About the Dataset -

- This dataset contains information about used cars which is available for sale.

Data dictionary -

- name - Name of the cars
- year - Year of the car when it was bought
- selling_price - Price at which the car is being sold
- km_driven - Number of Kilometres the car is driven
- fuel - Fuel type of car (petrol / diesel / CNG / LPG / electric)
- seller_type - Tells if a Seller is Individual or a Dealer
- transmission - Gear transmission of the car (Automatic/Manual)
- Owner - Number of previous owners of the car.

Importing Required Libraries

In [1]:
```
#Mathematical operation
import numpy as np

#Data Manipulation
import pandas as pd

#Data Visualizaion
import matplotlib.pyplot as plt
import seaborn as sns

#ML Algorithm
from sklearn import linear_model
from sklearn.metrics import accuracy_score
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder
from sklearn.metrics import mean_squared_error

#Remove Warnings
import warnings
warnings.filterwarnings('ignore')
```

In [2]:
```
#Load the dataset
df=pd.read_csv(r"C:\Users\Lenovo\Documents\jupyter\DataSets\CAR DETAILS FROM CAI
df.sample(10)
df1=df.copy()
```

Data Preprocessing

- In the data preprocessing phase we first examined the shape of the data to understand its dimension
- Next, We checked for null values in the dataset and removed if any were found

- Additionally, we performed a check for duplicate values and removed them to ensure data integrity
- To gain insights into relationships between different variables we performed univariate,bivariate and multivariate analysis and then visualized the correlation map using a heatmap. This visualization allowed us to identify the patterns and dependencies among the features in the dataset.

In [3]:
```
#Check info
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4340 entries, 0 to 4339
Data columns (total 8 columns):
 #   Column         Non-Null Count  Dtype 
---  ------         --------------  ----- 
 0   name           4340 non-null   object
 1   year           4340 non-null   int64 
 2   selling_price  4340 non-null   int64 
 3   km_driven      4340 non-null   int64 
 4   fuel           4340 non-null   object
 5   seller_type    4340 non-null   object
 6   transmission   4340 non-null   object
 7   owner          4340 non-null   object
dtypes: int64(3), object(5)
memory usage: 271.4+ KB
```

From above cell we see that there are 4340 observations and 8 columns in our dataset and there are 3 columns contain integer and 5 column contain object value and there are no null values in our dataset

In [4]:
```
#check for duplicates
df.duplicated().sum()
```

Out[4]: 763

From above cell we see that there are 763 duplicates observations in our dataset

In [5]:
```
#Print all duplicate values
df[df.duplicated()]
```

Out[5]:

	name	year	selling_price	km_driven	fuel	seller_type	transmission	owner
13	Maruti 800 AC	2007	60000	70000	Petrol	Individual	Manual	First Owner
14	Maruti Wagon R LXI Minor	2007	135000	50000	Petrol	Individual	Manual	First Owner
15	Hyundai Verna 1.6 SX	2012	600000	100000	Diesel	Individual	Manual	First Owner
16	Datsun RediGO T Option	2017	250000	46000	Petrol	Individual	Manual	First Owner
17	Honda Amaze VX i-DTEC	2014	450000	141000	Diesel	Individual	Manual	Second Owner
...	...	...	...	...	...	...	...	...
4307	Mahindra Xylo H4	2019	599000	15000	Diesel	Individual	Manual	Third Owner
4308	Maruti Alto 800 LXI	2018	200000	35000	Petrol	Individual	Manual	First Owner
4309	Datsun GO Plus T	2017	350000	10171	Petrol	Dealer	Manual	First Owner
4310	Renault Duster 110PS Diesel RxL	2015	465000	41123	Diesel	Dealer	Manual	First Owner
4311	Toyota Camry Hybrid 2.5	2017	1900000	20118	Petrol	Dealer	Automatic	First Owner

763 rows × 8 columns

In [6]:
```
#drop duplicates
df.drop_duplicates(inplace=True)
```

In [7]:
```
#check for shape after droping duplicates
df.shape
```

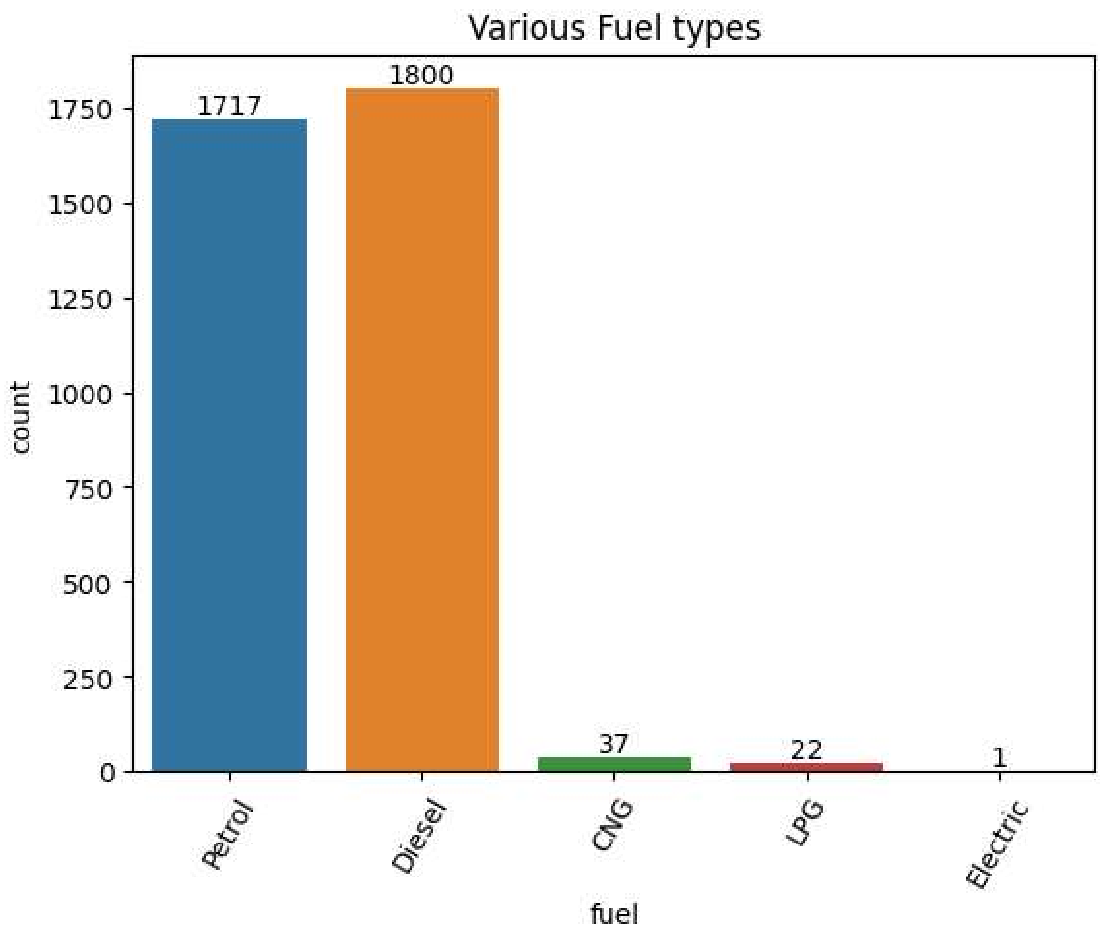
Out[7]: (3577, 8)

From above cell we see that after dropping duplicates there are 3577 observations and 8 columns in our dataset

Univariate analysis

Fuel

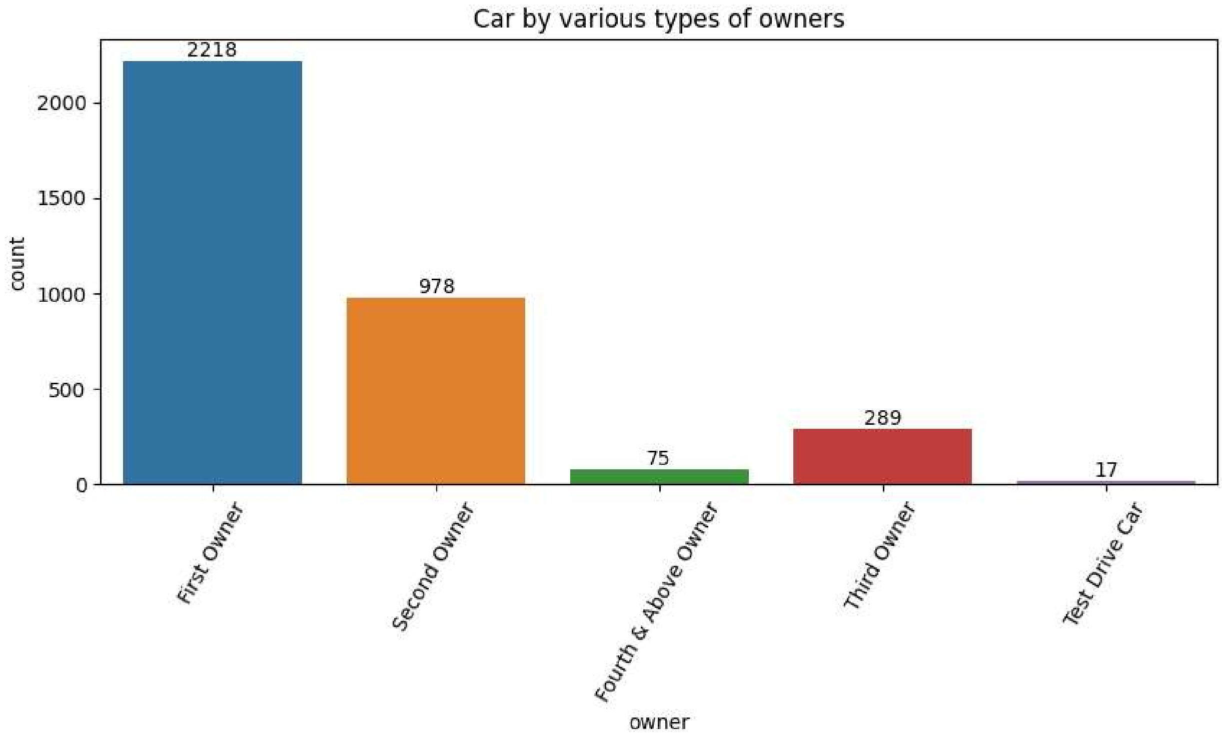
In [8]:
```
ax=sns.countplot(x='fuel',data=df)
for i in ax.containers:
    ax.bar_label(i)
plt.xticks(rotation=60)
plt.title("Various Fuel types")
plt.show()
```



From above countplot we observe that there are majority of petrol and diesel car

Owner

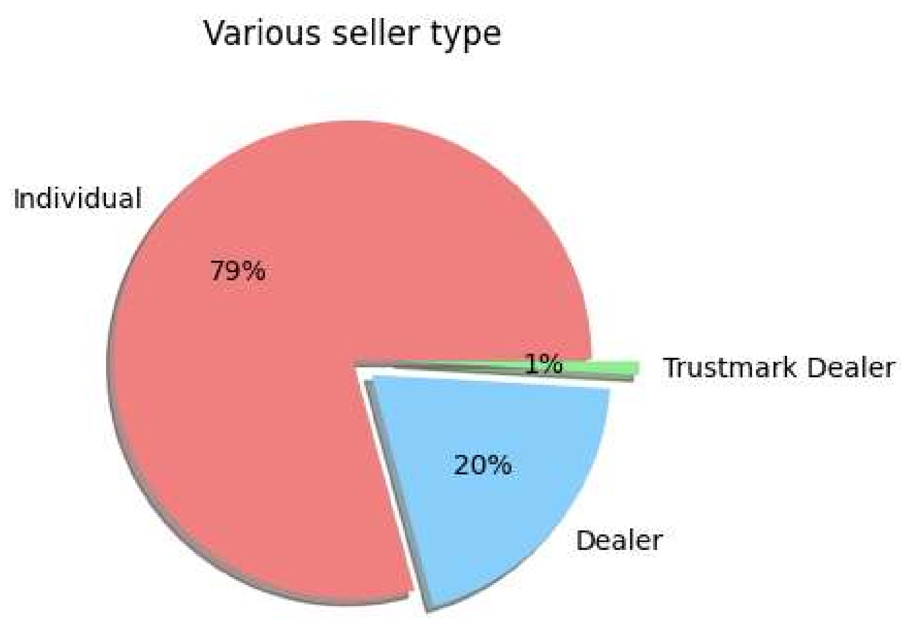
In [9]:
```
plt.figure(figsize=(10,4))
ax=sns.countplot(x='owner',data=df)
for i in ax.containers:
    ax.bar_label(i)
plt.xticks(rotation=60)
plt.title("Car by various types of owners")
plt.show()
```



From above cell we see that there are majority of first owner car's with 2832 counts

seller_type

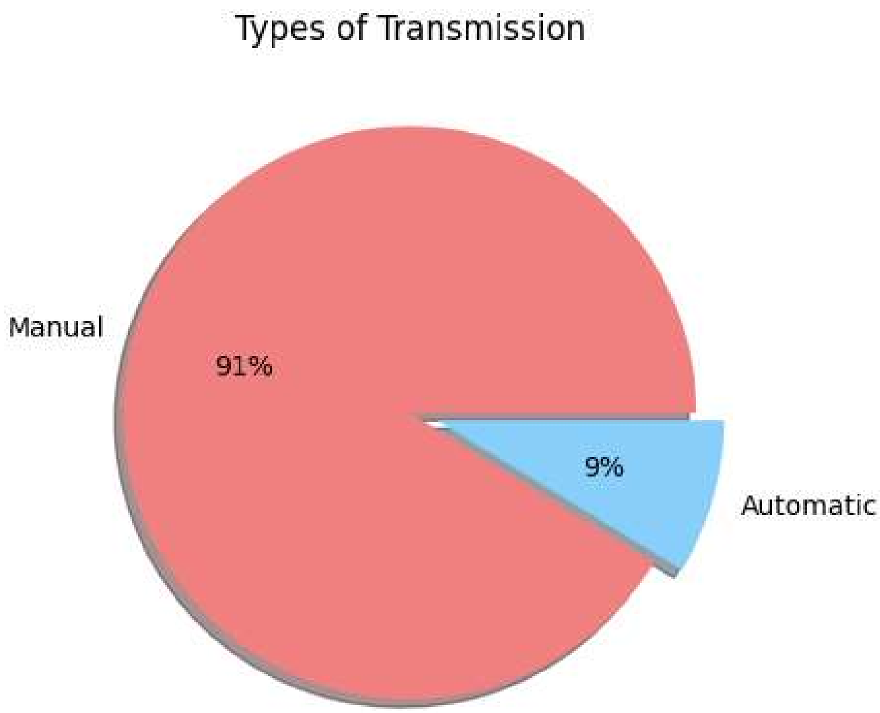
In [10]:
```
x=df['seller_type'].value_counts()
y=x.index
plt.figure(figsize=(10,4))
plt.pie(x=x,labels=y, autopct='%.0f%%',shadow=True,colors = ['lightcoral', 'ligl
plt.title("Various seller type")
plt.show()
```



From above pie plot we see that there are 75% individual car seller's and 23% dealer and 2% trustmark dealer

Transmission

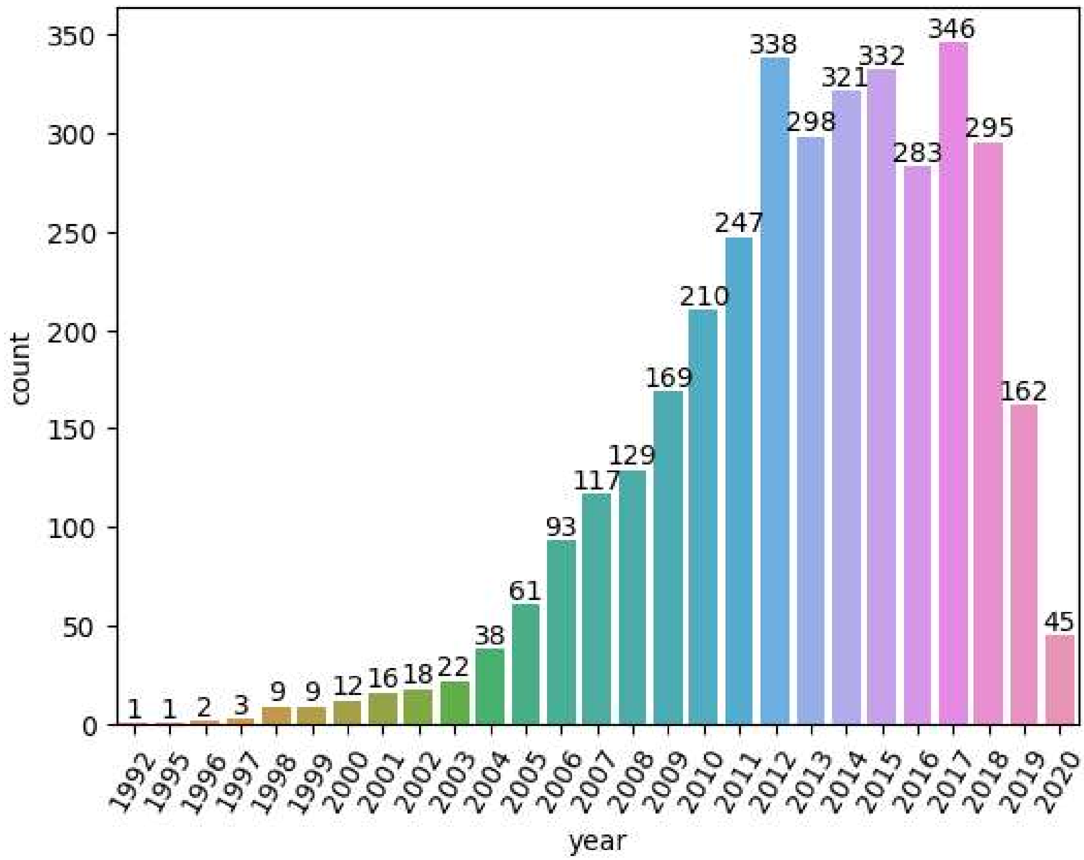
In [11]:
```
x=df['transmission'].value_counts()
y=x.index
plt.pie(x=x,labels=y,autopct='%.0f%%',shadow=True,colors = ['lightcoral', 'ligh
plt.title('Types of Transmission')
plt.xticks(rotation=60)
plt.show()
```



From above pie plot we see that there are 90% manual car and 10% Automatic car's.

Year

In [12]:
```
ax=sns.countplot(x='year',data=df)
for i in ax.containers:
    ax.bar_label(i)
plt.xticks(rotation=60)
plt.show()
```

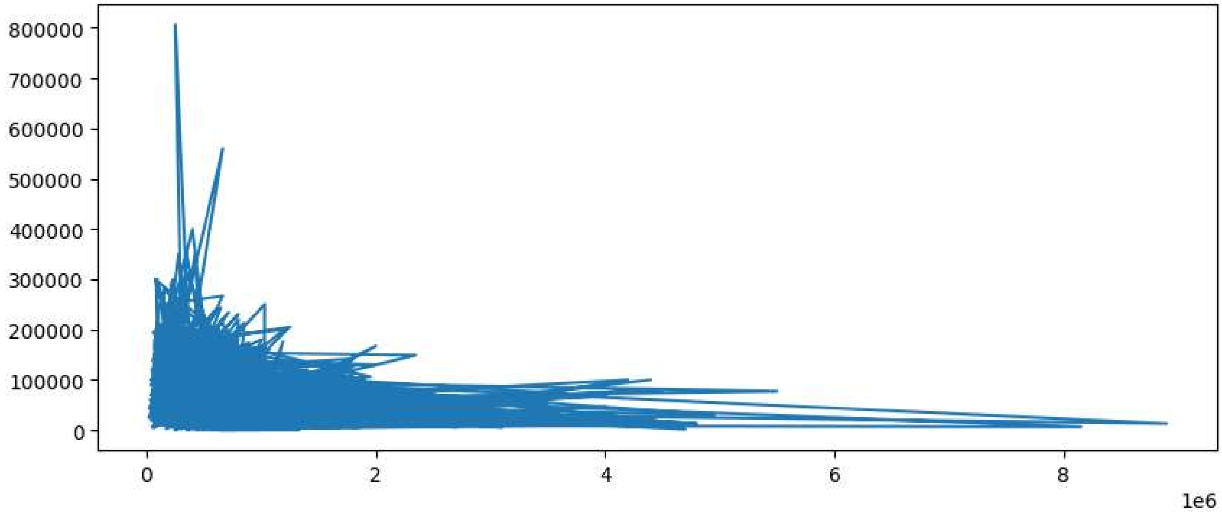


From above count plot we see that there are maximum car is from 2017 and we have car from year 1992 to 2020.

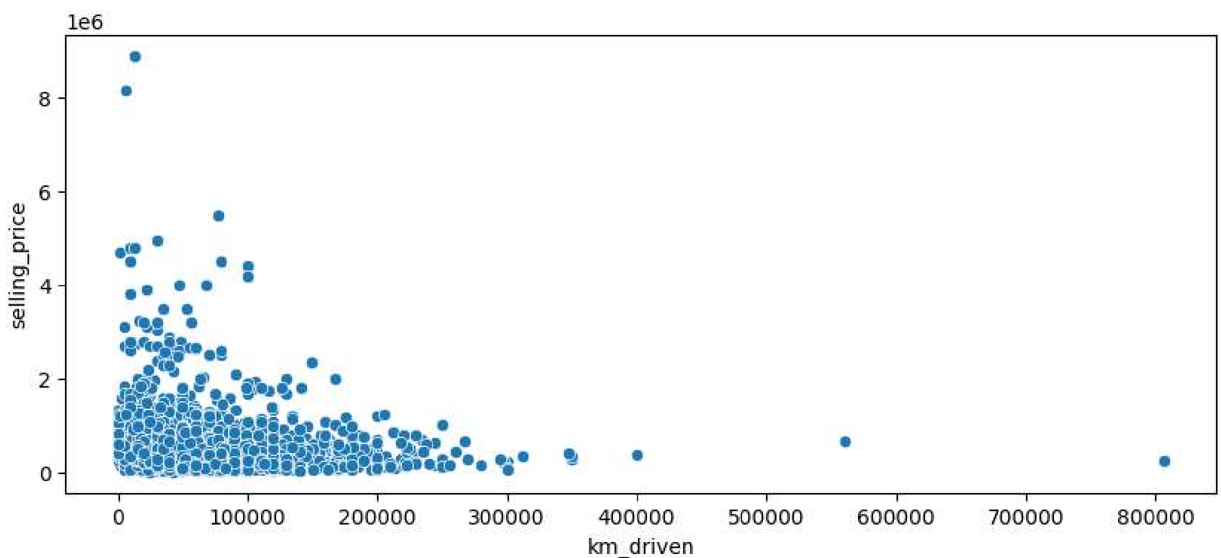
Bivariate analysis

Selling_price and Km_driven

In [13]:
```
plt.figure(figsize=(10,4))
plt.plot(df['selling_price'],df['km_driven'])
plt.show()
```

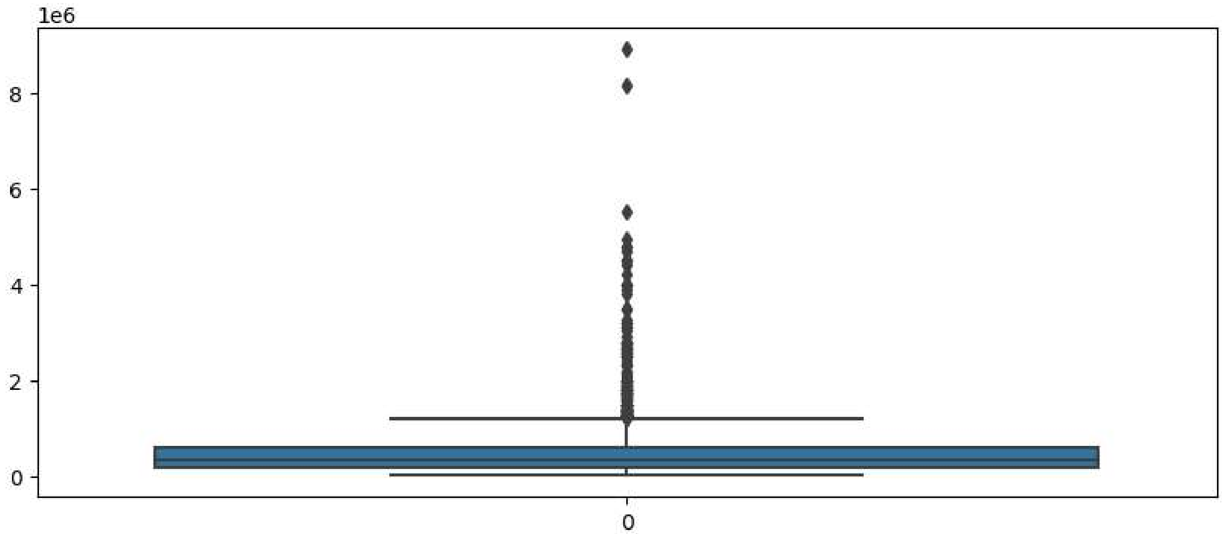


In [14]:
```
plt.figure(figsize=(10,4))
sns.scatterplot(x=df['km_driven'],y=df['selling_price'])
plt.show()
```



From above scatter plot we observe that there are outliers in the selling price and also in km_driven columns let's visualize boxplot

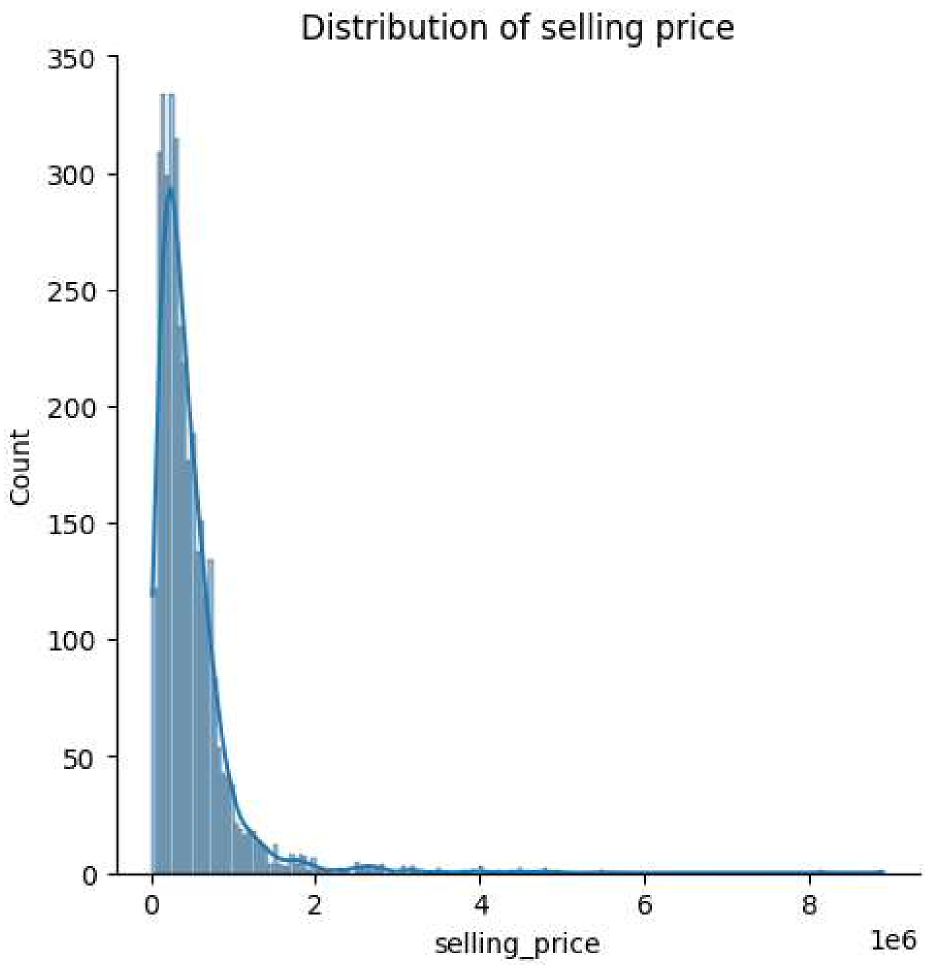
In [15]:
```
plt.figure(figsize=(10,4))
sns.boxplot(df['selling_price'])
plt.show()
```



From above boxplot we see that there are many outliers in our selling_price column

In [16]:
```
sns.displot(df['selling_price'],kind='hist',kde=True)
plt.title("Distribution of selling price")
```

Out[16]: Text(0.5, 1.0, 'Distribution of selling price')



From above displot we see that in selling price there are right skewed data majority of the data is from 0X10^6 to 4X10^6 so we can drop outliers from 4X10^6 to last.

In [17]:
```
#Print outliers values
df[df['selling_price']>4000000]
```

Out[17]:

	name	year	selling_price	km_driven	fuel	seller_type	transmission	owner
89	Mercedes-Benz S-Class S 350d Connoisseurs Edition	2017	8150000	6500	Diesel	Dealer	Automatic	First Owner
101	Mercedes-Benz E-Class Exclusive E 200 BSIV	2018	4500000	9800	Petrol	Dealer	Automatic	First Owner
539	Mercedes-Benz GL-Class 350 CDI Blue Efficiency	2014	4400000	100000	Diesel	Individual	Automatic	Second Owner
555	BMW X5 xDrive 30d xLine	2019	4950000	30000	Diesel	Dealer	Automatic	First Owner
963	Audi A5 Sportback	2020	4700000	1500	Diesel	Individual	Automatic	First Owner
3453	BMW 5 Series 520d Luxury Line	2018	4800000	9422	Diesel	Individual	Automatic	First Owner
3872	Audi RS7 2015-2019 Sportback Performance	2016	8900000	13000	Petrol	Dealer	Automatic	First Owner
3875	Land Rover Range Rover 4.4 Diesel LWB Vogue SE	2010	4200000	100000	Diesel	Dealer	Automatic	First Owner
3883	BMW 5 Series 520d Luxury Line	2019	4800000	12999	Diesel	Dealer	Automatic	First Owner
3969	Mercedes-Benz GLS 2016-2020 350d 4MATIC	2016	5500000	77350	Diesel	Dealer	Automatic	First Owner
4047	Volvo XC 90 D5 Inscription BSIV	2017	4500000	80000	Diesel	Individual	Automatic	First Owner

From above cell we see that there are costly car's like as Mercedes-Benz,Audi,BMW etc. so we can say that this data is not useful for our

In [18]:
```
#Extract indeex of outliers
x=df[df['selling_price']>4000000].index.to_list()
x
```

Out[18]:
```
[89, 101, 539, 555, 963, 3453, 3872, 3875, 3883, 3969, 4047]
```

In [19]:
```
#Drop outliers
df.drop(index=x,inplace=True)
```

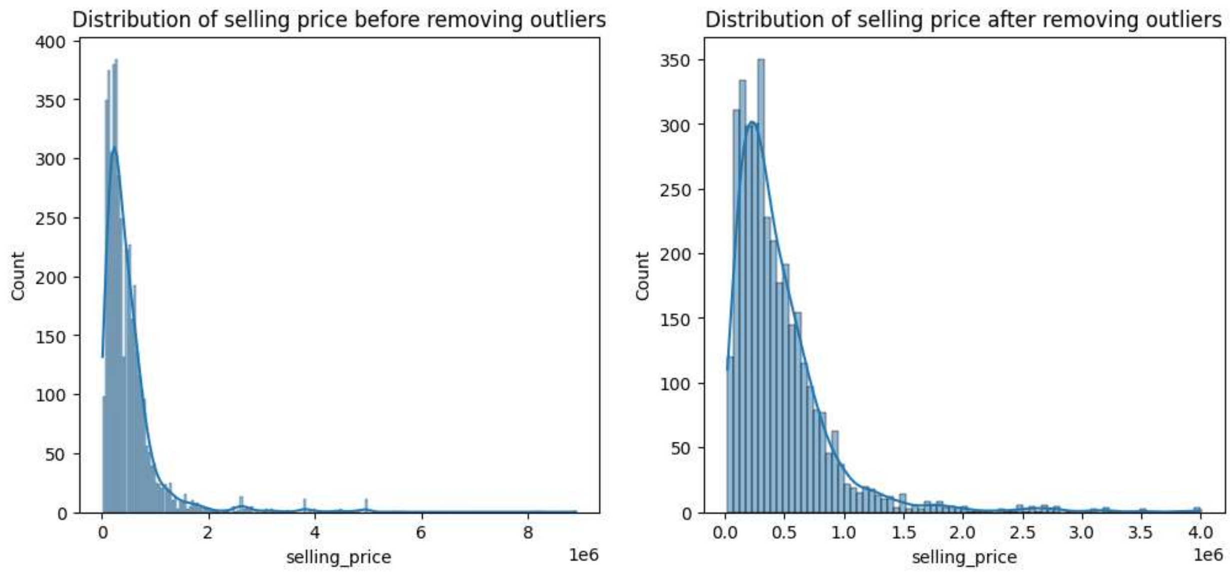
In [20]:
```
#check for outliers remove or not
df[df['selling_price']>4000000]
```

Out[20]:

name	year	selling_price	km_driven	fuel	seller_type	transmission	owner

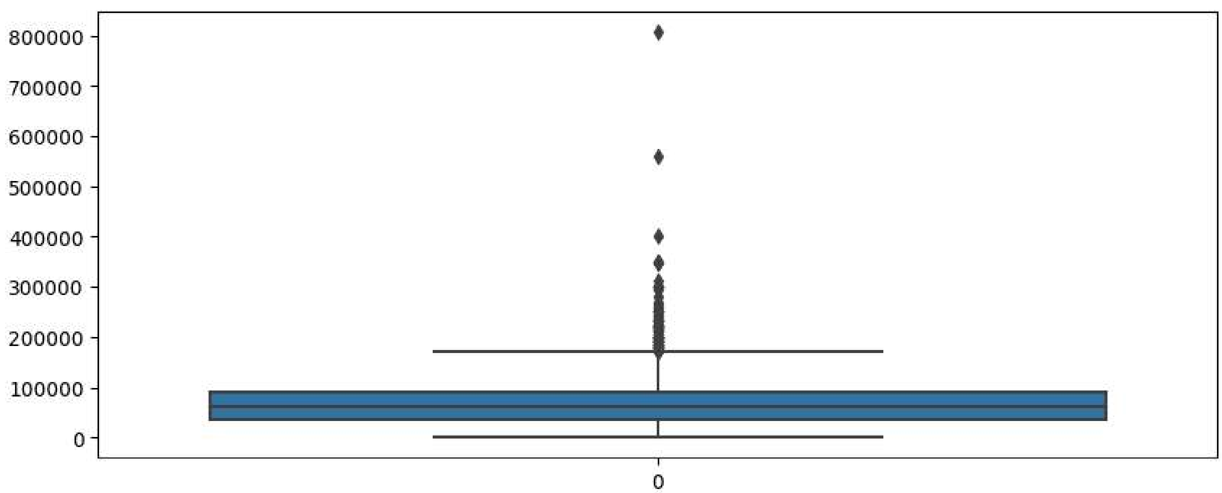
In [21]:

```
fig, axes = plt.subplots(nrows=1, ncols=2,figsize=(12,5))

sns.histplot(df['selling_price'],kde=True,ax=axes[1])
sns.histplot(df1['selling_price'],kde=True,ax=axes[0])
axes[0].set_title('Distribution of selling price before removing outliers')
axes[1].set_title('Distribution of selling price after removing outliers')

plt.show()
```



In [22]:

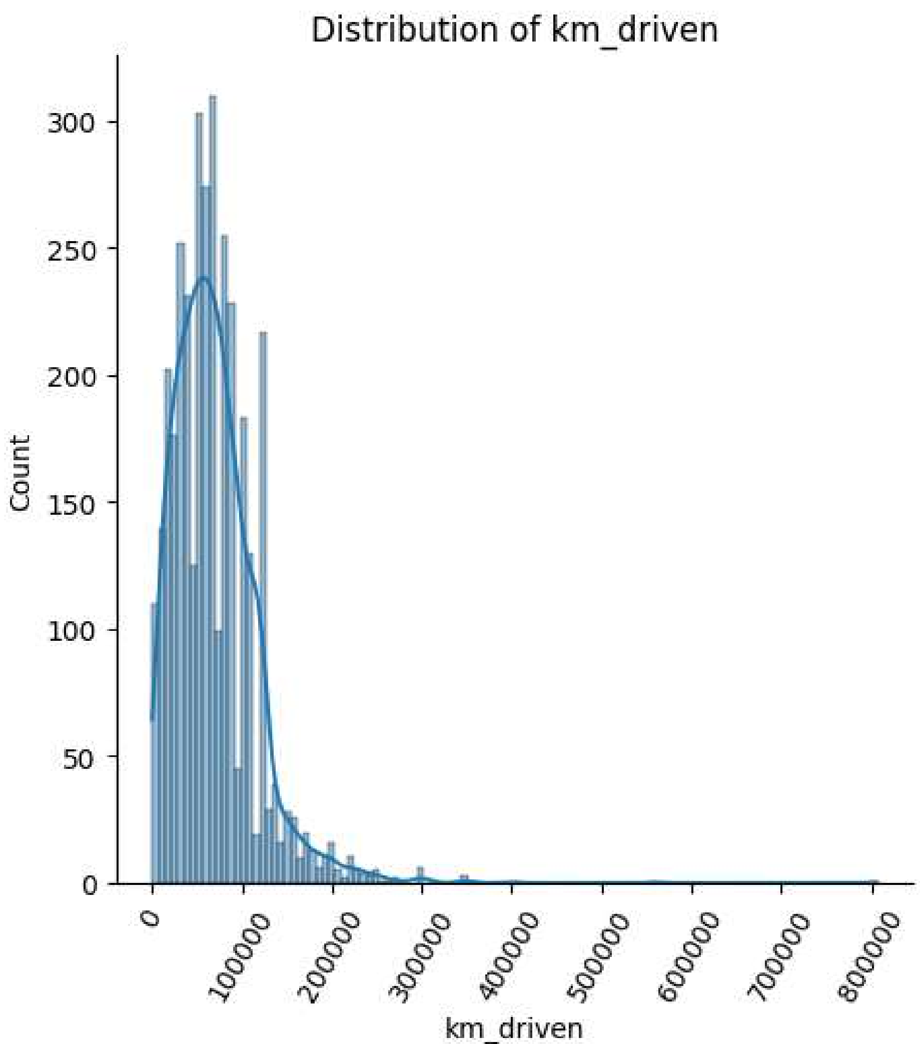
```
plt.figure(figsize=(10,4))
sns.boxplot(df['km_driven'])
plt.show()
```



From above boxplot we see that outliers is also present in our km_driven column let's see the distribution of km_driven column

In [23]:
```
sns.displot(df['km_driven'],kde=True)
plt.xticks(rotation=60)
plt.title("Distribution of km_driven")
```

Out[23]: Text(0.5, 1.0, 'Distribution of km_driven')



From above displot we see that in km_driven column there are right skewed data and majority of the data is present in the range 0-200000 kilometer so we can remove the outlier from 200000 to last let's do it

In [24]:

```
z=df[df['km_driven']>200000].index.to_list()
df[df['km_driven']>200000]

```

Out[24]:

	name	year	selling_price	km_driven	fuel	seller_type	transmission	owner
69	Chevrolet Tavera Neo LS B3 - 7(C) seats BSIII	2010	280000	350000	Diesel	Individual	Manual	Second Owner
70	Toyota Corolla Altis Diesel D4DG	2011	350000	230000	Diesel	Individual	Manual	First Owner
197	Mahindra Xylo E4	2009	229999	230000	Diesel	Individual	Manual	Third Owner
225	Mahindra Renault Logan 1.5 DLS	2008	89999	213000	Diesel	Individual	Manual	First Owner
324	Mahindra XUV500 W8 2WD	2012	850000	212814	Diesel	Dealer	Manual	First Owner
394	Mahindra Scorpio REV 116	2006	220000	220000	Petrol	Individual	Manual	Second Owner
502	Maruti Swift Ldi BSIII	2009	300000	217871	Diesel	Dealer	Manual	First Owner
525	Maruti SX4 S Cross DDiS 320 Delta	2016	665000	560000	Diesel	Dealer	Manual	First Owner
656	Tata Safari Storme VX	2013	360000	206500	Diesel	Individual	Manual	First Owner
821	Hyundai EON Magna Plus	2013	125000	205000	Petrol	Individual	Manual	First Owner
1101	Tata Indica DLS	2006	85000	300000	Diesel	Individual	Manual	Second Owner
1116	Toyota Innova 2.5 V Diesel 7-seater	2005	200000	223000	Diesel	Individual	Manual	First Owner
1243	Maruti Swift VXI BSIII	2009	250000	806599	Petrol	Dealer	Manual	First Owner
1253	Toyota Corolla Altis D-4D J	2014	715000	234000	Diesel	Individual	Manual	First Owner
1414	Skoda Superb Elegance 2.0 TDI CR AT	2011	450000	235000	Diesel	Individual	Automatic	First Owner
1426	Mahindra Scorpio VLX AT 2WD BSIII	2004	225000	223660	Diesel	Individual	Automatic	Third Owner
1659	Toyota Innova 2.5 G (Diesel) 8 Seater BS IV	2006	229999	300000	Diesel	Individual	Manual	First Owner
1668	Toyota Innova 2.5 GX (Diesel) 7 Seater	2014	650000	244000	Diesel	Individual	Manual	First Owner
1674	Volkswagen Jetta 2.0 TDI Comfortline	2011	350000	312000	Diesel	Individual	Manual	Third Owner
1923	Mahindra Bolero SLE BSIII	2007	185000	230000	Diesel	Individual	Manual	Second Owner
2278	Hyundai Accent CRDi	2006	170000	245244	Diesel	Individual	Manual	Fourth & Above Owner
2394	Toyota Innova 2.5 V Diesel 8-seater	2009	350000	350000	Diesel	Individual	Manual	First Owner

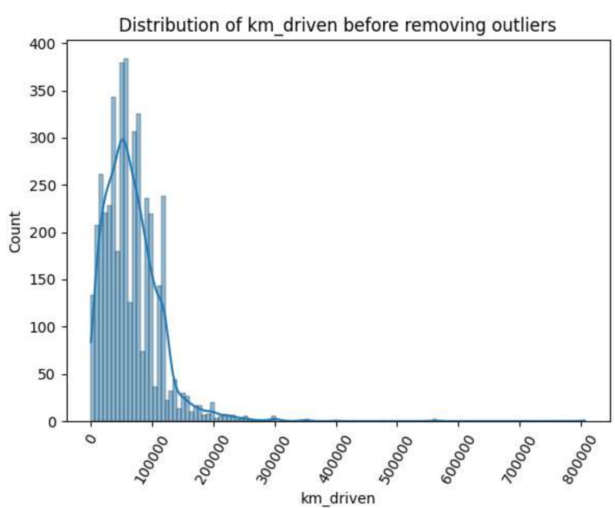
	name	year	selling_price	km_driven	fuel	seller_type	transmission	owner
2401	Toyota Innova 2.5 E Diesel MS 7-seater	2011	665000	267000	Diesel	Individual	Manual	Second Owner
2402	Mahindra Scorpio 2.6 CRDe	2005	175000	250000	Diesel	Individual	Manual	Second Owner
2672	Maruti Swift Vdi BSIII	2009	180000	220000	Diesel	Individual	Manual	First Owner
2760	Tata New Safari DICOR 2.2 EX 4x2	2010	300000	250000	Diesel	Individual	Manual	Second Owner
2855	Mahindra Scorpio 2.6 CRDe	2005	229999	221000	Diesel	Individual	Manual	Third Owner
2955	Toyota Innova 2.5 G4 Diesel 7-seater	2007	440000	223000	Diesel	Individual	Manual	Fourth & Above Owner
2961	Mahindra Scorpio VLS 2.2 mHawk	2008	300000	270000	Diesel	Individual	Manual	Third Owner
2964	Maruti Swift VDI	2012	225000	296823	Diesel	Individual	Manual	First Owner
3171	Maruti Swift Dzire VDI	2014	450000	260000	Diesel	Individual	Manual	Second Owner
3447	Mahindra Ingenio CRDe	2015	210000	210000	Diesel	Individual	Manual	First Owner
3461	Toyota Innova 2.5 EV Diesel PS 7 Seater BSIII	2012	300000	250000	Diesel	Individual	Manual	First Owner
3470	Mahindra Xylo Celebration Edition BSIV	2010	200000	240000	Diesel	Individual	Manual	Third Owner
3531	Ford Endeavour 2.5L 4X2	2011	500000	224642	Diesel	Dealer	Manual	Second Owner
3541	Mahindra Scorpio 2.6 CRDe	2006	180000	222435	Diesel	Individual	Manual	Second Owner
3572	Mahindra Scorpio VLX 2WD AIRBAG BSIV	2014	600000	238000	Diesel	Individual	Manual	First Owner
3611	Hyundai Verna 1.6 SX	2012	434999	235000	Diesel	Individual	Manual	Second Owner
3675	Mahindra Xylo E9	2012	300000	295000	Diesel	Individual	Manual	First Owner
3679	Toyota Innova 2.5 G (Diesel) 7 Seater BS IV	2006	400000	400000	Diesel	Individual	Manual	Third Owner
3718	Toyota Innova 2.5 GX 8 STR BSIV	2009	420000	347089	Diesel	Dealer	Manual	First Owner
3734	Mahindra XUV500 W8 2WD	2013	550000	222252	Diesel	Individual	Manual	First Owner
3782	Toyota Fortuner 3.0 Diesel	2010	1250000	205000	Diesel	Individual	Manual	Second Owner
3787	Hyundai Santa Fe 4X4	2011	800000	220000	Diesel	Individual	Manual	First Owner

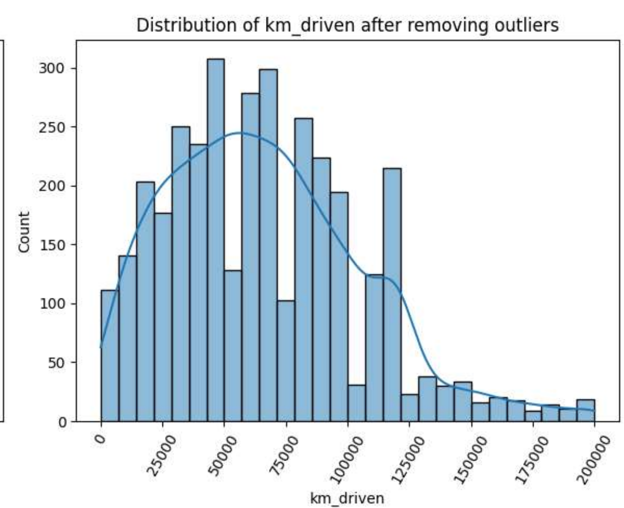
	name	year	selling_price	km_driven	fuel	seller_type	transmission	owner
3898	Tata Indica GLS BS IV	2010	90000	300000	Petrol	Individual	Manual	Third Owner
3979	Mahindra Verito 1.5 D2 BSIII	2011	150000	280000	Diesel	Individual	Manual	First Owner
3981	Toyota Innova 2.5 VX (Diesel) 8 Seater	2014	1030000	250000	Diesel	Individual	Manual	Second Owner
3994	Tata Indica GLS BS IV	2010	75000	300000	Petrol	Individual	Manual	Third Owner
4088	Maruti 800 AC	2009	120000	250000	Petrol	Individual	Manual	Second Owner
4208	Toyota Qualis FS B3	2001	150000	256000	Diesel	Dealer	Manual	First Owner
4231	Toyota Innova 2.5 G (Diesel) 8 Seater BS IV	2011	800000	230000	Diesel	Individual	Manual	First Owner
4255	Mahindra XUV500 W8 2WD	2014	650000	218000	Diesel	Individual	Manual	Second Owner
4286	Fiat Punto 1.3 Emotion	2010	130000	210000	Diesel	Individual	Manual	Second Owner

From above cell we see that there are 53 observations in our data with outlier so let's remove it

In [25]:
```
df.drop(index=z,inplace=True)
```

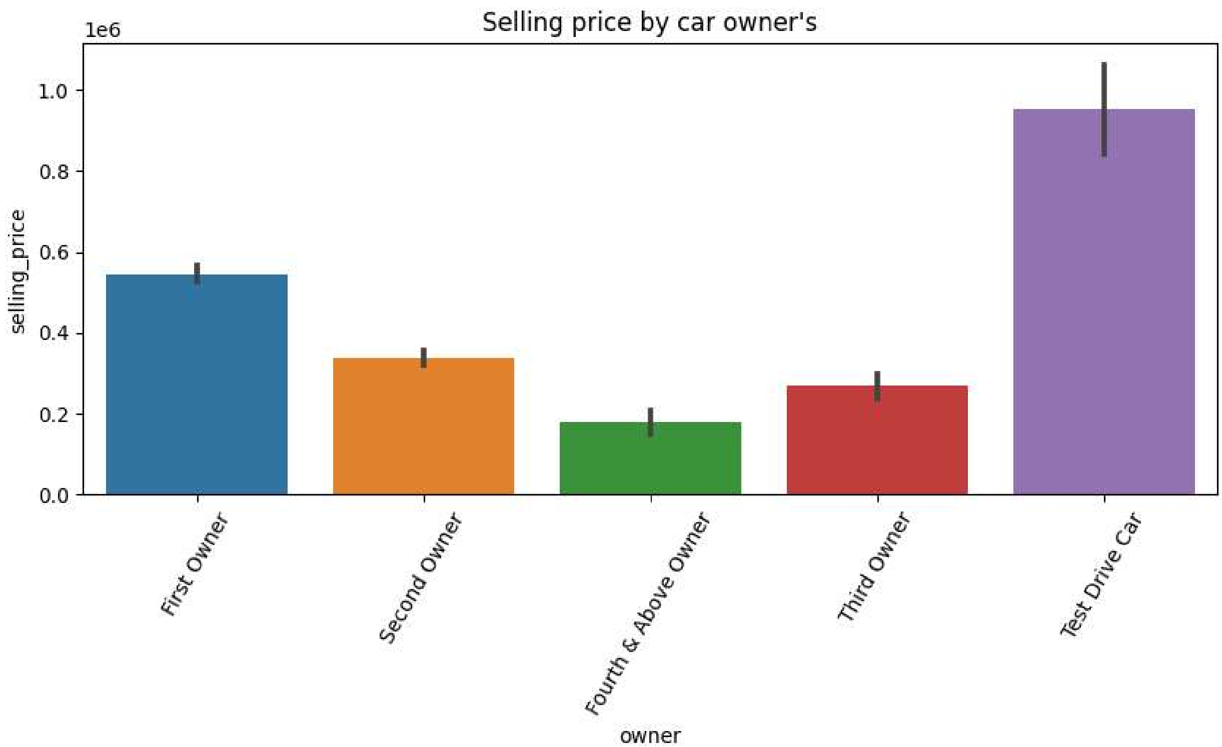
In [26]:
```
fig, axes = plt.subplots(nrows=1, ncols=2, figsize=(12, 5))

sns.histplot(df['km_driven'], kde=True, ax=axes[1])
sns.histplot(df1['km_driven'], kde=True, ax=axes[0])
axes[0].set_title('Distribution of km_driven before removing outliers')
axes[1].set_title('Distribution of km_driven after removing outliers')
axes[0].tick_params(axis='x', rotation=60)
axes[1].tick_params(axis='x', rotation=60)

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





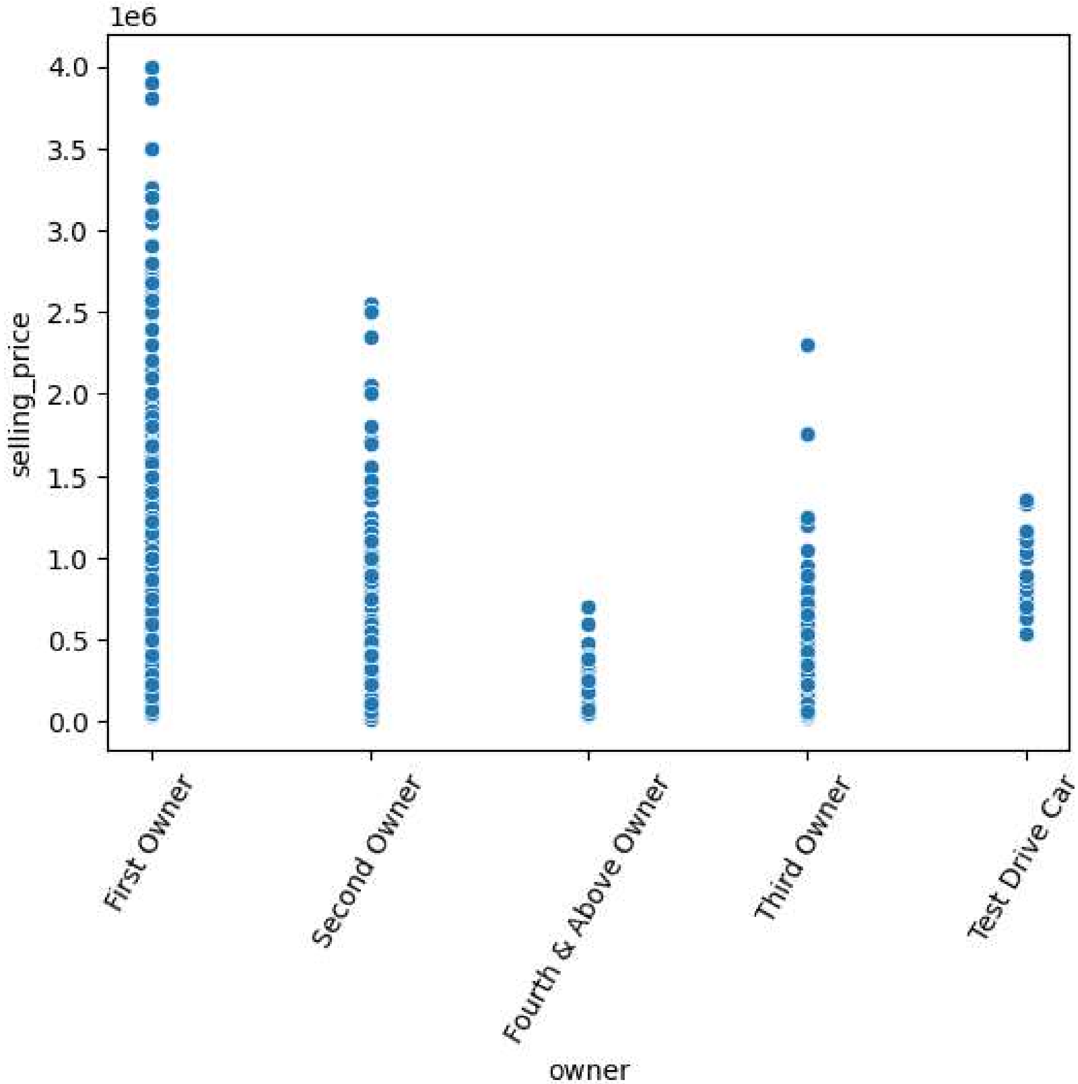
owner and selling_price

In [27]:
```
plt.figure(figsize=(10,4))
sns.barplot(x='owner',y='selling_price',data=df)

plt.title("Selling price by car owner's")

plt.xticks(rotation=60)
plt.show()
```



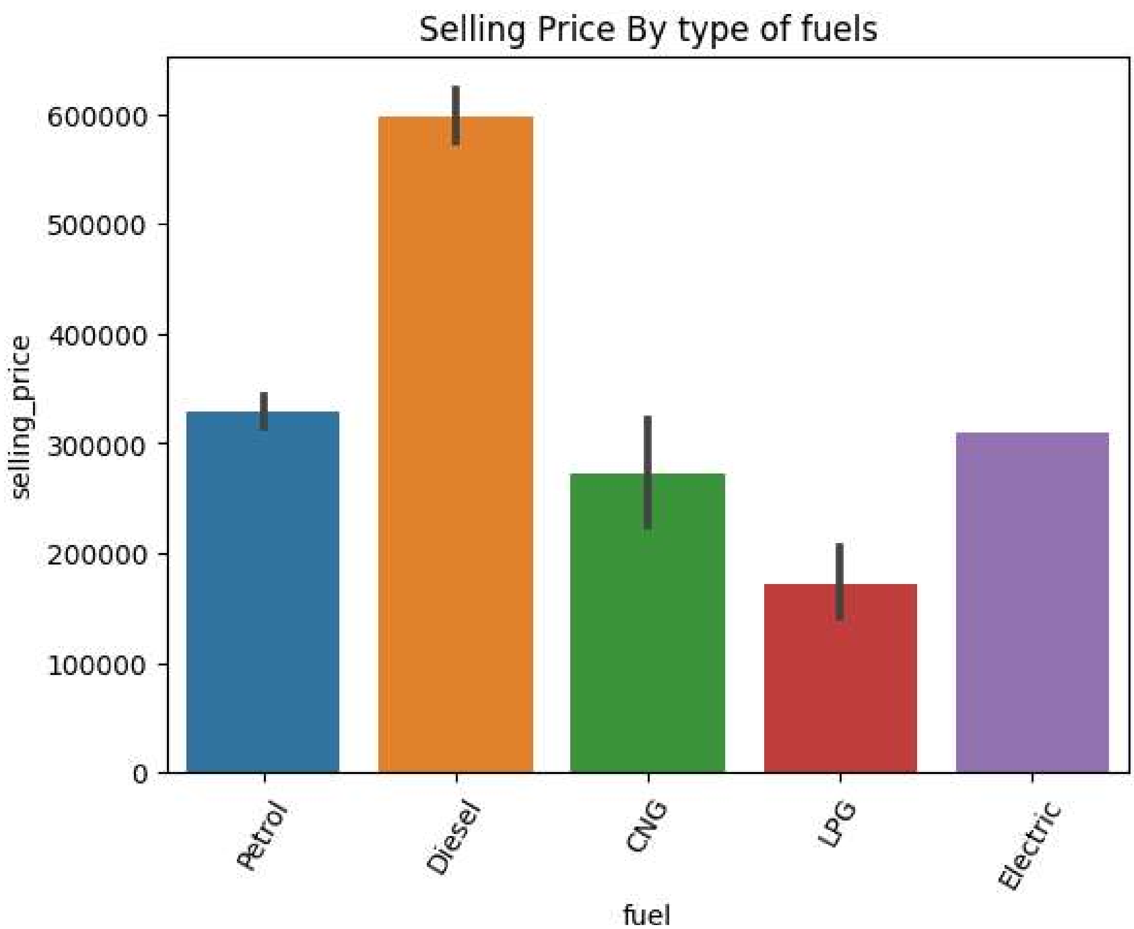
From above barplot we see that there are average price of Test drive car is high and second highest price of first owners car

In [28]:
```
sns.scatterplot(x='owner',y='selling_price',data=df)
plt.xticks(rotation=60)
plt.show()
```



In [29]:

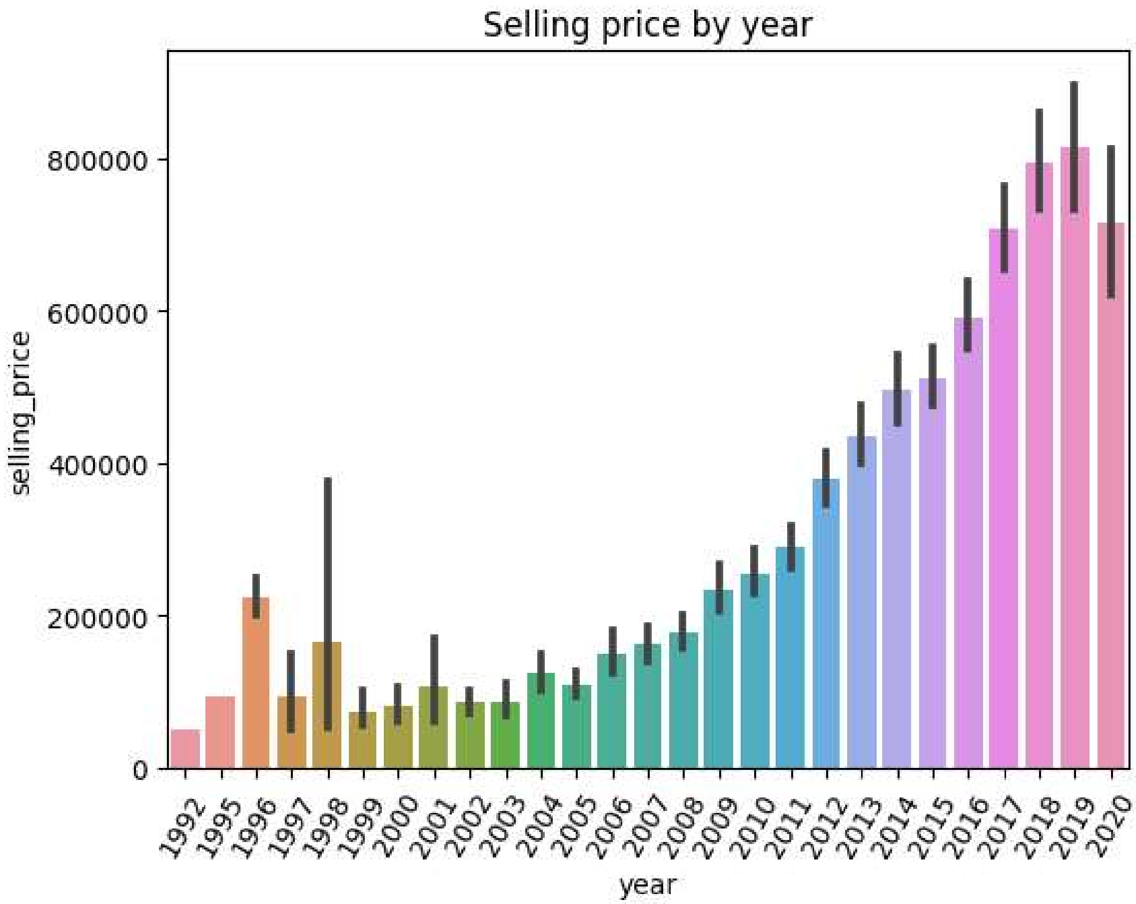
```
sns.barplot(x='fuel',y='selling_price',data=df)
plt.xticks(rotation=60)
plt.title("Selling Price By type of fuels")
plt.show()
```



From above barplot we see that average price of diesel car is high in comparison of another type of car

In [30]:

```
sns.barplot(x='year',y='selling_price',data=df)
plt.xticks(rotation=60)
plt.title("Selling price by year")
plt.show()
```



From above plot we see that most expensive car's is from 2019 year

Ml modelling

In [31]:

```
#Label Encoding
le=LabelEncoder()
df['owner']=le.fit_transform(df['owner'])
df['fuel']=le.fit_transform(df['fuel'])
df['seller_type']=le.fit_transform(df['seller_type'])
df['transmission']=le.fit_transform(df['transmission'])
```

We know that in our data there is categorical column so we have to convert these columns values into discrete(numeric) for ml modelling for this we use label encoder to encode these values

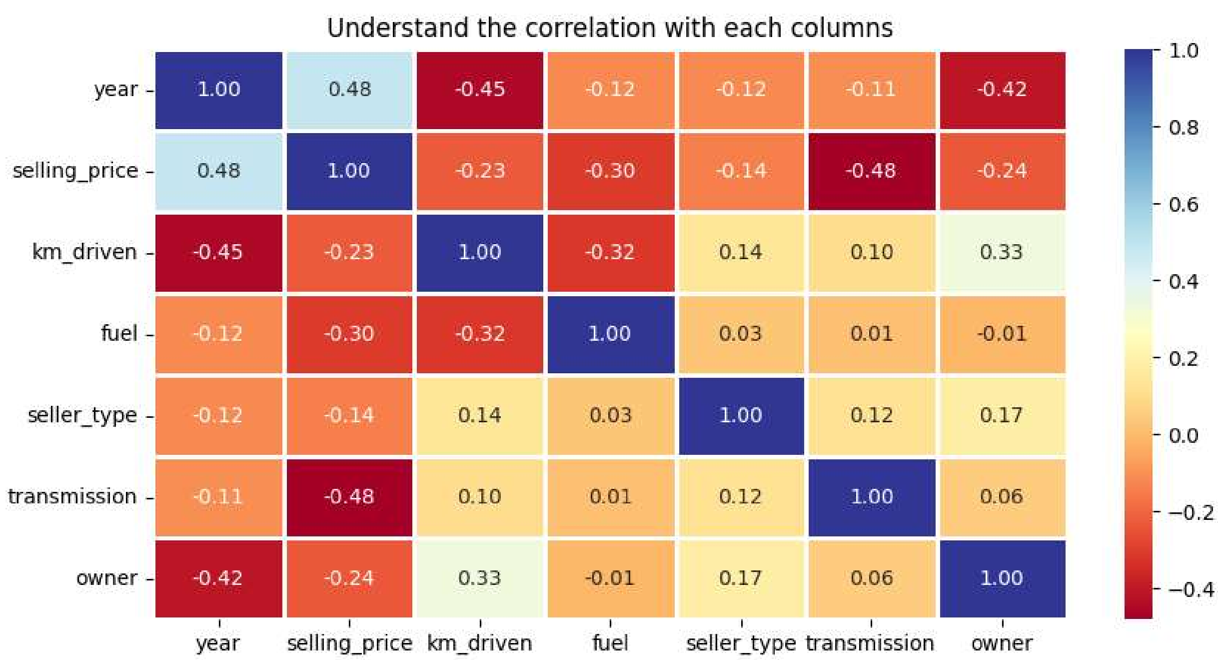
In [32]:
```
df
```

Out[32]:

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

3513 rows × 8 columns

In [33]:
```
# Visualize the correlation map
plt.figure(figsize=(10,5))
sns.heatmap(df.corr(),annot=True,cmap='RdYlBu',fmt='.2f',
    annot_kws=None,
    linewidths=1)
plt.title("Understand the correlation with each columns")
plt.show()
```



From above heatmap we see that the year and transmission is highly correlated with our target variable selling_price apart from this fuel km_driven and owner is also correlated with target feature

In [34]:
```
df.columns
```

Out[34]:
```
Index(['name', 'year', 'selling_price', 'km_driven', 'fuel', 'seller_type',
       'transmission', 'owner'],
      dtype='object')
```

In [35]:
```
x=df[[ 'year', 'km_driven', 'fuel', 'seller_type',
       'transmission', 'owner']]
y=df[['selling_price']]
```

In above cell i created two dataframe x and y where x contain highly correlated features and y contain target variable

In [36]:
```
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.3,random_state=1
```

In Above cell-

- The code splits the dataset into `training` and `testing` sets using the `train_test_split()` function from sklearn.
- The training set is used to train the models, and the testing set is used to evaluate their performance.
- Take `test_size` ratio of `70:30` it means we give 70% data to training and 30% for testing
- `random_state = 1` (it means that it takes one observations randomly.)

In [37]:
```
reg=linear_model.LinearRegression()
#fit the model
reg.fit(x_train,y_train)
```

Out[37]:
```
▾ LinearRegression
LinearRegression()
```

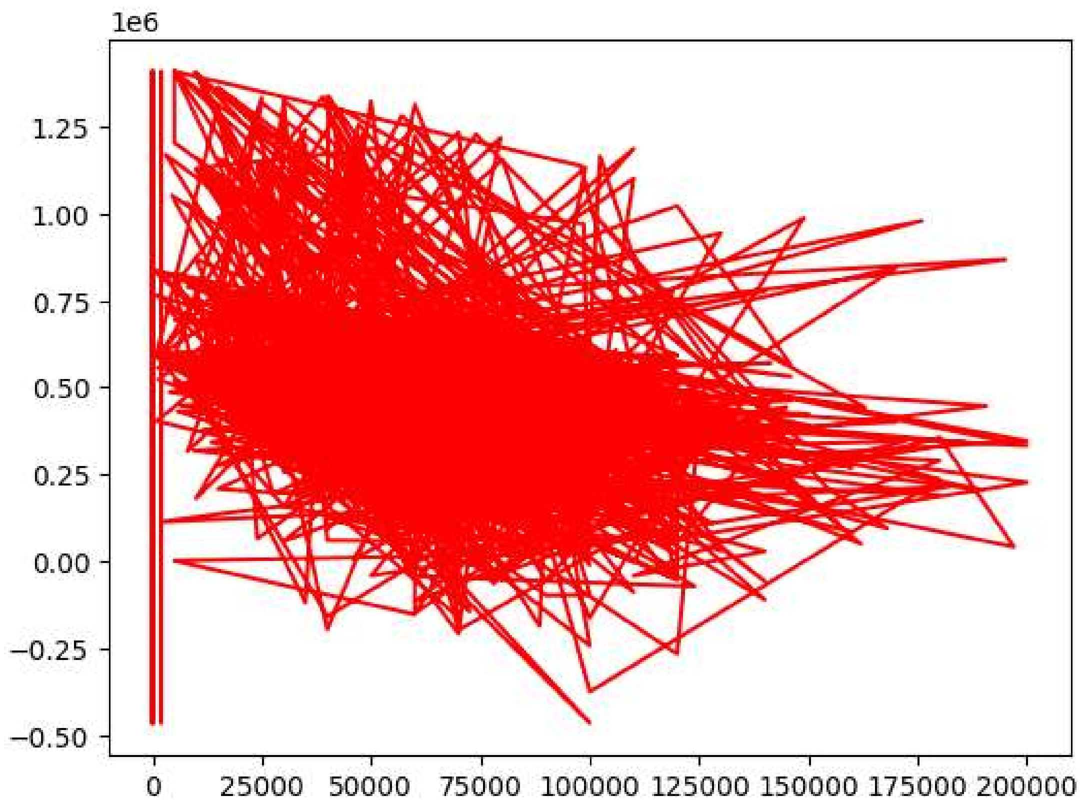
In above cell we fit the linear regression ml model on training dataset

In [38]:
```

regp=reg.predict(x_test)
```

In above cell we predict the value of selling price using trained model

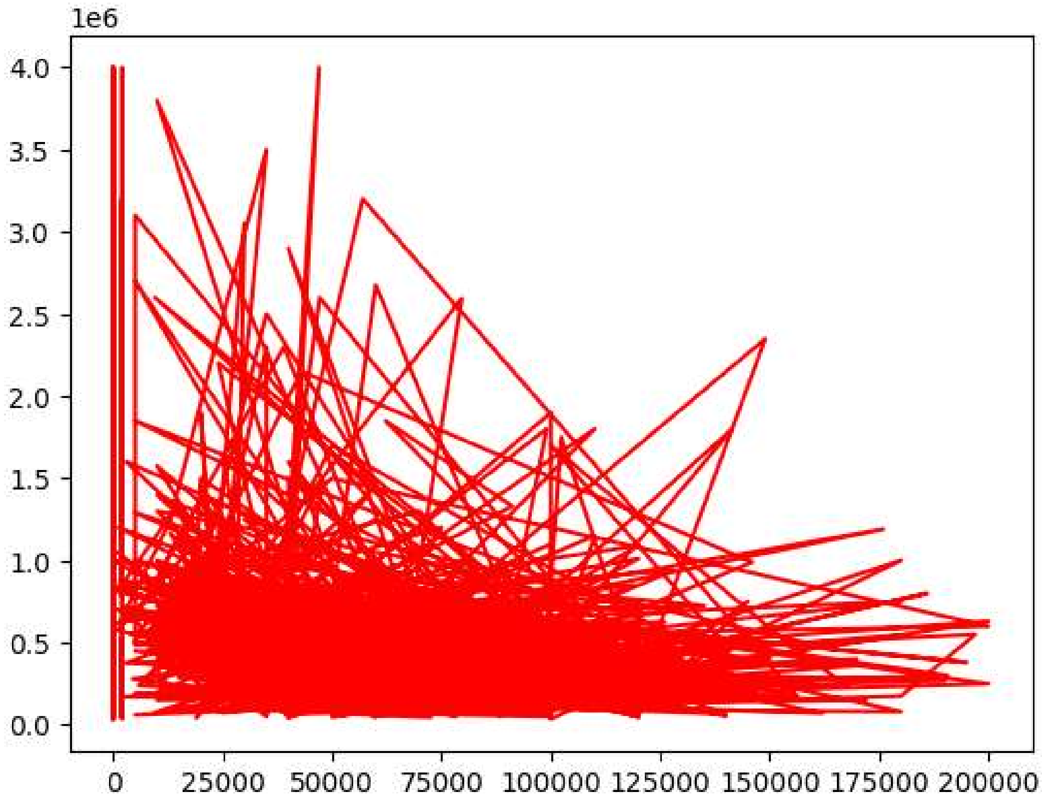
In [39]:
```
#Reshaping the predicted  array
regp
regp = np.array(regp).reshape(-1)
```

In [40]:
```
plt.plot(x_test, regp, color = 'red')
plt.show()
```



In [41]:

```
plt.plot(x_test, y_test, color = 'red')
plt.show()
```



In [42]:

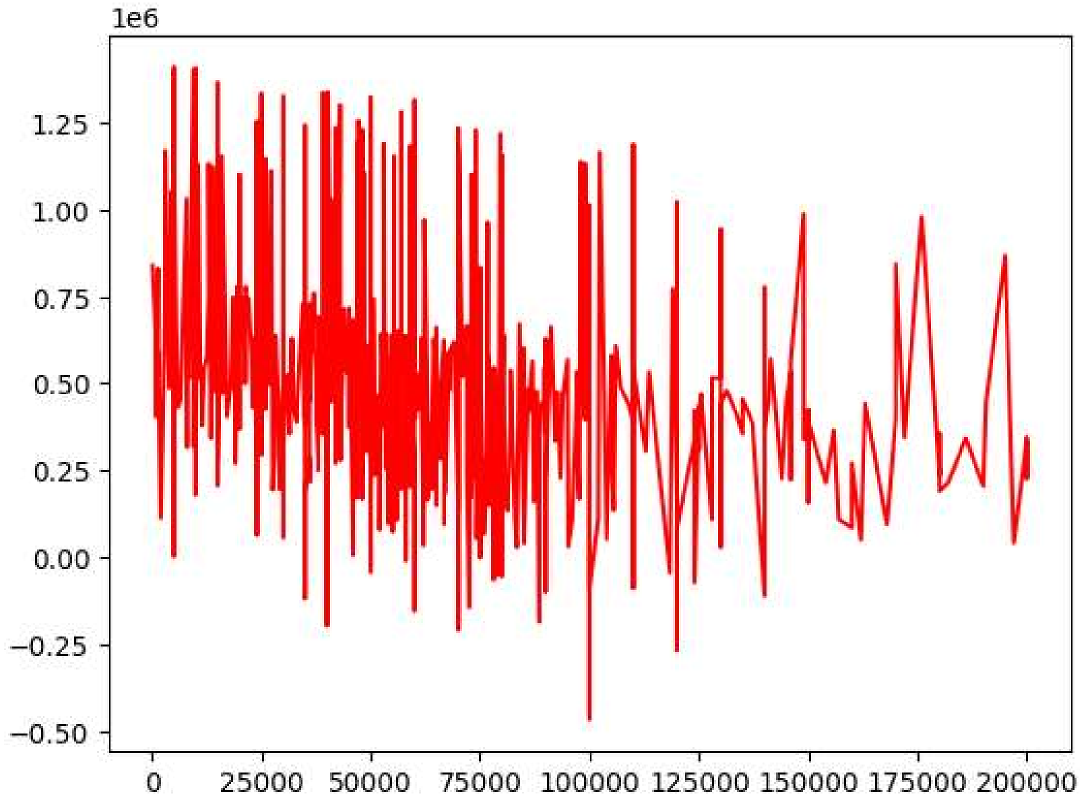
```
new = pd.concat([x_test.km_driven.reset_index(drop = True), pd.Series(regp)], a
new.sort_values(by='km_driven',inplace=True)
new
```

Out[42]:

	km_driven	0
180	101	839004.126027
907	1000	589981.077294
729	1000	764679.718474
983	1001	404166.107466
813	1010	597077.637472
...	...	...
702	195000	866733.281972
42	197000	43236.256674
781	200000	346750.753640
271	200000	227930.362645
208	200000	333243.558485

1054 rows × 2 columns

In [43]:
```
plt.plot(new['km_driven'], new[0],color= 'red')
plt.show()
```



In [44]:
```


rmse = np.sqrt(mean_squared_error(y_test, regp))
print("RMSE:", rmse)


```

```
RMSE: 318072.7053235516
```

In [ ]:
```

```