By Naresh kumar

** importing libaries

In [1]:
```
import numpy as np
import pandas as pd
```

uploading dataset

In [2]:
```
df=pd.read_csv(r'C:\Users\hp\Downloads\CAR DETAILS (1).csv')
```

Reading dataset

In [4]:
```
df
```

Out[4]:

	name	year	selling_price	km_driven	fuel	seller_type	transmission	owner
0	Maruti 800 AC	2007	60000	70000	Petrol	Individual	Manual	First Owner
1	Maruti Wagon R LXI Minor	2007	135000	50000	Petrol	Individual	Manual	First Owner
2	Hyundai Verna 1.6 SX	2012	600000	100000	Diesel	Individual	Manual	First Owner
3	Datsun RediGO T Option	2017	250000	46000	Petrol	Individual	Manual	First Owner
4	Honda Amaze VX i-DTEC	2014	450000	141000	Diesel	Individual	Manual	Second Owner
...	...	...	...	...	...	...	...	...
4335	Hyundai i20 Magna 1.4 CRDi (Diesel)	2014	409999	80000	Diesel	Individual	Manual	Second Owner
4336	Hyundai i20 Magna 1.4 CRDi	2014	409999	80000	Diesel	Individual	Manual	Second Owner
4337	Maruti 800 AC BSIII	2009	110000	83000	Petrol	Individual	Manual	Second Owner
4338	Hyundai Creta 1.6 CRDi SX Option	2016	865000	90000	Diesel	Individual	Manual	First Owner
4339	Renault KWID RXT	2016	225000	40000	Petrol	Individual	Manual	First Owner

4340 rows × 8 columns

In [5]:
```
df.head()
```

Out[5]:

	name	year	selling_price	km_driven	fuel	seller_type	transmission	owner
0	Maruti 800 AC	2007	60000	70000	Petrol	Individual	Manual	First Owner
1	Maruti Wagon R LXI Minor	2007	135000	50000	Petrol	Individual	Manual	First Owner
2	Hyundai Verna 1.6 SX	2012	600000	100000	Diesel	Individual	Manual	First Owner
3	Datsun RediGO T Option	2017	250000	46000	Petrol	Individual	Manual	First Owner
4	Honda Amaze VX i-DTEC	2014	450000	141000	Diesel	Individual	Manual	Second Owner

In [6]:
```
df.sample(5)
```

Out[6]:

	name	year	selling_price	km_driven	fuel	seller_type	transmission	owner
976	Mahindra Thar CRDe	2018	950000	20000	Diesel	Individual	Manual	First Owner
4022	Maruti Wagon R LXI Minor	2008	200000	90000	Petrol	Individual	Manual	Second Owner
2287	Hyundai Santro Xing XG	2005	70000	68500	Petrol	Dealer	Manual	First Owner
452	Maruti Alto 800 LXI	2018	310000	5000	Petrol	Individual	Manual	First Owner
2191	Tata Tiago 1.2 Revotron XZ	2018	539000	10000	Petrol	Individual	Manual	First Owner

In [7]:
```
df.shape
```

Out[7]:
```
(4340, 8)
```

Data preprocessing

rows = 4340
columns = 8

df.info()

In the data set

we clearly see year column is int data type form but we known year is the date data type

In [8]:
```
df.isnull().sum()
```

Out[8]:
```
name             0
year             0
selling_price    0
km_driven        0
fuel             0
seller_type      0
transmission     0
owner            0
dtype: int64
```

** their is no null values

In [3]:
```
df.duplicated().sum()
```

Out[3]:
```
763
```

** we have 763 duplicate values

In [4]:
```
df.drop_duplicates(inplace=True)
```

In [5]:
```
df.shape
```

Out[5]:
```
(3577, 8)
```

In [6]:
```
df.duplicated().sum()
```

Out[6]:
```
0
```

In [7]:
```
df["name"].nunique()
```

Out[7]:
```
1491
```

** we have 1491 unique values

In [8]:
```
car_names=list(df['name'])
#print(car_names)
print(len(car_names))
```

```
3577
```

In [9]:
```
brand,model,sub_class=[],[],[]
for car in car_names:
    parts=car.split()
    x=parts[0]
    y=parts[1]
    z=parts[2:]
    brand.append(x)
    model.append(y)
    sub_class.append(z)

print(len(brand))
print(len(model))
print(len(sub_class))
```

```
3577
3577
3577
```

In [10]:
```
sub_class=[' '.join(map(str, item)) for item in sub_class]
df['brand']=brand
df['model']=model
df['sub_class']=sub_class
df.head()
```

Out[10]:

	name	year	selling_price	km_driven	fuel	seller_type	transmission	owner	brand
0	Maruti 800 AC	2007	60000	70000	Petrol	Individual	Manual	First Owner	Maruti
1	Maruti Wagon R LXI Minor	2007	135000	50000	Petrol	Individual	Manual	First Owner	Maruti
2	Hyundai Verna 1.6 SX	2012	600000	100000	Diesel	Individual	Manual	First Owner	Hyundai
3	Datsun RediGO T Option	2017	250000	46000	Petrol	Individual	Manual	First Owner	Datsun
4	Honda Amaze VX i-DTEC	2014	450000	141000	Diesel	Individual	Manual	Second Owner	Honda

In [11]:
```
df.drop('name',axis=1,inplace=True)
df.head()
```

Out[11]:

	year	selling_price	km_driven	fuel	seller_type	transmission	owner	brand	model
0	2007	60000	70000	Petrol	Individual	Manual	First Owner	Maruti	800
1	2007	135000	50000	Petrol	Individual	Manual	First Owner	Maruti	Wagon
2	2012	600000	100000	Diesel	Individual	Manual	First Owner	Hyundai	Verna
3	2017	250000	46000	Petrol	Individual	Manual	First Owner	Datsun	RediGO
4	2014	450000	141000	Diesel	Individual	Manual	Second Owner	Honda	Amaze

In [12]:
```
# Get the count of unique values in the 'brand' column
brand_counts = df['brand'].value_counts()
```

In [13]:
```
brand_counts
```

Out[13]:
```
Maruti            1072
Hyundai            637
Mahindra           328
Tata               308
Ford               220
Honda              216
Toyota             170
Chevrolet          151
Renault            110
Volkswagen          93
Nissan              52
Skoda               49
Fiat                32
Audi                31
Datsun              29
BMW                 25
Mercedes-Benz       21
Jaguar               5
Mitsubishi           5
Land                 5
Volvo                4
Jeep                 3
Ambassador           3
MG                   2
OpelCorsa            2
Daewoo               1
Force                1
Isuzu                1
Kia                  1
Name: brand, dtype: int64
```

In [14]:
```
# correlation
df.corr()
```

Out[14]:

	year	selling_price	km_driven
year	1.00000	0.424260	-0.417490
selling_price	0.42426	1.000000	-0.187359
km_driven	-0.41749	-0.187359	1.000000

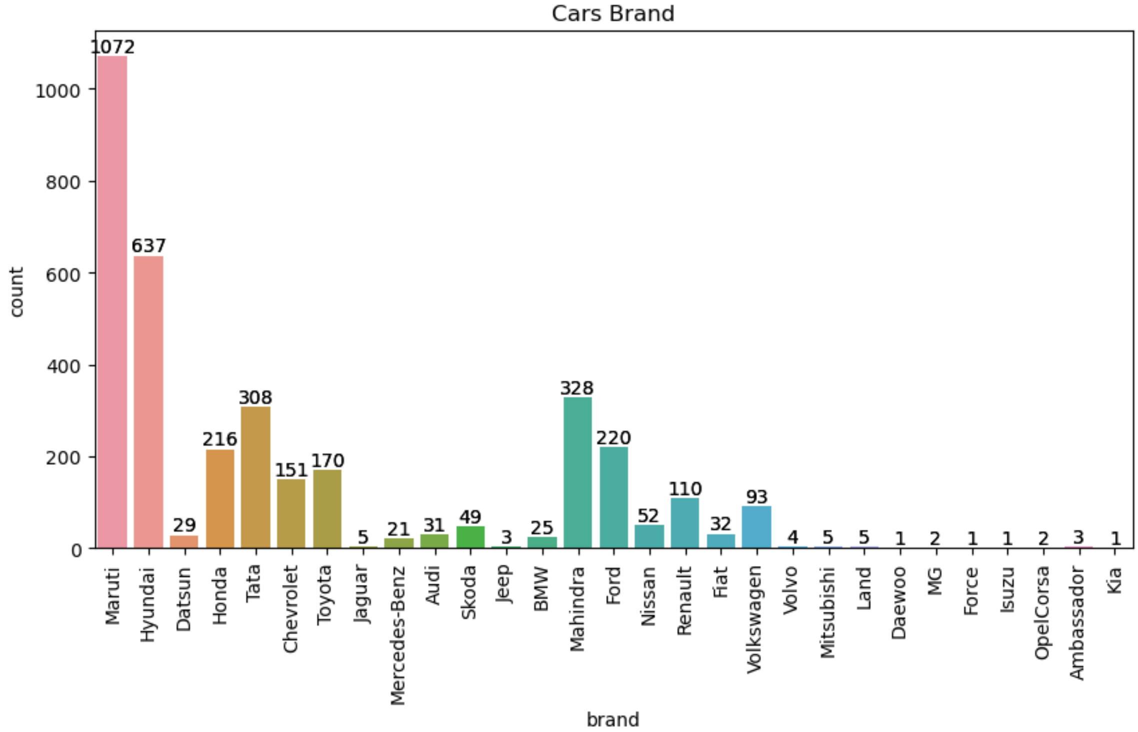
EDA

In [15]:
```
## importing data visulization libaries
```

In [16]:
```
import matplotlib.pyplot as plt
import seaborn as sns
```

ploting the count of the brand

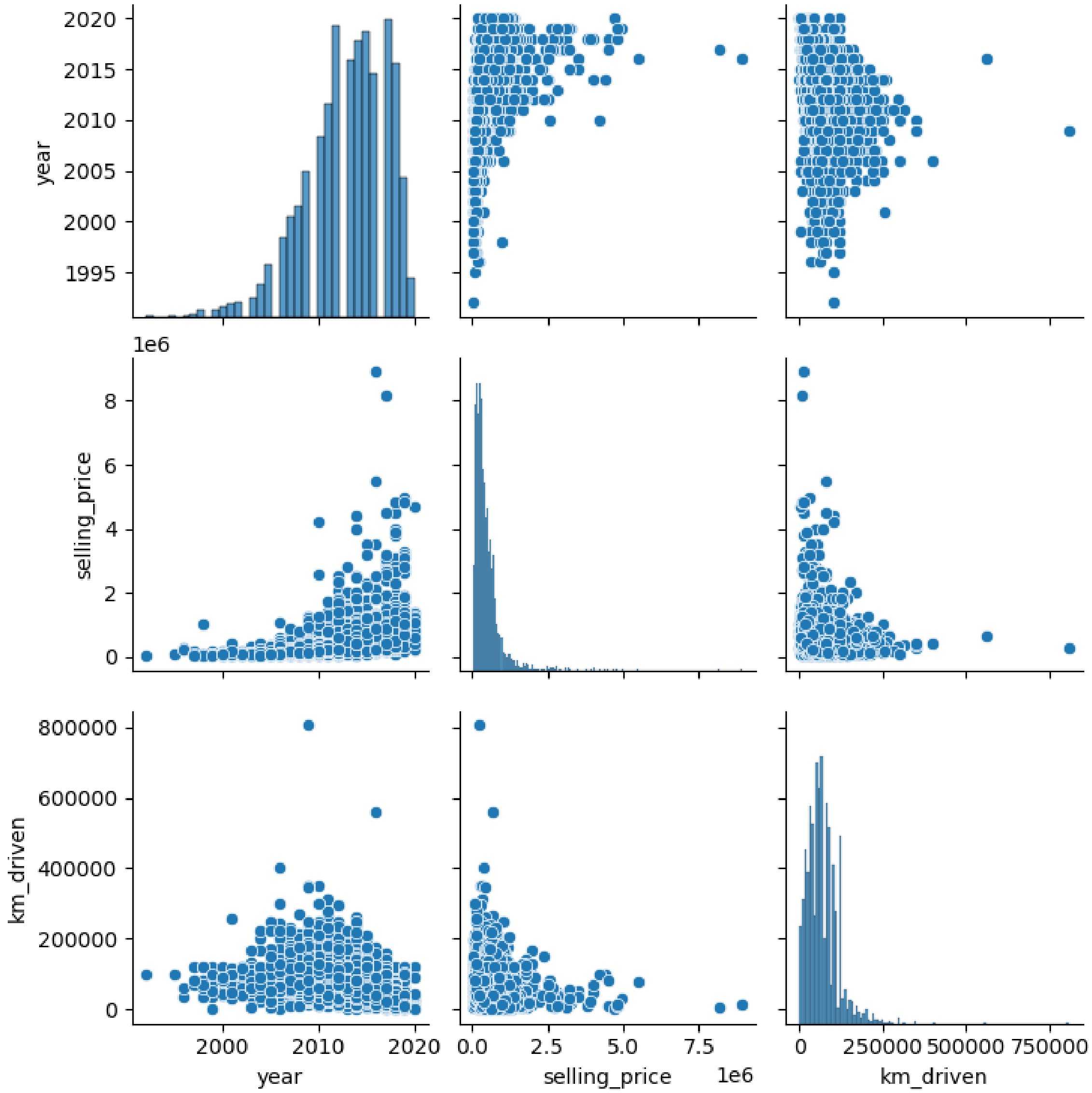
In [23]:
```
plt.figure(figsize=(10,5))
sns.countplot(x=df.brand)
plt.title("Cars Brand")
plt.xticks(rotation=90)
ax=sns.countplot(x='brand',data=df)
for bars in ax.containers:
    ax.bar_label(bars)
```



all numerical columns pair plot

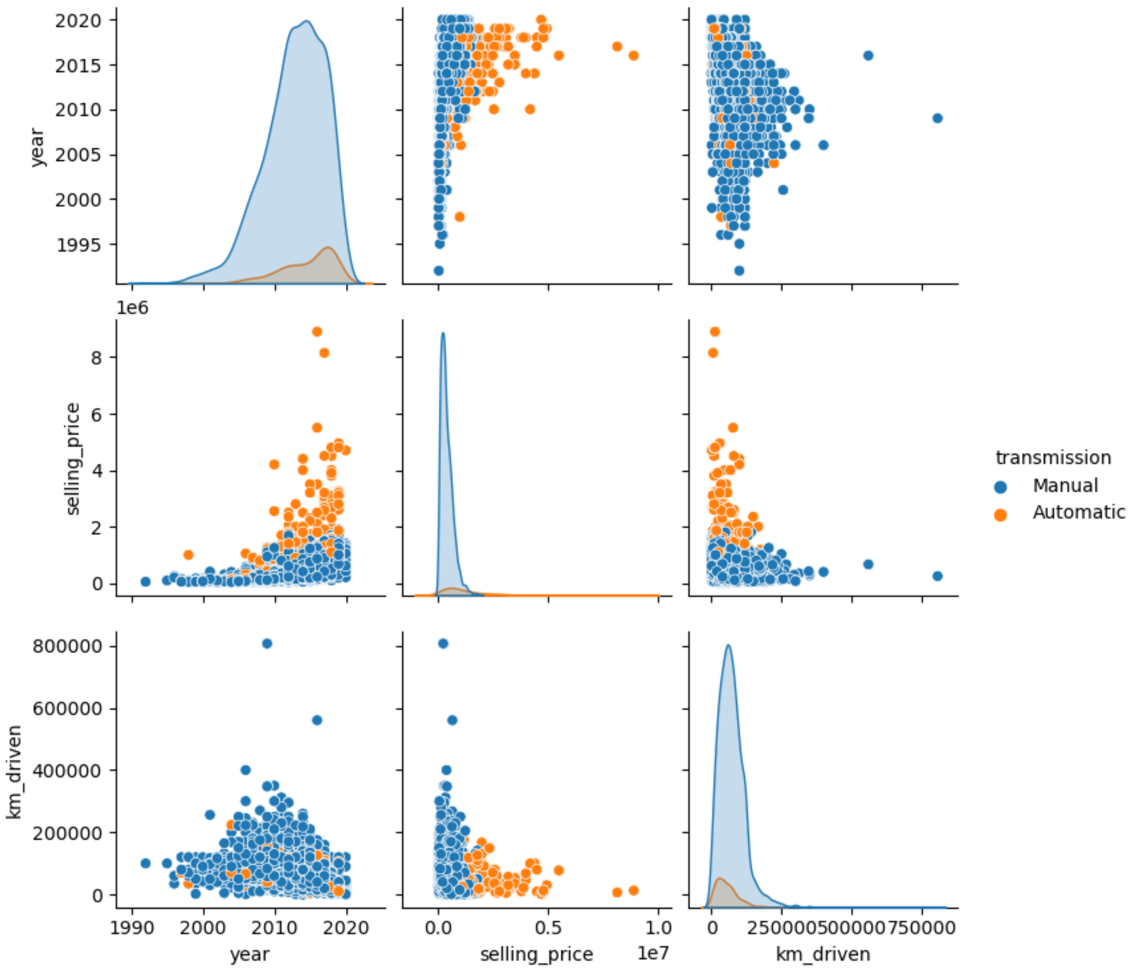
In [23]:
```
sns.pairplot(df)
```

Out[23]: <seaborn.axisgrid.PairGrid at 0x2000262cf10>



In [24]:
```
sns.pairplot(df,hue='transmission')
```

Out[24]: <seaborn.axisgrid.PairGrid at 0x20004767e80>

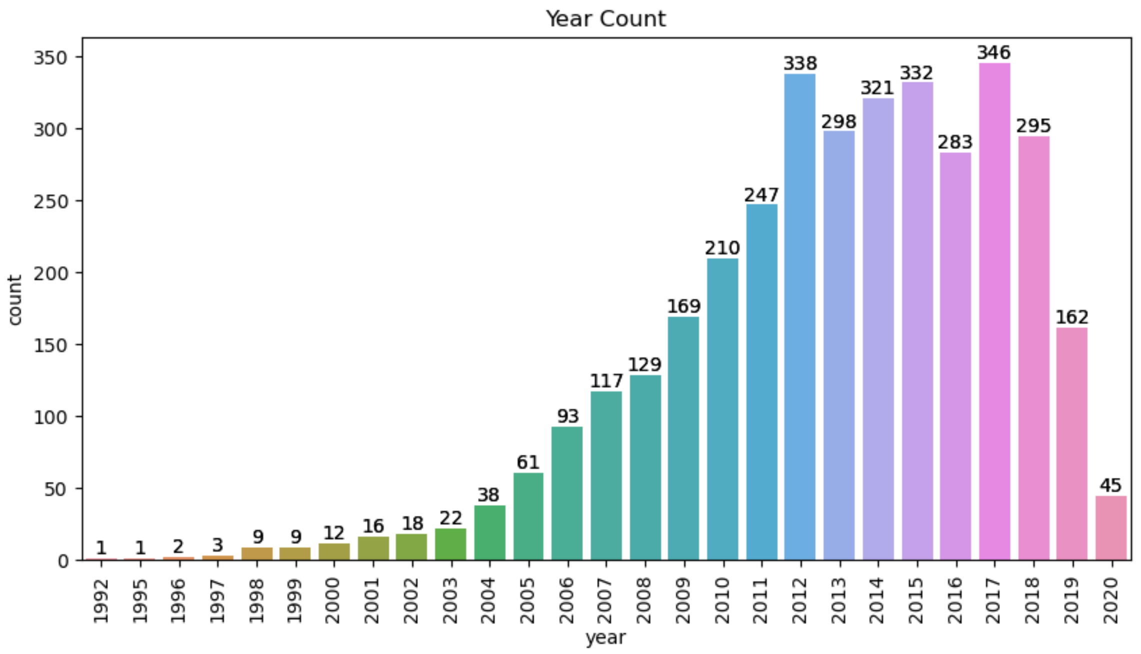


In [25]:
```
df.year.value_counts()
```

Out[25]:
```
2017    346
2012    338
2015    332
2014    321
2013    298
2018    295
2016    283
2011    247
2010    210
2009    169
2019    162
2008    129
2007    117
2006     93
2005     61
2020     45
2004     38
2003     22
2002     18
2001     16
2000     12
1998      9
1999      9
1997      3
1996      2
1995      1
1992      1
Name: year, dtype: int64
```

ploting count of the years

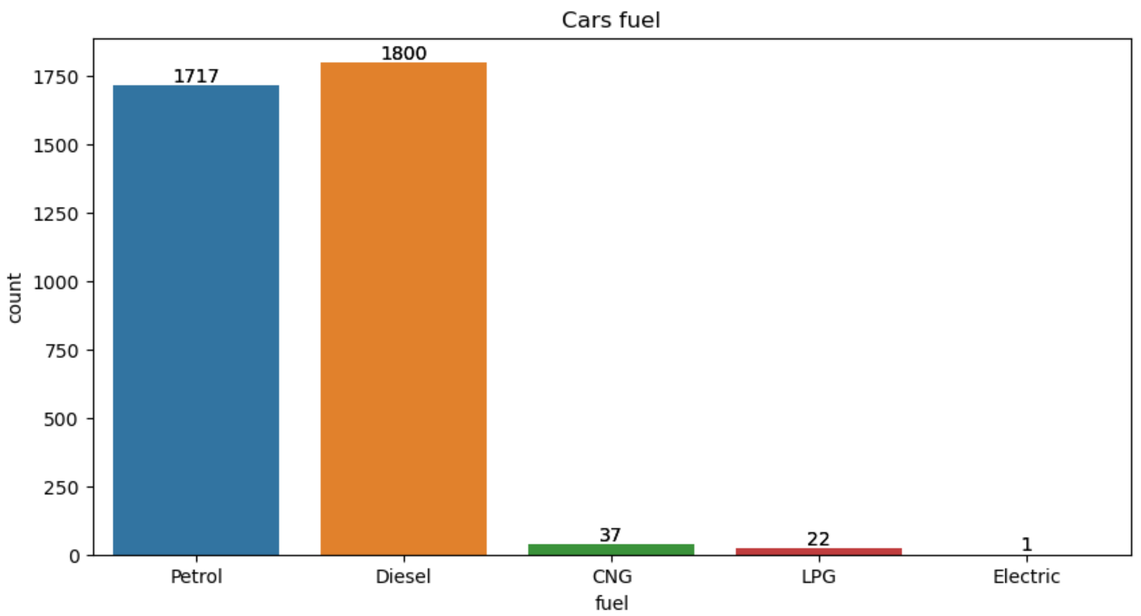
In [26]:
```
plt.figure(figsize=(10,5))
sns.countplot(x=df.year)
plt.title("Year Count")
plt.xlabel("year")
plt.xticks(rotation=90)
ax=sns.countplot(x='year',data=df)
for bars in ax.containers:
    ax.bar_label(bars)
```



ploting count of fuel types

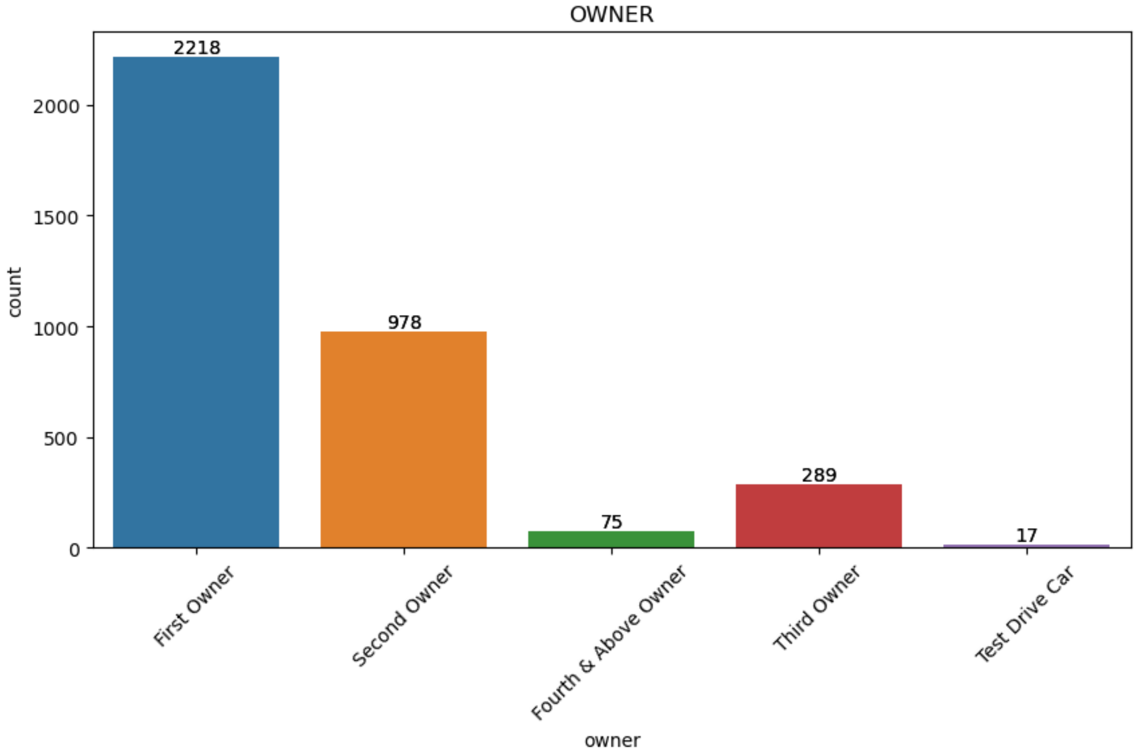
In [27]:
```
plt.figure(figsize=(10,5))
sns.countplot(x=df.fuel)
plt.title("Cars fuel")

ax=sns.countplot(x='fuel',data=df)
for bars in ax.containers:
    ax.bar_label(bars)
```



ploting count of owner types

In [28]:
```
plt.figure(figsize=(10,5))
sns.countplot(x=df.owner)
plt.title("OWNER")
plt.xticks(rotation=45)
ax=sns.countplot(x='owner',data=df)
for bars in ax.containers:
    ax.bar_label(bars)
```



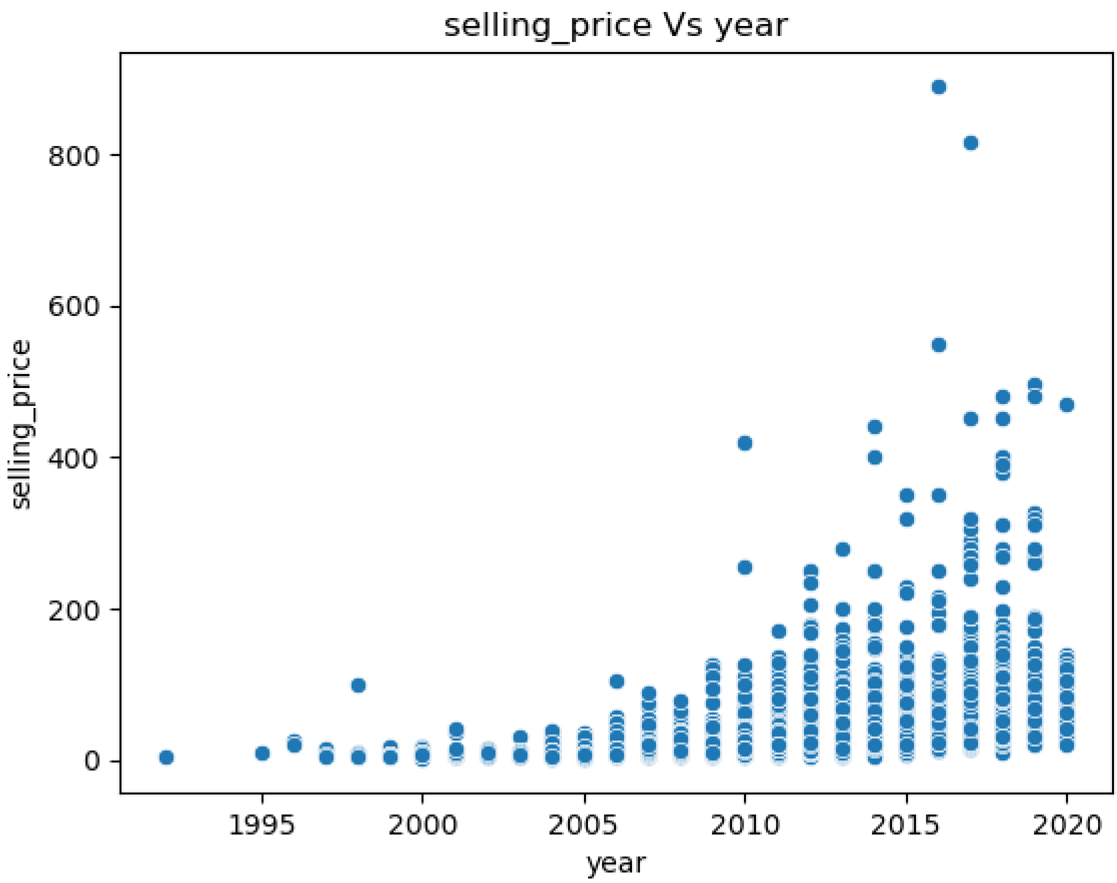
how does the year effect the price of sell?

In [17]:
```
# selling price convert into multiplus of 10 thousands form
selling_price=df.selling_price/10000
```

In [18]:
```
selling_price
```

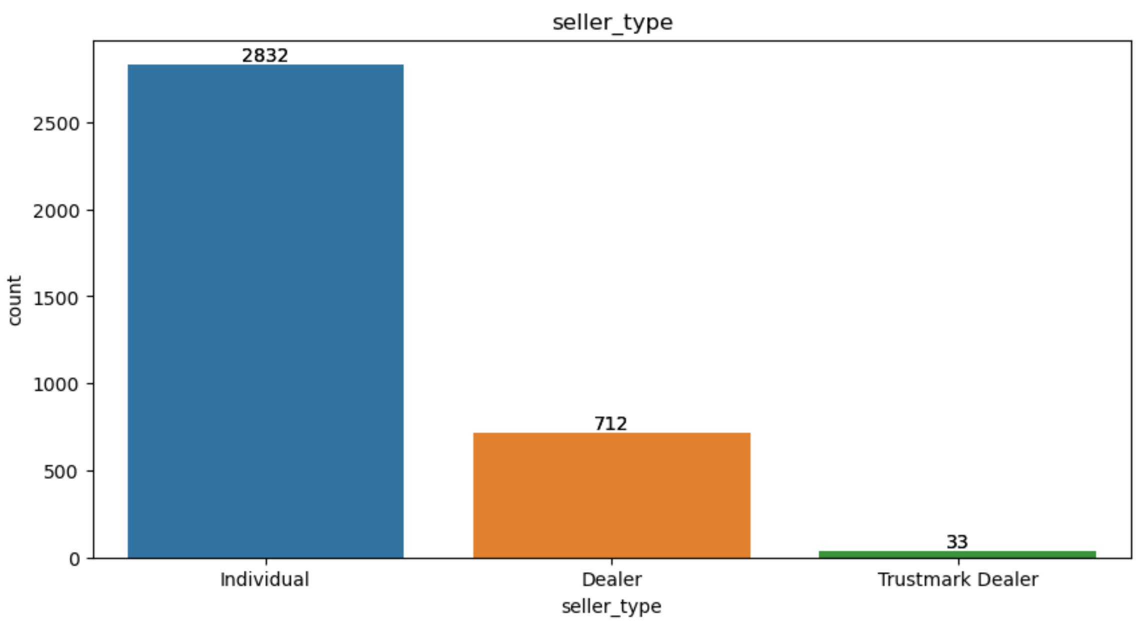
Out[18]:
```
0        6.0000
1       13.5000
2       60.0000
3       25.0000
4       45.0000
          ...
4335    40.9999
4336    40.9999
4337    11.0000
4338    86.5000
4339    22.5000
Name: selling_price, Length: 3577, dtype: float64
```

In [27]:
```
sns.scatterplot(y=selling_price,x=df.year)
plt.title("selling_price Vs year")
plt.show()
```



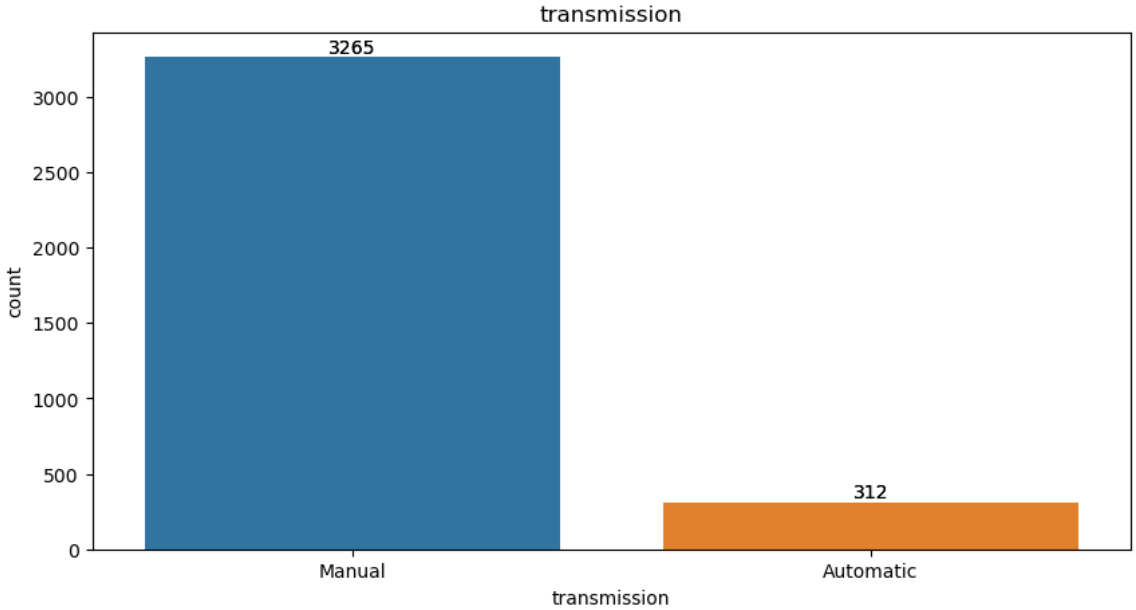
ploting count of selling types

In [28]:
```
plt.figure(figsize=(10,5))
sns.countplot(x=df.seller_type)
plt.title("seller_type")
ax=sns.countplot(x='seller_type',data=df)
for bars in ax.containers:
    ax.bar_label(bars)
```



ploting count of transmission

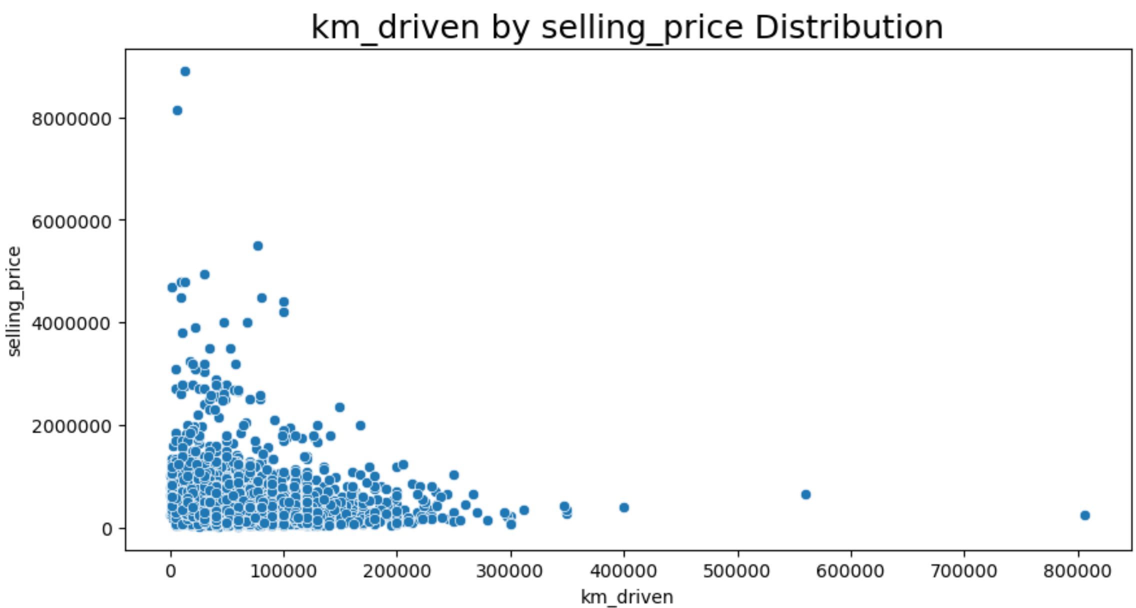
In [29]:
```
plt.figure(figsize=(10,5))
sns.countplot(x=df.transmission)
plt.title("transmission")
ax=sns.countplot(x='transmission',data=df)
for bars in ax.containers:
    ax.bar_label(bars)
```



Correlation Between selling_price and km_driven

In [30]:
```
plt.figure(figsize=(10,5))
plt.title('km_driven by selling_price Distribution', fontsize=18)
sns.scatterplot(data=df, x='km_driven', y='selling_price')

plt.ticklabel_format(style='plain', axis='y')
```



ploting corelation

In [31]:
```
sns.heatmap(df.corr(),annot=True)
```

Out[31]: <AxesSubplot:>

Data prepration Model

In [19]:
```
df2=df.copy
```

In [20]:
```
df.columns
```

Out[20]:
```
Index(['year', 'selling_price', 'km_driven', 'fuel', 'seller_type',
       'transmission', 'owner', 'brand', 'model', 'sub_class'],
      dtype='object')
```

In [21]:
```
df.head()
```

Out[21]:

	year	selling_price	km_driven	fuel	seller_type	transmission	owner	brand	model
0	2007	60000	70000	Petrol	Individual	Manual	First Owner	Maruti	800
1	2007	135000	50000	Petrol	Individual	Manual	First Owner	Maruti	Wagon
2	2012	600000	100000	Diesel	Individual	Manual	First Owner	Hyundai	Verna
3	2017	250000	46000	Petrol	Individual	Manual	First Owner	Datsun	RediGO
4	2014	450000	141000	Diesel	Individual	Manual	Second Owner	Honda	Amaze

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

Out[22]:

	year	selling_price	km_driven	fuel	seller_type	transmission	owner	brand	model
0	2007	60000	70000	Petrol	Individual	Manual	First Owner	Maruti	800
1	2007	135000	50000	Petrol	Individual	Manual	First Owner	Maruti	Wagon
2	2012	600000	100000	Diesel	Individual	Manual	First Owner	Hyundai	Verna
3	2017	250000	46000	Petrol	Individual	Manual	First Owner	Datsun	RediGO
4	2014	450000	141000	Diesel	Individual	Manual	Second Owner	Honda	Amaze

In [23]:
```
df.drop(['model'],axis=1,inplace=True)
df.head()
```

Out[23]:

	year	selling_price	km_driven	fuel	seller_type	transmission	owner	brand
0	2007	60000	70000	Petrol	Individual	Manual	First Owner	Maruti
1	2007	135000	50000	Petrol	Individual	Manual	First Owner	Maruti
2	2012	600000	100000	Diesel	Individual	Manual	First Owner	Hyundai
3	2017	250000	46000	Petrol	Individual	Manual	First Owner	Datsun
4	2014	450000	141000	Diesel	Individual	Manual	Second Owner	Honda

In [24]:
```
df.columns
```

Out[24]:
```
Index(['year', 'selling_price', 'km_driven', 'fuel', 'seller_type',
       'transmission', 'owner', 'brand'],
      dtype='object')
```

In [25]:
```
df.shape
```
Out[25]:
```
(3577, 8)
```

Applying one hot encoding

In [26]:
```
dummy_df=pd.get_dummies(df)
```
In [27]:
```
dummy_df
```
Out[27]:

	year	selling_price	km_driven	fuel_CNG	fuel_Diesel	fuel_Electric	fuel_LPG	fuel_Petr
0	2007	60000	70000	0	0	0	0	
1	2007	135000	50000	0	0	0	0	
2	2012	600000	100000	0	1	0	0	
3	2017	250000	46000	0	0	0	0	
4	2014	450000	141000	0	1	0	0	
...	...	...	...	...	...	...	...	
4335	2014	409999	80000	0	1	0	0	
4336	2014	409999	80000	0	1	0	0	
4337	2009	110000	83000	0	0	0	0	
4338	2016	865000	90000	0	1	0	0	
4339	2016	225000	40000	0	0	0	0	

3577 rows × 47 columns

In [28]:
```
dummy_df.shape
```
Out[28]:
```
(3577, 47)
```

In [29]:
```
pd.get_dummies(df,drop_first=True)
```

Out[29]:

	year	selling_price	km_driven	fuel_Diesel	fuel_Electric	fuel_LPG	fuel_Petrol	seller_t
0	2007	60000	70000	0	0	0	1	
1	2007	135000	50000	0	0	0	1	
2	2012	600000	100000	1	0	0	0	
3	2017	250000	46000	0	0	0	1	
4	2014	450000	141000	1	0	0	0	
...	...	...	...	...	...	...	...	
4335	2014	409999	80000	1	0	0	0	
4336	2014	409999	80000	1	0	0	0	
4337	2009	110000	83000	0	0	0	1	
4338	2016	865000	90000	1	0	0	0	
4339	2016	225000	40000	0	0	0	1	

3577 rows × 42 columns

Spliting data into training and test set

In [30]:
```
x=dummy_df.drop('selling_price',axis=1)
```

In [31]:
```
x
```

Out[31]:

	year	km_driven	fuel_CNG	fuel_Diesel	fuel_Electric	fuel_LPG	fuel_Petrol	seller_type
0	2007	70000	0	0	0	0	1	
1	2007	50000	0	0	0	0	1	
2	2012	100000	0	1	0	0	0	
3	2017	46000	0	0	0	0	1	
4	2014	141000	0	1	0	0	0	
...	...	...	...	...	...	...	...	
4335	2014	80000	0	1	0	0	0	
4336	2014	80000	0	1	0	0	0	
4337	2009	83000	0	0	0	0	1	
4338	2016	90000	0	1	0	0	0	
4339	2016	40000	0	0	0	0	1	

3577 rows × 46 columns

In [32]:
```
y=dummy_df['selling_price']
```

In [33]:
```
y
```

Out[33]:
```
0        60000
1       135000
2       600000
3       250000
4       450000
         ...
4335    409999
4336    409999
4337    110000
4338    865000
4339    225000
Name: selling_price, Length: 3577, dtype: int64
```

In [34]:
```
from sklearn.model_selection import train_test_split

# Assuming x and y are your feature and target variable, respectively
# Your data preprocessing and feature engineering steps would go here

# Check the lengths of x and y
print(len(x))
print(len(y))

# Split the data into training and testing sets
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.2, rar
```

```
3577
3577
```

In [35]:
```
x_train, x_test, y_train, y_test
```

Out[35]:
```
(      year  km_driven  fuel_CNG  fuel_Diesel  fuel_Electric  fuel_LPG  
\
 3078  2011     120000         0            1              0         0
 2702  2012      26000         0            1              0         0
 2381  2015      55000         0            1              0         0
 693   2016      80000         0            1              0         0
 3529  2015     146000         0            1              0         0
 ...    ...        ...       ...          ...            ...       ...
 1941  2004     100000         0            0              0         0
 1968  2011      50000         0            0              0         0
 500   2016     155201         0            1              0         0
 2467  2012      60236         0            1              0         0
 3658  2013      75000         0            1              0         0

       fuel_Petrol  seller_type_Dealer  seller_type_Individual  \
 3078            0                   0                       1
 2702            0                   0                       1
 2381            0                   1                       0
 693             0                   0                       1
```

In [36]:
```
print("X_train:", x_train.shape)
print("X_test:", x_test.shape)
print("y_train:", y_train.shape)
print("y_test:", y_test.shape)
```

```
X_train: (2861, 46)
X_test: (716, 46)
y_train: (2861,)
y_test: (716,)
```

Features Scaling

In [53]:
```
from sklearn.preprocessing import StandardScaler
```

In [54]:
```
scaler=StandardScaler()
```

In [55]:
```
scaler.fit(x_train)
```

Out[55]:
```
StandardScaler()
```

In [56]:
```
x_train_scaled=scaler.transform(x_train)
x_test_scaled=scaler.transform(x_test)
```

In [57]:
```
# Create DataFrames with columns
x_train_df = pd.DataFrame(x_train_scaled, columns=x_train.columns)
x_test_df = pd.DataFrame(x_test_scaled, columns=x_test.columns)

# Check the first few rows of the DataFrames
print(x_train_df.head())
print(x_test_df.head())
```

```
       year  km_driven  fuel_CNG  fuel_Diesel  fuel_Electric  fuel_LPG  \
0 -0.471714   1.090132 -0.104662     0.995466            0.0  -0.07957   
1 -0.234572  -0.917559 -0.104662     0.995466            0.0  -0.07957   
2  0.476853  -0.298165 -0.104662     0.995466            0.0  -0.07957   
3  0.713995   0.235796 -0.104662     0.995466            0.0  -0.07957   
4  0.476853   1.645451 -0.104662     0.995466            0.0  -0.07957   

   fuel_Petrol  seller_type_Dealer  seller_type_Individual  \
0    -0.961927           -0.500437                 0.51514   
1    -0.961927           -0.500437                 0.51514   
2    -0.961927            1.998254                -1.94122   
3    -0.961927           -0.500437                 0.51514   
4    -0.961927            1.998254                -1.94122   

   seller_type_Trustmark Dealer  ...  brand_Mercedes-Benz  brand_Mitsubish
i  \
0                     -0.097607  ...            -0.081764         -0.04184
1   
1                     -0.097607  ...            -0.081764         -0.04184
1   
2                     -0.097607  ...            -0.081764         -0.04184
1   
3                     -0.097607  ...            -0.081764         -0.04184
1   
4                     -0.097607  ...            -0.081764         -0.04184
1   

   brand_Nissan  brand_OpelCorsa  brand_Renault  brand_Skoda  brand_Tata
\
0     -0.126412        -0.026449      -0.182277    -0.120578   -0.312138   
1     -0.126412        -0.026449      -0.182277    -0.120578   -0.312138   
2     -0.126412        -0.026449      -0.182277    -0.120578   -0.312138   
3     -0.126412        -0.026449      -0.182277    -0.120578   -0.312138   
4     -0.126412        -0.026449      -0.182277    -0.120578   -0.312138   

   brand_Toyota  brand_Volkswagen  brand_Volvo  
0     -0.221671         -0.166307    -0.037418  
1     -0.221671         -0.166307    -0.037418  
2     -0.221671         -0.166307    -0.037418  
3      4.511180         -0.166307    -0.037418  
4     -0.221671         -0.166307    -0.037418  

[5 rows x 46 columns]
       year  km_driven  fuel_CNG  fuel_Diesel  fuel_Electric  fuel_LPG  \
0  0.476853   0.125159 -0.104662     0.995466            0.0  -0.07957   
1  0.002570  -0.768050 -0.104662     0.995466            0.0  -0.07957   
2  0.002570   2.905598 -0.104662    -1.004554            0.0  -0.07957   
3  0.239711   0.235796 -0.104662     0.995466            0.0  -0.07957   
4 -1.183140  -0.404957 -0.104662    -1.004554            0.0  -0.07957   

   fuel_Petrol  seller_type_Dealer  seller_type_Individual  \
0    -0.961927           -0.500437                 0.51514   
1    -0.961927           -0.500437                 0.51514   
2     1.039580           -0.500437                 0.51514   
3    -0.961927            1.998254                -1.94122   
4     1.039580           -0.500437                 0.51514   

   seller_type_Trustmark Dealer  ...  brand_Mercedes-Benz  brand_Mitsubish
i  \
0                     -0.097607  ...            -0.081764         -0.04184
1   
```

```
1                    -0.097607  ...           -0.081764          -0.04184
1
2                    -0.097607  ...           -0.081764          -0.04184
1
3                    -0.097607  ...           -0.081764          -0.04184
1
4                    -0.097607  ...           -0.081764          -0.04184
1

   brand_Nissan  brand_OpelCorsa  brand_Renault  brand_Skoda  brand_Tata
\
0     -0.126412        -0.026449      -0.182277    -0.120578   -0.312138
1     -0.126412        -0.026449      -0.182277    -0.120578   -0.312138
2     -0.126412        -0.026449      -0.182277    -0.120578   -0.312138
3     -0.126412        -0.026449      -0.182277    -0.120578   -0.312138
4     -0.126412        -0.026449      -0.182277    -0.120578   -0.312138

   brand_Toyota  brand_Volkswagen  brand_Volvo
0     -0.221671         -0.166307    -0.037418
1     -0.221671         -0.166307    -0.037418
2     -0.221671         -0.166307    -0.037418
3     -0.221671         -0.166307    -0.037418
4     -0.221671         -0.166307    -0.037418

[5 rows x 46 columns]
```

In [58]:
```
x_train_df.describe().round(2)
```

Out[58]:

	year	km_driven	fuel_CNG	fuel_Diesel	fuel_Electric	fuel_LPG	fuel_Petrol	seller_t
count	2861.00	2861.00	2861.00	2861.0	2861.0	2861.00	2861.00	
mean	-0.00	0.00	-0.00	0.0	0.0	0.00	0.00	
std	1.00	1.00	1.00	1.0	0.0	1.00	1.00	
min	-4.98	-1.47	-0.10	-1.0	0.0	-0.08	-0.96	
25%	-0.71	-0.70	-0.10	-1.0	0.0	-0.08	-0.96	
50%	0.00	-0.17	-0.10	1.0	0.0	-0.08	-0.96	
75%	0.71	0.45	-0.10	1.0	0.0	-0.08	1.04	
max	1.66	15.75	9.55	1.0	0.0	12.57	1.04	

8 rows × 46 columns

Model Evaluation

In [89]:
```
from sklearn.metrics import *
```

In [90]:
```
def model_eval(x_train,x_test,y_train,y_test,model,mname):
    model.fit(x_train,y_train)
    ypred=model.predict(x_test)
    mae=mean_absolute_error(y_test,ypred)
    mse=mean_squared_error(y_test,ypred)
    rmse=np.sqrt(mse)
    train_scr=model.score(x_train,y_train)
    test_scr=model.score(x_test,y_test)
    res=pd.DataFrame({"Train_scr":train_scr,"Test_scr":test_scr,'RMSE':rmse,
                "MAE":mae},index=[mname])
    return res

def mscore(model):
    train_scr=model.score(x_train,y_train)
    test_scr=model.score(x_test,y_test)
    print("Training Score",train_scr)
    print("Testing Score",test_scr)
```

In [91]:
```
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
```

In [92]:
```
x.head()
```

Out[92]:

	year	km_driven	fuel_CNG	fuel_Diesel	fuel_Electric	fuel_LPG	fuel_Petrol	seller_type_De
0	2007	70000	0	0	0	0	1	
1	2007	50000	0	0	0	0	1	
2	2012	100000	0	1	0	0	0	
3	2017	46000	0	0	0	0	1	
4	2014	141000	0	1	0	0	0	

5 rows × 46 columns

In [93]:
```
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.25,random_sta
print(x_train.shape)
print(x_test.shape)
print(y_train.shape)
print(y_test.shape)
```

```
(2682, 46)
(895, 46)
(2682,)
(895,)
```

In [94]:
```
print(x.columns)
```

```
Index(['year', 'km_driven', 'fuel_CNG', 'fuel_Diesel', 'fuel_Electric',
       'fuel_LPG', 'fuel_Petrol', 'seller_type_Dealer',
       'seller_type_Individual', 'seller_type_Trustmark Dealer',
       'transmission_Automatic', 'transmission_Manual', 'owner_First Owne
r',
       'owner_Fourth & Above Owner', 'owner_Second Owner',
       'owner_Test Drive Car', 'owner_Third Owner', 'brand_Ambassador',
       'brand_Audi', 'brand_BMW', 'brand_Chevrolet', 'brand_Daewoo',
       'brand_Datsun', 'brand_Fiat', 'brand_Force', 'brand_Ford',
       'brand_Honda', 'brand_Hyundai', 'brand_Isuzu', 'brand_Jaguar',
       'brand_Jeep', 'brand_Kia', 'brand_Land', 'brand_MG', 'brand_Mahindr
a',
       'brand_Maruti', 'brand_Mercedes-Benz', 'brand_Mitsubishi',
       'brand_Nissan', 'brand_OpelCorsa', 'brand_Renault', 'brand_Skoda',
       'brand_Tata', 'brand_Toyota', 'brand_Volkswagen', 'brand_Volvo'],
      dtype='object')
```

In [95]:
```
from sklearn.linear_model import LinearRegression,Lasso,Ridge
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor,BaggingRegressor,AdaBoost
from sklearn.neighbors import KNeighborsRegressor
```

linear Regression

In [96]:
```
lg=LinearRegression()
lg_res=model_eval(x_train,x_test,y_train,y_test,lg,"Linear")
lg_res
```

Out[96]:

	Train_scr	Test_scr	RMSE	MSE	MAE
Linear	0.640987	0.625082	277079.445306	7.677302e+10	173418.33341

Ridge Regression

In [97]:
```
rd=Ridge(0.75)
rd_res=model_eval(x_train,x_test,y_train,y_test,rd,"Ridge")
rd_res
```

Out[97]:

	Train_scr	Test_scr	RMSE	MSE	MAE
Ridge	0.639284	0.627576	276156.305652	7.626231e+10	173932.885676

Lasso

In [98]:
```
ls=Lasso(alpha=0.8)
ls_res=model_eval(x_train,x_test,y_train,y_test,rd,"Lasso")
ls_res
```

Out[98]:

	Train_scr	Test_scr	RMSE	MSE	MAE
Lasso	0.639284	0.627576	276156.305652	7.626231e+10	173932.885676

DecisionTreeRegressor

In [99]:
```
dt=DecisionTreeRegressor(max_depth=10,min_samples_split=10,random_state=40)
dt_res=model_eval(x_train,x_test,y_train,y_test,dt,"Decision Tree")
dt_res
```

Out[99]:

	Train_scr	Test_scr	RMSE	MSE	MAE
Decision Tree	0.759999	0.583758	291950.481368	8.523508e+10	160529.58527

BaggingRegressor for Decision Tree

In [115]:
```
# Create the BaggingRegressor
bg1 = BaggingRegressor(n_estimators=100, base_estimator=dt, max_features=x_t

# Fit the model
bg1.fit(x_train, y_train)

# Make predictions
predictions = bg1.predict(x_test)
bag1_res=model_eval(x_train,x_test,y_train,y_test,dt,"Bagging for DT")
bag1_res
```

Out[115]:

	Train_scr	Test_scr	RMSE	MSE	MAE
Bagging for DT	0.759999	0.583758	291950.481368	8.523508e+10	160529.58527

AdaBoostRegressor for DEcision Tree

In [102]:
```
adboost1=AdaBoostRegressor(n_estimators=45)
ada1_res=model_eval(x_train,x_test,y_train,y_test,dt,"AddaBoost for DT")
ada1_res
```

Out[102]:

	Train_scr	Test_scr	RMSE	MSE	MAE
AddaBoost for DT	0.759999	0.583758	291950.481368	8.523508e+10	160529.58527

RandomForestRegressor

In [103]:
```
rf=RandomForestRegressor(n_estimators=60,max_depth=14,min_samples_split=7)
rf_res=model_eval(x_train,x_test,y_train,y_test,dt,"Random Forest")
rf_res
```

Out[103]:

	Train_scr	Test_scr	RMSE	MSE	MAE
Random Forest	0.759999	0.583758	291950.481368	8.523508e+10	160529.58527

BaggingRegressor for RandomForestRegressor

In [116]:
```
# Create a RandomForestRegressor directly
rf = RandomForestRegressor(n_estimators=80, max_features=x_train.shape[1], r

# Fit the model
rf.fit(x_train, y_train)

# Make predictions
predictions = rf.predict(x_test)
bag2_res=model_eval(x_train,x_test,y_train,y_test,dt,"Bagging for RF")
bag2_res
```

Out[116]:

	Train_scr	Test_scr	RMSE	MSE	MAE
Bagging for RF	0.759999	0.583758	291950.481368	8.523508e+10	160529.58527

AdaBoostRegressor for RandomForestRegressor

In [106]:
```
adaboost2=AdaBoostRegressor(n_estimators=120)
ada2_res=model_eval(x_train,x_test,y_train,y_test,rf,"AdaBoost for RF")
ada2_res
```

Out[106]:

	Train_scr	Test_scr	RMSE	MSE	MAE
AdaBoost for RF	0.856569	0.732001	234262.707443	5.487902e+10	138771.396774

KNeighborsRegressor

In [107]:
```
Knn1=KNeighborsRegressor(n_neighbors=5)
knn1_res=model_eval(x_train,x_test,y_train,y_test,Knn1,"KNeighbours")
knn1_res
```

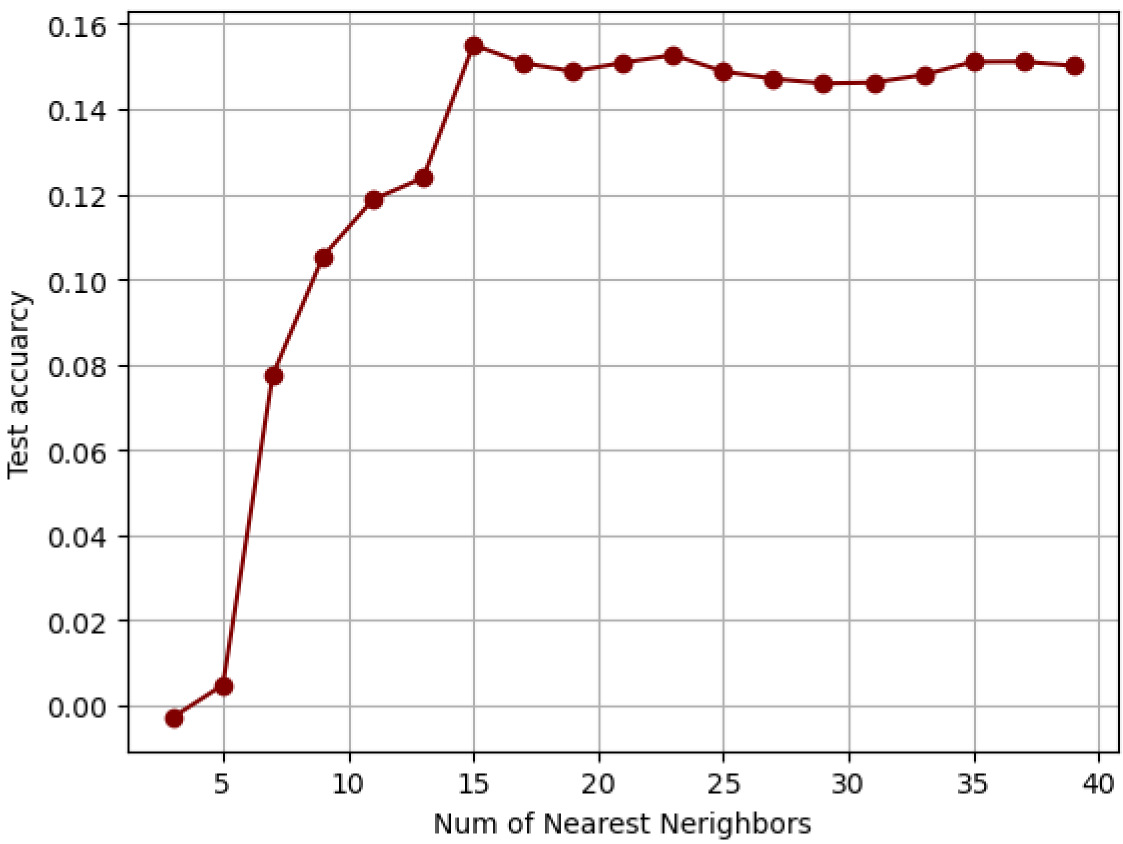
Out[107]:

	Train_scr	Test_scr	RMSE	MSE	MAE
KNeighbours	0.429181	0.004778	451436.032237	2.037945e+11	249125.330503

In [108]:
```
def optimal_K():
    k = list(range(3,40,2)) # k= 3,5,7,9....,35,37,39
    acc = []
    for i in range(len(k)):
        knn_model = KNeighborsRegressor(n_neighbors=k[i])
        knn_model.fit(x_train,y_train)
        acc.append(knn_model.score(x_test,y_test))
    print('Accuracy\n',acc)
    plt.plot(k,acc,color='maroon',marker='o')
    plt.xlabel('Num of Nearest Nerighbors')
    plt.ylabel('Test accuarcy')
    plt.grid()
    plt.show()
```

In [109]:
```
optimal_K()
```

```
Accuracy
 [-0.0027976510246443542, 0.004778188410675233, 0.07757046668527001, 0.105
35116054475568, 0.11875875125184099, 0.1238196002215517, 0.155077074239280
3, 0.15082602948093904, 0.14883914387539754, 0.15088802298234916, 0.152699
7322771103, 0.1488271234223285, 0.14712155149288997, 0.14601567374480295,
0.14622468858640614, 0.1480448528319832, 0.15109342451752694, 0.1511501211
8580518, 0.15016118627837216]
```



BaggingRegressor for KNeighborsRegressor

In [111]:
```
bag3=BaggingRegressor(n_estimators=25)
bag3_res=model_eval(x_train,x_test,y_train,y_test,Knn1,"Bagging for KN")
bag3_res
```

Out[111]:

	Train_scr	Test_scr	RMSE	MSE	MAE
Bagging for KN	0.429181	0.004778	451436.032237	2.037945e+11	249125.330503

AdaBoostRegressor for KNeighborsRegressor

In [112]:
```
adaboost3=AdaBoostRegressor(n_estimators=70)
ada3_res=model_eval(x_train,x_test,y_train,y_test,Knn1,"AdaBoost for KN")
ada3_res.round(5)
```

Out[112]:

	Train_scr	Test_scr	RMSE	MSE	MAE
AdaBoost for KN	0.42918	0.00478	451436.03224	2.037945e+11	249125.3305

In [117]:
```
res=pd.concat([lg_res,rd_res,ls_res,dt_res,bag1_res,ada1_res,rf_res,bag2_res
               knn1_res,bag3_res,ada3_res])
res.round(3)
```

Out[117]:

	Train_scr	Test_scr	RMSE	MSE	MAE
Linear	0.641	0.625	277079.445	7.677302e+10	173418.333
Ridge	0.639	0.628	276156.306	7.626231e+10	173932.886
Lasso	0.639	0.628	276156.306	7.626231e+10	173932.886
Decision Tree	0.760	0.584	291950.481	8.523508e+10	160529.585
Bagging for DT	0.760	0.584	291950.481	8.523508e+10	160529.585
AddaBoost for DT	0.760	0.584	291950.481	8.523508e+10	160529.585
Random Forest	0.760	0.584	291950.481	8.523508e+10	160529.585
Bagging for RF	0.760	0.584	291950.481	8.523508e+10	160529.585
AdaBoost for RF	0.857	0.732	234262.707	5.487902e+10	138771.397
KNeighbours	0.429	0.005	451436.032	2.037945e+11	249125.331
Bagging for KN	0.429	0.005	451436.032	2.037945e+11	249125.331
AdaBoost for KN	0.429	0.005	451436.032	2.037945e+11	249125.331

Hyper Parameter Tunning

In [ ]:
```
from sklearn.model_selection import GridSearchCV
```

In [*]:
```

# Define the hyperparameter grid to search
param_grid = {
    'n_estimators': [50, 100, 200],
    'max_depth': [ 10,15,20],
    'min_samples_split': [2, 5, 10,15],
    'min_samples_leaf': [1, 2, 4]
}

# Create the GridSearchCV object
grid_search = GridSearchCV(rf, param_grid, cv=5)

# Fit the grid search to the data
grid_search.fit(x_train, y_train)

# Print the best hyperparameters
print("Best hyperparameters found:")
print(grid_search.best_params_)

# Evaluate the model with the best hyperparameters on the test set
best_rf_model = grid_search.best_estimator_
accuracy = best_rf_model.score(x_test, y_test)
print(f"Accuracy on the test set: {accuracy:.2f}")
```

In [*]:
```
rf1=RandomForestRegressor(n_estimators=200,max_depth=15,min_samples_split=5,
rf_res=model_eval(x_train,x_test,y_train,y_test,rf1,"Random Forest")
rf_res
```

In [ ]:
```
bg4=BaggingRegressor(n_estimators=200,estimator=rf1,max_features=x_train.sha
                        max_samples=x_train.shape[0])
bag1_res=model_eval(x_train,x_test,y_train,y_test,rf1,"Bagging for Rf")
bag1_res
```

In [ ]:
```
add5=BaggingRegressor(n_estimators=100,estimator=rf1)
bag1_res=model_eval(x_train,x_test,y_train,y_test,rf1,"adda for rf")
bag1_res
```

Choosing the Best model

In [ ]:
```
import pickle
```

In [ ]:
```
final_model=RandomForestRegressor(n_estimators=200,max_depth=15,min_samples_
final_model.fit(x_train,y_train)
```

In [ ]:
```
pickle.dump(final_model,open('final.pkl','wb'))
```

Analysing data in Details for Web Devolp

In [ ]:
```
df2=pd.read_csv(r'C:\Users\hp\Downloads\CAR DETAILS (1).csv')
df2.head()
```

In [ ]:
```
brand=set(brand)
print(brand)
```

In [ ]:
```
fuel=set(df2['fuel'])
fuel
```

In [ ]:
```
car_name=list(df2['name'])
#print(car_names)
print(len(car_names))
```

In [ ]:
```
brand,model,sub_class=[],[],[]
for car in car_name:
    parts=car.split()
    x=parts[0]
    y=parts[1]
    z=parts[2:]
    brand.append(x)
    model.append(y)
    sub_class.append(z)

print(len(brand))
print(len(model))
print(len(sub_class))
```

In [ ]:
```
sub_class=[' '.join(map(str, item)) for item in sub_class]
```

In [ ]:
```
df2['brand1']=brand
df2['model1']=model
df2.head()
```

In [ ]:
```
df2.columns
```

In [ ]:
```
seller_type=set(df2['seller_type'])
seller_type
```

In [ ]:
```
transmission=set(df2['transmission'])
transmission
```

In [ ]:
```
owner=set(df2['owner'])
owner
```

In [ ]:
```
model=set(df2['model1'])
print(model)
```