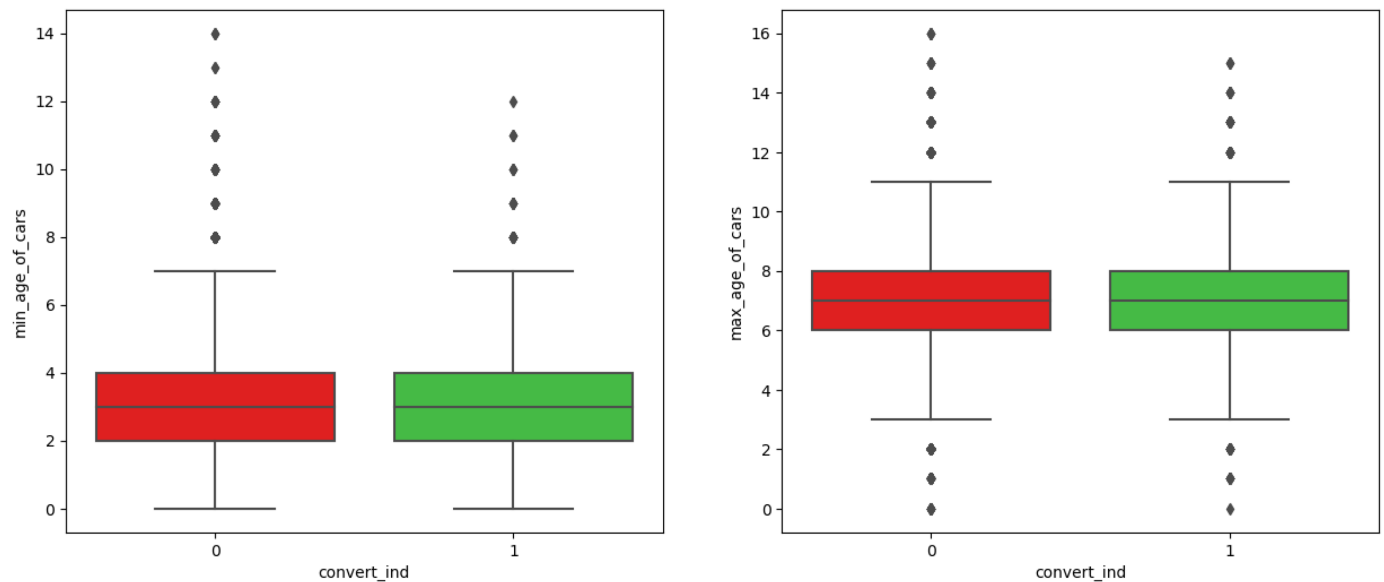
| | | |
|---|---|---|
| **4.857143** | 28 | 2 |
| **4.875000** | 3 | 1 |
| **5.000000** | 3202 | 448 |
| **5.142857** | 22 | 3 |
| **5.166667** | 119 | 20 |
| **5.200000** | 323 | 47 |
| **5.250000** | 672 | 76 |
| **5.285714** | 23 | 2 |
| **5.333333** | 989 | 134 |
| **5.375000** | 2 | 1 |
| **5.400000** | 337 | 33 |
| **5.428571** | 20 | 6 |
| **5.500000** | 1451 | 203 |
| **5.571429** | 19 | 3 |
| **5.600000** | 314 | 40 |
| **5.625000** | 3 | 0 |
| **5.666667** | 836 | 116 |
| **5.714286** | 19 | 2 |
| **5.750000** | 550 | 71 |
| **5.800000** | 290 | 29 |
| **5.833333** | 65 | 9 |
| **5.857143** | 14 | 0 |
| **5.875000** | 4 | 0 |
| **6.000000** | 2285 | 283 |
| **6.142857** | 15 | 0 |
| **6.166667** | 50 | 6 |
| **6.200000** | 178 | 14 |
| **6.250000** | 349 | 40 |
| **6.285714** | 7 | 1 |
| **6.333333** | 539 | 65 |
| **6.375000** | 1 | 0 |
| **6.400000** | 150 | 17 |
| **6.428571** | 6 | 2 |
| **6.500000** | 725 | 99 |
| **6.571429** | 6 | 1 |
| **6.600000** | 123 | 9 |
| **6.666667** | 450 | 45 |
| **6.714286** | 8 | 0 |

| | | |
|---|---|---|
| **6.750000** | 226 | 24 |
| **6.800000** | 82 | 10 |
| **6.833333** | 17 | 3 |
| **6.857143** | 4 | 0 |
| **7.000000** | 1162 | 118 |
| **7.142857** | 1 | 0 |
| **7.166667** | 12 | 1 |
| **7.200000** | 43 | 3 |
| **7.250000** | 86 | 11 |
| **7.285714** | 3 | 0 |
| **7.333333** | 200 | 23 |
| **7.400000** | 41 | 0 |
| **7.500000** | 310 | 30 |
| **7.600000** | 13 | 2 |
| **7.666667** | 131 | 14 |
| **7.750000** | 49 | 1 |
| **7.800000** | 8 | 1 |
| **7.833333** | 1 | 0 |
| **7.857143** | 1 | 0 |
| **8.000000** | 387 | 48 |
| **8.200000** | 5 | 0 |
| **8.250000** | 16 | 5 |
| **8.333333** | 40 | 5 |
| **8.400000** | 3 | 2 |
| **8.500000** | 95 | 12 |
| **8.666667** | 31 | 3 |
| **8.750000** | 4 | 0 |
| **8.800000** | 1 | 0 |
| **9.000000** | 136 | 9 |
| **9.333333** | 10 | 0 |
| **9.500000** | 22 | 1 |
| **9.666667** | 6 | 0 |
| **10.000000** | 54 | 4 |
| **10.500000** | 4 | 0 |
| **11.000000** | 20 | 4 |
| **11.500000** | 2 | 1 |
| **12.000000** | 12 | 1 |

| | | |
|---|---|---|
| **12.500000** | 1 | 0 |
| **13.000000** | 2 | 0 |
| **14.000000** | 3 | 0 |

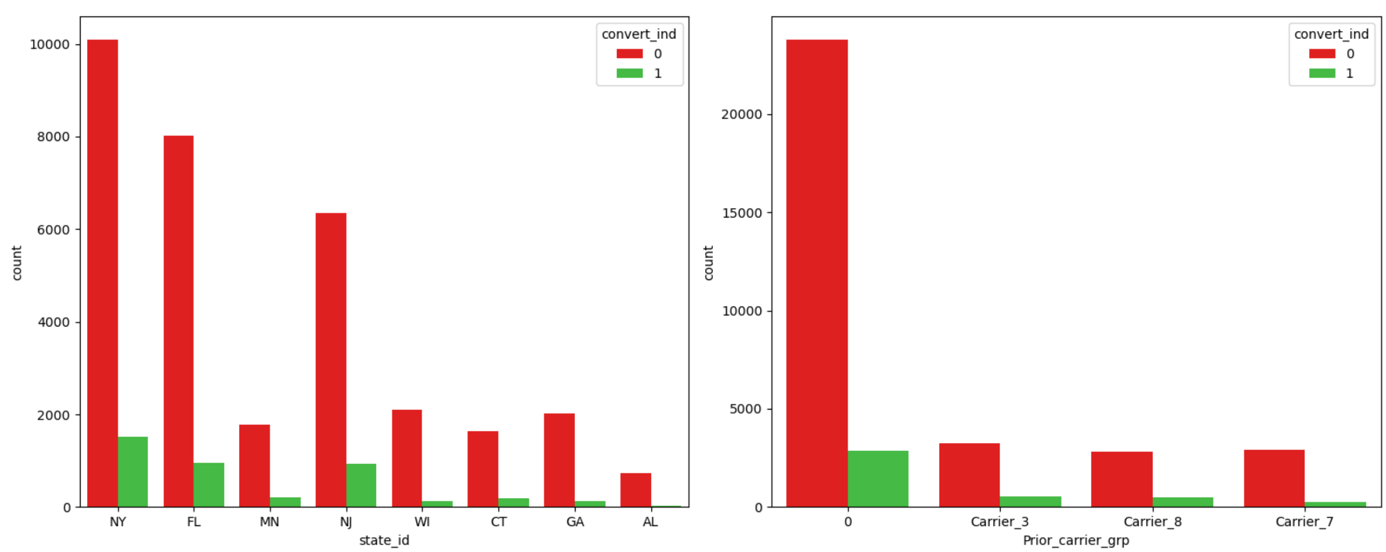
In [91]:
```
# Plotting boxplots of min and max age of cars vs conversion indicator
fig, (ax1,ax2) = plt.subplots(1,2, figsize = (15,6))

sns.boxplot(x='convert_ind', y='age_min', data=df_policy, palette = ['Red','limegreen'],
sns.boxplot(x='convert_ind', y='age_max', data=df_policy, palette = ['Red','limegreen'],
ax1.set_ylabel('min_age_of_cars')
ax2.set_ylabel('max_age_of_cars')
```

Out[91]:
```
Text(0, 0.5, 'max_age_of_cars')
```




**There doesn't seem to be any difference in conversion by min and max age of cars.**

In [92]:
```
# Plotting state id and prior carrier group vs conversion indicator

fig, (ax1,ax2) = plt.subplots(1,2, figsize = (15,6))
sns.countplot(x='state_id', hue='convert_ind', data=df_policy, ax = ax1, palette = ['Red
sns.countplot(x='Prior_carrier_grp', hue='convert_ind', data=df_policy, ax = ax2, palett
fig.tight_layout()
```




In [93]:
```
# Tabulating percentage conversions by state ids
pd.crosstab(df_policy['state_id'], df_policy['convert_ind'], normalize='index') * 100
```

Out[93]:

| convert_ind | 0 | 1 |
|---|---|---|
| **state_id** | | |
| **AL** | 95.501285 | 4.498715 |
| **CT** | 90.021930 | 9.978070 |
| **FL** | 89.412027 | 10.587973 |
| **GA** | 93.543892 | 6.456108 |
| **MN** | 89.093625 | 10.906375 |
| **NJ** | 87.137955 | 12.862045 |
| **NY** | 86.907838 | 13.092162 |
| **WI** | 93.886658 | 6.113342 |

**NY seems to have highest converion rate and it is the state with highest number of policies being quoted and sold by the company. NY, FL and NJ are the three states that cover a large proportion of the policies quoted and sold by the company.**

In [94]:

```
# Tabulating percentage conversions by prior carrier groups
pd.crosstab(df_policy['Prior_carrier_grp'], df_policy['convert_ind'], normalize='index')
```

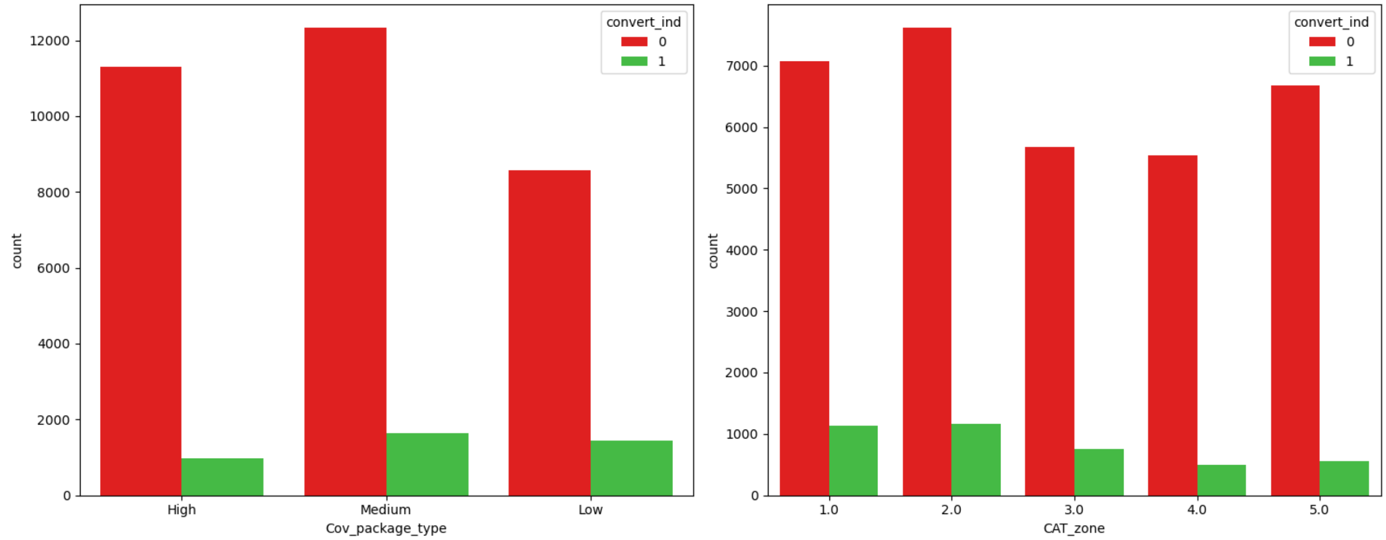
Out[94]:

| convert_ind | 0 | 1 |
|---|---|---|
| **Prior_carrier_grp** | | |
| **0** | 89.255143 | 10.744857 |
| **Carrier_3** | 86.021791 | 13.978209 |
| **Carrier_7** | 92.080153 | 7.919847 |
| **Carrier_8** | 85.507683 | 14.492317 |

**People with Prior Carrier Group 3 and 8 seem to have a higher conversion rate when compared with people having other prior carriers.**

In [95]:

```
#Plotting coverage package type and CAT Zone vs conversion indicator

fig, (ax1,ax2) = plt.subplots(1,2, figsize = (15,6))
sns.countplot(x='Cov_package_type', hue='convert_ind', data=df_policy, ax = ax1, palette
sns.countplot(x='CAT_zone', hue='convert_ind', data=df_policy, ax = ax2, palette = ['Red
fig.tight_layout()
```




In [96]:
```
# Tabulating percentage conversions by coverage package type
pd.crosstab(df_policy['Cov_package_type'], df_policy['convert_ind'], normalize='index')
```

Out[96]:

| convert_ind | 0 | 1 |
|---|---|---|
| **Cov_package_type** | | |
| **High** | 92.053411 | 7.946589 |
| **Low** | 85.553228 | 14.446772 |
| **Medium** | 88.319966 | 11.680034 |

**Conversions are highest with low coverage type policies, and the company sells the least number of policies in Low coverage type amongst the three, and highest in the Medium coverage type.**

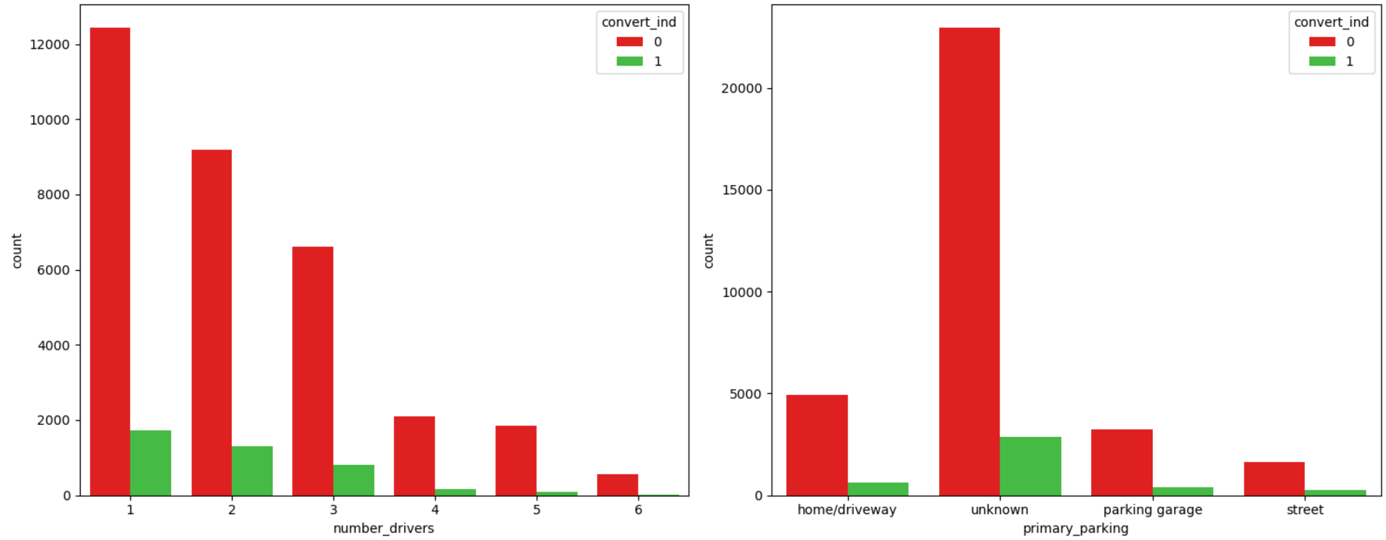
In [97]:
```
# Tabulating percentage conversions by CAT Zones
pd.crosstab(df_policy['CAT_zone'], df_policy['convert_ind'], normalize='index') * 100
```

Out[97]:

| convert_ind | 0 | 1 |
|---|---|---|
| **CAT_zone** | | |
| **1.0** | 86.178763 | 13.821237 |
| **2.0** | 86.773753 | 13.226247 |
| **3.0** | 88.369192 | 11.630808 |
| **4.0** | 91.771523 | 8.228477 |
| **5.0** | 92.234351 | 7.765649 |

**For lower CAT zones, the conversion percentages are higher, while the maximum policies are quoted in CAT zone 2, and the lesat in CAT zone 4.**

In [98]:
```
# Plotting number of drivers and total number of vehicles vs conversion indicator

fig, (ax1,ax2) = plt.subplots(1,2, figsize = (15,6))
sns.countplot(x='number_drivers', hue='convert_ind', data=df_policy, ax = ax1, palette =
sns.countplot(x='primary_parking', hue='convert_ind', data=df_policy, ax = ax2, palette
fig.tight_layout()
```




In [99]:

```
# Tabulating percentage conversions by number of drivers
pd.crosstab(df_policy['number_drivers'], df_policy['convert_ind'], normalize='index') *
```

Out[99]:

| convert_ind<br>number_drivers | 0 | 1 |
|---|---|---|
| 1 | 87.782326 | 12.217674 |
| 2 | 87.535680 | 12.464320 |
| 3 | 89.086740 | 10.913260 |
| 4 | 93.108048 | 6.891952 |
| 5 | 95.125705 | 4.874295 |
| 6 | 96.858639 | 3.141361 |

**Conversions are highest when number of drivers are fewer in a policy, and the company sells the maximum policies where there are fewer drivers.**

In [100…

```
# Tabulating percentage conversions by parking type
pd.crosstab(df_policy['primary_parking'], df_policy['convert_ind'], normalize='index') *
```

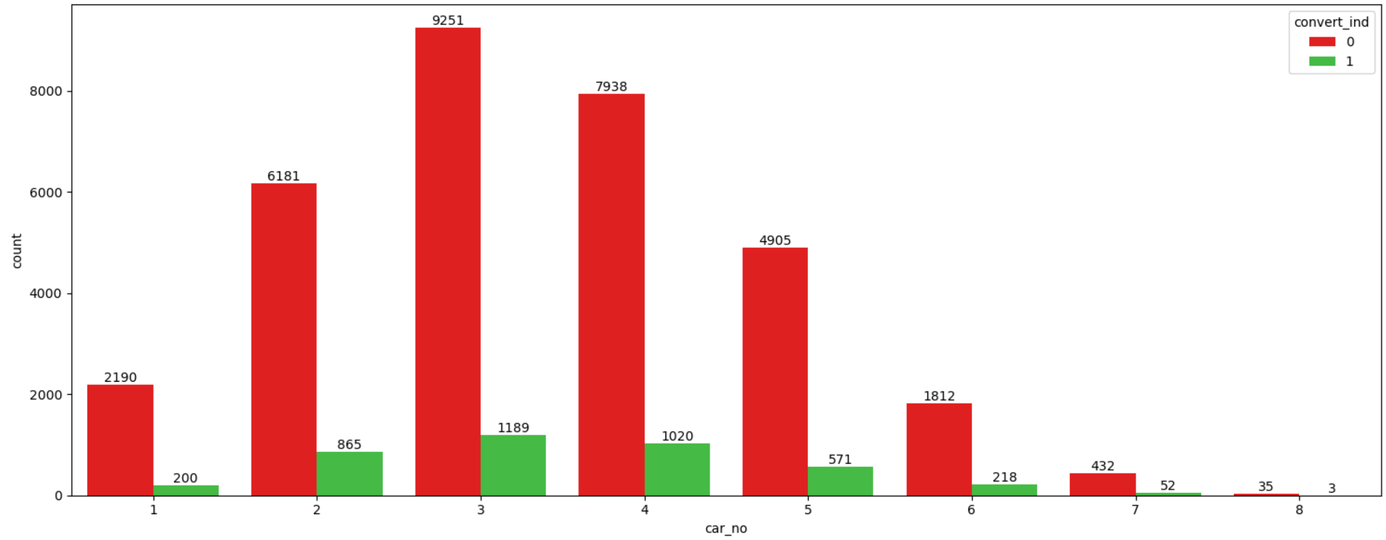
Out[100]:

| convert_ind<br>primary_parking | 0 | 1 |
|---|---|---|
| home/driveway | 89.105339 | 10.894661 |
| parking garage | 89.222222 | 10.777778 |
| street | 86.507937 | 13.492063 |
| unknown | 88.884157 | 11.115843 |

**Nothing much can be inferred from the parking types.**

In [101…

```
# Plotting no. of cars in policy by conversion type

fig, ax = plt.subplots(figsize = (15,6))
sns.countplot(x='car_no', hue='convert_ind', data=df_policy, ax = ax, palette = ['Red','
ax.bar_label(container=ax.containers[0])
ax.bar_label(container=ax.containers[1])
fig.tight_layout()
```




In [102…

```
# Tabulating percentage conversions by no. of cars in policy
pd.crosstab(df_policy['car_no'], df_policy['convert_ind'], normalize='index') * 100
```

Out[102]:

| convert_ind | 0 | 1 |
|---|---|---|
| **car_no** | | |
| **1** | 91.631799 | 8.368201 |
| **2** | 87.723531 | 12.276469 |
| **3** | 88.611111 | 11.388889 |
| **4** | 88.613530 | 11.386470 |
| **5** | 89.572681 | 10.427319 |
| **6** | 89.261084 | 10.738916 |
| **7** | 89.256198 | 10.743802 |
| **8** | 92.105263 | 7.894737 |

**The conversion rates are highest when there 2,3 or 4 cars in a policy, and the maximum policies are quoted and sold to families with 3 or 4 cars.**

## Checking Correlation

In [103…

```
# Checking the datatypes
df_policy.dtypes
```

Out[103]:

```
Unnamed: 0              int64
Quote_dt               object
discount               object
Home_policy_ind        object
zip                   float64
state_id               object
county_name            object
Agent_cd              float64
quoted_amt             object
Prior_carrier_grp      object
credit_score          float64
Cov_package_type       object
CAT_zone              float64
policy_id              object
number_drivers          int64
num_loaned_veh          int64
```

```
num_owned_veh                  int64
num_leased_veh                 int64
total_number_veh               int64
convert_ind                    int64
split                         object
primary_parking               object
car_no                         int64
age                          float64
age_min                      float64
age_max                      float64
ownership_type_leased          uint8
ownership_type_loaned          uint8
ownership_type_owned           uint8
color_black                    uint8
color_blue                     uint8
color_gray                     uint8
color_other                    uint8
color_red                      uint8
color_silver                   uint8
color_white                    uint8
make_AUDI                      uint8
make_BMW                       uint8
make_CHEVROLET                 uint8
make_HONDA                     uint8
make_MERCEDES-BENZ             uint8
safty_rating                 float64
safety_min                   float64
safety_max                   float64
gender_F                       uint8
gender_M                       uint8
living_status_dependent        uint8
living_status_own              uint8
living_status_rent             uint8
Age Group_15-25                uint8
Age Group_26-35                uint8
Age Group_36-45                uint8
Age Group_46-55                uint8
Age Group_56-65                uint8
Age Group_65+                  uint8
high_education_ind_0.0         uint8
high_education_ind_1.0         uint8
quote                        float64
quote_range                 category
log_quote                    float64
total_drivers                  uint8
safety_rating               category
credit_score_range          category
dtype: object
```

In [104…

```
# Getting just the numerical features
numerical = df_policy.select_dtypes(include=['int64','float64','Int64'])[:]
numerical
```

Out[104]:

| | Unnamed: 0 | zip | Agent_cd | credit_score | CAT_zone | number_drivers | num_loaned_veh | num_owned_veh |
|---|---|---|---|---|---|---|---|---|
| **0** | 1 | 10465.0 | 15973623.0 | 613.0 | 2.0 | 2 | 1 | 2 |
| **1** | 3 | 11548.0 | 32759856.0 | 631.0 | 2.0 | 2 | 1 | 2 |
| **2** | 5 | 14622.0 | 15675431.0 | 602.0 | 4.0 | 2 | 0 | 1 |
| **3** | 6 | 32811.0 | 91762319.0 | 704.0 | 1.0 | 1 | 2 | 2 |
| **4** | 7 | 10306.0 | 97388179.0 | 611.0 | 4.0 | 4 | 2 | 2 |
| **...** | ... | ... | ... | ... | ... | ... | ... | ... |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| **36857** | 49158 | 32601.0 | 61229929.0 | 590.0 | 4.0 | 1 | 2 | 2 |
| **36858** | 49159 | 11553.0 | 33958256.0 | 688.0 | 2.0 | 2 | 2 | 2 |
| **36859** | 49160 | 33027.0 | 92637408.0 | 637.0 | 2.0 | 1 | 1 | 3 |
| **36860** | 49161 | 11561.0 | 33958256.0 | 581.0 | 4.0 | 2 | 2 | 2 |
| **36861** | 49162 | 8724.0 | 46902238.0 | 778.0 | 4.0 | 3 | 2 | 1 |

36862 rows × 20 columns

In [105…

```
numerical = numerical.drop(["zip","Agent_cd"], axis = 1)
numerical.dtypes
```

Out[105]:

```
Unnamed: 0            int64
credit_score        float64
CAT_zone            float64
number_drivers        int64
num_loaned_veh        int64
num_owned_veh         int64
num_leased_veh        int64
total_number_veh      int64
convert_ind           int64
car_no                int64
age                 float64
age_min             float64
age_max             float64
safty_rating        float64
safety_min          float64
safety_max          float64
quote               float64
log_quote           float64
dtype: object
```

In [106…

```
# Creating correlation matrix
correlation = numerical.dropna().corr()
correlation
```

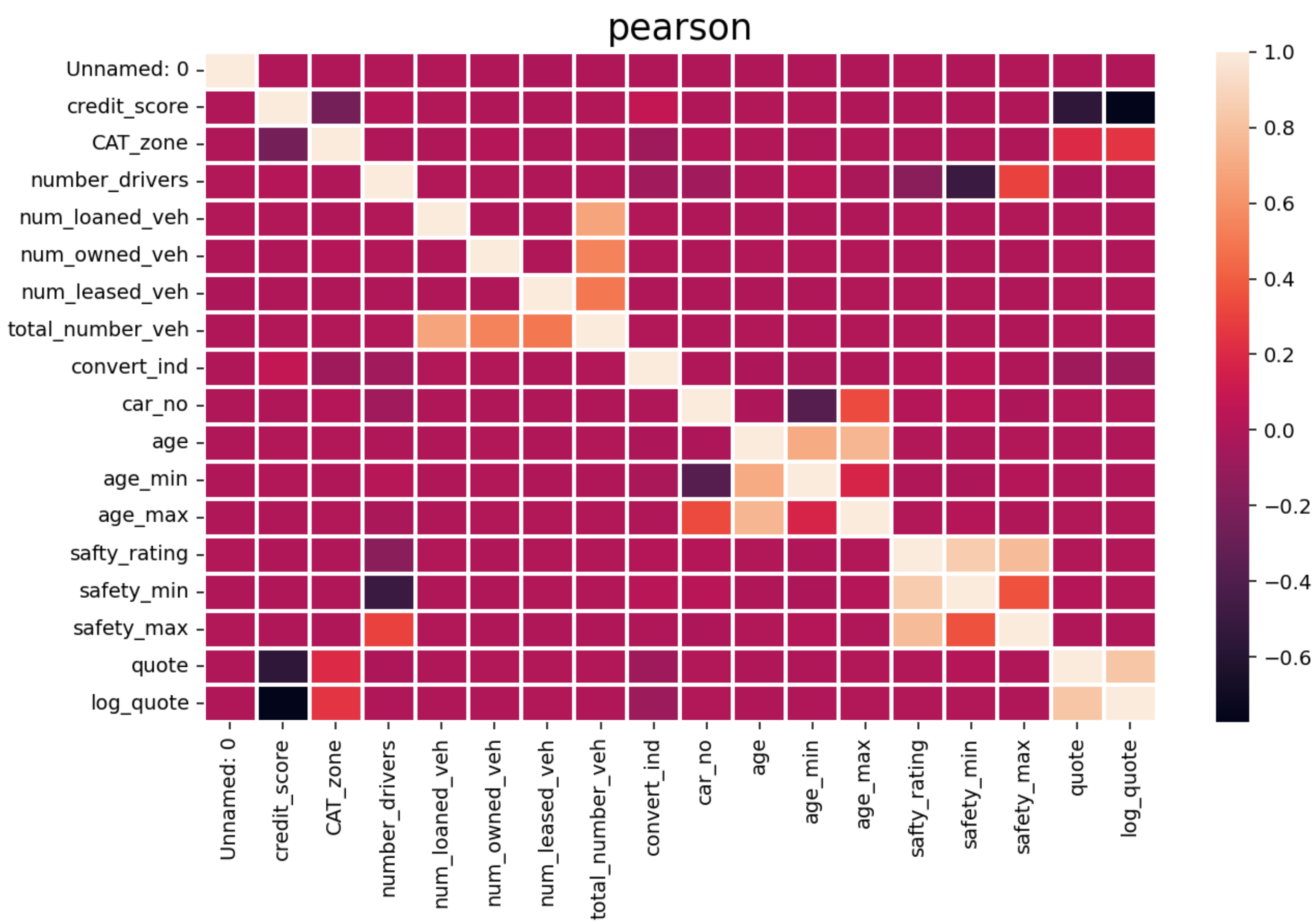
Out[106]:

| | Unnamed: 0 | credit_score | CAT_zone | number_drivers | num_loaned_veh | num_owned_veh | num_lea |
|---|---|---|---|---|---|---|---|
| **Unnamed: 0** | 1.000000 | 0.000984 | 0.002536 | 0.004584 | 0.002867 | -0.003182 | -0 |
| **credit_score** | 0.000984 | 1.000000 | -0.246360 | 0.010131 | 0.009434 | -0.002339 | 0 |
| **CAT_zone** | 0.002536 | -0.246360 | 1.000000 | -0.010495 | -0.001070 | 0.010568 | 0 |
| **number_drivers** | 0.004584 | 0.010131 | -0.010495 | 1.000000 | 0.005387 | 0.003813 | -0 |
| **num_loaned_veh** | 0.002867 | 0.009434 | -0.001070 | 0.005387 | 1.000000 | 0.001837 | -0 |
| **num_owned_veh** | -0.003182 | -0.002339 | 0.010568 | 0.003813 | 0.001837 | 1.000000 | -0 |
| **num_leased_veh** | -0.013169 | 0.000291 | 0.001413 | -0.002505 | -0.001502 | -0.005172 | 1 |
| **total_number_veh** | -0.006388 | 0.005245 | 0.005731 | 0.004457 | 0.675597 | 0.542402 | 0 |
| **convert_ind** | 0.000859 | 0.072391 | -0.077166 | -0.062884 | 0.004189 | 0.003138 | -0 |
| **car_no** | -0.006681 | -0.004828 | 0.010103 | -0.062441 | 0.001148 | -0.005102 | -0 |
| **age** | -0.007891 | 0.004160 | 0.005533 | -0.001213 | -0.001635 | 0.006660 | 0 |
| **age_min** | -0.003311 | 0.005869 | 0.001241 | 0.027024 | 0.002428 | 0.003335 | -0 |
| **age_max** | -0.006899 | 0.000963 | 0.005141 | -0.030593 | -0.001122 | 0.006328 | 0 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| **safty_rating** | 0.007341 | -0.002822 | -0.001532 | -0.160588 | 0.005685 | -0.003238 | ( |
| **safety_min** | 0.001512 | -0.007293 | 0.001410 | -0.501435 | 0.001444 | -0.001806 | ( |
| **safety_max** | 0.008805 | 0.002197 | -0.004254 | 0.300615 | 0.007605 | -0.005559 | -( |
| **quote** | 0.000667 | -0.552545 | 0.198996 | -0.012994 | -0.000678 | 0.003741 | ( |
| **log_quote** | -0.002214 | -0.772746 | 0.251992 | -0.008986 | -0.003500 | 0.002488 | ( |

In [107…

```
# plotting heatmap usill all methods for all numerical variables
plt.figure(figsize=(36,6), dpi=140)
for j,i in enumerate(['pearson']):
  plt.subplot(1,3,j+1)
  correlation = numerical.dropna().corr(method=i)
  sns.heatmap(correlation, linewidth = 2)
  plt.title(i, fontsize=18)
```




**We can see that there is high correlation between min car age, max car age with mean car age in policy and min safety, max safety with mean safety rating in a policy. These features have been added by us to check for some hidden trend if possible, and we will keep these for now and do not remove them from our dataset.**

In [108…

```
df_policy.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 36862 entries, 0 to 36861
Data columns (total 63 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   Unnamed: 0              36862 non-null  int64
 1   Quote_dt                36862 non-null  object
 2   discount                36862 non-null  object
```

```
 3   Home_policy_ind          36862 non-null  object
 4   zip                      36510 non-null  float64
 5   state_id                 36862 non-null  object
 6   county_name              36862 non-null  object
 7   Agent_cd                 32791 non-null  float64
 8   quoted_amt               36775 non-null  object
 9   Prior_carrier_grp        36862 non-null  object
 10  credit_score             36638 non-null  float64
 11  Cov_package_type         36269 non-null  object
 12  CAT_zone                 36681 non-null  float64
 13  policy_id                36862 non-null  object
 14  number_drivers           36862 non-null  int64
 15  num_loaned_veh           36862 non-null  int64
 16  num_owned_veh            36862 non-null  int64
 17  num_leased_veh           36862 non-null  int64
 18  total_number_veh         36862 non-null  int64
 19  convert_ind              36862 non-null  int64
 20  split                    36862 non-null  object
 21  primary_parking          36862 non-null  object
 22  car_no                   36862 non-null  int64
 23  age                      36852 non-null  float64
 24  age_min                  36852 non-null  float64
 25  age_max                  36852 non-null  float64
 26  ownership_type_leased    36862 non-null  uint8
 27  ownership_type_loaned    36862 non-null  uint8
 28  ownership_type_owned     36862 non-null  uint8
 29  color_black              36862 non-null  uint8
 30  color_blue               36862 non-null  uint8
 31  color_gray               36862 non-null  uint8
 32  color_other              36862 non-null  uint8
 33  color_red                36862 non-null  uint8
 34  color_silver             36862 non-null  uint8
 35  color_white              36862 non-null  uint8
 36  make_AUDI                36862 non-null  uint8
 37  make_BMW                 36862 non-null  uint8
 38  make_CHEVROLET           36862 non-null  uint8
 39  make_HONDA               36862 non-null  uint8
 40  make_MERCEDES-BENZ       36862 non-null  uint8
 41  safty_rating             36849 non-null  float64
 42  safety_min               36849 non-null  float64
 43  safety_max               36849 non-null  float64
 44  gender_F                 36862 non-null  uint8
 45  gender_M                 36862 non-null  uint8
 46  living_status_dependent  36862 non-null  uint8
 47  living_status_own        36862 non-null  uint8
 48  living_status_rent       36862 non-null  uint8
 49  Age Group_15-25          36862 non-null  uint8
 50  Age Group_26-35          36862 non-null  uint8
 51  Age Group_36-45          36862 non-null  uint8
 52  Age Group_46-55          36862 non-null  uint8
 53  Age Group_56-65          36862 non-null  uint8
 54  Age Group_65+            36862 non-null  uint8
 55  high_education_ind_0.0   36862 non-null  uint8
 56  high_education_ind_1.0   36862 non-null  uint8
 57  quote                    36775 non-null  float64
 58  quote_range              36775 non-null  category
 59  log_quote                36775 non-null  float64
 60  total_drivers            36862 non-null  uint8
 61  safety_rating            36846 non-null  category
 62  credit_score_range       36638 non-null  category
dtypes: category(3), float64(12), int64(8), object(11), uint8(29)
memory usage: 10.1+ MB
```

In [109…

```python
# Dropping quoted amt, as a numerical column for same has been created, and dropping tot
df_policy.drop(['quoted_amt', 'total_drivers'], axis = 1, inplace = True)
```

# Feature Engineering

**We add safety range as the difference of max and min safety ratings in a policy, and car age range as the difference between the oldest and newest car in a policy.**

In [110…
```
df_policy['safety_range'] = df_policy['safety_max'] - df_policy['safety_min']
df_policy['car_age_range'] = df_policy['age_max'] - df_policy['age_min']
```

**We will extract month, quarter and year from date to check if some insights could be obtained from these new features.**

In [111…
```
df_policy['Quote_dt'] = pd.to_datetime(df_policy['Quote_dt'], infer_datetime_format = Tr
```

In [112…
```
df_policy['Quote_month'] = df_policy['Quote_dt'].dt.month
df_policy['Quote_month'].value_counts()
```

Out[112]:
```
10    3263
11    3197
5     3164
7     3142
8     3114
3     3113
12    3096
1     3060
9     2966
4     2940
6     2934
2     2873
Name: Quote_month, dtype: int64
```

In [113…
```
pd.crosstab(df_policy['Quote_month'], df_policy['convert_ind'], normalize='index') * 100
```

Out[113]:

| convert_ind | 0 | 1 |
|---|---|---|
| Quote_month | | |
| 1 | 89.281046 | 10.718954 |
| 2 | 88.722590 | 11.277410 |
| 3 | 89.013813 | 10.986187 |
| 4 | 88.571429 | 11.428571 |
| 5 | 88.242731 | 11.757269 |
| 6 | 88.275392 | 11.724608 |
| 7 | 88.796945 | 11.203055 |
| 8 | 89.306358 | 10.693642 |
| 9 | 88.840189 | 11.159811 |
| 10 | 88.905915 | 11.094085 |
| 11 | 89.114795 | 10.885205 |
| 12 | 88.824289 | 11.175711 |

**There doesn't seems to any significant difference in month wise conversion percentage.**

In [114…

```
df_policy['Quote_quarter'] = df_policy['Quote_dt'].dt.quarter
df_policy['Quote_quarter'].value_counts()
```

Out[114]:

```
4    9556
3    9222
1    9046
2    9038
Name: Quote_quarter, dtype: int64
```

In [115…

```
pd.crosstab(df_policy['Quote_quarter'], df_policy['convert_ind'], normalize='index') * 1
```

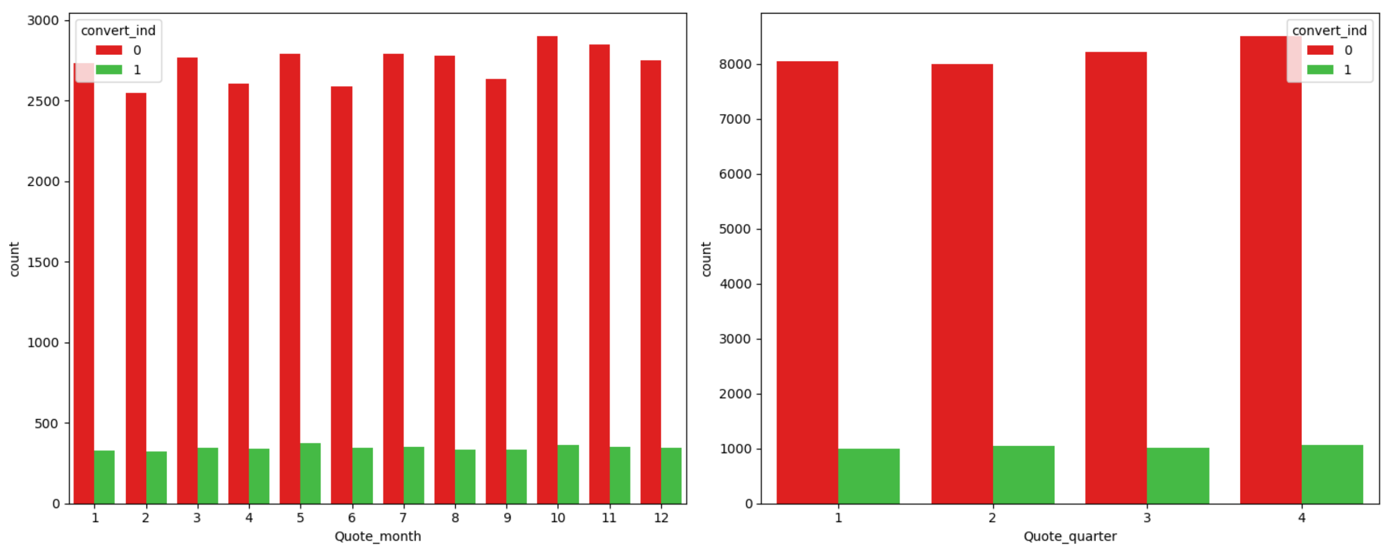
Out[115]:

| convert_ind | 0 | 1 |
|---|---|---|
| **Quote_quarter** | | |
| **1** | 89.011718 | 10.988282 |
| **2** | 88.360257 | 11.639743 |
| **3** | 88.982867 | 11.017133 |
| **4** | 88.949351 | 11.050649 |

**There doesn't seems to any significant difference in quarter wise conversion percentage.**

In [116…

```
fig, (ax1,ax2) = plt.subplots(1,2, figsize = (15,6))
sns.countplot(x='Quote_month', hue='convert_ind', data=df_policy, ax = ax1, palette = ['
sns.countplot(x='Quote_quarter', hue='convert_ind', data=df_policy, ax = ax2, palette =
fig.tight_layout()
```




**There doesn't seems to any significant difference in quarter wise and month wise conversion count.**

In [117…

```
df_policy['Quote_year'] = df_policy['Quote_dt'].dt.year
df_policy['Quote_year'].value_counts()
```

Out[117]:

```
2016    12142
2015    10879
2018     8575
2017     5266
Name: Quote_year, dtype: int64
```

In [118…

```
pd.crosstab(df_policy['Quote_year'], df_policy['convert_ind'], normalize='index') * 100
```

Out[118]:

| convert_ind | 0 | 1 |
|---|---|---|

| Quote_year | | |
|---|---|---|
| **2015** | 87.903300 | 12.096700 |
| **2016** | 88.840389 | 11.159611 |
| **2017** | 89.346753 | 10.653247 |
| **2018** | 89.667638 | 10.332362 |

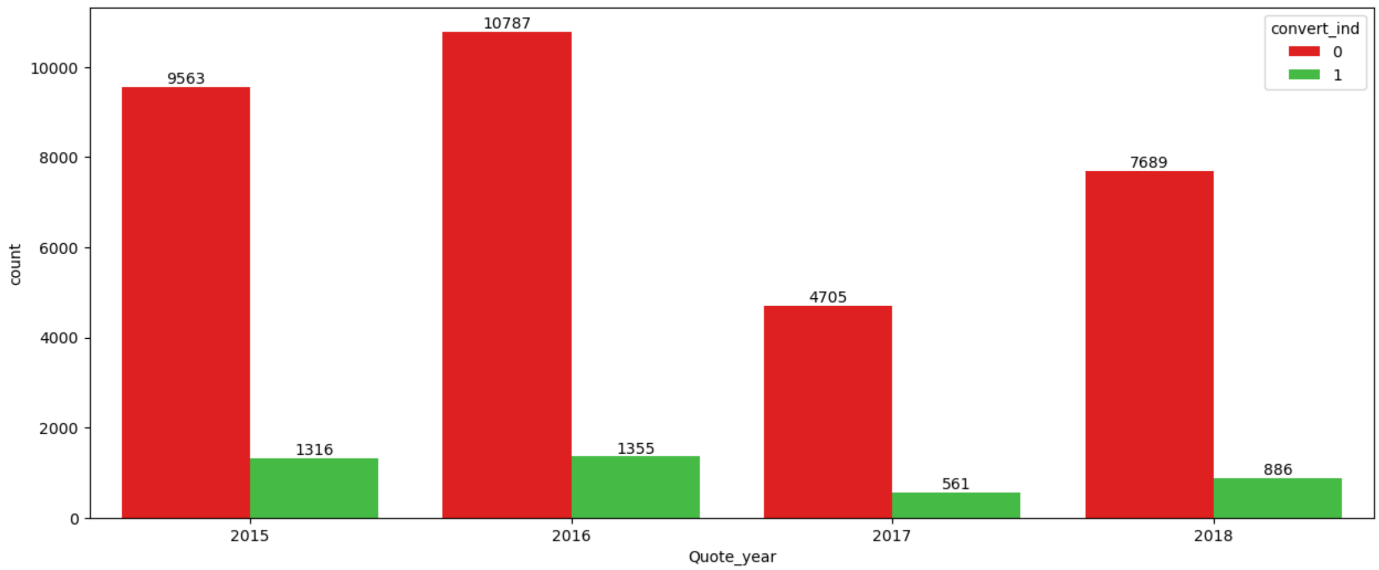
**Converion percentages have declined from 2015 to 2018.**

In [119…

```
fig, ax = plt.subplots(figsize = (15,6))
sns.countplot(x='Quote_year', hue='convert_ind', data=df_policy, palette = ['Red','limeg
ax.bar_label(container=ax.containers[0])
ax.bar_label(container=ax.containers[1])
```

Out[119]:

```
[Text(0, 0, '1316'), Text(0, 0, '1355'), Text(0, 0, '561'), Text(0, 0, '886')]
```




**There were very few policies quoted in the year 2017 when compared to other years.**

In [120…

```
# Creating a copy of dataset
x = df_policy
```

In [121…

```
# Dropping redundant columns
x.drop(['split', 'Unnamed: 0', 'Quote_dt', 'zip', 'Agent_cd', 'policy_id'], axis = 1, in
```

In [122…

```
x.head(15)
```

Out[122]:

| | discount | Home_policy_ind | state_id | county_name | Prior_carrier_grp | credit_score | Cov_package_type | CAT_zon |
|---|---|---|---|---|---|---|---|---|
| **0** | Yes | Y | NY | 0 | 0 | 613.0 | High | 2. |
| **1** | No | N | NY | 0 | 0 | 631.0 | Medium | 2. |
| **2** | No | N | NY | 0 | Carrier_3 | 602.0 | Medium | 4. |
| **3** | No | N | FL | 0 | 0 | 704.0 | High | 1. |
| **4** | No | N | NY | 0 | 0 | 611.0 | High | 4. |
| **5** | No | N | MN | 0 | 0 | 668.0 | Medium | 2. |
| **6** | No | N | FL | 0 | 0 | 772.0 | Low | 2. |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| **7** | Yes | Y | NJ | 0 | 0 | 568.0 | Low | 4. |
| **8** | No | N | FL | 0 | 0 | 621.0 | High | 5. |
| **9** | No | N | NJ | 0 | 0 | 723.0 | Low | 2. |
| **10** | No | N | NJ | 0 | 0 | 773.0 | High | 5. |
| **11** | No | N | NJ | 0 | 0 | 596.0 | Medium | 2. |
| **12** | No | N | MN | 0 | 0 | 776.0 | Low | 4. |
| **13** | No | N | WI | 0 | Carrier_3 | 486.0 | Medium | 4. |
| **14** | No | N | FL | 0 | Carrier_8 | 656.0 | Low | 2. |

In [123…

```
# Checking datatypes
x.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 36862 entries, 0 to 36861
Data columns (total 60 columns):
 #   Column                     Non-Null Count  Dtype  
---  ------                     --------------  -----  
 0   discount                   36862 non-null  object 
 1   Home_policy_ind            36862 non-null  object 
 2   state_id                   36862 non-null  object 
 3   county_name                36862 non-null  object 
 4   Prior_carrier_grp          36862 non-null  object 
 5   credit_score               36638 non-null  float64
 6   Cov_package_type           36269 non-null  object 
 7   CAT_zone                   36681 non-null  float64
 8   number_drivers             36862 non-null  int64  
 9   num_loaned_veh             36862 non-null  int64  
 10  num_owned_veh              36862 non-null  int64  
 11  num_leased_veh             36862 non-null  int64  
 12  total_number_veh           36862 non-null  int64  
 13  convert_ind                36862 non-null  int64  
 14  primary_parking            36862 non-null  object 
 15  car_no                     36862 non-null  int64  
 16  age                        36852 non-null  float64
 17  age_min                    36852 non-null  float64
 18  age_max                    36852 non-null  float64
 19  ownership_type_leased      36862 non-null  uint8  
 20  ownership_type_loaned      36862 non-null  uint8  
 21  ownership_type_owned       36862 non-null  uint8  
 22  color_black                36862 non-null  uint8  
 23  color_blue                 36862 non-null  uint8  
 24  color_gray                 36862 non-null  uint8  
 25  color_other                36862 non-null  uint8  
 26  color_red                  36862 non-null  uint8  
 27  color_silver               36862 non-null  uint8  
 28  color_white                36862 non-null  uint8  
 29  make_AUDI                  36862 non-null  uint8  
 30  make_BMW                   36862 non-null  uint8  
 31  make_CHEVROLET             36862 non-null  uint8  
 32  make_HONDA                 36862 non-null  uint8  
 33  make_MERCEDES-BENZ         36862 non-null  uint8  
 34  safty_rating               36849 non-null  float64
 35  safety_min                 36849 non-null  float64
 36  safety_max                 36849 non-null  float64
 37  gender_F                   36862 non-null  uint8  
 38  gender_M                   36862 non-null  uint8  
 39  living_status_dependent    36862 non-null  uint8  
 40  living_status_own          36862 non-null  uint8  
 41  living_status_rent         36862 non-null  uint8  
```

```
 42  Age Group_15-25          36862 non-null  uint8
 43  Age Group_26-35          36862 non-null  uint8
 44  Age Group_36-45          36862 non-null  uint8
 45  Age Group_46-55          36862 non-null  uint8
 46  Age Group_56-65          36862 non-null  uint8
 47  Age Group_65+            36862 non-null  uint8
 48  high_education_ind_0.0   36862 non-null  uint8
 49  high_education_ind_1.0   36862 non-null  uint8
 50  quote                    36775 non-null  float64
 51  quote_range              36775 non-null  category
 52  log_quote                36775 non-null  float64
 53  safety_rating            36846 non-null  category
 54  credit_score_range       36638 non-null  category
 55  safety_range             36849 non-null  float64
 56  car_age_range            36852 non-null  float64
 57  Quote_month              36862 non-null  int64
 58  Quote_quarter            36862 non-null  int64
 59  Quote_year               36862 non-null  int64
dtypes: category(3), float64(12), int64(10), object(7), uint8(28)
memory usage: 9.5+ MB
```

In [124…
```
# One-hot encoding for categorical features
x1 = pd.get_dummies(x, columns = ['state_id','Prior_carrier_grp', 'primary_parking', 'co
```

In [125…
```
x1.head(15)
```

Out[125]:

| | discount | Home_policy_ind | credit_score | Cov_package_type | CAT_zone | number_drivers | num_loaned_veh | num |
|---|---|---|---|---|---|---|---|---|
| **0** | Yes | Y | 613.0 | High | 2.0 | 2 | 1 | |
| **1** | No | N | 631.0 | Medium | 2.0 | 2 | 1 | |
| **2** | No | N | 602.0 | Medium | 4.0 | 2 | 0 | |
| **3** | No | N | 704.0 | High | 1.0 | 1 | 2 | |
| **4** | No | N | 611.0 | High | 4.0 | 4 | 2 | |
| **5** | No | N | 668.0 | Medium | 2.0 | 1 | 1 | |
| **6** | No | N | 772.0 | Low | 2.0 | 3 | 2 | |
| **7** | Yes | Y | 568.0 | Low | 4.0 | 4 | 0 | |
| **8** | No | N | 621.0 | High | 5.0 | 2 | 1 | |
| **9** | No | N | 723.0 | Low | 2.0 | 1 | 1 | |
| **10** | No | N | 773.0 | High | 5.0 | 5 | 0 | |
| **11** | No | N | 596.0 | Medium | 2.0 | 2 | 1 | |
| **12** | No | N | 776.0 | Low | 4.0 | 4 | 0 | |
| **13** | No | N | 486.0 | Medium | 4.0 | 4 | 0 | |
| **14** | No | N | 656.0 | Low | 2.0 | 1 | 1 | |

In [126…
```
x1['discount'] = x1['discount'].astype('category')
x1['Home_policy_ind'] = x1['Home_policy_ind'].astype('category')
x1['Cov_package_type'] = x1['Cov_package_type'].astype('category')
```

In [127…
```
# Creating numerical codes for categorical features so that the entire dataset is numeri

x1['credit_score_range'] = x1['credit_score_range'].cat.codes
```

```
x1['Home_policy_ind'] = x1['Home_policy_ind'].cat.codes
x1['Cov_package_type'] = x1['Cov_package_type'].cat.codes
x1['safety_rating'] = x1['safety_rating'].cat.codes
x1['discount'] = x1['discount'].cat.codes
x1['quote_range'] = x1['quote_range'].cat.codes
```

In [128…

```
x1.head()
```

Out[128]:

| | discount | Home_policy_ind | credit_score | Cov_package_type | CAT_zone | number_drivers | num_loaned_veh | num_ |
|---|---|---|---|---|---|---|---|---|
| **0** | 1 | 1 | 613.0 | 0 | 2.0 | 2 | 1 | |
| **1** | 0 | 0 | 631.0 | 2 | 2.0 | 2 | 1 | |
| **2** | 0 | 0 | 602.0 | 2 | 4.0 | 2 | 0 | |
| **3** | 0 | 0 | 704.0 | 0 | 1.0 | 1 | 2 | |
| **4** | 0 | 0 | 611.0 | 0 | 4.0 | 4 | 2 | |

In [129…

```
x1.columns
```

Out[129]:

```
Index(['discount', 'Home_policy_ind', 'credit_score', 'Cov_package_type',
       'CAT_zone', 'number_drivers', 'num_loaned_veh', 'num_owned_veh',
       'num_leased_veh', 'total_number_veh', 'convert_ind', 'car_no', 'age',
       'age_min', 'age_max', 'ownership_type_leased', 'ownership_type_loaned',
       'ownership_type_owned', 'color_black', 'color_blue', 'color_gray',
       'color_other', 'color_red', 'color_silver', 'color_white', 'make_AUDI ',
       'make_BMW ', 'make_CHEVROLET ', 'make_HONDA ', 'make_MERCEDES-BENZ ',
       'safty_rating', 'safety_min', 'safety_max', 'gender_F', 'gender_M',
       'living_status_dependent', 'living_status_own', 'living_status_rent',
       'Age Group_15-25', 'Age Group_26-35', 'Age Group_36-45',
       'Age Group_46-55', 'Age Group_56-65', 'Age Group_65+',
       'high_education_ind_0.0', 'high_education_ind_1.0', 'quote',
       'quote_range', 'log_quote', 'safety_rating', 'credit_score_range',
       'safety_range', 'car_age_range', 'Quote_month', 'Quote_quarter',
       'Quote_year', 'state_id_AL', 'state_id_CT', 'state_id_FL',
       'state_id_GA', 'state_id_MN', 'state_id_NJ', 'state_id_NY',
       'state_id_WI', 'Prior_carrier_grp_0', 'Prior_carrier_grp_Carrier_3',
       'Prior_carrier_grp_Carrier_7', 'Prior_carrier_grp_Carrier_8',
       'primary_parking_home/driveway', 'primary_parking_parking garage',
       'primary_parking_street', 'primary_parking_unknown', 'county_name_0',
       'county_name_Kings', 'county_name_New York'],
      dtype='object')
```

In [130…

```
# Dropping redundant features that we came to know of after running XGBoost and checking
x1.drop(['log_quote', 'Prior_carrier_grp_0', 'county_name_0'], axis = 1, inplace=True)
```

In [131…

```
# Dropping redundant features that we came to know of after running XGBoost and checking
x1.drop(['primary_parking_home/driveway', 'primary_parking_parking garage',
       'primary_parking_street', 'primary_parking_unknown', 'state_id_AL', 'state_id_CT'
       'state_id_GA', 'state_id_MN', 'state_id_NJ',
       'state_id_WI'], axis = 1, inplace = True)
```

In [132…

```
# Seperating target variable from the dataset
y = x1['convert_ind']
x1 = x1.drop(['convert_ind'], axis = 1)
```

In [133…

```
y.value_counts()
```

Out[133]:

```
0    32744
1     4118
```

```
Name: convert_ind, dtype: int64
```

In [134…
```
# Scaling the dataset
from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler()
train_x_scaled = scaler.fit_transform(x1)
train_x_scaled = pd.DataFrame(train_x_scaled, columns=x1.columns)
```

In [135…
```
#x1.to_csv('train_x_unscaled.csv')
```

---

# XGBoost Model

---

In [136…
```
# Importing necessary packages
import xgboost as xgb
from sklearn.metrics import accuracy_score
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report as rep
```

---

## Grid Search and Randomized Search Optimization

In [137…
```
# Creating XGBoost object
estimator = xgb.XGBClassifier(objective ='binary:logistic', tree_method = 'gpu_hist',sam
```

In [138…
```
# Splitting into train and validation
X_train, X_test, y_train, y_test = train_test_split(train_x_scaled, y, test_size=0.2, st
```

**Initially, Grid Search CV was utilized to find the optimal hyperparameters, but better results were obtained by using randomized search cross-validation used below.**

In [139…
```
'''from scipy.stats import randint as sp_randint
from scipy.stats import uniform as sp_uniform

param_test = {
    'colsample_bytree': sp_uniform(loc=0.4, scale=0.6),
    'max_depth': range (6, 8, 1),
    'n_estimators': sp_randint(100, 800),
    'learning_rate': [0.025, 0.1, 0.01, 0.05],
    'num_rounds': [5,10,15],
    'reg_alpha': [0, 1e-1, 1, 2, 5, 7, 10, 50, 100],
    'reg_lambda': [0, 1e-1, 1, 5, 10, 20, 50, 100],
        'scale_pos_weight': sp_randint(4, 15)
}'''
```

Out[139]:
```
"from scipy.stats import randint as sp_randint\nfrom scipy.stats import uniform as sp_un
iform\n\nparam_test = {\n    'colsample_bytree': sp_uniform(loc=0.4, scale=0.6),\n    'm
ax_depth': range (6, 8, 1),\n    'n_estimators': sp_randint(100, 800),\n    'learning_ra
te': [0.025, 0.1, 0.01, 0.05],\n    'num_rounds': [5,10,15],\n    'reg_alpha': [0, 1e-1,
1, 2, 5, 7, 10, 50, 100],\n    'reg_lambda': [0, 1e-1, 1, 5, 10, 20, 50, 100],\n
'scale_pos_weight': sp_randint(4, 15)\n}"
```

**The randomized search code takes a lot of time to run, so the optimal parameters have been hard coded below.**

In [140…
```
'''n_HP_points_to_test = 500
from sklearn.model_selection import RandomizedSearchCV, GridSearchCV
```

```
gs = RandomizedSearchCV(
    estimator=estimator, param_distributions=param_test,
    n_iter=n_HP_points_to_test,
    scoring='roc_auc',
    cv=3,
    refit=True,
    random_state=1,
    verbose=True)'''
```

Out[140]:

```
"n_HP_points_to_test = 500\nfrom sklearn.model_selection import RandomizedSearchCV, Grid
SearchCV\n\ngs = RandomizedSearchCV(\n    estimator=estimator, param_distributions=param
_test,\n    n_iter=n_HP_points_to_test,\n    scoring='roc_auc',\n    cv=3,\n    refit=Tr
ue,\n    random_state=1,\n    verbose=True)"
```

In [141…

```
# gs.fit(X_train, y_train)
```

In [142…

```
#print('Best score reached: {} with params: {} '.format(gs.best_score_, gs.best_params_)
```

### Best score reached: 0.6846207236377041 with params: {'colsample_bytree': 0.5019644285303547, 'learning_rate': 0.025, 'max_depth': 6, 'n_estimators': 555, 'num_rounds': 5, 'reg_alpha': 100, 'reg_lambda': 50, 'scale_pos_weight': 13}

### Fitting the model with optimal parameters

In [143…

```
xgb_final = xgb.XGBClassifier(objective ='binary:logistic', tree_method = 'gpu_hist',sam
              colsample_bylevel=1, colsample_bynode=1,
              colsample_bytree=0.5019644285303547, early_stopping_rounds=None,
              enable_categorical=False, eval_metric=None, feature_types=None,
              gamma=0, gpu_id=0, grow_policy='depthwise', importance_type=None,
              interaction_constraints='', learning_rate=0.025, max_bin=256,
              max_cat_threshold=64, max_cat_to_onehot=4, max_delta_step=0,
              max_depth=6, max_leaves=0, min_child_weight=1,
              monotone_constraints='()', n_estimators=555, n_jobs=4, nthread=4,
              num_parallel_tree=1, num_rounds=5, reg_alpha = 100, reg_lambda = 50, scale
```

In [144…

```
xgb_final.fit(X_train,y_train)
```

```
[17:12:59] WARNING: C:/buildkite-agent/builds/buildkite-windows-cpu-autoscaling-group-i-
03de431ba26204c4d-1/xgboost/xgboost-ci-windows/src/learner.cc:767:
Parameters: { "num_rounds" } are not used.
```

Out[144]:

```
XGBClassifier(base_score=0.5, booster='gbtree', callbacks=None,
              colsample_bylevel=1, colsample_bynode=1,
              colsample_bytree=0.5019644285303547, early_stopping_rounds=None,
              enable_categorical=False, eval_metric=None, feature_types=None,
              gamma=0, gpu_id=0, grow_policy='depthwise', importance_type=None,
              interaction_constraints='', learning_rate=0.025, max_bin=256,
              max_cat_threshold=64, max_cat_to_onehot=4, max_delta_step=0,
              max_depth=6, max_leaves=0, min_child_weight=1, missing=nan,
              monotone_constraints='()', n_estimators=555, n_jobs=4, nthread=4,
              num_parallel_tree=1, num_rounds=5, ...)
```

In [145…

```
# Generating predictions on validation data set
preds_test = xgb_final.predict(X_test)
```

In [146…

```
# Getting prediction probabilities
test_prob = xgb_final.predict_proba(X_test)
test_prob
```

Out[146]:

```
array([[0.5180911 , 0.48190892],
       [0.42148727, 0.5785127 ],
       [0.502321  , 0.49767897],
```

```
...,
[0.40528148, 0.5947185 ],
[0.52318585, 0.47681418],
[0.43583268, 0.5641673 ]], dtype=float32)
```

In [147…

```
# Getting the AUC score
from sklearn.metrics import roc_auc_score
auc = roc_auc_score(y_test,test_prob[:,1])
print('AUC: %.3f' % auc)
```

```
AUC: 0.692
```

---

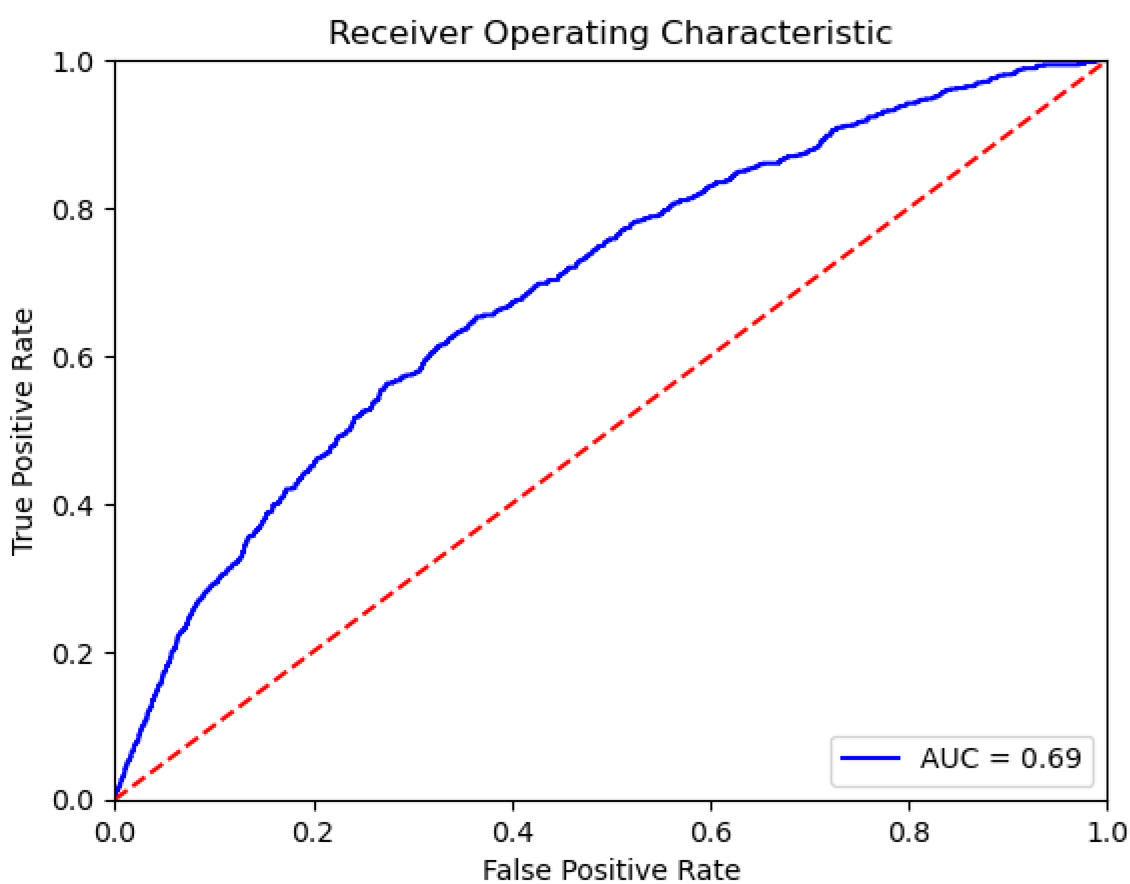
## AUC Curve

In [148…

```
import sklearn.metrics as metrics
# calculate the fpr and tpr for all thresholds of the classification
probs = xgb_final.predict_proba(X_test)
preds = probs[:,1]
fpr, tpr, threshold = metrics.roc_curve(y_test, preds)
roc_auc = metrics.auc(fpr, tpr)
```

In [149…

```
# Plotting AUC Curve

import matplotlib.pyplot as plt
plt.title('Receiver Operating Characteristic')
plt.plot(fpr, tpr, 'b', label = 'AUC = %0.2f' % roc_auc)
plt.legend(loc = 'lower right')
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([0, 1])
plt.ylim([0, 1])
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()
```



In [150…
```
print(rep( y_test , preds_test ))
```

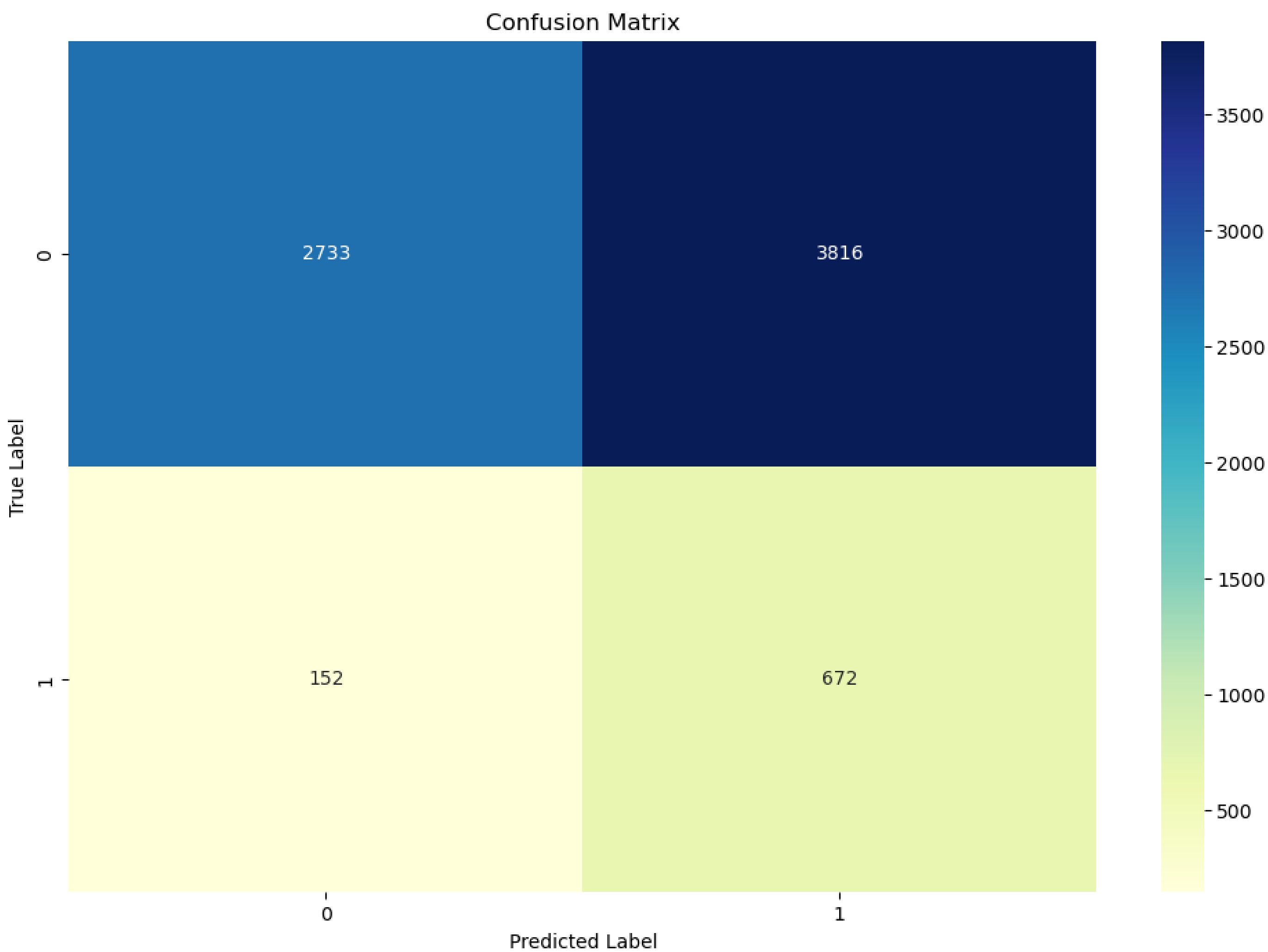
```
              precision    recall  f1-score   support

           0       0.95      0.42      0.58      6549
           1       0.15      0.82      0.25       824

    accuracy                           0.46      7373
   macro avg       0.55      0.62      0.42      7373
weighted avg       0.86      0.46      0.54      7373
```

---

## Confusion Matrix

In [151…
```
from sklearn.metrics import confusion_matrix
fig, ax = plt.subplots(figsize=(12,8))
sns.heatmap(confusion_matrix(y_test, preds_test), annot = True, fmt = 'd', cmap="YlGnBu"
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.title('Confusion Matrix')
```

Out[151]:
```
Text(0.5, 1.0, 'Confusion Matrix')
```

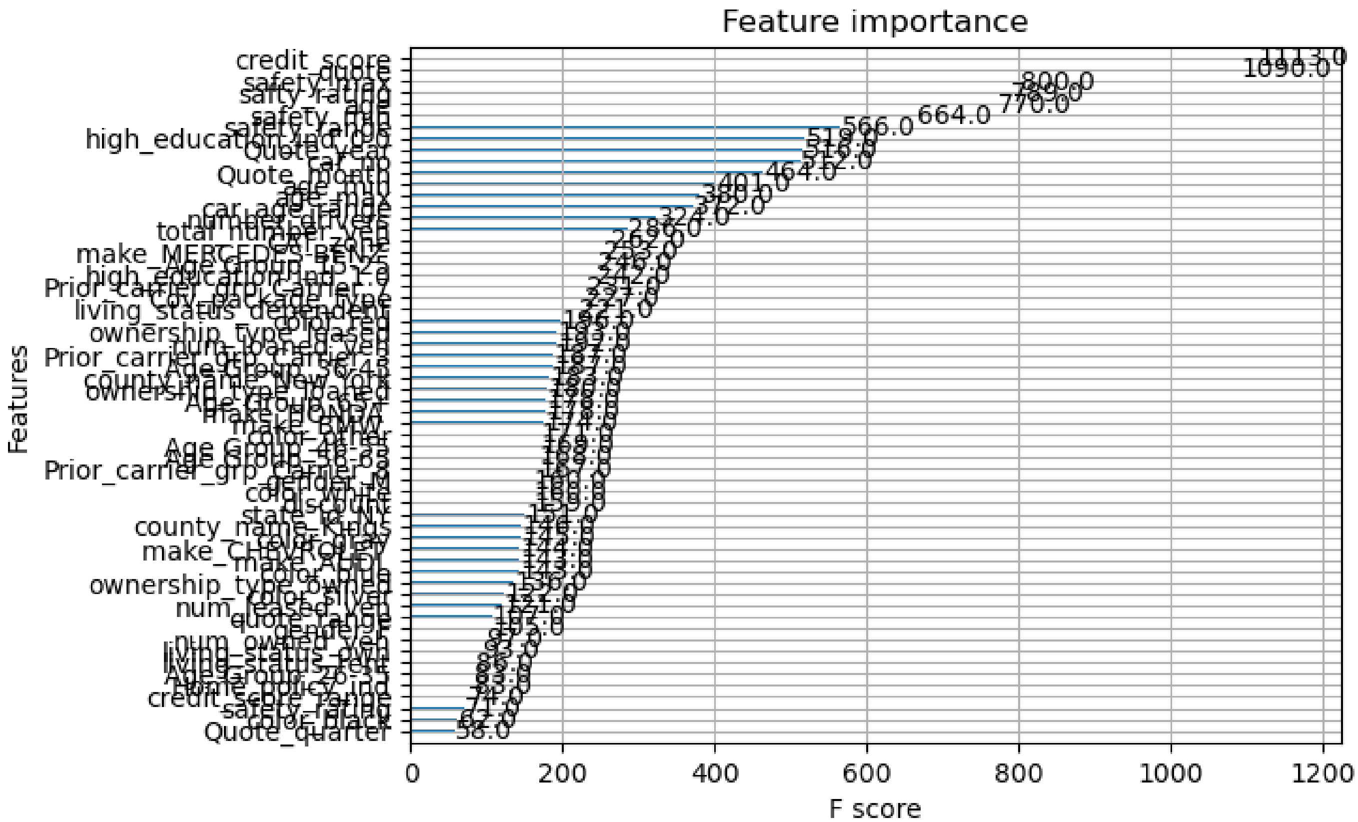



---

## Feature Importance Plot

In [152…
```
# Plotting Feature importance
```

```
xgb.plot_importance(xgb_final)
plt.rcParams['figure.figsize'] = [15, 15]
plt.show()
plt.savefig('sample.pdf')
```




```
<Figure size 1500x1500 with 0 Axes>
```

---

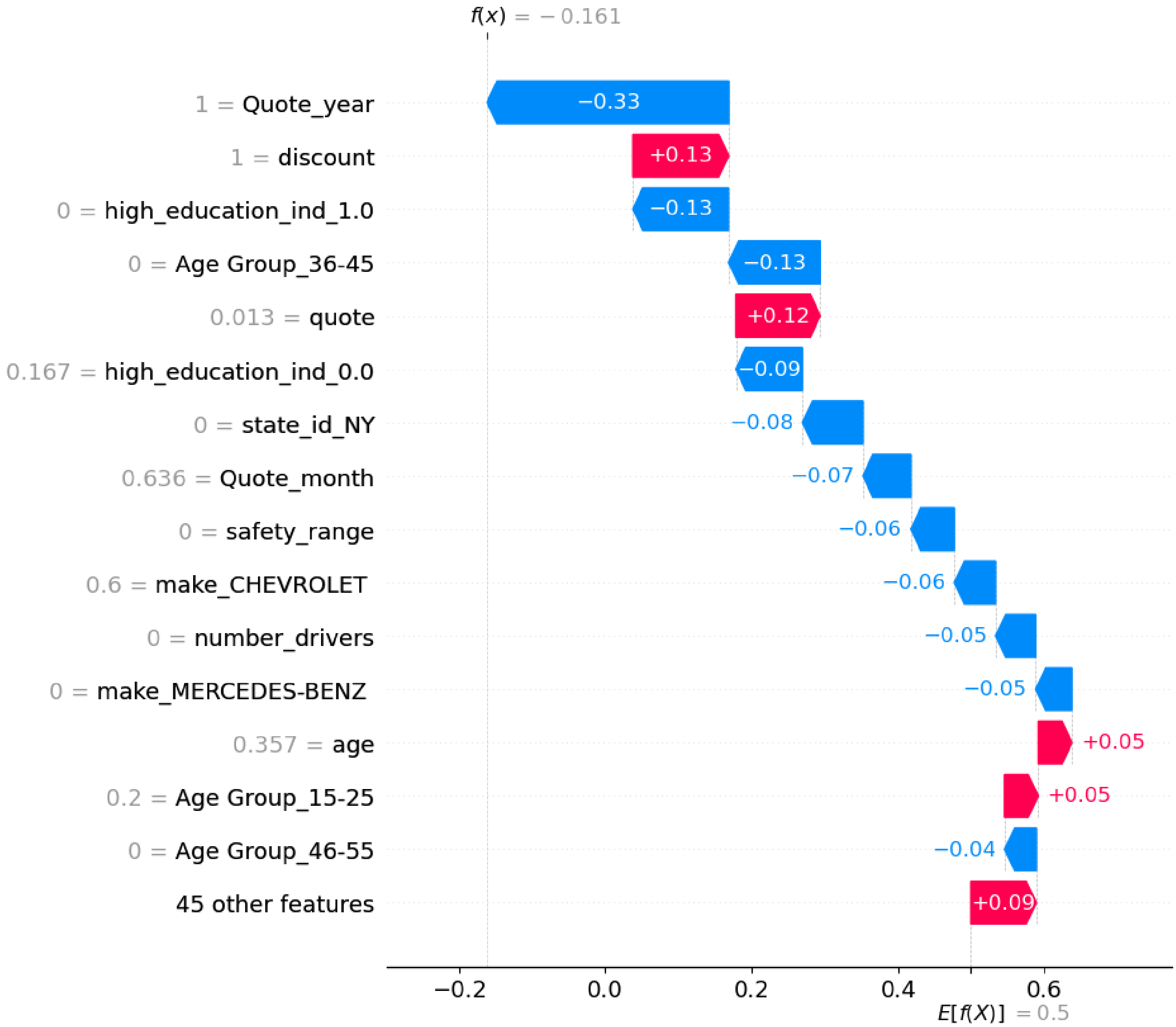
## SHAP Values

In [153...
```
import shap
```

In [154...
```
explainer = shap.Explainer(xgb_final)
shap_values = explainer(X_train)
```

```
ntree_limit is deprecated, use `iteration_range` or model slicing instead.
```

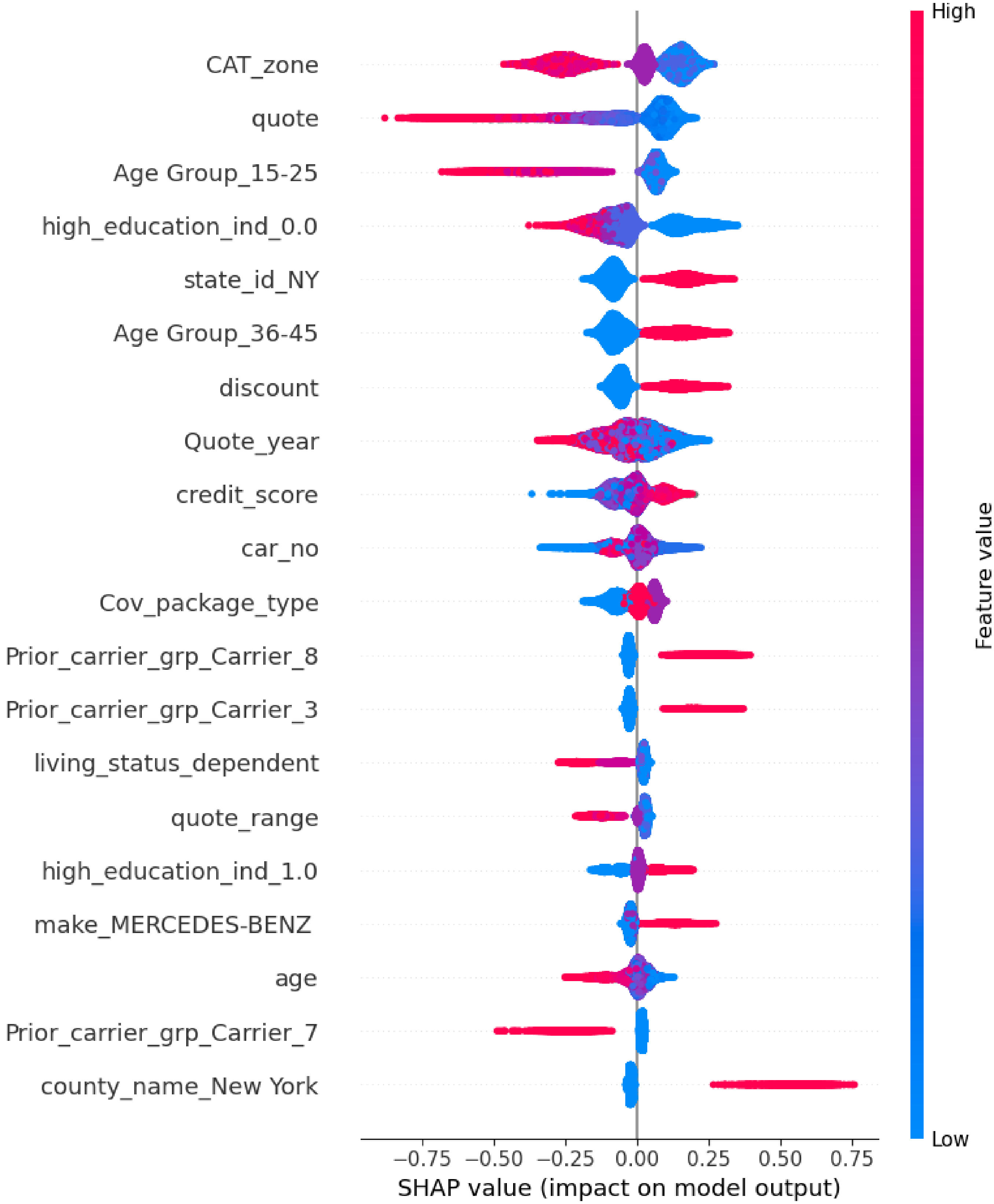
In [155...
```
# SHAP waterfall plot
shap.plots.waterfall(shap_values[0], max_display = 16)
```




In [156…

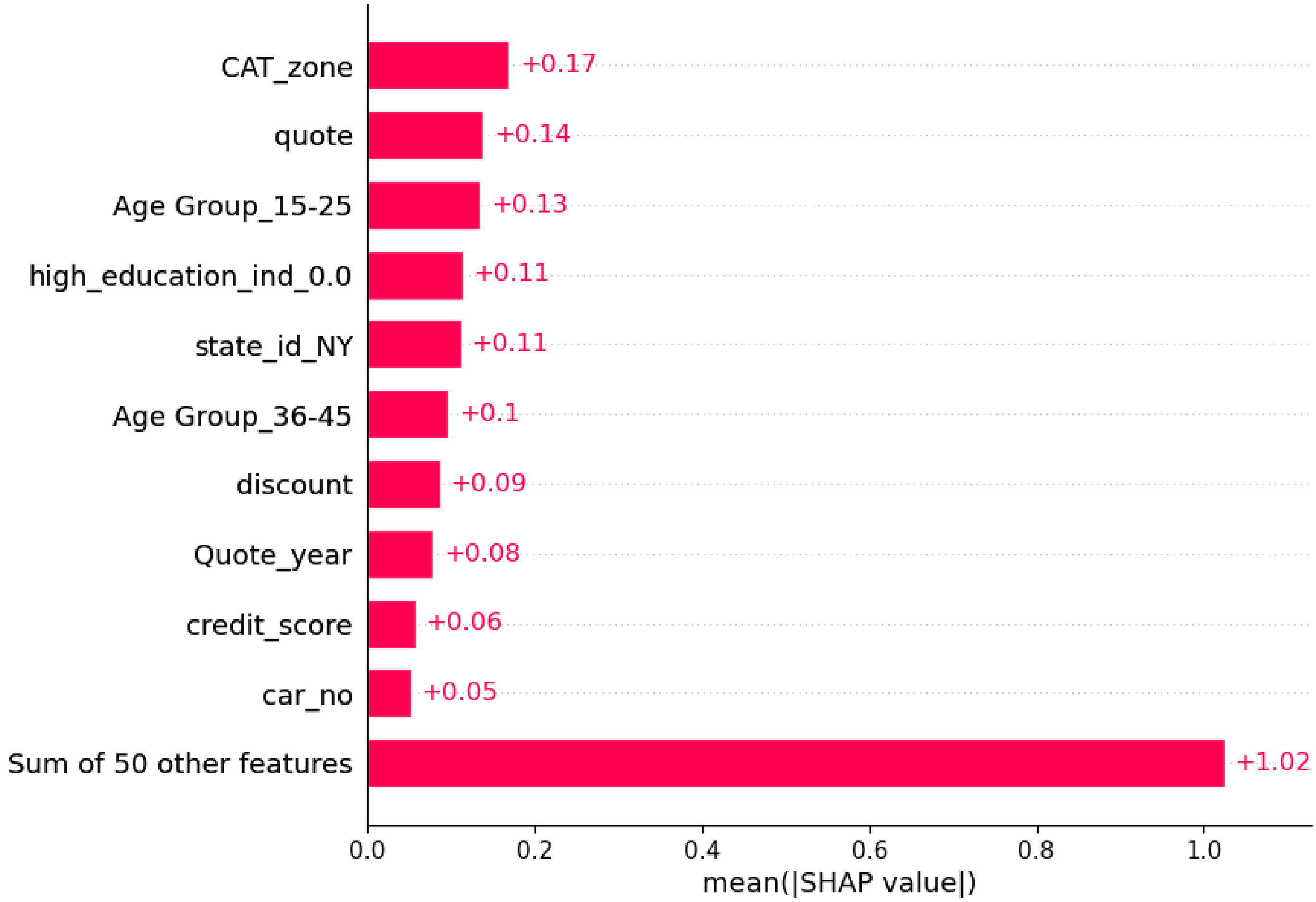
```
# SHAP Beeswarm Plot
shap.summary_plot(shap_values, X_train)
```

```
No data for colormapping provided via 'c'. Parameters 'vmin', 'vmax' will be ignored
```



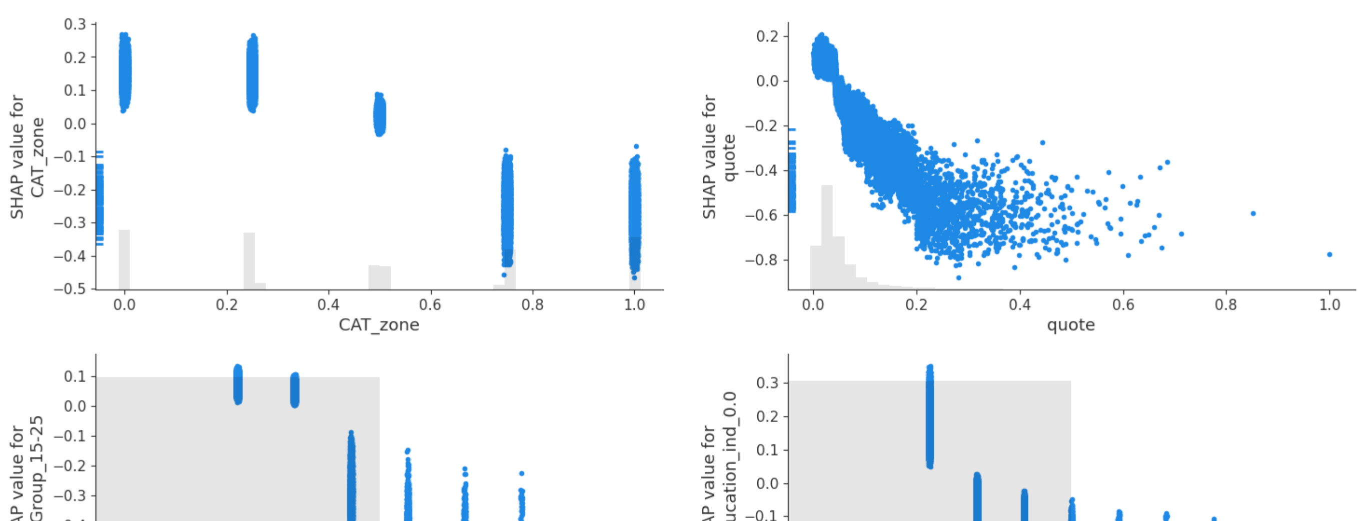

In [157…

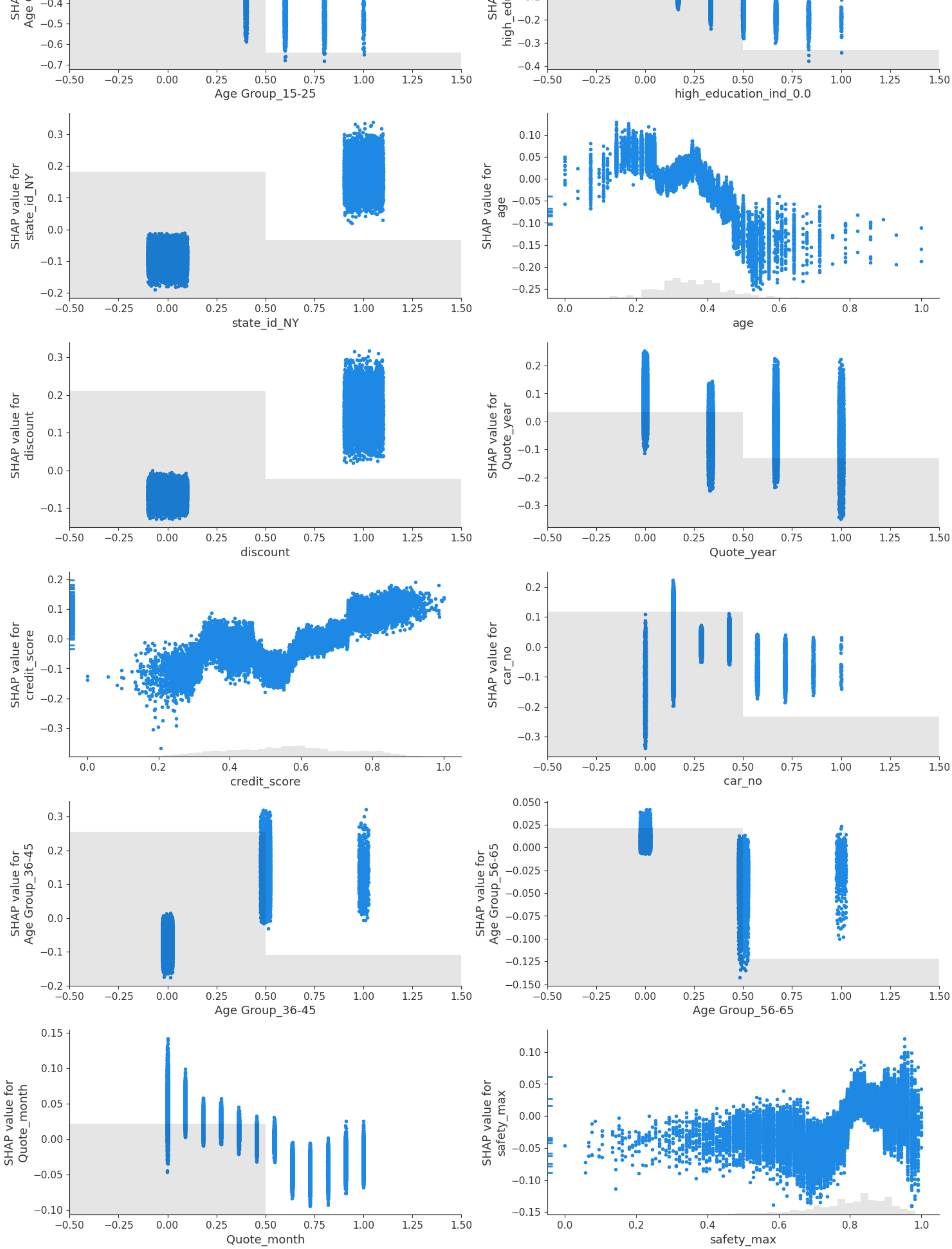
```
# Shap Bar plot with top 10 features with highest SHAP values
shap.plots.bar(shap_values, max_display = 11)
```




In [158…

```python
# Plotting SHAP values against features of high importance

fig, ax = plt.subplots(nrows=7, ncols=2,figsize=(15,25))
shap.plots.scatter(shap_values[:,"CAT_zone"],ax=ax[0][0],show=False)
shap.plots.scatter(shap_values[:,"quote"],ax=ax[0][1],show=False)
shap.plots.scatter(shap_values[:,"Age Group_15-25"],ax=ax[1][0],show=False)
shap.plots.scatter(shap_values[:,"high_education_ind_0.0"],ax=ax[1][1],show=False)
shap.plots.scatter(shap_values[:,"state_id_NY"],ax=ax[2][0],show=False)
shap.plots.scatter(shap_values[:,"age"],ax=ax[2][1],show=False)
shap.plots.scatter(shap_values[:,"discount"],ax=ax[3][0],show=False)
shap.plots.scatter(shap_values[:,"Quote_year"],ax=ax[3][1],show=False)
shap.plots.scatter(shap_values[:,"credit_score"],ax=ax[4][0],show=False)
shap.plots.scatter(shap_values[:,"car_no"],ax=ax[4][1],show=False)
shap.plots.scatter(shap_values[:,"Age Group_36-45"],ax=ax[5][0],show=False)
shap.plots.scatter(shap_values[:,"Age Group_56-65"],ax=ax[5][1],show=False)
shap.plots.scatter(shap_values[:,"Quote_month"],ax=ax[6][0],show=False)
fig.tight_layout()
shap.plots.scatter(shap_values[:,"safety_max"],ax=ax[6][1])
```






# Findings

## Characteristics of customers likely to convert

- Customers in lower CAT zones
- Lower quotes
- State ID NY
- More individuals with education indicator as 1
- Offered Discount
- Prior carrier group 3 and 8
- Higher credit score
- Policies having customers in age group 36-45

### Characteristics of customers not likely to convert

- Higher CAT zones
- Higher quote
- More individuals with education indicator as 0
- Policies not having individuals in age group 15-25
- Higher Vehicle age
- Higher living status dependency
- Having prior carrier group_7
- Lower credit score

## Recommendations:

- **Target customers in New York living in lower CAT zones.**
- **Focus on families with more individuals in the 36-45 age brackets and not in 15-25 age bracket**
- **Policies should be offered at discount and have lower quotes to increase conversions to customers with high credit scores.**
- **Customers having extremely old cars should be avoided.**
- **Pursue higher educated customers who either own or rent homes and are not dependent.**

### Feature additions to Dataset that could help make better Predictions

- Discount Percentage
- Agent rating / Experience
- Prior Insurance Quote
- Car Price
- Annual Income
- Driver Marital Status

---

# Kaggle Leaderboard

**Team Name: Rovers**

Public Private

The private leaderboard is calculated with approximately 70% of the test data.
This competition has completed. This leaderboard reflects the final standings.

| # | △ | Team | Members | Score | Entries | Last | Solution |
|---|---|---|---|---|---|---|---|
| 1 | ▲1 | UMass Stats Team | | 0.70115 | 24 | 2mo | |
| 2 | ▲1 | Ace@uri | | 0.70109 | 22 | 2mo | |
| 3 | ▲1 | Data Moguls | | 0.69387 | 5 | 2mo | |
| 4 | ▲2 | **Rovers** | | 0.69154 | 18 | 2mo | |
| 5 | ▲2 | Free Thinkers | | 0.69117 | 12 | 2mo | |

# Predicting on Test Dataset for Kaggle

In [171…
```
test.shape
```
Out[171]:
```
(12291, 22)
```

In [172…
```
test = pd.merge(left = test, right = vvdata, how = 'inner', on = 'policy_id')
test.head()
```
Out[172]:

| | Unnamed: 0 | Quote_dt | discount | Home_policy_ind | zip | state_id | county_name | Agent_cd | quoted_amt | Pri |
|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 2 | 12-02-2015 | No | N | 12801.0 | NY | Warren | 46978147.0 | $9,870 | |
| **1** | 4 | 28-07-2015 | No | N | 33141.0 | FL | Miami-Dade | 47310293.0 | $2,860 | |
| **2** | 8 | 22-01-2015 | No | N | 8904.0 | NJ | Middlesex | 45747860.0 | $2,980 | |
| **3** | 9 | 15-01-2018 | No | N | 6907.0 | CT | Fairfield | 30895563.0 | $1,945 | |
| **4** | 10 | 01-08-2017 | No | N | 11550.0 | NY | Nassau | 33958256.0 | $5,829 | |

In [173…
```
test.shape
```
Out[173]:
```
(12291, 55)
```

In [174…
```
test = pd.merge(left = test, right = dddata, how = 'left', on = 'policy_id')
test.head()
```
Out[174]:

| | Unnamed: 0 | Quote_dt | discount | Home_policy_ind | zip | state_id | county_name | Agent_cd | quoted_amt | Pri |
|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 2 | 12-02-2015 | No | N | 12801.0 | NY | Warren | 46978147.0 | $9,870 | |
| **1** | 4 | 28-07-2015 | No | N | 33141.0 | FL | Miami-Dade | 47310293.0 | $2,860 | |
| **2** | 8 | 22-01- | No | N | 8904.0 | NJ | Middlesex | 45747860.0 | $2,980 | |

| | | 2015 | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| **3** | 9 | 15-01-2018 | No | N | 6907.0 | CT | Fairfield | 30895563.0 | $1,945 |
| **4** | 10 | 01-08-2017 | No | N | 11550.0 | NY | Nassau | 33958256.0 | $5,829 |

In [175…
```
test.shape
```
Out[175]:
```
(12291, 71)
```

In [176…
```
submission = pd.DataFrame(columns = ['policy_id', 'TARGET'])
submission['policy_id'] = test['policy_id']
```

In [177…
```
test['quote'] = test['quoted_amt'].str.replace(',','')
test['quote'] = test['quote'].str.replace('$','')
test['quote'] = pd.to_numeric(test['quote'], errors='coerce')
test['quote'].dtype
```
```
The default value of regex will change from True to False in a future version. In additi
on, single character regular expressions will *not* be treated as literal strings when r
egex=True.
```
Out[177]:
```
dtype('float64')
```

In [178…
```
bins = [0,2500,5000,7500,10000,200000]
labels = ['Very Low','Low','Medium','High','Very High']
test['quote_range'] = pd.cut(test['quote'], bins = bins, labels = labels)
test.head()
```
Out[178]:

| | Unnamed: 0 | Quote_dt | discount | Home_policy_ind | zip | state_id | county_name | Agent_cd | quoted_amt | Pri |
|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 2 | 12-02-2015 | No | N | 12801.0 | NY | Warren | 46978147.0 | $9,870 | |
| **1** | 4 | 28-07-2015 | No | N | 33141.0 | FL | Miami-Dade | 47310293.0 | $2,860 | |
| **2** | 8 | 22-01-2015 | No | N | 8904.0 | NJ | Middlesex | 45747860.0 | $2,980 | |
| **3** | 9 | 15-01-2018 | No | N | 6907.0 | CT | Fairfield | 30895563.0 | $1,945 | |
| **4** | 10 | 01-08-2017 | No | N | 11550.0 | NY | Nassau | 33958256.0 | $5,829 | |

In [179…
```
test['log_quote'] = np.log(test['quote'])
```

In [180…
```
test.shape
```
Out[180]:
```
(12291, 74)
```

In [181…
```
test['total_drivers'] = df_policy['gender_F']+df_policy['gender_M']
```

In [182…
```
#test.drop(test[test['number_drivers'] != test['total_drivers']].index, axis = 0, inplac
```

In [183…
```
test.shape
```

Out[183]: (12291, 75)

In [184…
```
bins = [0,59,69,79,89,100]
labels = ['Very Low','Low','Medium','High','Very High']
test['safety_rating'] = pd.cut(test['safty_rating'], bins = bins, labels = labels)
test.head(5)
```

Out[184]:

| | Unnamed: 0 | Quote_dt | discount | Home_policy_ind | zip | state_id | county_name | Agent_cd | quoted_amt | Pri |
|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 2 | 12-02-2015 | No | N | 12801.0 | NY | Warren | 46978147.0 | $9,870 | |
| **1** | 4 | 28-07-2015 | No | N | 33141.0 | FL | Miami-Dade | 47310293.0 | $2,860 | |
| **2** | 8 | 22-01-2015 | No | N | 8904.0 | NJ | Middlesex | 45747860.0 | $2,980 | |
| **3** | 9 | 15-01-2018 | No | N | 6907.0 | CT | Fairfield | 30895563.0 | $1,945 | |
| **4** | 10 | 01-08-2017 | No | N | 11550.0 | NY | Nassau | 33958256.0 | $5,829 | |

In [185…
```
test['county_name'] = np.where((test['county_name'] == 'New York')|(test['county_name']
```

In [186…
```
test['Prior_carrier_grp'] = np.where((test['Prior_carrier_grp'] == 'Carrier_3')|(test['P
```

In [187…
```
test.drop(['make_ACURA ', 'make_BUICK ', 'make_CADILLAC ', 'make_CHRYSLER ', 'make_DODGE
                   'make_NISSAN ','make_RAM ','make_SATURN ','make_SMART ','make_SUBARU ','
```

In [188…
```
test.columns
```

Out[188]:
```
Index(['Unnamed: 0', 'Quote_dt', 'discount', 'Home_policy_ind', 'zip',
       'state_id', 'county_name', 'Agent_cd', 'quoted_amt',
       'Prior_carrier_grp', 'credit_score', 'Cov_package_type', 'CAT_zone',
       'policy_id', 'number_drivers', 'num_loaned_veh', 'num_owned_veh',
       'num_leased_veh', 'total_number_veh', 'convert_ind', 'split',
       'primary_parking', 'car_no', 'age', 'age_min', 'age_max',
       'ownership_type_leased', 'ownership_type_loaned',
       'ownership_type_owned', 'color_black', 'color_blue', 'color_gray',
       'color_other', 'color_red', 'color_silver', 'color_white', 'make_AUDI ',
       'make_BMW ', 'make_CHEVROLET ', 'make_HONDA ', 'make_MERCEDES-BENZ ',
       'safty_rating', 'safety_min', 'safety_max', 'gender_F', 'gender_M',
       'living_status_dependent', 'living_status_own', 'living_status_rent',
       'Age Group_15-25', 'Age Group_26-35', 'Age Group_36-45',
       'Age Group_46-55', 'Age Group_56-65', 'Age Group_65+',
       'high_education_ind_0.0', 'high_education_ind_1.0', 'quote',
       'quote_range', 'log_quote', 'total_drivers', 'safety_rating'],
      dtype='object')
```

In [ ]:

In [ ]:

In [189…
```
bins = [0,500,600,700,800,850]
labels = ['Very Low','Low','Medium','High','Very High']
test['credit_score_range'] = pd.cut(test['credit_score'], bins = bins, labels = labels)
```

In [190…
```
test.drop(['quoted_amt', 'total_drivers'], axis = 1, inplace = True)
```

In [191…

```
test['safety_range'] = test['safety_max'] - test['safety_min']
test['car_age_range'] = test['age_max'] - test['age_min']
```

In [192…

```
test['Quote_dt'] = pd.to_datetime(test['Quote_dt'])
```

In [193…

```
test['Quote_month'] = test['Quote_dt'].dt.month
test['Quote_quarter'] = test['Quote_dt'].dt.quarter
test['Quote_year'] = test['Quote_dt'].dt.year
```

In [194…

```
test.drop(['split', 'Unnamed: 0', 'Quote_dt', 'zip', 'Agent_cd', 'policy_id'], axis = 1,
```

In [195…

```
test = pd.get_dummies(test, columns = ['state_id','Prior_carrier_grp', 'primary_parking'
```

In [196…

```
test['discount'] = test['discount'].astype('category')
test['Home_policy_ind'] = test['Home_policy_ind'].astype('category')
test['Cov_package_type'] = test['Cov_package_type'].astype('category')
```

In [197…

```
test['credit_score_range'] = test['credit_score_range'].cat.codes
test['Home_policy_ind'] = test['Home_policy_ind'].cat.codes
test['Cov_package_type'] = test['Cov_package_type'].cat.codes
test['safety_rating'] = test['safety_rating'].cat.codes
test['discount'] = test['discount'].cat.codes
test['quote_range'] = test['quote_range'].cat.codes
```

In [198…

```
test.drop(['primary_parking_home/driveway', 'primary_parking_parking garage',
       'primary_parking_street', 'primary_parking_unknown', 'state_id_AL', 'state_id_CT'
       'state_id_GA', 'state_id_MN', 'state_id_NJ',
       'state_id_WI'], axis = 1, inplace = True)
```

In [199…

```
test.columns
```

Out[199]:

```
Index(['discount', 'Home_policy_ind', 'credit_score', 'Cov_package_type',
       'CAT_zone', 'number_drivers', 'num_loaned_veh', 'num_owned_veh',
       'num_leased_veh', 'total_number_veh', 'convert_ind', 'car_no', 'age',
       'age_min', 'age_max', 'ownership_type_leased', 'ownership_type_loaned',
       'ownership_type_owned', 'color_black', 'color_blue', 'color_gray',
       'color_other', 'color_red', 'color_silver', 'color_white', 'make_AUDI ',
       'make_BMW ', 'make_CHEVROLET ', 'make_HONDA ', 'make_MERCEDES-BENZ ',
       'safty_rating', 'safety_min', 'safety_max', 'gender_F', 'gender_M',
       'living_status_dependent', 'living_status_own', 'living_status_rent',
       'Age Group_15-25', 'Age Group_26-35', 'Age Group_36-45',
       'Age Group_46-55', 'Age Group_56-65', 'Age Group_65+',
       'high_education_ind_0.0', 'high_education_ind_1.0', 'quote',
       'quote_range', 'log_quote', 'safety_rating', 'credit_score_range',
       'safety_range', 'car_age_range', 'Quote_month', 'Quote_quarter',
       'Quote_year', 'state_id_NY', 'Prior_carrier_grp_0',
       'Prior_carrier_grp_Carrier_3', 'Prior_carrier_grp_Carrier_7',
       'Prior_carrier_grp_Carrier_8', 'county_name_0', 'county_name_Kings',
       'county_name_New York'],
      dtype='object')
```

In [200…

```
test.drop(['log_quote', 'Prior_carrier_grp_0', 'county_name_0'], axis = 1, inplace=True)
```

In [201…

```
test.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 12291 entries, 0 to 12290
Data columns (total 61 columns):
 #   Column                      Non-Null Count  Dtype
---  ------                      --------------  -----
 0   discount                    12291 non-null  int8
 1   Home_policy_ind             12291 non-null  int8
```

```
 2   credit_score               12215 non-null  float64
 3   Cov_package_type           12291 non-null  int8
 4   CAT_zone                   12222 non-null  float64
 5   number_drivers             12291 non-null  int64
 6   num_loaned_veh             12291 non-null  int64
 7   num_owned_veh              12291 non-null  int64
 8   num_leased_veh             12291 non-null  int64
 9   total_number_veh           12291 non-null  int64
 10  convert_ind                0 non-null      float64
 11  car_no                     12291 non-null  int64
 12  age                        12288 non-null  float64
 13  age_min                    12288 non-null  float64
 14  age_max                    12288 non-null  float64
 15  ownership_type_leased      12291 non-null  uint8
 16  ownership_type_loaned      12291 non-null  uint8
 17  ownership_type_owned       12291 non-null  uint8
 18  color_black                12291 non-null  uint8
 19  color_blue                 12291 non-null  uint8
 20  color_gray                 12291 non-null  uint8
 21  color_other                12291 non-null  uint8
 22  color_red                  12291 non-null  uint8
 23  color_silver               12291 non-null  uint8
 24  color_white                12291 non-null  uint8
 25  make_AUDI                  12291 non-null  uint8
 26  make_BMW                   12291 non-null  uint8
 27  make_CHEVROLET             12291 non-null  uint8
 28  make_HONDA                 12291 non-null  uint8
 29  make_MERCEDES-BENZ         12291 non-null  uint8
 30  safty_rating               12283 non-null  float64
 31  safety_min                 12283 non-null  float64
 32  safety_max                 12283 non-null  float64
 33  gender_F                   12285 non-null  float64
 34  gender_M                   12285 non-null  float64
 35  living_status_dependent    12285 non-null  float64
 36  living_status_own          12285 non-null  float64
 37  living_status_rent         12285 non-null  float64
 38  Age Group_15-25            12285 non-null  float64
 39  Age Group_26-35            12285 non-null  float64
 40  Age Group_36-45            12285 non-null  float64
 41  Age Group_46-55            12285 non-null  float64
 42  Age Group_56-65            12285 non-null  float64
 43  Age Group_65+              12285 non-null  float64
 44  high_education_ind_0.0     12285 non-null  float64
 45  high_education_ind_1.0     12285 non-null  float64
 46  quote                      12266 non-null  float64
 47  quote_range                12291 non-null  int8
 48  safety_rating              12291 non-null  int8
 49  credit_score_range         12291 non-null  int8
 50  safety_range               12283 non-null  float64
 51  car_age_range              12288 non-null  float64
 52  Quote_month                12291 non-null  int64
 53  Quote_quarter              12291 non-null  int64
 54  Quote_year                 12291 non-null  int64
 55  state_id_NY                12291 non-null  uint8
 56  Prior_carrier_grp_Carrier_3  12291 non-null  uint8
 57  Prior_carrier_grp_Carrier_7  12291 non-null  uint8
 58  Prior_carrier_grp_Carrier_8  12291 non-null  uint8
 59  county_name_Kings          12291 non-null  uint8
 60  county_name_New York       12291 non-null  uint8
dtypes: float64(25), int64(9), int8(6), uint8(21)
memory usage: 3.6 MB
```

In [202…
```python
test_x = test.drop(['convert_ind'], axis = 1)
```

In [203…
```python
scaler = MinMaxScaler()
```

```
test_x_scaled = scaler.fit_transform(test_x)
test_x_scaled = pd.DataFrame(test_x_scaled, columns=test_x.columns)
```

In [204…:

```
#xgb_final.fit(train_x_scaled,y)
```

In [205…:

```
test_y = xgb_final.predict(test_x_scaled)
```

In [206…:

```
#print("Accuracy of Model::",accuracy_score(test_y,test_preds))
```

In [207…:

```
test_prob = xgb_final.predict_proba(test_x_scaled)
test_prob
```

Out[207]:

```
array([[0.6839777 , 0.31602228],
       [0.35455137, 0.6454486 ],
       [0.71101224, 0.2889878 ],
       ...,
       [0.65635157, 0.34364843],
       [0.5269954 , 0.4730046 ],
       [0.56227374, 0.43772626]], dtype=float32)
```

In [208…:

```
submission.shape
```

Out[208]:

```
(12291, 2)
```

In [209…:

```
c = pd.DataFrame(test_prob[:,1].tolist(), columns = ['predictions'])
c.head()
```

Out[209]:

| | predictions |
|---|---|
| 0 | 0.316022 |
| 1 | 0.645449 |
| 2 | 0.288988 |
| 3 | 0.631269 |
| 4 | 0.462470 |

In [210…:

```
submission['TARGET'] = c['predictions']
```

In [211…:

```
submission.head()
```

Out[211]:

| | policy_id | TARGET |
|---|---|---|
| 0 | policy_89288 | 0.316022 |
| 1 | policy_23460 | 0.645449 |
| 2 | policy_43809 | 0.288988 |
| 3 | policy_4590 | 0.631269 |
| 4 | policy_65525 | 0.462470 |

In [212…:

```
#submission.to_csv('test_predictions18.csv')
```

In [ ]:

```

```