st125066_KaungNyoLwin_A3_Assignment

October 7, 2024

1 Car Price Prediction

The goal is to predict car price

The followings describe the features in the dataset

- **name** : Brand and series of the car
- **Year** : The year when the car is produced
- **selling_price** : Selling price of the car
- **km_driven** : The amount of kilometer that the car was driven before selling the car
- **fuel** : The type of fuel used in the car
- **seller_type** : The channel through which the deal of car is organized
- **transmission** : The gear transmission type that is used in the car
- **owner** : The number of times that the car was traded before
- **mileage** : The kilometers that can be traveled by using the fuel of 1 liter or 1 kg
- **engine** : The size of the engine
- **max_power** : The maximum power of engine measured in bhp. (BHP - the brake horsepower is the horse power after taking account of losses due to friction)
- **torque** : Torque
- **seats** : The number of seats in the car

1.1 Importing libraries

[1]:
```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import warnings
import os
import mlflow

warnings.filterwarnings('ignore')
```

[2]:
```
import matplotlib
np.__version__, pd.__version__, sns.__version__, matplotlib.__version__
```

[2]:
```
('1.26.4', '2.2.2', '0.13.2', '3.9.2')
```

1.2 1. Load data

[3]:
```
# Load the data
df = pd.read_csv(os.path.join(os.getcwd(),"data/Cars.csv"))
```

[4]:
```
# print the first rows of data
df.head()
```

[4]:
```
                          name  year  selling_price  km_driven    fuel  \
0       Maruti Swift Dzire VDI  2014         450000     145500  Diesel
1  Skoda Rapid 1.5 TDI Ambition  2014         370000     120000  Diesel
2     Honda City 2017-2020 EXi  2006         158000     140000  Petrol
3    Hyundai i20 Sportz Diesel  2010         225000     127000  Diesel
4       Maruti Swift VXI BSIII  2007         130000     120000  Petrol

  seller_type transmission         owner     mileage   engine   max_power  \
0  Individual       Manual   First Owner   23.4 kmpl  1248 CC      74 bhp
1  Individual       Manual  Second Owner  21.14 kmpl  1498 CC  103.52 bhp
2  Individual       Manual   Third Owner   17.7 kmpl  1497 CC      78 bhp
3  Individual       Manual   First Owner   23.0 kmpl  1396 CC      90 bhp
4  Individual       Manual   First Owner   16.1 kmpl  1298 CC    88.2 bhp

                    torque  seats
0           190Nm@ 2000rpm    5.0
1      250Nm@ 1500-2500rpm    5.0
2    12.7@ 2,700(kgm@ rpm)    5.0
3  22.4 kgm at 1750-2750rpm    5.0
4    11.5@ 4,500(kgm@ rpm)    5.0
```

[5]:
```
# Check the shape of your data
df.shape
```

[5]: (8128, 13)

[6]:
```
# Statistical info
df.describe()
```

[6]:
```
              year  selling_price     km_driven        seats
count  8128.000000   8.128000e+03  8.128000e+03  7907.000000
mean   2013.804011   6.382718e+05  6.981951e+04     5.416719
std       4.044249   8.062534e+05  5.655055e+04     0.959588
min    1983.000000   2.999900e+04  1.000000e+00     2.000000
25%    2011.000000   2.549990e+05  3.500000e+04     5.000000
50%    2015.000000   4.500000e+05  6.000000e+04     5.000000
75%    2017.000000   6.750000e+05  9.800000e+04     5.000000
max    2020.000000   1.000000e+07  2.360457e+06    14.000000
```

[7]:
```python
# Check Dtypes of data
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 8128 entries, 0 to 8127
Data columns (total 13 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   name           8128 non-null   object
 1   year           8128 non-null   int64
 2   selling_price  8128 non-null   int64
 3   km_driven      8128 non-null   int64
 4   fuel           8128 non-null   object
 5   seller_type    8128 non-null   object
 6   transmission   8128 non-null   object
 7   owner          8128 non-null   object
 8   mileage        7907 non-null   object
 9   engine         7907 non-null   object
 10  max_power      7913 non-null   object
 11  torque         7906 non-null   object
 12  seats          7907 non-null   float64
dtypes: float64(1), int64(3), object(9)
memory usage: 825.6+ KB
```

[8]:
```python
# Check the column names
df.columns
```

[8]:
```
Index(['name', 'year', 'selling_price', 'km_driven', 'fuel', 'seller_type',
       'transmission', 'owner', 'mileage', 'engine', 'max_power', 'torque',
       'seats'],
      dtype='object')
```

1.3 2. Exploratory Data Analysis

EDA is an essential step to inspect the data, so to better understand nature of the given data.

1.3.1 2.1 Data Cleansing

We need to perform data cleansing as the data is not tidy yet.

[9]:
```python
df.columns
```

[9]:
```
Index(['name', 'year', 'selling_price', 'km_driven', 'fuel', 'seller_type',
       'transmission', 'owner', 'mileage', 'engine', 'max_power', 'torque',
       'seats'],
      dtype='object')
```

[10]:
```python
df.head(10)
```

[10]:

```
                             name  year  selling_price  km_driven  \
0          Maruti Swift Dzire VDI  2014         450000     145500
1        Skoda Rapid 1.5 TDI Ambition  2014         370000     120000
2        Honda City 2017-2020 EXi  2006         158000     140000
3       Hyundai i20 Sportz Diesel  2010         225000     127000
4          Maruti Swift VXI BSIII  2007         130000     120000
5      Hyundai Xcent 1.2 VTVT E Plus  2017         440000      45000
6     Maruti Wagon R LXI DUO BSIII  2007          96000     175000
7              Maruti 800 DX BSII  2001          45000       5000
8                Toyota Etios VXD  2011         350000      90000
9  Ford Figo Diesel Celebration Edition  2013         200000     169000

     fuel seller_type transmission         owner     mileage   engine  \
0  Diesel  Individual       Manual   First Owner   23.4 kmpl  1248 CC
1  Diesel  Individual       Manual  Second Owner  21.14 kmpl  1498 CC
2  Petrol  Individual       Manual   Third Owner   17.7 kmpl  1497 CC
3  Diesel  Individual       Manual   First Owner   23.0 kmpl  1396 CC
4  Petrol  Individual       Manual   First Owner   16.1 kmpl  1298 CC
5  Petrol  Individual       Manual   First Owner  20.14 kmpl  1197 CC
6     LPG  Individual       Manual   First Owner  17.3 km/kg  1061 CC
7  Petrol  Individual       Manual  Second Owner   16.1 kmpl   796 CC
8  Diesel  Individual       Manual   First Owner  23.59 kmpl  1364 CC
9  Diesel  Individual       Manual   First Owner   20.0 kmpl  1399 CC

    max_power                    torque  seats
0      74 bhp            190Nm@ 2000rpm    5.0
1  103.52 bhp       250Nm@ 1500-2500rpm    5.0
2      78 bhp      12.7@ 2,700(kgm@ rpm)    5.0
3      90 bhp  22.4 kgm at 1750-2750rpm    5.0
4    88.2 bhp      11.5@ 4,500(kgm@ rpm)    5.0
5   81.86 bhp          113.75nm@ 4000rpm    5.0
6    57.5 bhp       7.8@ 4,500(kgm@ rpm)    5.0
7      37 bhp             59Nm@ 2500rpm    4.0
8    67.1 bhp       170Nm@ 1800-2400rpm    5.0
9    68.1 bhp            160Nm@ 2000rpm    5.0
```

2.1.1 - We will remove torque feature as we don't understand the feature

[11]:

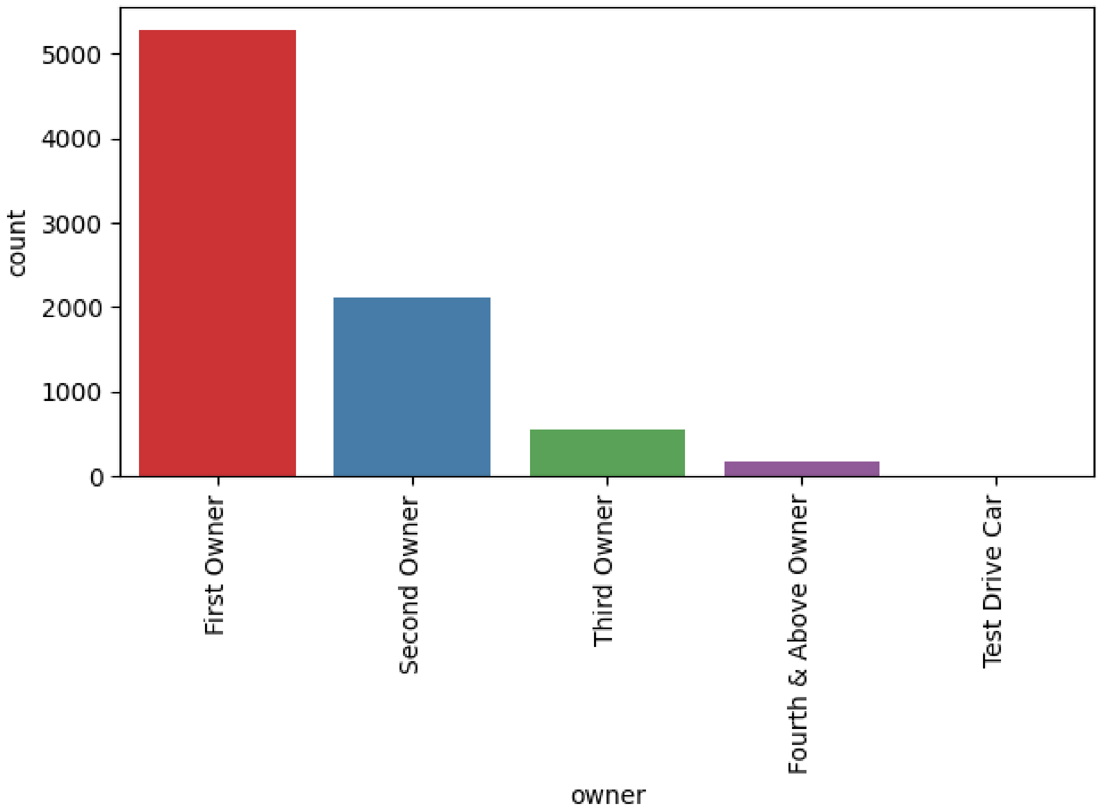
```python
# Remove torque feature
df.drop('torque',axis=1,inplace=True)
```

2.1.2 - We will remove the rows with owner "Test Drive Car" as the price is too high which makes them outliers and this only has 5 rows

[12]:

```python
# Checking counts of owner types
ax = sns.countplot(data = df, x = 'owner',palette= 'Set1')
ax.set_xticklabels(df['owner'].unique(),rotation=90)
plt.tight_layout()
```

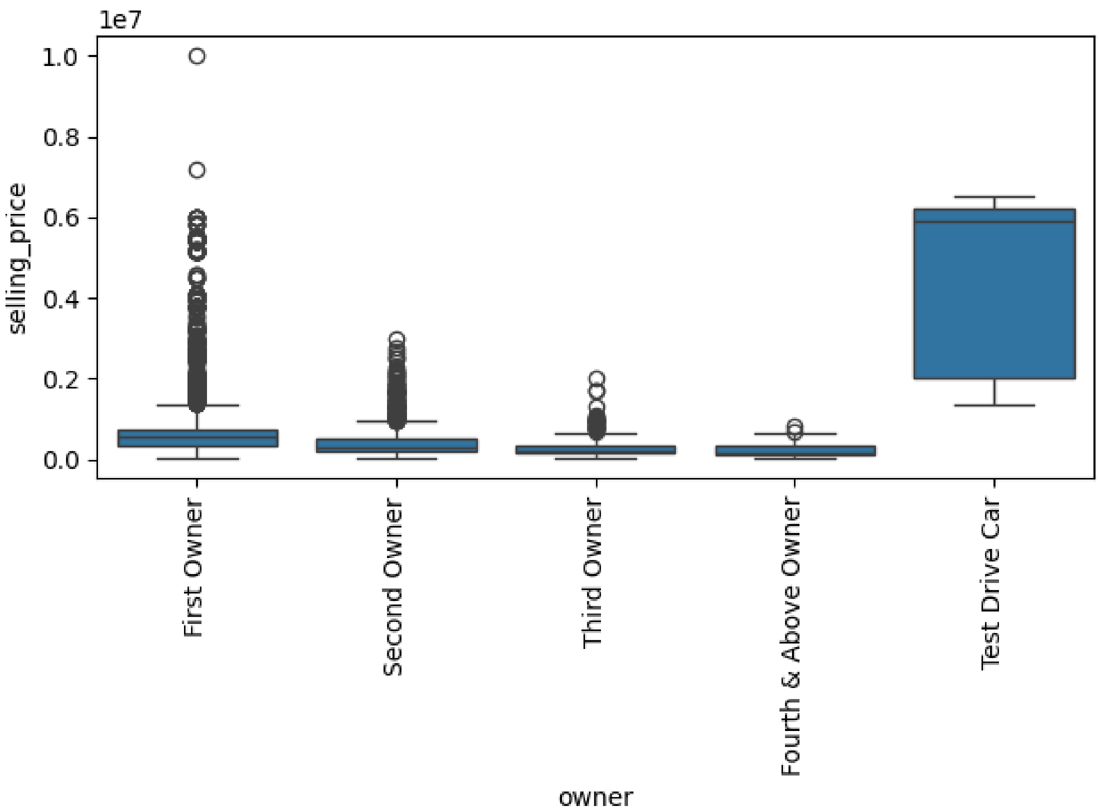
```
plt.show()
```



[13]:
```
# checking the count of test drive car
df.loc[df['owner'] == 'Test Drive Car','selling_price'].count()
```

[13]: 5

[14]:
```
# checking the distribution of owner types
ax = sns.boxplot(x = df["owner"], y = df["selling_price"])
ax.set_xticklabels(df['owner'].unique(),rotation=90)
plt.tight_layout()
plt.show()
```



[15]:
```
# Remove rows with "Test Drive Car"
df = df[df['owner'] != 'Test Drive Car']
```

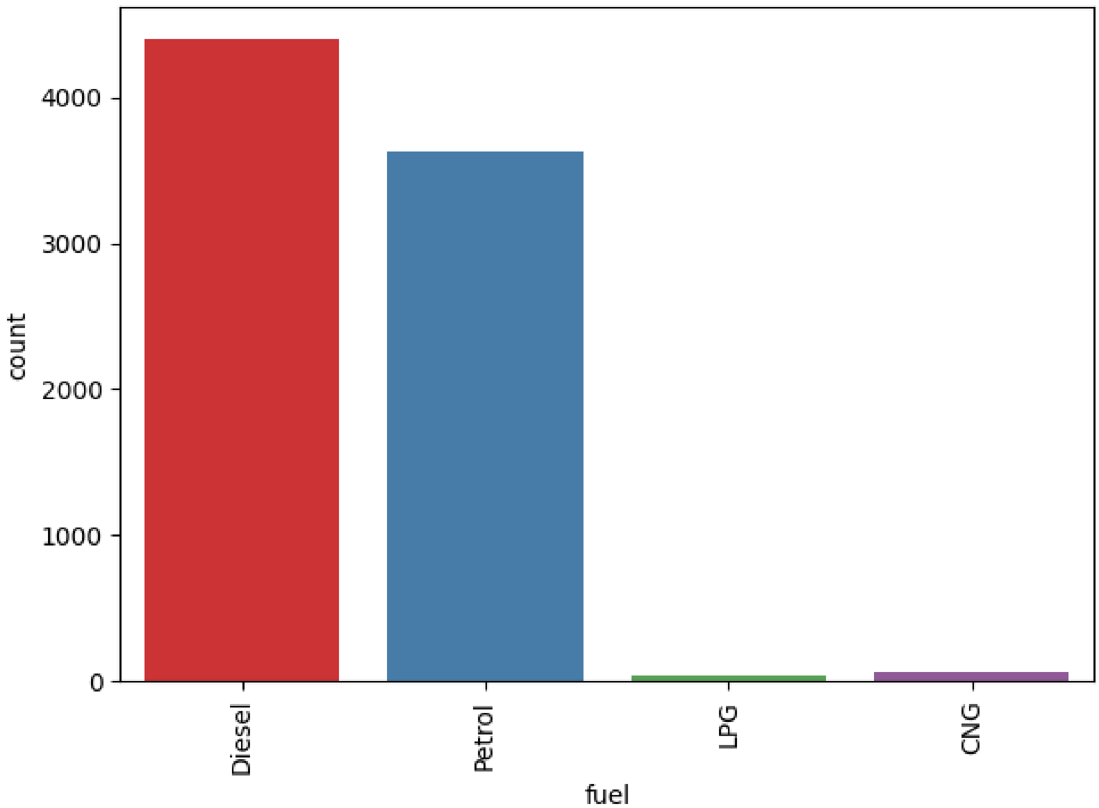
2.1.3 - We will map the owner types to 1 to 4

[16]:
```
owner = {'First Owner' : 1,
         'Second Owner' : 2,
         'Third Owner' : 3,
         'Fourth & Above Owner' : 4
         }

for k,v in owner.items():
    df.replace(k,v,inplace=True)
```

2.1.4 - We will remove the rows with fuel types "LPG" and "CNG" as they use different mileage units and it has only 38 rows

[17]:
```
# Checking counts of fuel types
ax = sns.countplot(data = df, x = 'fuel',palette= 'Set1')
ax.set_xticklabels(df['fuel'].unique(),rotation=90)
plt.tight_layout()
```

```
plt.show()
```




```
[18]: # Checking fuel milage units
df[df['fuel'].isin(['LPG','CND'])]['mileage'].head()
```

```
[18]: 6       17.3 km/kg
90      26.2 km/kg
870     26.2 km/kg
1511    26.2 km/kg
1658    17.3 km/kg
Name: mileage, dtype: object
```

```
[19]: # Checking the number of fuel types "LPG,CNd"
df[df['fuel'].isin(['LPG','CND'])].shape
```

```
[19]: (38, 12)
```

```
[20]: # Remove the rows with fuel types "LPG,CNd"
df = df[~df['fuel'].isin(['LPG', 'CNG'])]
df['fuel'].unique()
```

[20]: array(['Diesel', 'Petrol'], dtype=object)

2.1.5 - removing unit 'kmpl' in 'milage' feature and convert it into numerical feature

[21]:
```
# Replace 'kmpl' with blank
df.loc[df['mileage'].str.split(" ").str[1] == 'kmpl', 'mileage'] = df.
 ↪loc[df['mileage'].str.split(" ").str[1] == 'kmpl', 'mileage'].str.replace("␣
 ↪kmpl", "")
```

[22]:
```
# Convert mileage feature to float
df['mileage'] = df['mileage'].astype(float)
```

2.1.6 - removing unit 'CC' in 'engine' feature and convert it into numerical feature

[23]:
```
# Replace 'CC' with blank
df.loc[df['engine'].str.split(" ").str[1] == 'CC', 'engine'] = df.
 ↪loc[df['engine'].str.split(" ").str[1] == 'CC', 'engine'].str.replace(" CC",␣
 ↪"")
```

[24]:
```
# Convert engine feature to float
df['engine'] = df['engine'].astype(float)
```

2.1.7 - removing unit 'bhp' in 'max_power' feature and convert it into numerical feature

[25]:
```
# Replace 'bhp' with blank
df.loc[df['max_power'].str.split(" ").str[1] == 'bhp', 'max_power'] = df.
 ↪loc[df['max_power'].str.split(" ").str[1] == 'bhp', 'max_power'].str.
 ↪replace(" bhp", "")
```

[26]:
```
# Convert max_power feature to float
df['max_power'] = df['max_power'].astype(float)
```

2.1.8 - We will transform the name feature to brand feature by taking the first word of names

[27]:
```
# rename the column
df.rename(columns = {'name':'brand'}, inplace = True)
```

[28]:
```
# Taking the first word of name
df['brand'] = df['brand'].str.split(" ").str[0]
```

[29]:
```
# Checking clean data
df.head()
```

[29]:
```
     brand  year  selling_price  km_driven    fuel seller_type transmission  \
0   Maruti  2014         450000     145500  Diesel  Individual       Manual
1    Skoda  2014         370000     120000  Diesel  Individual       Manual
```

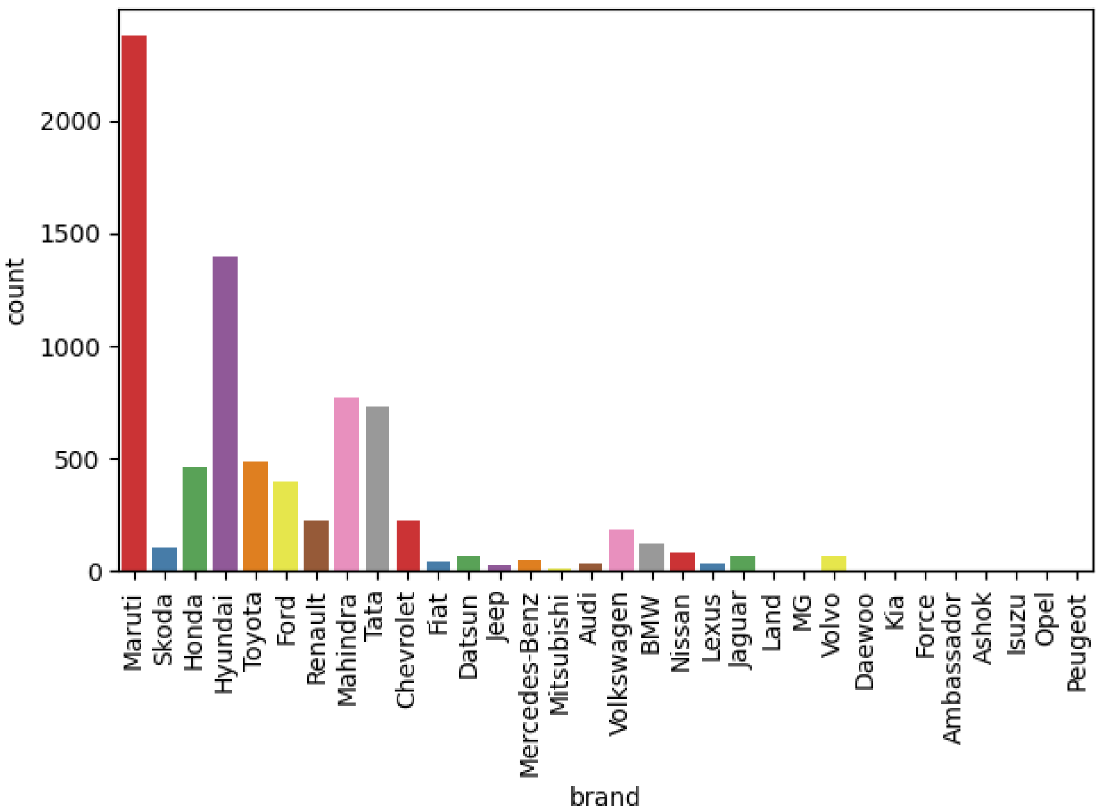
```
2    Honda  2006         158000     140000  Petrol  Individual        Manual
3  Hyundai  2010         225000     127000  Diesel  Individual        Manual
4   Maruti  2007         130000     120000  Petrol  Individual        Manual

   owner  mileage  engine  max_power  seats
0      1    23.40  1248.0      74.00    5.0
1      2    21.14  1498.0     103.52    5.0
2      3    17.70  1497.0      78.00    5.0
3      1    23.00  1396.0      90.00    5.0
4      1    16.10  1298.0      88.20    5.0
```

1.3.2 2.2 Univariate analysis

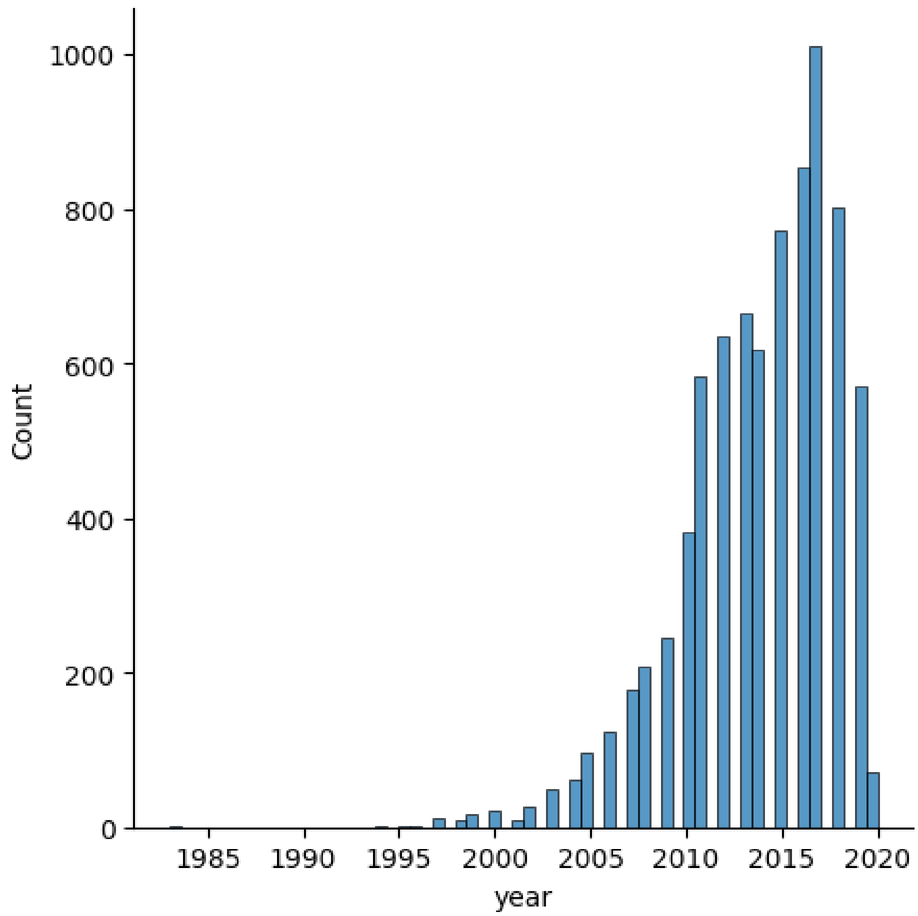
Single variable exploratory data anlaysis

Checking distributions

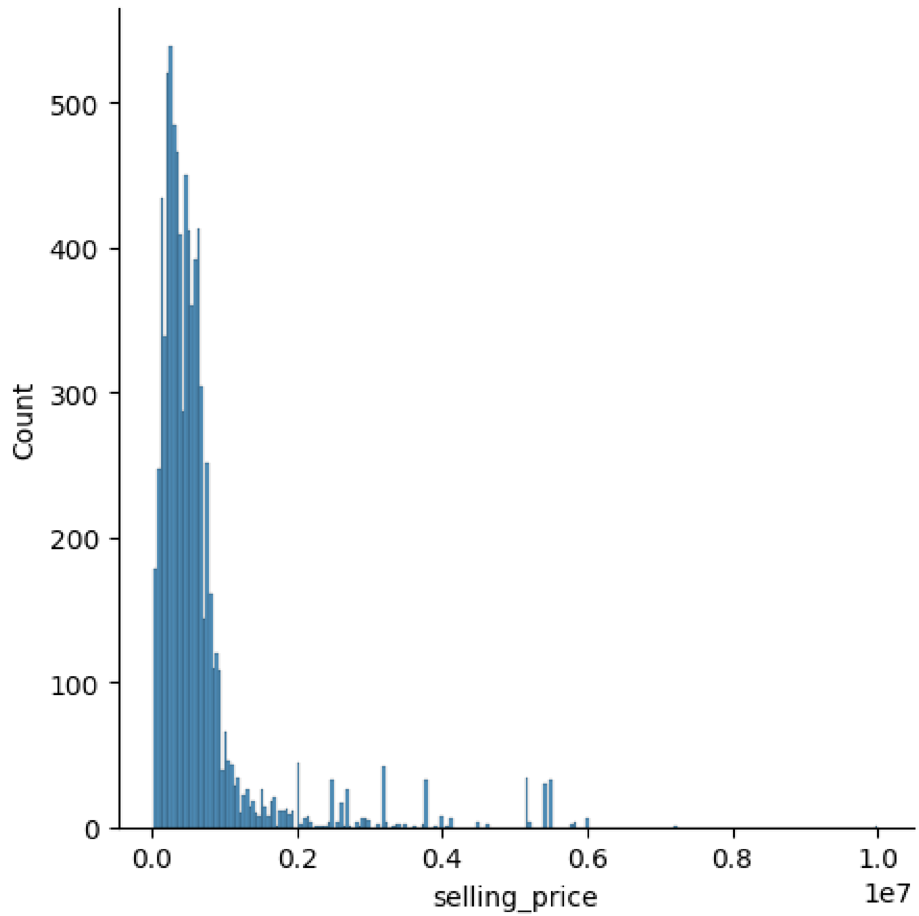
[30]:
```python
for j,i in enumerate(df.columns):
    if i == 'brand':
        ax = sns.countplot(data = df, x = i,palette= 'Set1')
        ax.set_xticklabels(df[i].unique(),rotation=90)
        plt.tight_layout()
        plt.show()
    else:
        sns.displot(data=df,x=df[i])
        plt.show()
```



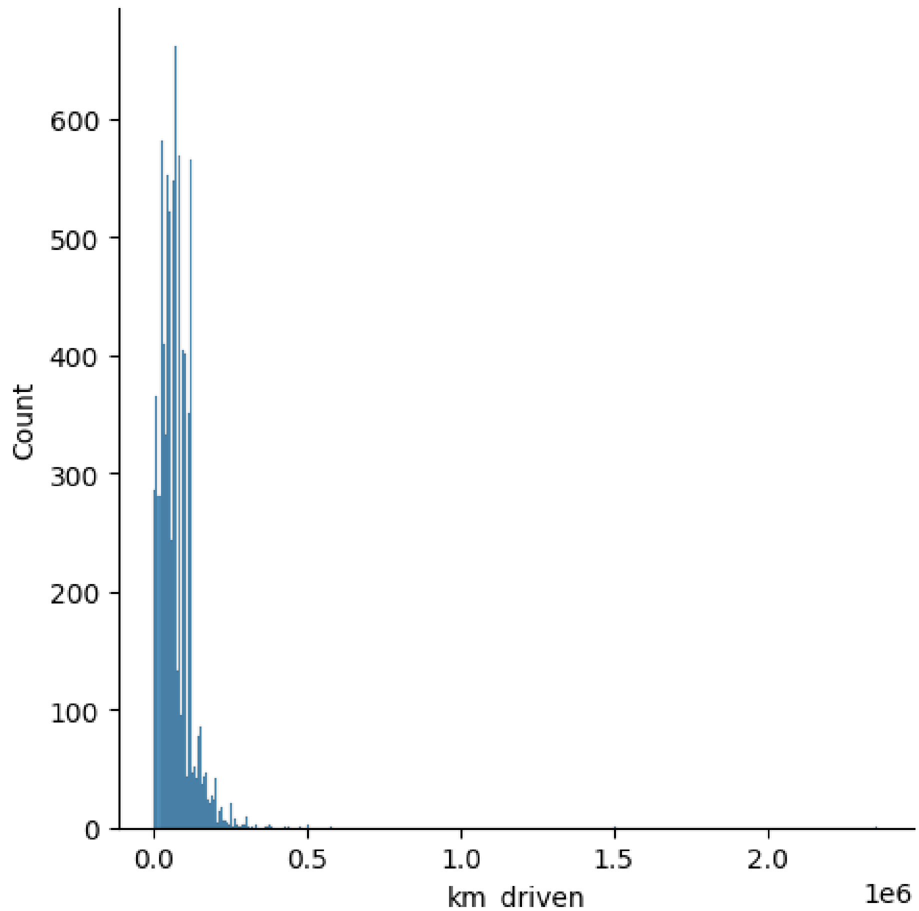
count
2000
1500
1000
500
0
Maruti
Skoda
Honda
Hyundai
Toyota
Ford
Renault
Mahindra
Tata
Chevrolet
Fiat
Datsun
Jeep
Mercedes-Benz
Mitsubishi
Audi
Volkswagen
BMW
Nissan
Lexus
Jaguar
Land
MG
Volvo
Daewoo
Kia
Force
Ambassador
Ashok
Isuzu
Opel
Peugeot
brand

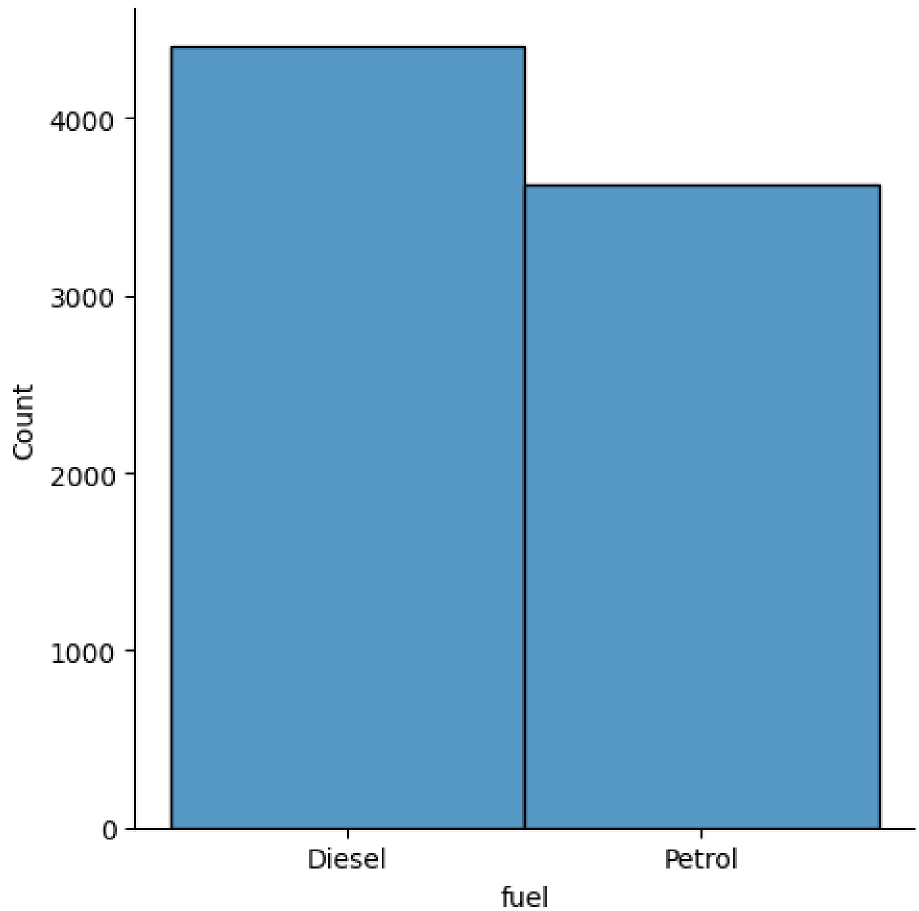


1000
800
600
400
200
0
Count
1985
1990
1995
2000
2005
2010
2015
2020
year

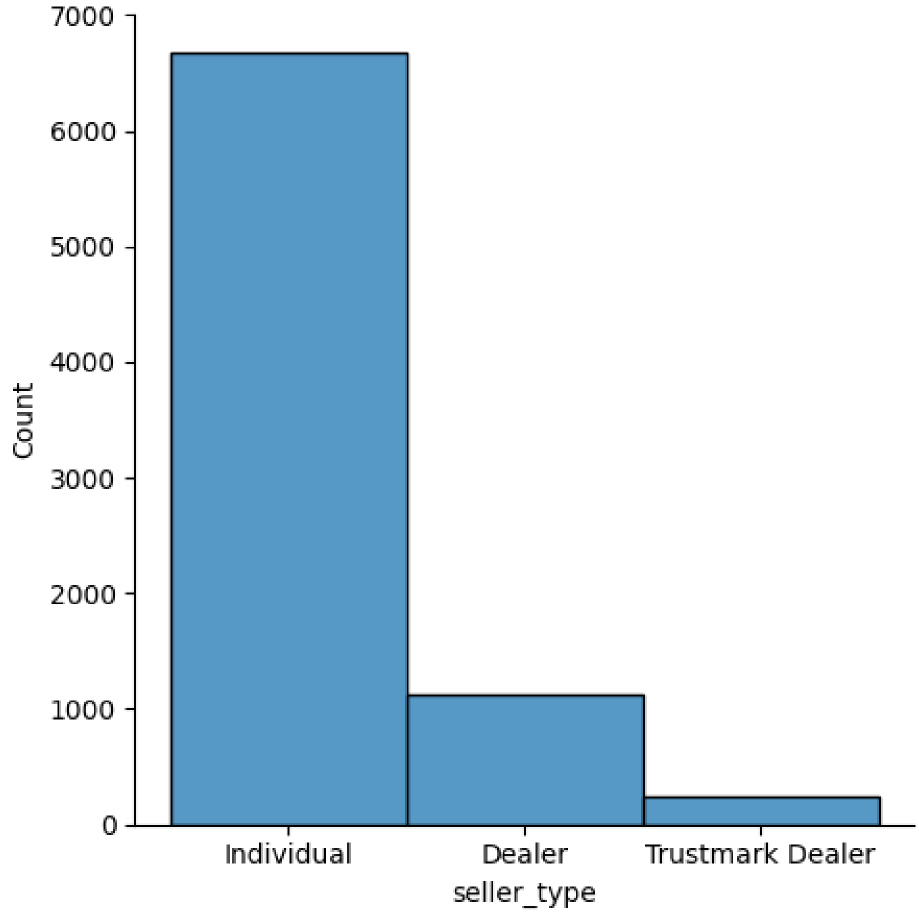


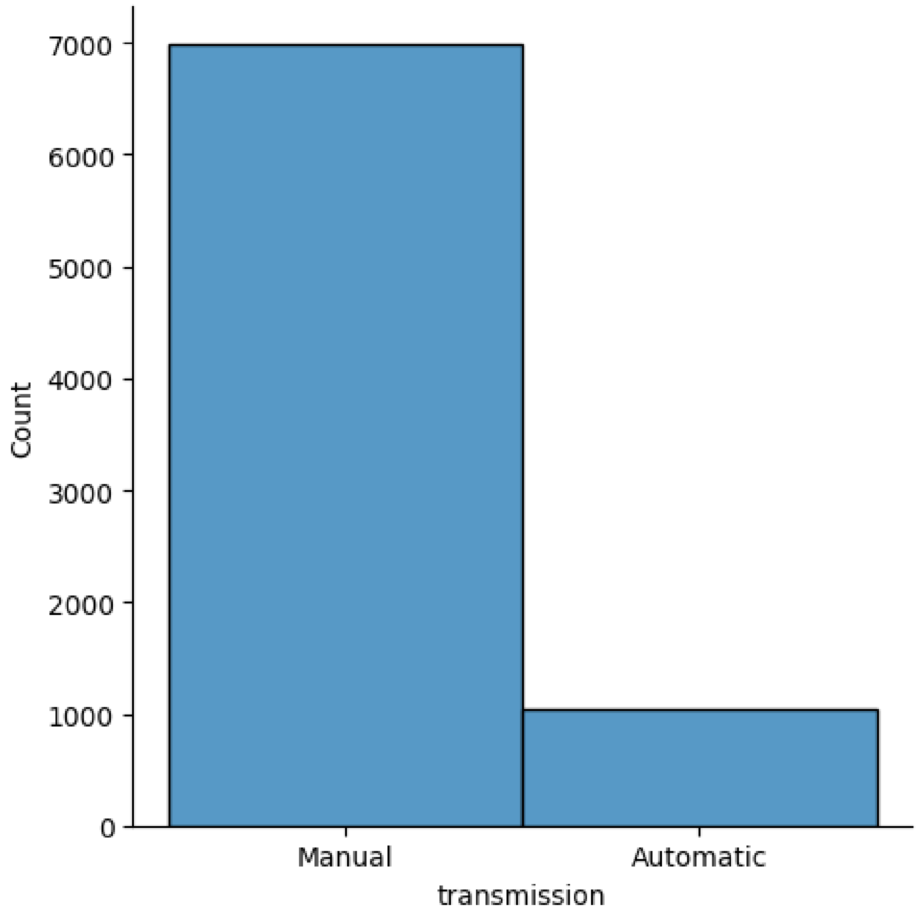
500
400
300
200
100
0
Count
0.0
0.2
0.4
0.6
0.8
1.0
1e7
selling_price


Count
600
500
400
300
200
100
0
0.0
0.5
1.0
1.5
2.0
1e6
km_driven

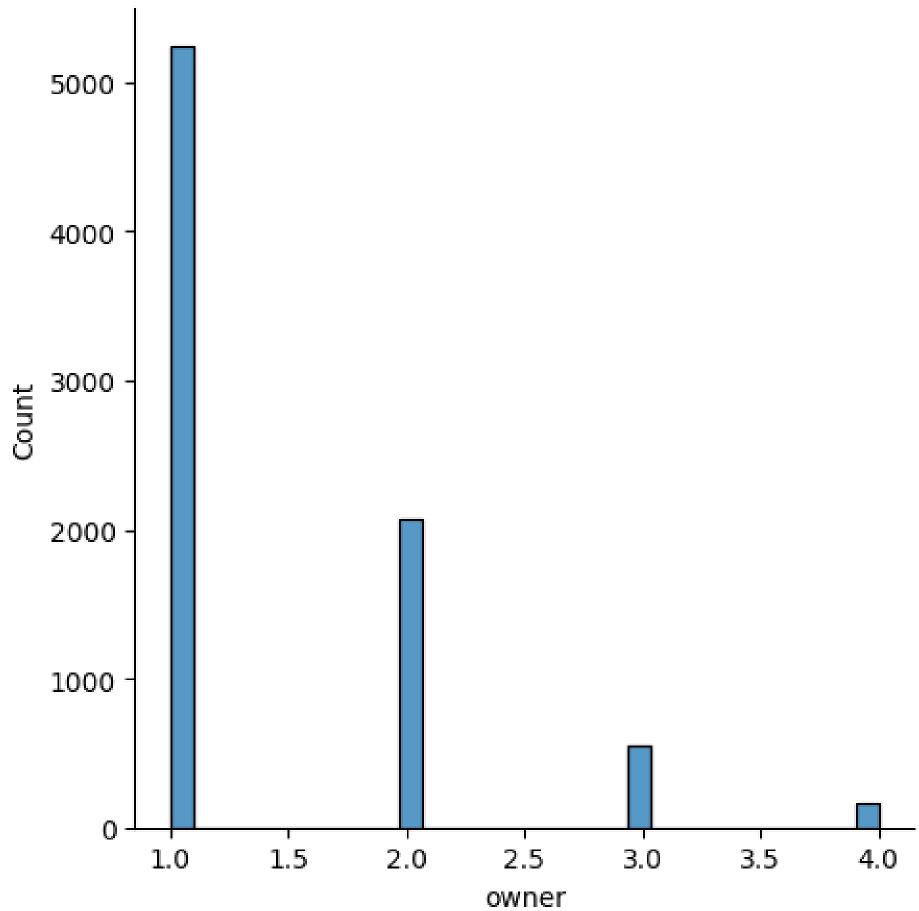


4000
3000
2000
1000
0
Count
Diesel
Petrol
fuel

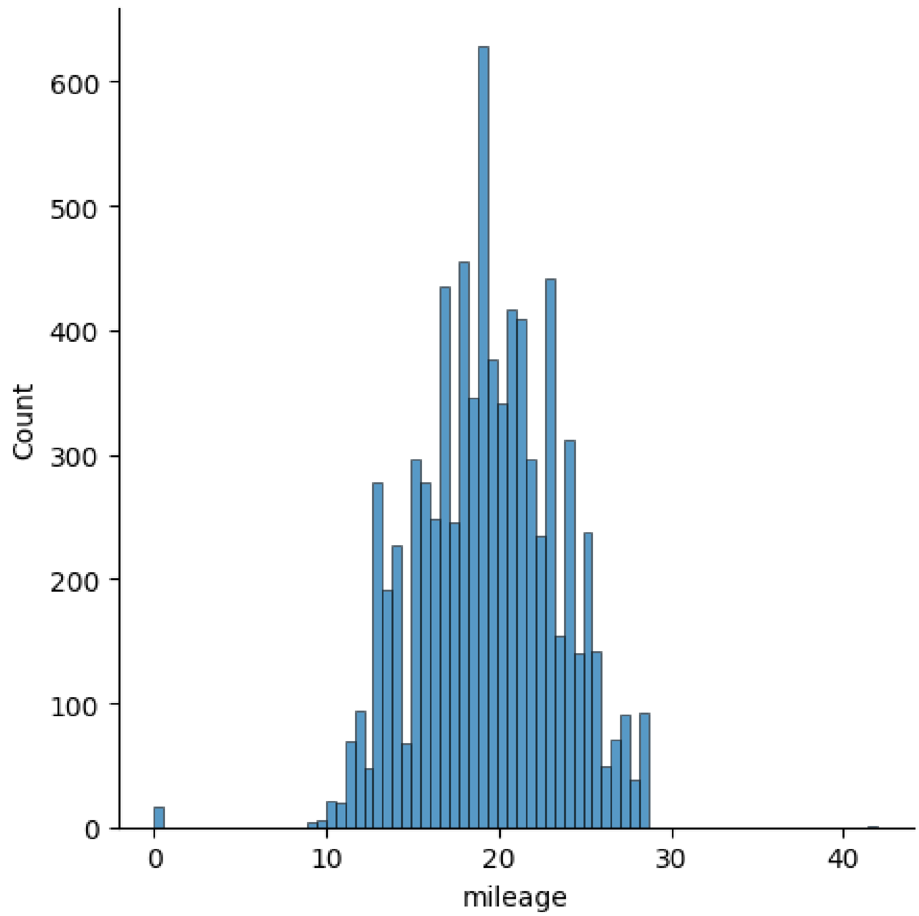

7000
6000
5000
4000
3000
2000
1000
0
Count
Individual
Dealer
Trustmark Dealer
seller_type

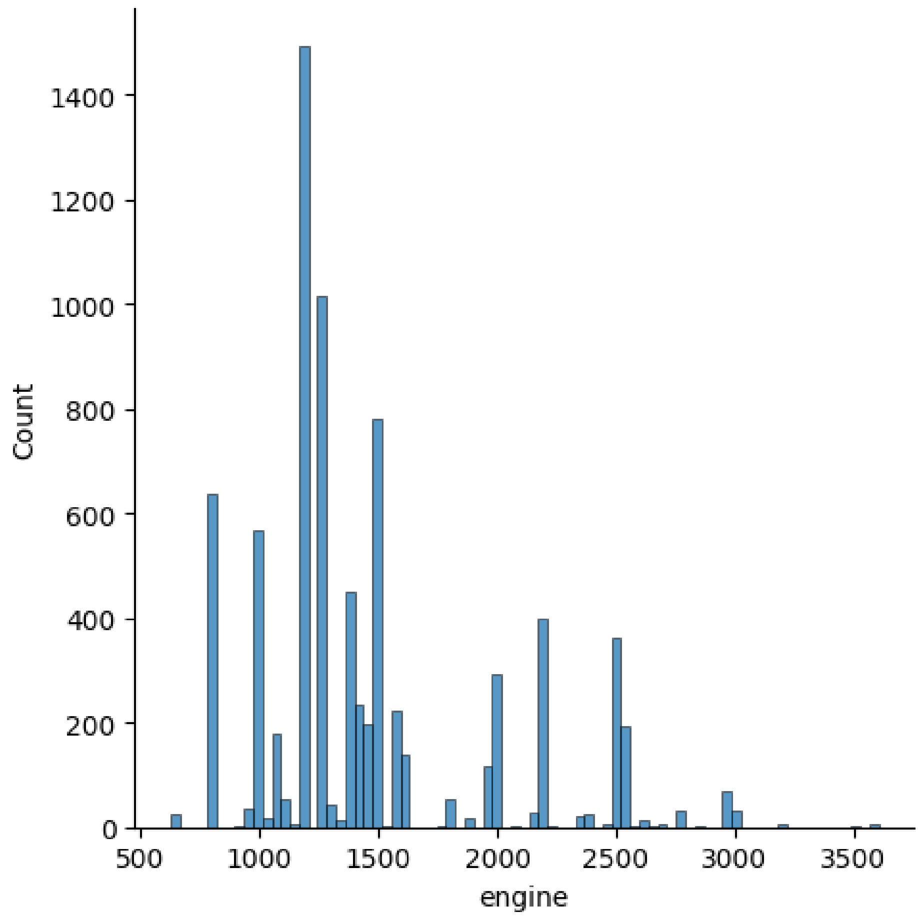


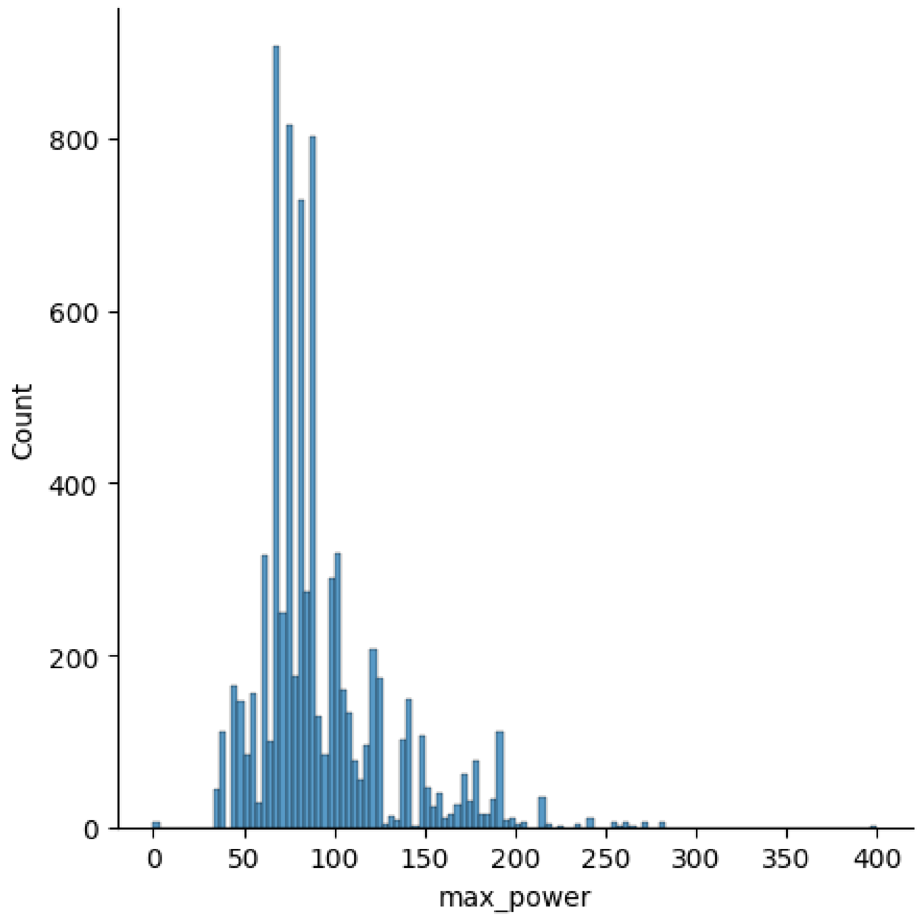
7000
6000
5000
4000
3000
2000
1000
0
Count
Manual
Automatic
transmission

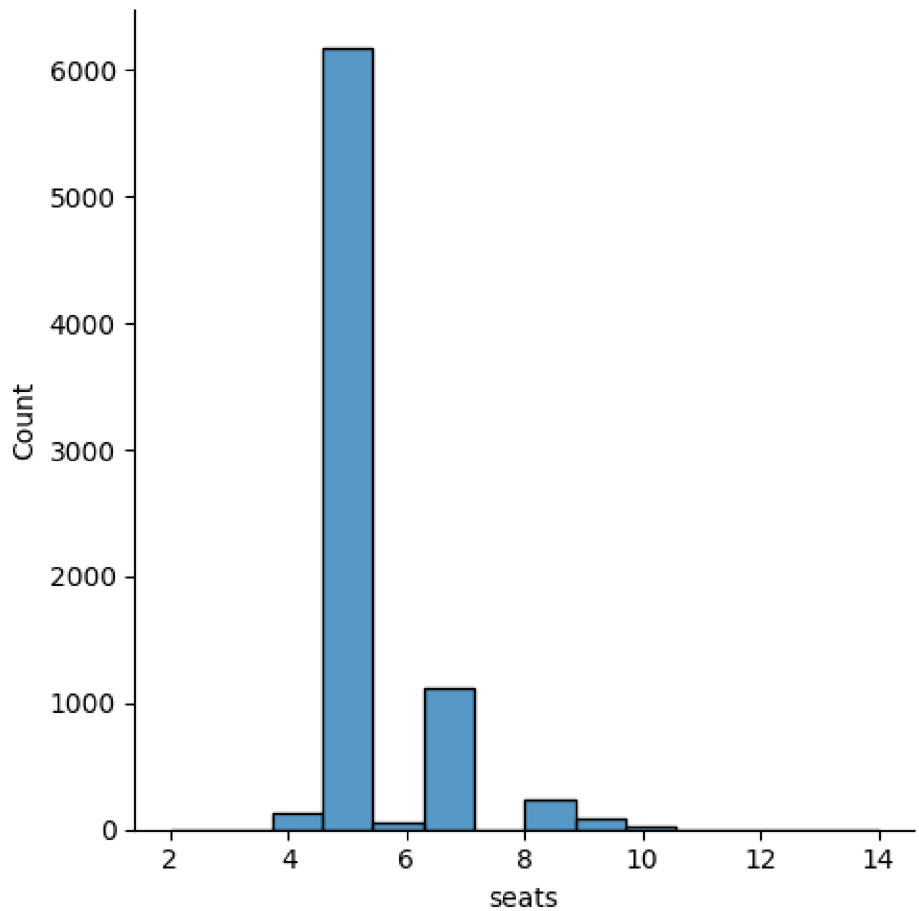


5000
4000
3000
2000
1000
0
Count
1.0
1.5
2.0
2.5
3.0
3.5
4.0
owner


600
500
400
300
200
100
0
Count
0
10
20
30
40
mileage


1400
1200
1000
800
600
400
200
0
Count
500
1000
1500
2000
2500
3000
3500
engine


Count
800
600
400
200
0
0
50
100
150
200
250
300
350
400
max_power



1.3.3 2.3 Multivariate analysis

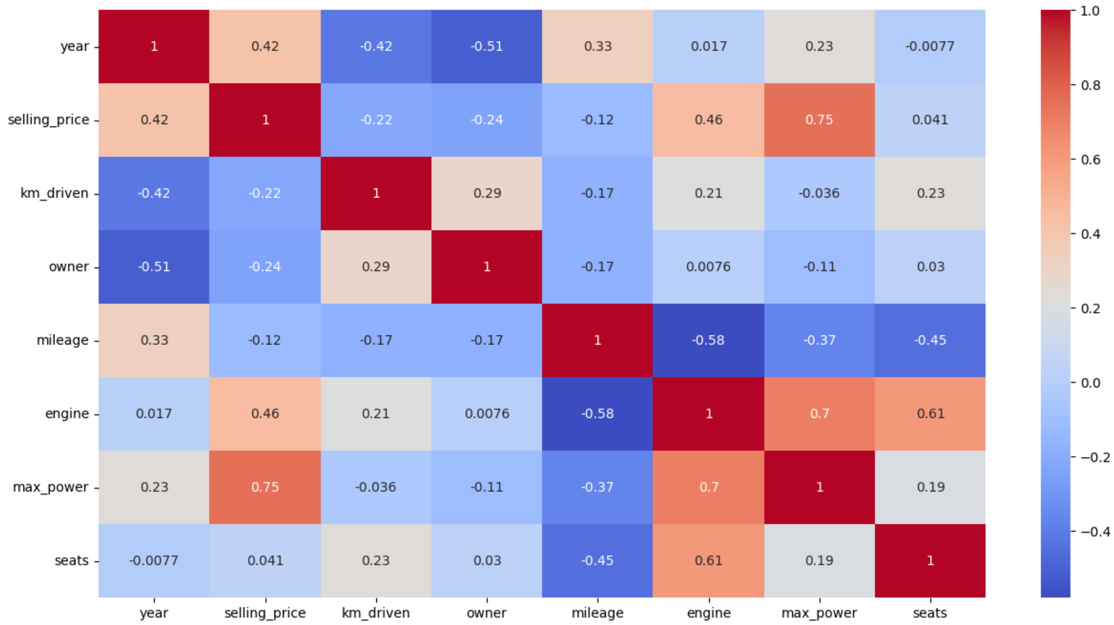
Multiple variable exploratory data analysis

Correlation Matrix Let's use correlation matrix to find strong factors predicting car price. It's also for checking whether certain features are too correlated.

[31]:
```
df_corr = df[[ 'year', 'selling_price', 'km_driven', 'owner', 'mileage',␣
↪'engine', 'max_power', 'seats']]
```

[32]:
```
# Let's check out heatmap
plt.figure(figsize = (15,8))
sns.heatmap(df_corr.corr(), annot=True, cmap="coolwarm")  #don't forget these␣
↪are not all variables! categorical is not here...
```

[32]: <Axes: >



Label encoding Apply Label encoding to categorical features to see the correlations

[33]:
```
# check unique values of four categorical features

print(f"brand : {len(df['brand'].unique())}")
print(f"fuel : {len(df['fuel'].unique())}")
print(f"transmission : {len(df['transmission'].unique())}")
print(f"seller_type : {len(df['seller_type'].unique())}")
```

```
brand : 32
fuel : 2
transmission : 2
seller_type : 3
```

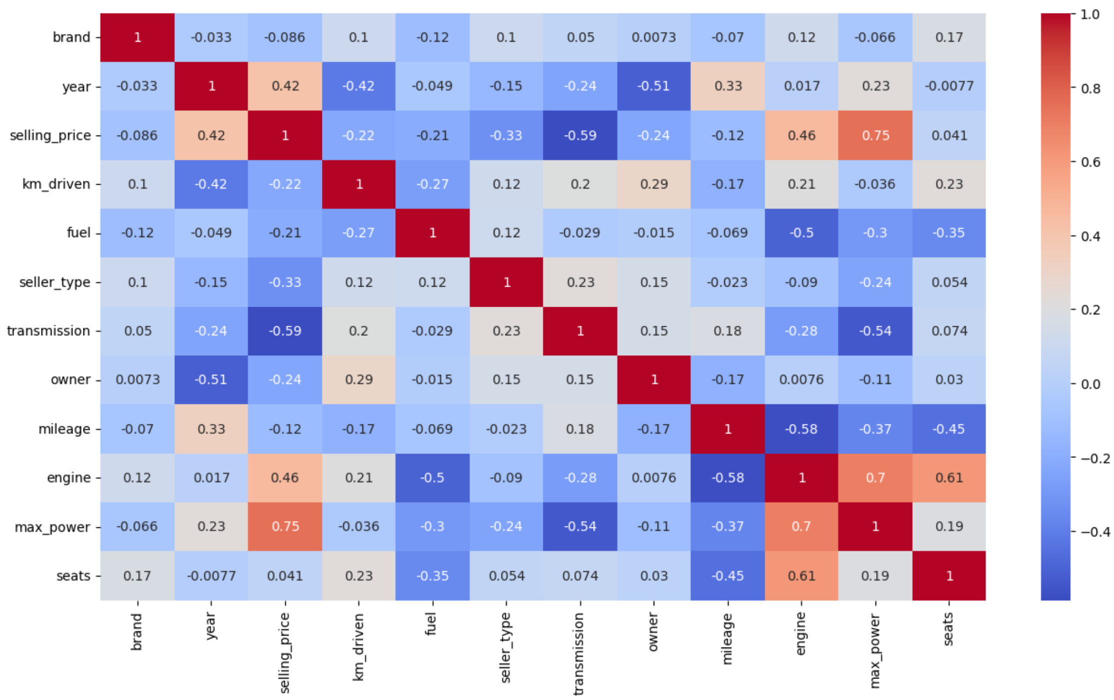
[34]:
```
# apply label encoding to check corelation
from sklearn.preprocessing import LabelEncoder

le = LabelEncoder()
df["fuel"] = le.fit_transform(df["fuel"])
df["transmission"] = le.fit_transform(df["transmission"])
df["brand"] = le.fit_transform(df["brand"])
df["seller_type"] = le.fit_transform(df["seller_type"])

print(df["fuel"].unique(),df["transmission"].unique())
print(df["brand"].unique(),df["seller_type"].unique())
```

```
[0 1] [1 0]
```

```
[20 27 10 11 29  9 26 19 28  4  7  6 14 21 22  2 30  3 23 17 13 16 18 31
  5 15  8  0  1 12 24 25] [1 0 2]
```

[35]:
```python
# Let's check out heatmap
plt.figure(figsize = (15,8))
sns.heatmap(df.corr(), annot=True, cmap="coolwarm")  #don't forget these are␣
↪not all variables! categorical is not here...
```

[35]: `<Axes: >`

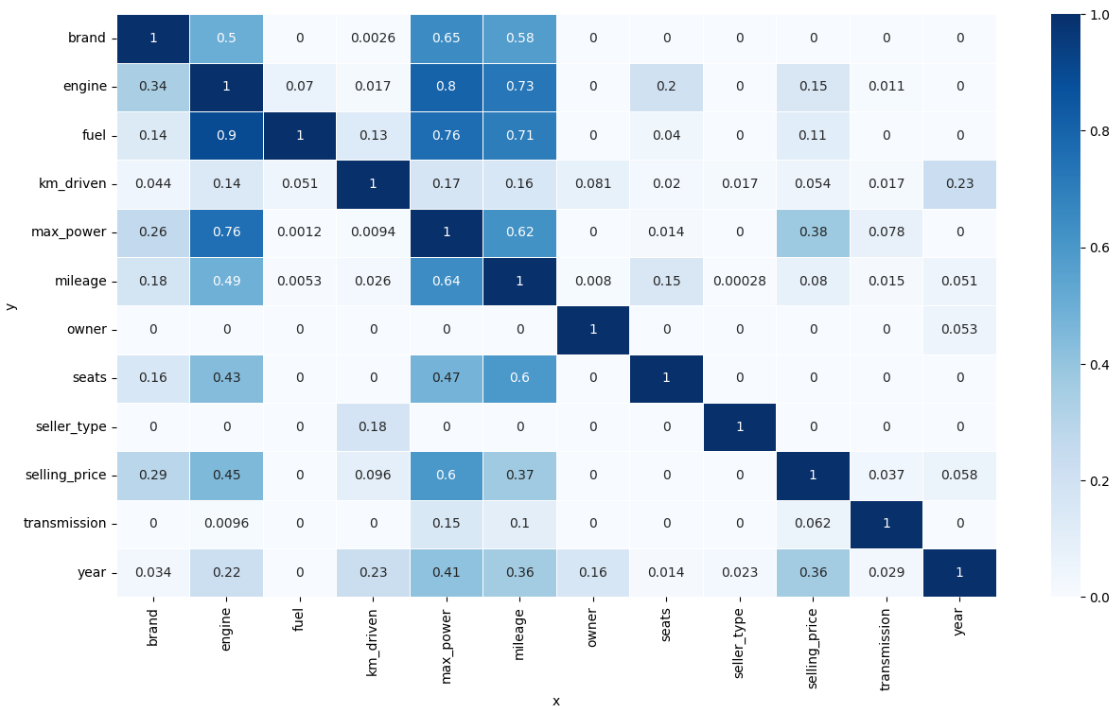


Predictive Power Score

[36]:
```python
import ppscore as pps

# before using pps, let's drop country and year
dfcopy = df.copy()
# dfcopy.drop(['country', 'year'], axis='columns', inplace=True)
# t = pps.matrix(dfcopy)[['x', 'y', 'ppscore']]
# t.pivot(index='x',columns='y',values='ppscore')
#this needs some minor preprocessing because seaborn.heatmap unfortunately does␣
↪not accept tidy data
matrix_df = pps.matrix(dfcopy)[['x', 'y', 'ppscore']].pivot(columns='x',␣
↪index='y', values='ppscore')

#plot
```

```python
plt.figure(figsize = (15,8))
sns.heatmap(matrix_df, vmin=0, vmax=1, cmap="Blues", linewidths=0.5, annot=True)
```

[36]: <Axes: xlabel='x', ylabel='y'>



The brand feature will not be chosen to train model as it does not explain much to selling price. The seller_type has three unique categories. So, this feature will be one-hot encoded.

[37]:
```python
df['seller_type'] = le.inverse_transform(df['seller_type'] )
```

[38]:
```python
df.head()
```

[38]:
```
   brand  year  selling_price  km_driven  fuel seller_type  transmission  \
0     20  2014         450000     145500     0  Individual             1
1     27  2014         370000     120000     0  Individual             1
2     10  2006         158000     140000     1  Individual             1
3     11  2010         225000     127000     0  Individual             1
4     20  2007         130000     120000     1  Individual             1

   owner  mileage  engine  max_power  seats
0      1    23.40  1248.0      74.00    5.0
1      2    21.14  1498.0     103.52    5.0
2      3    17.70  1497.0      78.00    5.0
```

```
3       1    23.00  1396.0       90.00    5.0
4       1    16.10  1298.0       88.20    5.0
```

[39]:
```python
df = pd.get_dummies(data=df,columns=['seller_type'],drop_first=True,dtype=int)
```

[40]:
```python
df.head()
```

[40]:
```
   brand  year  selling_price  km_driven  fuel  transmission  owner  mileage  \
0     20  2014         450000     145500     0             1      1    23.40
1     27  2014         370000     120000     0             1      2    21.14
2     10  2006         158000     140000     1             1      3    17.70
3     11  2010         225000     127000     0             1      1    23.00
4     20  2007         130000     120000     1             1      1    16.10

   engine  max_power  seats  seller_type_Individual  \
0  1248.0      74.00    5.0                       1
1  1498.0     103.52    5.0                       1
2  1497.0      78.00    5.0                       1
3  1396.0      90.00    5.0                       1
4  1298.0      88.20    5.0                       1

   seller_type_Trustmark Dealer
0                             0
1                             0
2                             0
3                             0
4                             0
```

[41]:
```python
# normalizing the feature
df['year'] = df['year'].apply(lambda x : (x - 1886) / (2024-1886) )
```

[42]:
```python
# binning the target
df['selling_price'] = pd.cut(df['selling_price'],4,labels=False)
```

[43]:
```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 8028 entries, 0 to 8127
Data columns (total 13 columns):
 #   Column                        Non-Null Count  Dtype
---  ------                        --------------  -----
 0   brand                         8028 non-null   int64
 1   year                          8028 non-null   float64
 2   selling_price                 8028 non-null   int64
 3   km_driven                     8028 non-null   int64
 4   fuel                          8028 non-null   int64
 5   transmission                  8028 non-null   int64
```

```
 6   owner                         8028 non-null   int64
 7   mileage                       7814 non-null   float64
 8   engine                        7814 non-null   float64
 9   max_power                     7820 non-null   float64
 10  seats                         7814 non-null   float64
 11  seller_type_Individual        8028 non-null   int64
 12  seller_type_Trustmark Dealer  8028 non-null   int64
dtypes: float64(5), int64(8)
memory usage: 878.1 KB
```

[44]:
```
df.head()
```

[44]:
```
   brand      year  selling_price  km_driven  fuel  transmission  owner  \
0     20  0.927536              0     145500     0             1      1
1     27  0.927536              0     120000     0             1      2
2     10  0.869565              0     140000     1             1      3
3     11  0.898551              0     127000     0             1      1
4     20  0.876812              0     120000     1             1      1

   mileage  engine  max_power  seats  seller_type_Individual  \
0    23.40  1248.0      74.00    5.0                       1
1    21.14  1498.0     103.52    5.0                       1
2    17.70  1497.0      78.00    5.0                       1
3    23.00  1396.0      90.00    5.0                       1
4    16.10  1298.0      88.20    5.0                       1

   seller_type_Trustmark Dealer
0                             0
1                             0
2                             0
3                             0
4                             0
```

1.4 3. Feature Engineering

We gonna skip Feature Engineering for now

1.5 4. Feature selection

According to the correlation matrix

- seats and brand have less than 0.2 of correlation scores with selling_price(target). So, these features will be removed.
- max_power and engine are highly correlated with 0.7. But, I will keep them both as high max_power with small engine might explain built quality of car (in terms of power losses due to friction)

According to the predictive power score

- transmission, owner, seller_type and km_driven has less than 0.1 score.

- But, only km_driven will be removed as the others have fair correlation scores with selling_price and also with assumption of they are somewhat important and nuanced features.

[45]:
```
df.columns
```

[45]:
```
Index(['brand', 'year', 'selling_price', 'km_driven', 'fuel', 'transmission',
       'owner', 'mileage', 'engine', 'max_power', 'seats',
       'seller_type_Individual', 'seller_type_Trustmark Dealer'],
      dtype='object')
```

[46]:
```
#x is our strong features
X = df[['year', 'fuel', 'seller_type_Individual', 'seller_type_Trustmark␣
 ↪Dealer',
        'transmission', 'owner', 'engine', 'max_power']]

#y is simply selling price
y = df["selling_price"]
```

[47]:
```
# check if y has missing values to remove
df["selling_price"].isna().sum()
```

[47]:
```
0
```

1.5.1 Train test split

[48]:
```
df.shape
```

[48]:
```
(8028, 13)
```

[49]:
```
# I assume only 10 percent of test data will be enough as it is around 800.
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.1,␣
 ↪random_state = 42)
```

1.6 5. Preprocessing

1.6.1 Null values

[50]:
```
#check for null values
X_train.isna().sum()
```

[50]:
```
year                            0
fuel                            0
seller_type_Individual          0
seller_type_Trustmark Dealer    0
transmission                    0
```

```
owner                          0
engine                       199
max_power                    193
dtype: int64
```

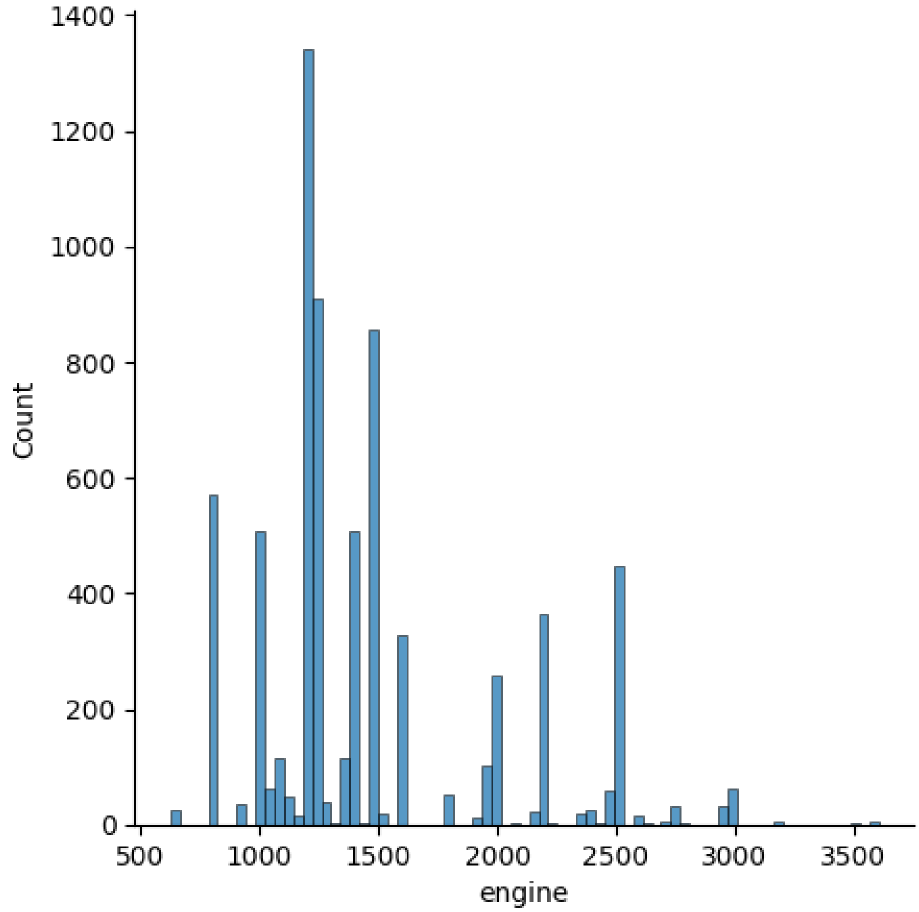
[51]:
```
X_test.isna().sum()
```

[51]:
```
year                         0
fuel                         0
seller_type_Individual       0
seller_type_Trustmark Dealer 0
transmission                 0
owner                        0
engine                      15
max_power                   15
dtype: int64
```

As the distributions of engine and max_power has right skewness, median values will be used to replace

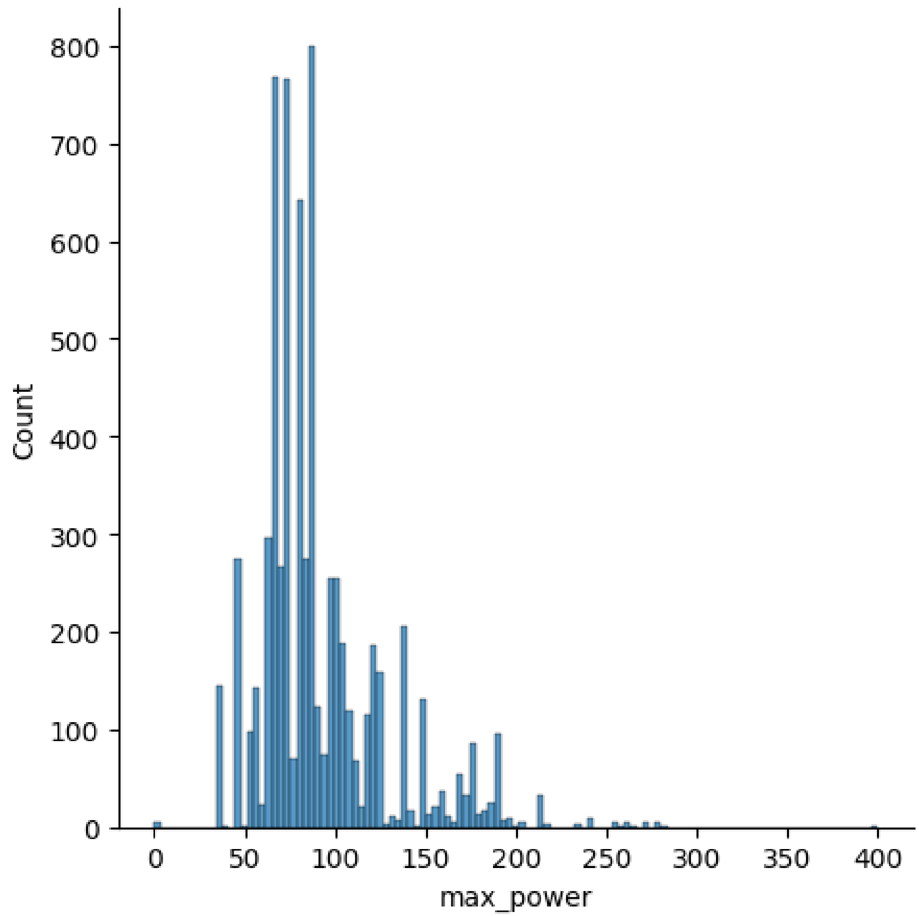
[52]:
```
sns.displot(data=X_train, x='engine')
```

[52]:
```
<seaborn.axisgrid.FacetGrid at 0x7f92c783f010>
```



[53]:
```python
sns.displot(data=X_train, x='max_power')
```

[53]: <seaborn.axisgrid.FacetGrid at 0x7f92c51b6bc0>



[54]:
```
#let's fill the testing set with the training distribution first!
# X_test['school'].fillna(X_train['school'].mean(), inplace=True)
X_train['engine'].fillna(X_train['engine'].median(), inplace=True)
X_train['max_power'].fillna(X_train['max_power'].median(), inplace=True)
```

[55]:
```
#let's fill the testing set with the training distribution first!
# X_test['school'].fillna(X_train['school'].mean(), inplace=True)
X_test['engine'].fillna(X_train['engine'].median(), inplace=True)
X_test['max_power'].fillna(X_train['max_power'].median(), inplace=True)
```

[56]:
```
#check again
X_train.isna().sum()
```

[56]:
```
year                            0
fuel                            0
seller_type_Individual          0
seller_type_Trustmark Dealer    0
transmission                    0
```

```
owner                         0
engine                        0
max_power                     0
dtype: int64
```

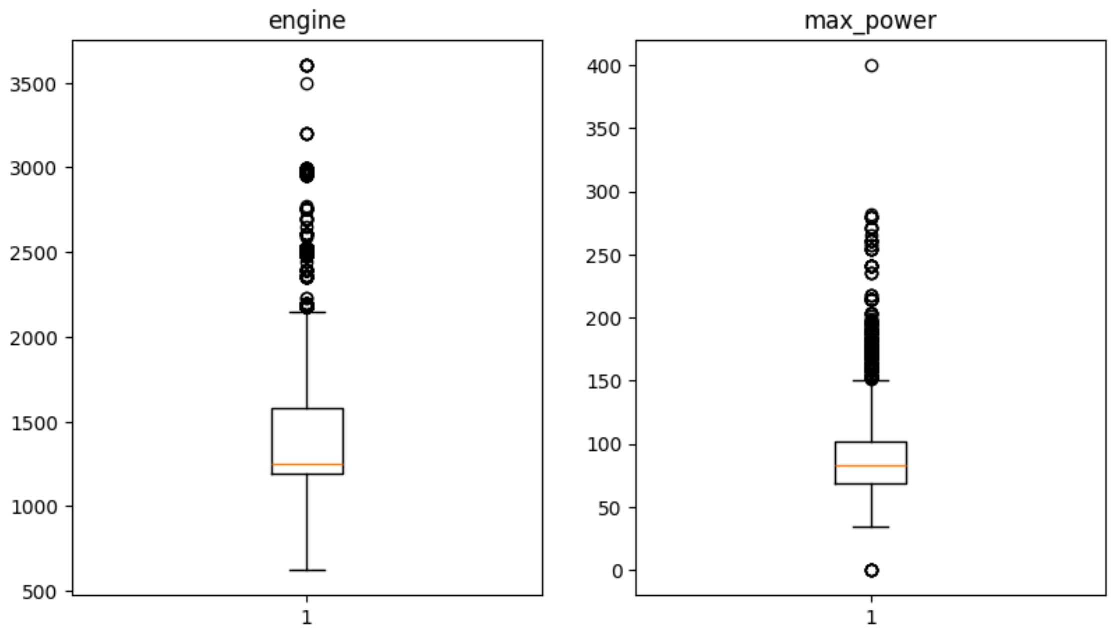
[57]:
```
X_test.isna().sum()
```

[57]:
```
year                          0
fuel                          0
seller_type_Individual        0
seller_type_Trustmark Dealer  0
transmission                  0
owner                         0
engine                        0
max_power                     0
dtype: int64
```

1.6.2 Checking Outliers

For two numerical features of engine and max__power, outliers need to be checked for scaling

[58]:
```
# Create a dictionary of columns.
col_dict = {'engine':1,'max_power':2}

# Detect outliers in each variable using box plots.
plt.figure(figsize=(20,30))

for variable,i in col_dict.items():
                     plt.subplot(5,4,i)
                     plt.boxplot(X_train[variable])
                     plt.title(variable)

plt.show()
```



[59]:
```
def outlier_count(col, data = X_train):

    # calculate your 25% quatile and 75% quatile
    q75, q25 = np.percentile(data[col], [75, 25])

    # calculate your inter quatile
    iqr = q75 - q25

    # min_val and max_val
    min_val = q25 - (iqr*1.5)
    max_val = q75 + (iqr*1.5)

    # count number of outliers, which are the data that are less than min_val␣
 ↪or more than max_val calculated above
    outlier_count = len(np.where((data[col] > max_val) | (data[col] <␣
 ↪min_val))[0])

    # calculate the percentage of the outliers
    outlier_percent = round(outlier_count/len(data[col])*100, 2)

    if(outlier_count > 0):
        print("\n"+15*'-' + col + 15*'-'+"\n")
        print('Number of outliers: {}'.format(outlier_count))
        print('Percent of data that is outlier: {}%'.format(outlier_percent))
```

[60]:
```
for col in ['engine','max_power']:
    outlier_count(col)
```

```
---------------engine---------------

Number of outliers: 1079
Percent of data that is outlier: 14.93%

---------------max_power---------------

Number of outliers: 519
Percent of data that is outlier: 7.18%
```

1.6.3 Scaling

As the features of engine and max_power has a considerable amount of outliers and skewness and they are not in a bounded range, standardization can be used to scale.

[61]:
```
from sklearn.preprocessing import StandardScaler

# feature scaling helps improve reach convergence faster
scaler = StandardScaler()
X_train[['engine','max_power']] = scaler.
 ↪fit_transform(X_train[['engine','max_power']])
X_test[['engine','max_power']]  = scaler.
 ↪transform(X_test[['engine','max_power']])
```

For selling_price(y), np.log will be used to scale

[62]:
```
from sklearn.preprocessing import OneHotEncoder
oh = OneHotEncoder(sparse_output=False)
oh.fit(y_train.to_numpy().reshape(-1,1))
Y_train = oh.transform(y_train.to_numpy().reshape(-1,1))
Y_test = oh.transform(y_test.to_numpy().reshape(-1,1))
```

[63]:
```
# Let's check shapes of all X_train, X_test, y_train, y_test
print("Shape of X_train: ", X_train.shape)
print("Shape of X_test: ", X_test.shape)
print("Shape of y_train: ", Y_train.shape)
print("Shape of y_test: ", Y_test.shape)
```

```
Shape of X_train:  (7225, 8)
Shape of X_test:  (803, 8)
Shape of y_train:  (7225, 4)
Shape of y_test:  (803, 4)
```

2 6. Modeling

Modifying the Multinomial Linear Regression class - add accuracy score function - add functions of precision, recall and f1-score for each class - add functions macro precision, macro recall and macro f1 - add functions weighted precision, weighted recall and weighted f1 - add ridge L2 penalty - compare the results of the implementation with scikit-learn classification report

[180]:
```
from sklearn.model_selection import KFold
import time
# from mlflow.pyfunc import PythonModel

class MultinomialLogisticRegression(object):

    kfold = KFold(n_splits=5)

    def __init__(self, k, n, method,class_weights = None,penalty = 0,cv=kfold,␣
↪alpha = 0.001, max_iter=5000):
        self.k = k
        self.n = n
        self.alpha = alpha
        self.max_iter = max_iter
        self.method = method
        self.cv = cv
        self.penalty = penalty
        self.class_weights =class_weights

    def fit_CV(self,X,Y):
        self.cv_metric = {}
        for fold, (train_idx, val_idx) in enumerate(self.cv.split(X)):
            X_cross_train = X[train_idx]
            Y_cross_train = Y[train_idx]
            X_cross_val   = X[val_idx]
            Y_cross_val   = np.argmax(Y[val_idx],axis=1)
            self.fit(X_cross_train,Y_cross_train)
            Y_hat = self.predict(X_cross_val)
            metric = {}
            metric['accuracy'] = self.accuracy(Y_cross_val,Y_hat)
            metric['precision'] = self.
↪macro_metric("precision",Y_cross_val,Y_hat,self.class_weights)
            metric['recall'] = self.
↪macro_metric("recall",Y_cross_val,Y_hat,self.class_weights)
            metric['f1_score'] = self.
↪macro_metric("f1_score",Y_cross_val,Y_hat,self.class_weights)
            self.cv_metric[fold] = metric
        print(self.cv_metric)

    def fit(self, X, Y):
```

```python
        self.W = np.random.rand(self.n, self.k)
        self.losses = []
        # Y = np.asarray(Y).copy()
        # print(Y.shape)
        if self.method == "batch":
            start_time = time.time()
            for i in range(self.max_iter):
                loss, grad =  self.gradient(X, Y)
                self.losses.append(loss)
                self.W = self.W - self.alpha * grad
                if i % 500 == 0:
                    print(f"Loss at iteration {i}", loss)
            print(f"time taken: {time.time() - start_time}")

        elif self.method == "minibatch":
            start_time = time.time()
            batch_size = int(0.3 * X.shape[0])
            for i in range(self.max_iter):
                ix = np.random.randint(0, X.shape[0]) #<----with replacement
                batch_X = X[ix:ix+batch_size]
                batch_Y = Y[ix:ix+batch_size]
                loss, grad = self.gradient(batch_X, batch_Y)
                self.losses.append(loss)
                self.W = self.W - self.alpha * grad
                if i % 500 == 0:
                    print(f"Loss at iteration {i}", loss)
            print(f"time taken: {time.time() - start_time}")

        elif self.method == "sto":
            start_time = time.time()
            list_of_used_ix = []
            for i in range(self.max_iter):
                idx = np.random.randint(X.shape[0])
                while i in list_of_used_ix:
                    idx = np.random.randint(X.shape[0])
                X_train = X[idx, :].reshape(1, -1)
                Y_train = Y[idx]
                loss, grad = self.gradient(X_train, Y_train)
                self.losses.append(loss)
                self.W = self.W - self.alpha * grad

                list_of_used_ix.append(i)
                if len(list_of_used_ix) == X.shape[0]:
                    list_of_used_ix = []
                if i % 500 == 0:
                    print(f"Loss at iteration {i}", loss)
            print(f"time taken: {time.time() - start_time}")
```

```python
        else:
            raise ValueError('Method must be one of the followings: "batch", "minibatch" or "sto".')


    def gradient(self, X, Y):
        m = X.shape[0]
        h = self.h_theta(X, self.W)
        loss = (- np.sum(np.multiply(Y,np.log(h)) / m)) + (self.penalty * np.sum(np.square(self.W)))
        print(loss)
        # print(type(h),type(Y))
        error = h - Y
        grad = self.softmax_grad(X, error)
        return loss, grad

    def softmax(self, theta_t_x):
        # print( np.sum(theta_t_x, axis=1, keepdims=True))
        return np.exp(theta_t_x) / np.sum(np.exp(theta_t_x), axis=1, keepdims=True)

    def softmax_grad(self, X, error):
        return  (X.T @ error) + (2*self.penalty*self.W)

    def h_theta(self, X, W):
        '''
        Input:
            X shape: (m, n)
            w shape: (n, k)
        Returns:
            yhat shape: (m, k)
        '''
        return self.softmax(X @ W)

    def predict(self, X_test):
        return np.argmax(self.h_theta(X_test, self.W), axis=1)

    def plot(self):
        plt.plot(np.arange(len(self.losses)) , self.losses, label = "Train Losses")
        plt.title("Losses")
        plt.xlabel("epoch")
        plt.ylabel("losses")
        plt.legend()

    def accuracy(self,Y_true,Y_pred):
```

```
        Y_true = Y_true.reshape(1,-1)[0]
        Y_pred = Y_pred.reshape(1,-1)[0]
        return len(Y_pred[Y_true == Y_pred]) /  len(Y_pred)

    def _confusion_class(self,Y_true,Y_pred,c):
        Y_true = Y_true.reshape(1,-1)[0]
        Y_pred = Y_pred.reshape(1,-1)[0]
        class_filter = (Y_true == c) | (Y_pred == c)
        Y_true_class = Y_true[class_filter]
        Y_pred_class = Y_pred[class_filter]
        TP  = len(Y_true_class[Y_true_class == Y_pred_class])
        FP  = len(Y_true_class[(Y_true_class != Y_pred_class)  & (Y_pred_class␣
↪== c)])
        FN  = len(Y_true_class[(Y_true_class != Y_pred_class)  & (Y_pred_class !
↪= c)])
        return (TP,FP,FN)

    def precision(self,Y_true,Y_pred,c):
        TP,FP,_ = self._confusion_class(Y_true,Y_pred,c)
        if  TP + FP == 0:
            p = 0
        else:
            p =  TP / (TP + FP)
        return p

    def recall(self,Y_true,Y_pred,c):
        TP,_,FN = self._confusion_class(Y_true,Y_pred,c)
        if  TP + FN == 0:
            r = 0
        else:
            r =  TP / (TP+FN)
        return r

    def f1_score(self,Y_true,Y_pred,c):
        p = self.precision(Y_true,Y_pred,c)
        r = self.recall(Y_true,Y_pred,c)
        if p + r == 0:
            f1 = 0
        else:
            f1 = 2 * p * r / (p + r)
        return f1

    def macro_metric(self,metric,Y_true,Y_pred,weighted=False):
        if metric == 'precision':
            macro_ = np.array([self.precision(Y_true,Y_pred,c) for c in np.
↪unique(Y_true)])
        elif metric == 'recall':
```

```
            macro_ =  np.array([self.recall(Y_true,Y_pred,c) for c in np.
↪unique(Y_true)])
        else:
            macro_  = np.array([self.f1_score(Y_true,Y_pred,c) for c in np.
↪unique(Y_true)])
        if  weighted == True:
            weights =  np.array([len(Y_true[Y_true == c]) / len(Y_true) for c␣
↪in np.unique(Y_true)])
            macro_m = np.sum(macro_ * weights)
        else:
            macro_m = np.mean(macro_)
        return macro_m
```

[181]:
```
lg = MultinomialLogisticRegression(k=4,n=8,method='batch',penalty=0.
↪9,max_iter=100)
```

[182]:
```
lg.fit(X=X_train.to_numpy(),Y=Y_train)
```

```
8.87144212951591
Loss at iteration 0 8.87144212951591
155.87475443443776
149.81715214429624
146.1302361616937
144.10900011274924
142.68564385989583
141.5641057571601
140.531489355333
139.5279114312616
138.54563921816782
137.57848900183723
136.6255591809052
135.68534182268783
134.75751056890186
133.84147332146648
132.93697233213496
132.0436556259019
131.16127768673687
130.28956408678266
129.42827939231364
128.57718280315194
127.73605127406994
126.90466451243033
126.08281280874756
125.27029176631186
124.46690486723817
123.67246150115216
```

122.88677771296975
122.10967537443146
121.34098230832615
120.58053186754942
119.82816285235158
119.08371924267195
118.34705005377513
117.61800913264881
116.89645500215045
116.18225068928768
115.4752635743434
114.77536523862328
114.08243132311745
113.39634139019232
112.71697879220277
112.04423054409395
111.37798720105083
110.71814273999232
110.06459444505694
109.41724279650695
108.77599136294361
108.14074669651659
107.51141823098338
106.88791818242899
106.27016145253049
105.65806553425408
105.05155041991155
104.45053851151688
103.85495453340805
103.26472544711226
102.67978036844754
102.1000504868638
101.52546898703407
100.95597097271255
100.39149339287776
99.83197497018232
99.27735613172716
98.72757894217767
98.18258703923414
97.64232557146389
97.10674113849637
96.57578173357598
96.04939668845924
95.52753662063608
95.01015338284672
94.49720001485794
93.98863069745464
93.4844007085963

```
92.9844663816798
92.48878506584505
91.99731508825323
91.51001571826376
91.02684713343054
90.5477703872362
90.07274737847885
89.60174082222589
89.13471422224684
88.67163184483815
88.21245869395213
87.75716048754515
87.30570363505971
86.85805521595942
86.41418295923711
85.97405522382039
85.53764097980229
85.10490979042798
84.67583179477334
84.25037769105467
83.8285187205133
83.41022665182298
82.99547376597278
82.58423284158104
82.1764771406019
time taken: 0.29651308059692383
```

[183]:
```python
y_hat = lg.predict(X_test=X_test.to_numpy())
```

[184]:
```python
lg.accuracy(Y_true=y_test.to_numpy(),Y_pred=y_hat)
```

[184]:
```
0.9713574097135741
```

[142]:
```python
for i in range(lg.k):
    print (f" Metric for the class {i}")
    print("="*30)
    print(f"Precision  : {lg.precision(Y_true=y_test.
↪to_numpy(),Y_pred=y_hat,c=i)}")
    print(f"Recall  : {lg.recall(Y_true=y_test.to_numpy(),Y_pred=y_hat,c=i)}")
    print(f"f1 score : {lg.f1_score(Y_true=y_test.to_numpy(),Y_pred=y_hat,c=i)}␣
↪\n")
```

```
 Metric for the class 0
==============================
Precision  : 0.9960681520314548
Recall  : 0.9921671018276762
f1 score : 0.9941137998691956
```

```
 Metric for the class 1
==============================
Precision  : 0.5142857142857142
Recall  : 0.782608695652174
f1 score : 0.6206896551724138

 Metric for the class 2
==============================
Precision  : 0.4
Recall  : 0.14285714285714285
f1 score : 0.21052631578947364

 Metric for the class 3
==============================
Precision  : 0
Recall  : 0
f1 score : 0
```

[143]:

```
print (f" Macro Metric")
print("="*30)
# print(lg.macro_metric(metric="precision",Y_true=y_test.
 ↪to_numpy(),Y_pred=y_hat))
p =  lg.macro_metric(metric="precision",Y_true=y_test.to_numpy(),Y_pred=y_hat)
r =   lg.macro_metric(metric="recall",Y_true=y_test.to_numpy(),Y_pred=y_hat)
f1  =  lg.macro_metric(metric="f1",Y_true=y_test.to_numpy(),Y_pred=y_hat)
print(f"Precision : {p}" )
print(f"Recall : {r}")
print(f"F1_score : {f1}")
```

```
 Macro Metric
==============================
Precision : 0.636784622105723
Recall : 0.639210980112331
F1_score : 0.6084432569436944
```

[144]:

```
print (f" Macro Metric with class weights")
print("="*30)
# print(lg.macro_metric(metric="precision",Y_true=y_test.
 ↪to_numpy(),Y_pred=y_hat))
p =  lg.macro_metric(metric="precision",Y_true=y_test.
 ↪to_numpy(),Y_pred=y_hat,weighted=True)
r =   lg.macro_metric(metric="recall",Y_true=y_test.
 ↪to_numpy(),Y_pred=y_hat,weighted=True)
f1  =  lg.macro_metric(metric="f1",Y_true=y_test.
 ↪to_numpy(),Y_pred=y_hat,weighted=True)
print(f"Precision : {p}" )
```

```
print(f"Recall : {r}")
print(f"F1_score : {f1}")
```

```
 Macro Metric with class weights
==============================
Precision : 0.9718764332312152
Recall : 0.9713574097135741
F1_score : 0.9697564149312852
```

[145]:
```
from sklearn.metrics import classification_report
print(classification_report(y_true=y_test,y_pred=y_hat))
```

```
              precision    recall  f1-score   support

           0       1.00      0.99      0.99       766
           1       0.51      0.78      0.62        23
           2       0.40      0.14      0.21        14

    accuracy                           0.97       803
   macro avg       0.64      0.64      0.61       803
weighted avg       0.97      0.97      0.97       803
```

The resluts of the implementations are almost the same with scikit-learn classification report, Here, support in the classification report is the number of samples that are used the calculating the metrics.

[198]:
```
# Creating experiment in MLflow
import mlflow
import os
mlflow.set_tracking_uri("http://mlflow.ml.brain.cs.ait.ac.th/")
os.environ['MLFLOW_TRACKING_USERNAME'] = 'admin'
os.environ['MLFLOW_TRACKING_PASSWORD'] = 'password'
os.environ['LOGNAME'] = 'st125066'
mlflow.set_experiment(experiment_name="st125066-a3")
```

[198]:
```
<Experiment: artifact_location='mlflow-artifacts:/881703814181867940',
creation_time=1728266589594, experiment_id='881703814181867940',
last_update_time=1728266589594, lifecycle_stage='active', name='st125066-a3',
tags={}>
```

[185]:
```
lg_cv = MultinomialLogisticRegression(k=4,n=8,method='batch',penalty=0.
 ↪9,max_iter=100)
```

[186]:
```
lg_cv.fit_CV(X=X_train.to_numpy(),Y=Y_train)
```

```
8.338207698921847
Loss at iteration 0 8.338207698921847
```

42.234760894393595
40.482614711123084
39.92354706282143
39.65463773733321
39.43841178788658
39.23088181611018
39.03307208154957
38.84207333011642
38.658160842817765
38.48064672057007
38.30930698715787
38.14376782032171
37.98374762447671
37.82895432109455
37.679126048986696
37.53401235497755
37.39338050908552
37.25701130540758
37.12469943991267
36.99625203097063
36.87148803219444
36.750237349469195
36.63234016867562
36.5176462687246
36.40601441165748
36.29731176422165
36.19141336540753
36.08820162868749
35.987565879322055
35.88940192243722
35.793611639991916
35.700102614061564
35.60878777449563
35.51958506903189
35.43241715420981
35.34721110555462
35.26389814566305
35.18241338894374
35.1026956018816
35.02468697779489
34.94833292514277
34.87358186851962
34.80038506154202
34.7286964108961
34.65847231086796
34.589671487729106
34.52225485339311
34.456185367799186

34.391427909514576
34.327949154080244
34.26571745965417
34.20470275953398
34.1448764611656
34.08621135126821
34.02868150672683
33.97226221092454
33.916929875204474
33.86266196516947
33.80943693154383
33.757234145336525
33.70603383706037
33.655817039774554
33.606565535731555
33.55826180642083
33.510888985813864
33.464430816625274
33.41887160941555
33.37419620437012
33.3303899355989
33.28743859780898
33.24532841521123
33.204046012529524
33.163578387988096
33.1239128881601
33.085037184566204
33.04693925191878
33.00960734791271
32.97302999446953
32.937195960346436
32.90209424502709
32.86771406381524
32.834044834057025
32.80107616242132
32.768797833172236
32.737199797370444
32.70627216294464
32.67600518557676
32.64638926034819
32.61741491409707
32.58907279843937
32.56135368340927
32.53424845167651
32.50774809330131
32.48184370098897
32.45652646580891
32.431787673344566

```
32.407618700242786
32.38401101113269
32.360956155886086
time taken: 0.20027804374694824
10.174126152719026
Loss at iteration 0 10.174126152719026
72.52681379272344
68.00874630703092
65.15172686005431
63.826419773979424
63.21177111079366
62.69805488573495
62.219553655426566
61.75540627045165
61.30176172060481
60.8560854104384
60.41775652121225
59.98624127111143
59.561345958398206
59.14287753949872
58.73070876184156
58.324709458159006
57.92476290519895
57.530751867375336
57.14256283917132
56.76008335486252
56.383203180368255
56.011813891694835
55.64580925684027
55.28508522461948
54.92954006219341
54.57907438518792
54.23359120353874
53.89299593088073
53.55719638691317
53.22610278373376
52.899627704219085
52.57768607198911
52.260195115831785
51.94707432944561
51.63824542786799
51.333632301389784
51.033160967736286
50.73675952307832
50.44435809234838
50.15588877922631
49.871285616084535
49.59048451411621
```

49.313423213817934
49.040041235956416
48.770279833114195
48.504081941883165
48.241392135752726
47.98215657872325
47.726322979662385
47.47384054741233
47.224659946648615
46.9787332544862
46.73601391782479
46.496456711423164
46.26001769669098
46.026654181185876
45.79632467880373
45.56898887065056
45.34460756658478
45.12314266741979
44.90455712777768
44.68881491958568
44.47588099620831
44.265721257208725
44.05830251373388
43.853592454518946
43.651559612506894
43.45217333208019
43.25540373690154
43.06122169836189
42.869598804633455
42.680507330326485
42.493920206748655
42.30981099276615
42.128153846265846
41.948923496218136
41.77209521534047
41.59764479336131
41.42554851088519
41.25578311385899
41.088325788640645
40.9231541376708
40.76024615574913
40.59958020691659
40.441135001945604
40.28488957644024
40.13082326954888
39.9789157032921
39.82914676250878
39.68149657542381

```
39.53594549484092
39.39247407996446
39.2510630788543
39.11169341151776
38.974346153643204
38.8390025209795
38.705643854365775
38.57425160541604
38.444807322862474
time taken: 0.22548866271972656
14.51083847786982
Loss at iteration 0 14.51083847786982
137.73163356366368
133.34773970506453
130.3346331186276
128.38166201221077
126.93105361019836
125.7284081668116
124.72975418641957
123.83230166016867
122.97300988635021
122.13520565241583
121.31272489235306
120.50272820839459
119.7037375678585
118.9148943508587
118.13565045345342
117.36562342565685
116.60452359743672
115.85211542592073
115.10819629236408
114.3725845935907
113.64511293018337
112.92562413937483
112.21396893397635
111.51000445560052
110.81359335248294
110.12460316123389
109.44290586715047
108.76837757166155
108.10089822606594
107.44035140808448
106.78662412760178
106.13960665356966
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104.86527756860092
104.23776144430411
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```

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102.39263651486176
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101.19281443378453
100.60171651203775
100.016381241785
99.43672664174389
98.86267271772962
98.29414139737585
97.73105646881291
97.17334352294203
96.62092989896671
96.07374463286389
95.5317184085001
94.99478351111671
94.46287378293074
93.9359245806164
93.41387273445278
92.89665650894197
92.38421556472109
91.87649092160949
91.3734249226502
90.87496119902198
90.38104463571436
89.89162133787397
89.40663859774514
88.92604486214167
88.44978970040023
87.97782377277734
87.51009879926406
87.04656752880196
86.58718370889402
86.13190205561183
85.68067822400913
85.233468778956
84.7902311664163
84.3509236851933
83.91550545917318
83.48393641009912
83.05617723090997
82.63218935967903
82.21193495418935
81.79537686718056
81.38247862230264
80.97320439080885
80.5675189690194
80.16538775658346
79.76677673556456

```
79.37165245037056
78.97998198854545
78.591732962436
78.20687349174146
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77.07232087779671
76.70071041165295
76.33233716084996
75.96717197208089
75.60518610168623
75.24635120500754
74.89063932649127
74.53802289050765
74.18847469284574
time taken: 0.21161460876464844
12.598088290297563
Loss at iteration 0 12.598088290297563
164.26551540996982
159.2526420458399
155.7718491087778
153.57992446304064
152.1970965694884
151.17593742260766
150.2217162560347
149.29823930818233
148.39083585572277
147.49739002918864
146.61575701718422
145.74528850905222
144.885350436701
144.0355965771647
143.19571145344233
142.3654504241166
141.54458846007876
140.7329239943066
139.93026757257954
139.1364412160713
138.3512754359532
137.5746084312498
136.8062850007432
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131.64973396117287
```

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130.24380535039785
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126.85041995685899
126.1917032886582
125.5394013084372
124.89341551483818
124.25364916620279
123.62000721155181
122.99239623066529
122.37072438220908
121.75490135895355
121.14483834922758
120.54044800384371
119.94164440781678
119.34834305627852
118.7604608340639
118.17791599850965
117.60062816506222
117.02851829534258
116.46150868735496
115.89952296756064
115.34248608456576
114.79032430419096
114.24296520570634
113.70033767902645
113.16237192266644
112.62899944226511
112.10015304948446
111.57576686109724
111.05577629807688
110.54011808450831
110.0287302461431
109.52155210842916
109.01852429385517
108.51958871846051
108.02468858737616
107.53376838927649
107.0467738896401
106.56365212273613
106.08435138227223
105.6088212106602
105.1370123868756
104.66887691290715
104.20436799881054

```
103.7434400463986
103.28604863161644
102.83215048566369
102.3817034749391
101.93466657989272
101.49099987287966
101.05066449511526
100.61362263283687
100.17983749277869
99.7492732770683
99.32189515765236
98.89766925035636
98.47656258868139
98.05854309743545
97.64357956629296
97.23164162336944
96.82269970889344
96.41672504905038
96.01368963006713
95.61356617259922
95.21632810647604
time taken: 0.23977112770080566
11.546784674510658
Loss at iteration 0 11.546784674510658
66.01070369476062
64.61128308043831
63.94178930918882
63.38495362550321
62.85364865880673
62.33661339658394
61.83061602640976
61.334663234160196
60.84823537429717
60.370997698265086
59.90267080446651
59.44300286765948
58.9917572740384
58.54870903449753
58.11364287133266
57.68635218407776
57.266638265807316
56.85430967412306
56.44918169202625
56.051075861350746
55.65981957608604
55.275245727839724
54.897192396782074
54.52550258239563
```

54.16002396893964
53.80060872106672
53.44711330548453
53.09939833496911
52.7573284314174
52.42077210497503
52.089601646599526
51.76369303171761
51.44292583291295
51.12718313983669
50.81635148477035
50.51032077248873
50.20898421327042
49.91223825808667
49.619982535164795
49.33211978727205
49.048555809199826
48.769199385046804
48.49396222500427
48.22275890143831
47.95550678414146
47.69212597469382
47.43253923992886
47.17667194454594
46.924451982947716
46.675809710410384
46.43067787371584
46.1889915413908
45.95068803370778
45.71570685260819
45.483989611708964
45.25547996655264
45.030123545255485
44.807867879702016
44.58866233742512
44.372458054301795
44.15920786818329
43.94886625356765
43.74138925741087
43.536734436161446
43.334860794091846
43.135728722989214
42.939299943257076
42.74553744646961
42.55440543941107
42.365869289623404
42.17989547247778
41.99645151977776

```
41.81550596989563
41.63702831943721
41.46098897642516
41.287359214986616
41.11611113152627
40.94721760236357
40.7806522428093
40.61638936765454
40.454403953043844
40.29467159970223
40.137168497485646
39.98187139122316
39.82875754781949
39.677804724586295
39.52899113877096
39.382295438252406
39.237696673373755
39.09517426988293
38.954708002953225
38.81627797225667
38.679864578064745
38.545448498351604
38.41301066687682
38.282532252225394
38.1539946377844
38.0273794026367
37.902668303353266
time taken: 0.2046196460723877
{0: {'accuracy': 0.9750865051903114, 'precision': 0.5450400430715391, 'recall':
0.4829939020780297, 'f1_score': 0.492434481137619}, 1: {'accuracy':
0.9847750865051903, 'precision': 0.8444830002335592, 'recall':
0.7653162689903219, 'f1_score': 0.7416574615327075}, 2: {'accuracy':
0.9771626297577855, 'precision': 0.8131162450700394, 'recall':
0.7396497821914187, 'f1_score': 0.7299068646378135}, 3: {'accuracy':
0.9854671280276817, 'precision': 0.7999532128564386, 'recall':
0.7704828987945053, 'f1_score': 0.7846770461199254}, 4: {'accuracy':
0.9840830449826989, 'precision': 0.8569027181688126, 'recall':
0.7193151342800513, 'f1_score': 0.7337308686145896}}
```

2.0.1 6.1 Experiment

Since the performance on the test runs in model selection is good enough, I will experiment only gradient method and learning rate.

[166]:
```python
# generating all possible experiments
import itertools
method = ['batch','minibatch','sto']
lr = [0.01,0.001,0.0001]
```

```
experiments = pd.DataFrame(list(itertools.product(method,lr)),
                           columns=['GD_methods','Learning_Rates'])
experiments
```

[166]:

	GD_methods	Learning_Rates
0	batch	0.0100
1	batch	0.0010
2	batch	0.0001
3	minibatch	0.0100
4	minibatch	0.0010
5	minibatch	0.0001
6	sto	0.0100
7	sto	0.0010
8	sto	0.0001

[205]:

```
# running the experiments
model = MultinomialLogisticRegression(k=4,n=8,method='batch',penalty=0.
↪9,max_iter=100)
for i,(method,lr) in experiments.iterrows():
    model.method = method
    model.alpha = lr
    # print("Logistic Regression with L2 regularizqtion")
    exp_name = f"method-{method}-lr-{lr}"
    print(exp_name)
    mlflow.start_run(run_name=exp_name, nested=True)
    model.fit_CV(X_train.to_numpy(), Y_train)

    params = {"method": method, "lr": lr}
    mlflow.log_params(params=params)

    y_hat = model.predict(X_test.to_numpy())

    accuracy = model.accuracy(Y_true=y_test.to_numpy(),Y_pred=y_hat)
    p =  model.macro_metric(metric="precision",Y_true=y_test.
↪to_numpy(),Y_pred=y_hat,weighted=True)
    r =   model.macro_metric(metric="recall",Y_true=y_test.
↪to_numpy(),Y_pred=y_hat,weighted=True)
    f2  =  model.macro_metric(metric="f1",Y_true=y_test.
↪to_numpy(),Y_pred=y_hat,weighted=True)

    mlflow.log_metric(key="accuracy", value=accuracy, step=i)
    mlflow.log_metric(key="weighted_precision", value=p, step=i)
    mlflow.log_metric(key="weighted_recall", value=r, step=i)
    mlflow.log_metric(key="weighted_f1_score", value=f2, step=i)

    signature = mlflow.models.infer_signature(X_train.to_numpy(), model.
↪predict(X_train.to_numpy()))
```

```python
    mlflow.sklearn.log_model(model, artifact_path='model', signature=signature)

    mlflow.end_run()
```

```
method-batch-lr-0.01
10.107689350717147
Loss at iteration 0 10.107689350717147
13527.557807277653
12615.538320014006
11892.367675046635
11309.219686279655
10770.675248204214
10280.409573548966
9836.388955345254
9433.113809712937
9058.479053939735
8701.192779643698
8356.838863985507
8026.5748618695925
7709.22726854489
7405.075383231195
7112.522721760343
6833.511838522128
6568.549154830945
6325.679307745537
6080.62202302363
5853.041978581116
5626.885201390507
5416.4664683194915
5207.957844946908
5012.891546853536
4820.652287023875
4640.129352656445
4462.8046669100595
4295.515066837718
4132.0523891486055
3977.1002532378843
3826.3460275544644
3682.5824418908724
3543.7558222800003
3410.452088762822
3282.561102279912
3158.6871113931784
3041.1901677390947
2926.1253263394988
2818.0727390853635
2710.89340782634
```

2612.0039234447668
2512.1600623784393
2421.4336890408126
2328.2009899505088
2245.5775366780276
2158.4034503003786
2082.763830678931
2001.1874527550117
1932.678834516721
1856.0971642351626
1793.4717260222924
1721.7589777235398
1665.327296669034
1597.7262825542462
1546.311409392513
1482.9875477276914
1436.818327039927
1376.9375075159287
1335.2079315369106
1278.9457513032053
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2024/10/07 15:24:36 INFO mlflow.tracking._tracking_service.client:   View run
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2024/10/07 15:24:55 INFO mlflow.tracking._tracking_service.client:   View run
method-batch-lr-0.0001 at: http://mlflow.ml.brain.cs.ait.ac.th/#/experiments/881
703814181867940/runs/7e7d49a17332451babe0d8ac0fffcde5.
2024/10/07 15:24:55 INFO mlflow.tracking._tracking_service.client:   View
experiment at:
http://mlflow.ml.brain.cs.ait.ac.th/#/experiments/881703814181867940.
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Loss at iteration 0 7.62521199863307
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859.1592120130367
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732.1203430901793
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575.9433556948413
552.8911303635401
531.326917056322
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490.31054855701285
472.12285407857416
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387.0653326013766
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357.8752409145698
343.5436834018218
330.6410784871775
317.87199239957926
305.8284641997177
294.13765655627884
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273.6206555904218
263.01306134310016
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243.75359295659516
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Loss at iteration 0 12.165040900768101
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Loss at iteration 0 9.281407078958562
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2024/10/07 15:25:05 INFO mlflow.tracking._tracking_service.client:  View run
method-minibatch-lr-0.01 at: http://mlflow.ml.brain.cs.ait.ac.th/#/experiments/8
81703814181867940/runs/5ea8707fd5834b62affa925e76f58526.
2024/10/07 15:25:05 INFO mlflow.tracking._tracking_service.client:  View
experiment at:
http://mlflow.ml.brain.cs.ait.ac.th/#/experiments/881703814181867940.

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Loss at iteration 0 10.68154772231648
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Loss at iteration 0 9.02388728228292
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2024/10/07 15:25:23 INFO mlflow.tracking._tracking_service.client:  View run
method-minibatch-lr-0.0001 at: http://mlflow.ml.brain.cs.ait.ac.th/#/experiments
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2024/10/07 15:25:23 INFO mlflow.tracking._tracking_service.client:  View
experiment at:
http://mlflow.ml.brain.cs.ait.ac.th/#/experiments/881703814181867940.

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2024/10/07 15:25:32 INFO mlflow.tracking._tracking_service.client:   View
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```
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2024/10/07 15:25:51 INFO mlflow.tracking._tracking_service.client:  View
experiment at:
http://mlflow.ml.brain.cs.ait.ac.th/#/experiments/881703814181867940.
2024/10/07 15:25:51 INFO mlflow.tracking._tracking_service.client:  View
experiment at:
http://mlflow.ml.brain.cs.ait.ac.th/#/experiments/881703814181867940.
```

According the experiment results, the mini-batch gradient method with learning rate 0.001 is the best model.

3 7. Testing

Now, the best model will be searched and loaded to test on test set

[206]:
```
model_uri = f"models:/st125066-a3-model@dsai-ait"
model = mlflow.sklearn.load_model(model_uri)
```

```
Downloading artifacts: 100%|     | 5/5 [00:00<00:00,  9.75it/s]
```

[210]:
```
# do inference on the test set
yhat = model.predict(X_test.to_numpy())
```

[1004]:
```
# accuracy of the test set
model.accuracy(Y_true=y_test.to_numpy(),Y_pred=y_hat)
```

[1004]:
```
np.float64(1.5635440164345504)
```

[1005]:
```
# weighted precision of the test set
model.macro_metric(metric="precision",Y_true=y_test.
  ↪to_numpy(),Y_pred=y_hat,weighted=True)
```

[1005]:
```
np.float64(0.551287877583187)
```

[ ]:
```
# weighted
model.macro_metric(metric="recall",Y_true=y_test.
  ↪to_numpy(),Y_pred=y_hat,weighted=True)
```

[ ]:
```
# weighted f1 score
model.macro_metric(metric="f1",Y_true=y_test.
  ↪to_numpy(),Y_pred=y_hat,weighted=True)
```

4 8. Inference

[219]:
```
# predicted value
model.predict([X_test.iloc[0]])
```

[219]: array([0])

[215]:
```
# true value
y_test.iloc[0]
```

[215]: 0