Here I am using the dataset only for assignment purpose. I am going to predict the price of the car using Linear Regression algorithm.

Used car Price Prediction

- This dataset contains information about used cars.
- Details of dataset is as follows:
    - name: different company name of cars
    - Year: purchase year of car.
    - Seling_Price: the price,owner wants to sell the car at.
    - km_driven: the distance travelled by the car in km.
    - fuel: Fuel type of the car
    - seller_type: Defines whether the seller is a dealer or an individual.
    - transmission: Defines whether the car is manual or automatic.
    - owner: Defines the number of owners the car has previously had.

- we are constructing the model for price prediction

In [1]:
```
# Import liberaries
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import warnings
warnings.filterwarnings('ignore')
```

In [2]:
```
# read the data
df = pd.read_csv('Used car details.csv')
df.head()
```

Out[2]:

	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 [3]:
```
df.shape
```

Out[3]:
```
(4340, 8)
```

In [4]:
```
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
```

In [5]:
```
df.isna().sum()
```

Out[5]:
```
name             0
year             0
selling_price    0
km_driven        0
fuel             0
seller_type      0
transmission     0
owner            0
dtype: int64
```

No null values found in data

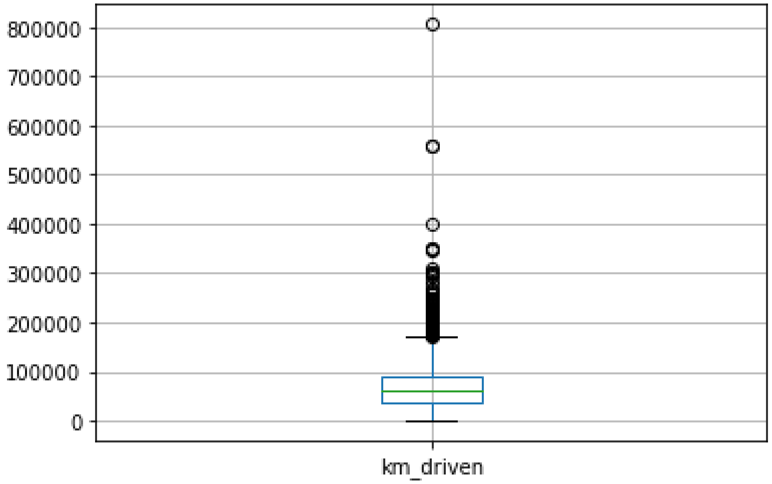
In [6]:
```
df.describe().T
```

Out[6]:

	count	mean	std	min	25%	50%	75%	max
year	4340.0	2013.090783	4.215344	1992.0	2011.00	2014.0	2016.0	2020.0
selling_price	4340.0	504127.311751	578548.736139	20000.0	208749.75	350000.0	600000.0	8900000.0
km_driven	4340.0	66215.777419	46644.102194	1.0	35000.00	60000.0	90000.0	806599.0

Here, the 75% selling_price is around 6 lacs and the maximum is around 90 lacs this indicates some outliers. also, in km driven 75% is 90k and max is around 8.6 lacs indicating outliers

In [7]:
```
#Lets plot the box plot to check the outliers of km driven
df.boxplot(column='km_driven')
plt.show()
```



In [8]:
```
##check the rows of outliers
df[df['km_driven']>500000]
```

Out[8]:

	name	year	selling_price	km_driven	fuel	seller_type	transmission	owner
525	Maruti SX4 S Cross DDiS 320 Delta	2016	665000	560000	Diesel	Dealer	Manual	First Owner
1243	Maruti Swift VXI BSIII	2009	250000	806599	Petrol	Dealer	Manual	First Owner
4184	Maruti SX4 S Cross DDiS 320 Delta	2016	665000	560000	Diesel	Dealer	Manual	First Owner

We can clearly see that only 3 values are present above 5 lacs.we need to remove that outliers

In [9]:
```
# drop the rows of outliers
df=df[df['km_driven']<500000].reset_index(drop=True)
df
```

Out[9]:

	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
...	...	...	...	...	...	...	...	...
4332	Hyundai i20 Magna 1.4 CRDi (Diesel)	2014	409999	80000	Diesel	Individual	Manual	Second Owner
4333	Hyundai i20 Magna 1.4 CRDi	2014	409999	80000	Diesel	Individual	Manual	Second Owner
4334	Maruti 800 AC BSIII	2009	110000	83000	Petrol	Individual	Manual	Second Owner
4335	Hyundai Creta 1.6 CRDi SX Option	2016	865000	90000	Diesel	Individual	Manual	First Owner
4336	Renault KWID RXT	2016	225000	40000	Petrol	Individual	Manual	First Owner

4337 rows × 8 columns

In [10]:
```
#let's check how many values lies in the selling_price more than 6 lacs
df[df['selling_price']>6e6]
```

Out[10]:

	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
3870	Audi RS7 2015-2019 Sportback Performance	2016	8900000	13000	Petrol	Dealer	Automatic	First Owner

Only 2 values this could cause the data to maybe fit to the wrong values and might not work with new data.

In [11]:
```
#Lets remove the rows of outliers
df=df[df['selling_price']<6e6].reset_index(drop=True)
df
```

Out[11]:

	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
...	...	...	...	...	...	...	...	...
4330	Hyundai i20 Magna 1.4 CRDi (Diesel)	2014	409999	80000	Diesel	Individual	Manual	Second Owner
4331	Hyundai i20 Magna 1.4 CRDi	2014	409999	80000	Diesel	Individual	Manual	Second Owner
4332	Maruti 800 AC BSIII	2009	110000	83000	Petrol	Individual	Manual	Second Owner
4333	Hyundai Creta 1.6 CRDi SX Option	2016	865000	90000	Diesel	Individual	Manual	First Owner
4334	Renault KWID RXT	2016	225000	40000	Petrol	Individual	Manual	First Owner

4335 rows × 8 columns

As now we can see the shape of the data is 4335x8 that means total 5 rows of outlirs are deleted

In [12]:
```
# Find unique values
print("Fuel unique values: ", df['fuel'].unique())

print("seller_type unique values: ", df['seller_type'].unique())

print("transmission unique values: ", df['transmission'].unique())

print("owner unique values: ", df['owner'].unique())
```

```
Fuel unique values:  ['Petrol' 'Diesel' 'CNG' 'LPG' 'Electric']
seller_type unique values:  ['Individual' 'Dealer' 'Trustmark Dealer']
transmission unique values:  ['Manual' 'Automatic']
owner unique values:  ['First Owner' 'Second Owner' 'Fourth & Above Owner' 'Third Owner'
 'Test Drive Car']
```

In [13]:
```
# make a column of car age
df['car_age'] = 2022 - df['year']
df['car_age']
```

Out[13]:
```
0       15
1       15
2       10
3        5
4        8
        ..
4330     8
4331     8
4332    13
4333     6
4334     6
Name: car_age, Length: 4335, dtype: int64
```

In [14]:
```
df.head()
```

Out[14]:

	name	year	selling_price	km_driven	fuel	seller_type	transmission	owner	car_age
0	Maruti 800 AC	2007	60000	70000	Petrol	Individual	Manual	First Owner	15
1	Maruti Wagon R LXI Minor	2007	135000	50000	Petrol	Individual	Manual	First Owner	15
2	Hyundai Verna 1.6 SX	2012	600000	100000	Diesel	Individual	Manual	First Owner	10
3	Datsun RediGO T Option	2017	250000	46000	Petrol	Individual	Manual	First Owner	5
4	Honda Amaze VX i-DTEC	2014	450000	141000	Diesel	Individual	Manual	Second Owner	8

In [15]:
```
# There is no need of year column, drop that column:

df.drop('year', inplace=True, axis=1)
df.head()
```

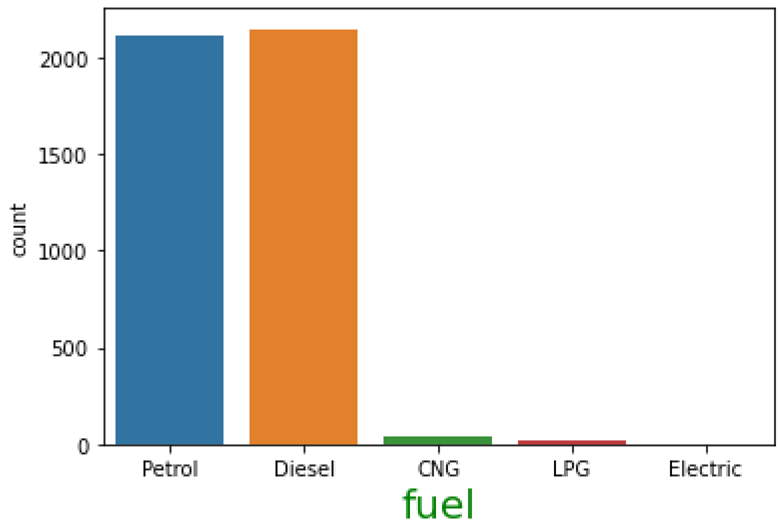
Out[15]:

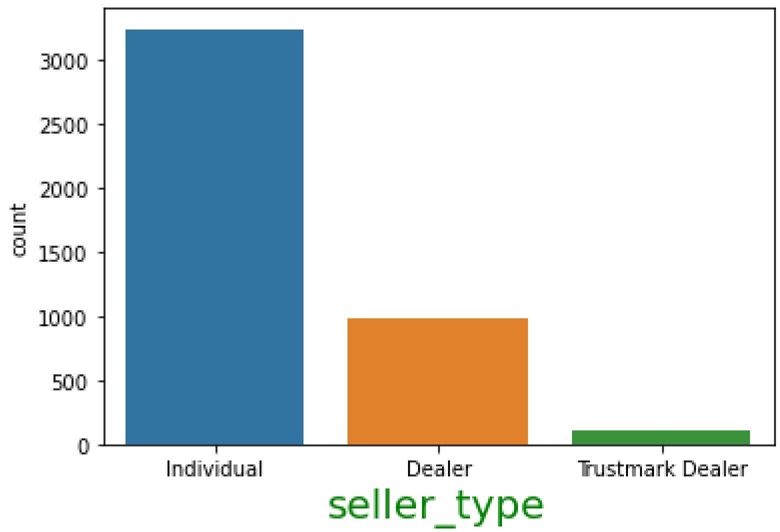
	name	selling_price	km_driven	fuel	seller_type	transmission	owner	car_age
0	Maruti 800 AC	60000	70000	Petrol	Individual	Manual	First Owner	15
1	Maruti Wagon R LXI Minor	135000	50000	Petrol	Individual	Manual	First Owner	15
2	Hyundai Verna 1.6 SX	600000	100000	Diesel	Individual	Manual	First Owner	10
3	Datsun RediGO T Option	250000	46000	Petrol	Individual	Manual	First Owner	5
4	Honda Amaze VX i-DTEC	450000	141000	Diesel	Individual	Manual	Second Owner	8

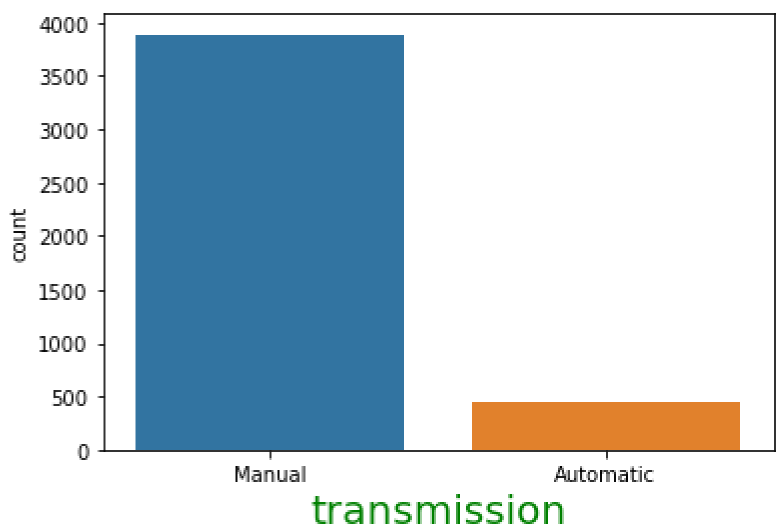
Exploratory data analysis

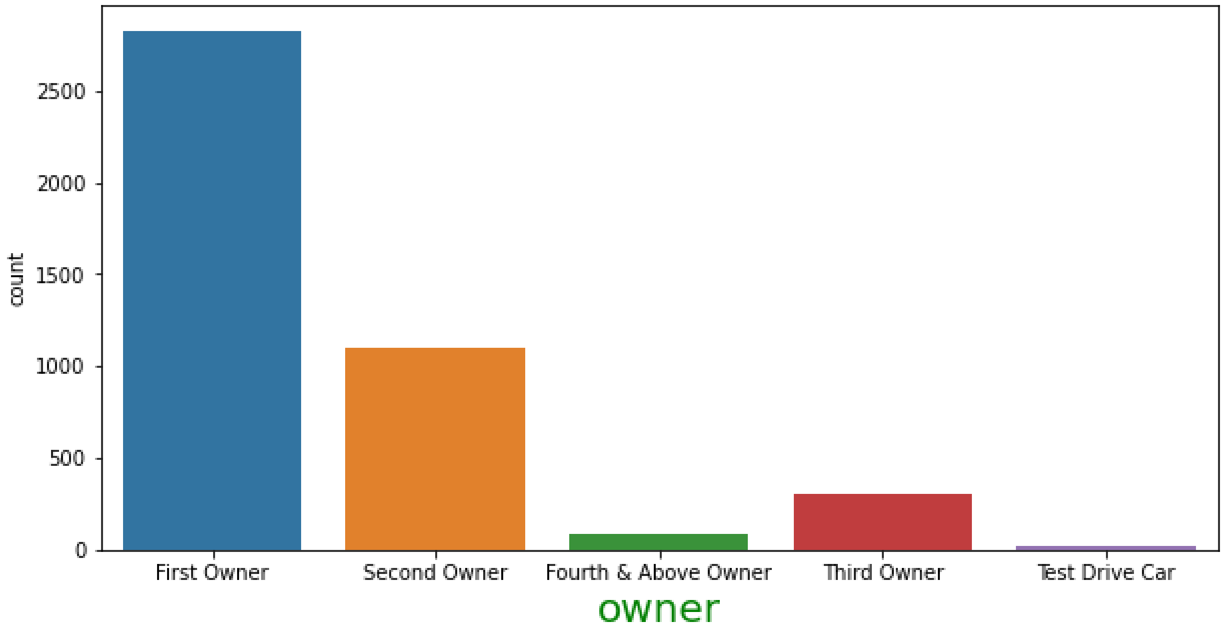
In [16]:
```
# Plot the graph
```

In [17]:
```
sns.countplot(x='fuel', data=df)
plt.xlabel('fuel', fontdict={'fontsize':20, 'color':'Green'})
plt.show()

sns.countplot(x='seller_type', data=df)
plt.xlabel('seller_type', fontdict={'fontsize':20, 'color':'Green'})
plt.show()

sns.countplot(x='transmission', data=df)
plt.xlabel('transmission', fontdict={'fontsize':20, 'color':'Green'})
plt.show()

plt.figure(figsize=(10,5))
sns.countplot(x='owner', data=df)
plt.xlabel('owner', fontdict={'fontsize':20, 'color':'Green'})
plt.show()
```



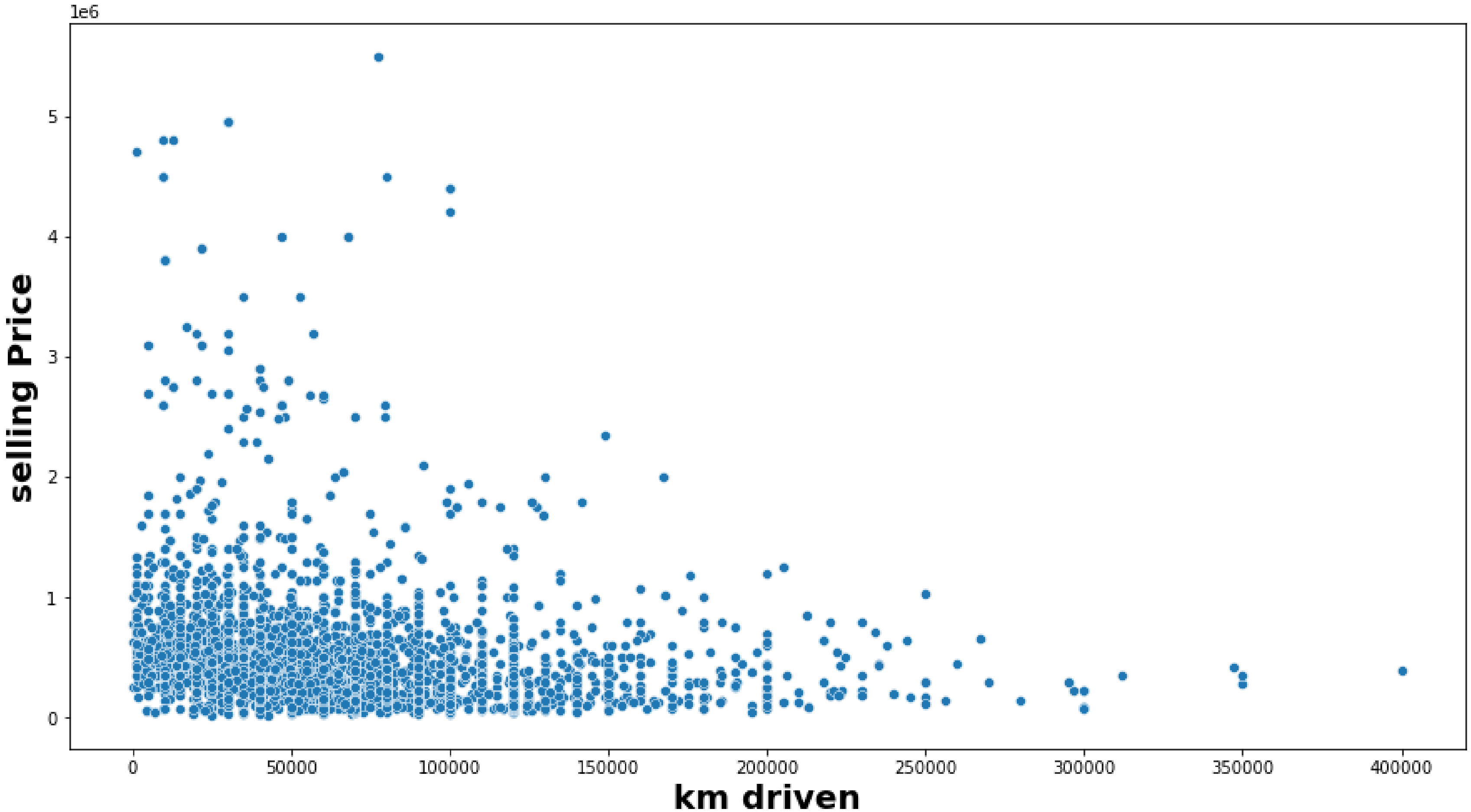

count
0
500
1000
1500
2000
2500
3000
Individual
Dealer
Trustmark Dealer
seller_type


count
0
500
1000
1500
2000
2500
3000
3500
4000
Manual
Automatic
transmission



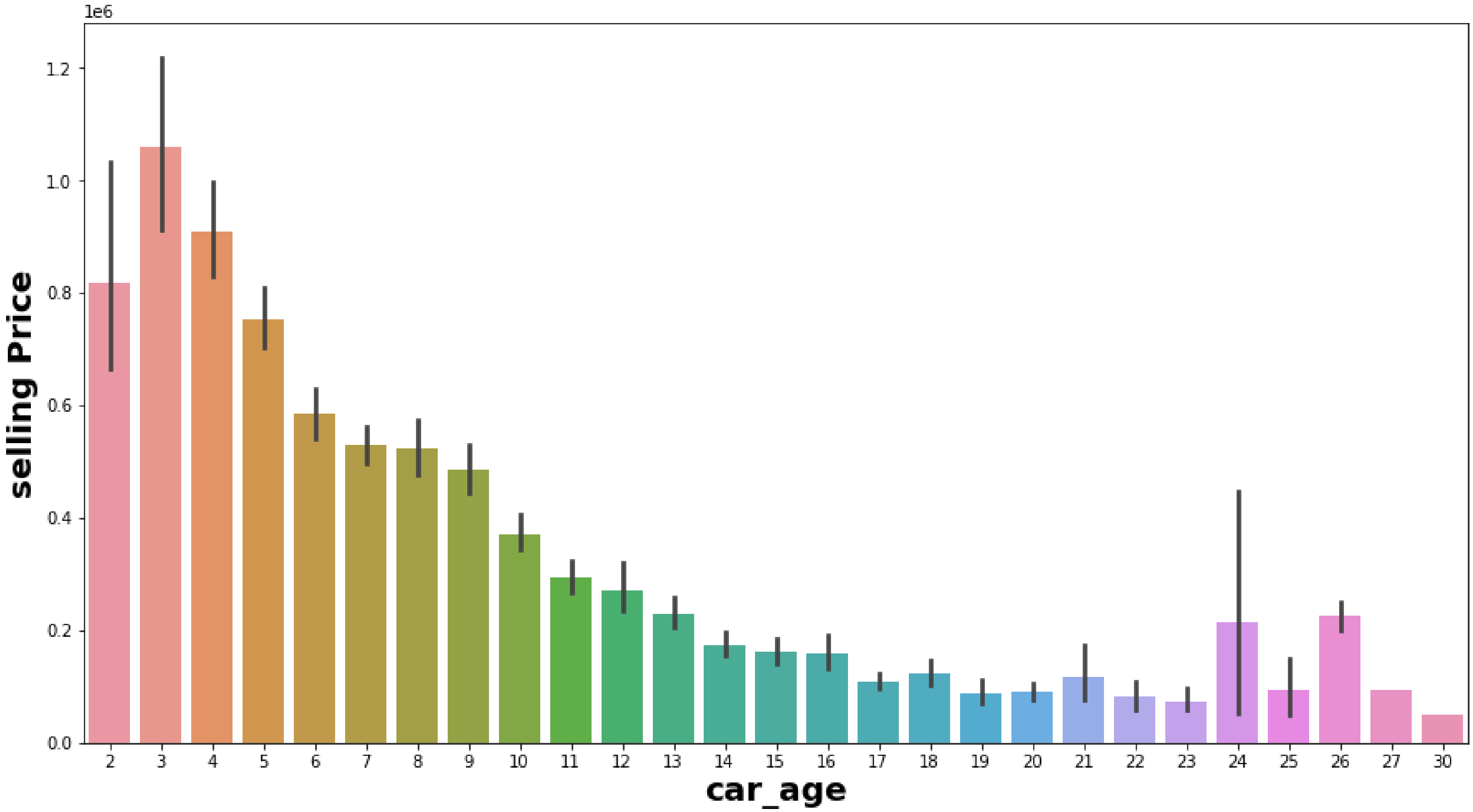
- Inference:
  - Majority of car use Petrol and Diesel as fuel
  - individual seller are more than other seller.
  - majority of vehicle transmission is mannual.
  - First owners are more who want to sell the car.

In [18]:
```
plt.figure(figsize=(15,8))
sns.scatterplot(data = df, x = "km_driven", y = "selling_price")
plt.xlabel("km driven", fontdict={'fontsize':20, 'color':'Black', 'fontweight':'bold'})
plt.ylabel("selling Price", fontdict={'fontsize':20, 'color':'Black', 'fontweight':'bold'})
plt.show()
```



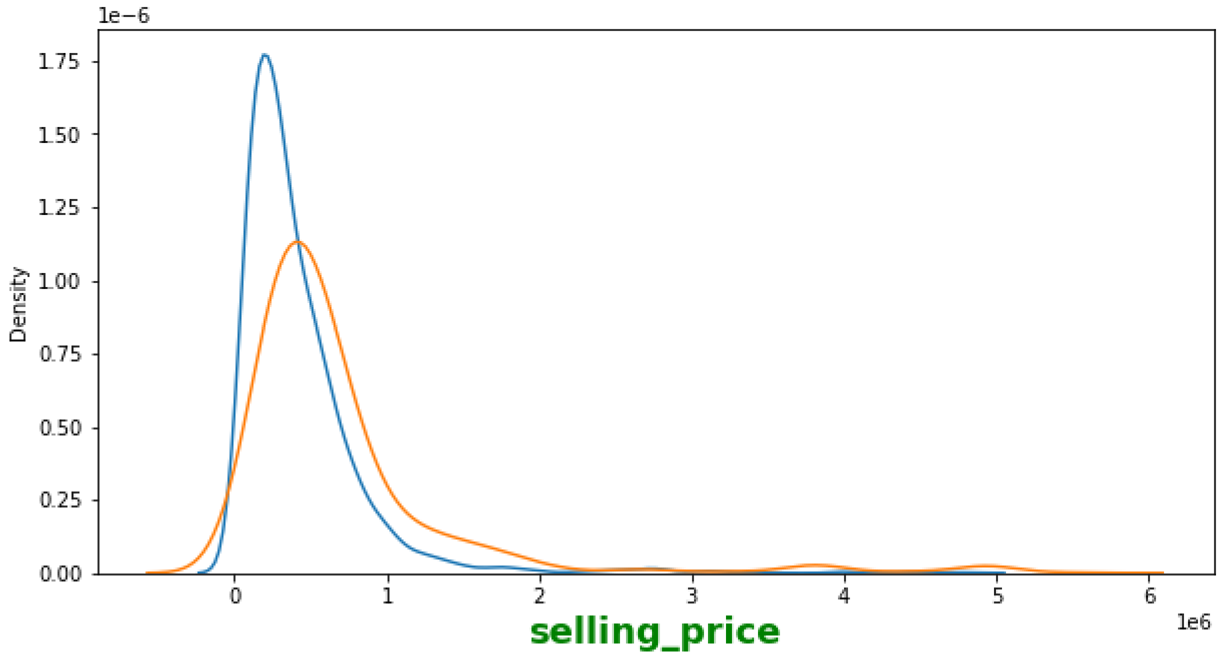
- Inference: Selling Price is inversly propotional to distance travelled by a vehicle.

In [19]:
```
plt.figure(figsize=(15,8))
sns.barplot(data = df, x = "car_age", y = "selling_price")
plt.xlabel("car_age", fontdict={'fontsize':20, 'color':'Black', 'fontweight':'bold'})
plt.ylabel("selling Price", fontdict={'fontsize':20, 'color':'Black', 'fontweight':'bold'})
plt.show()
```



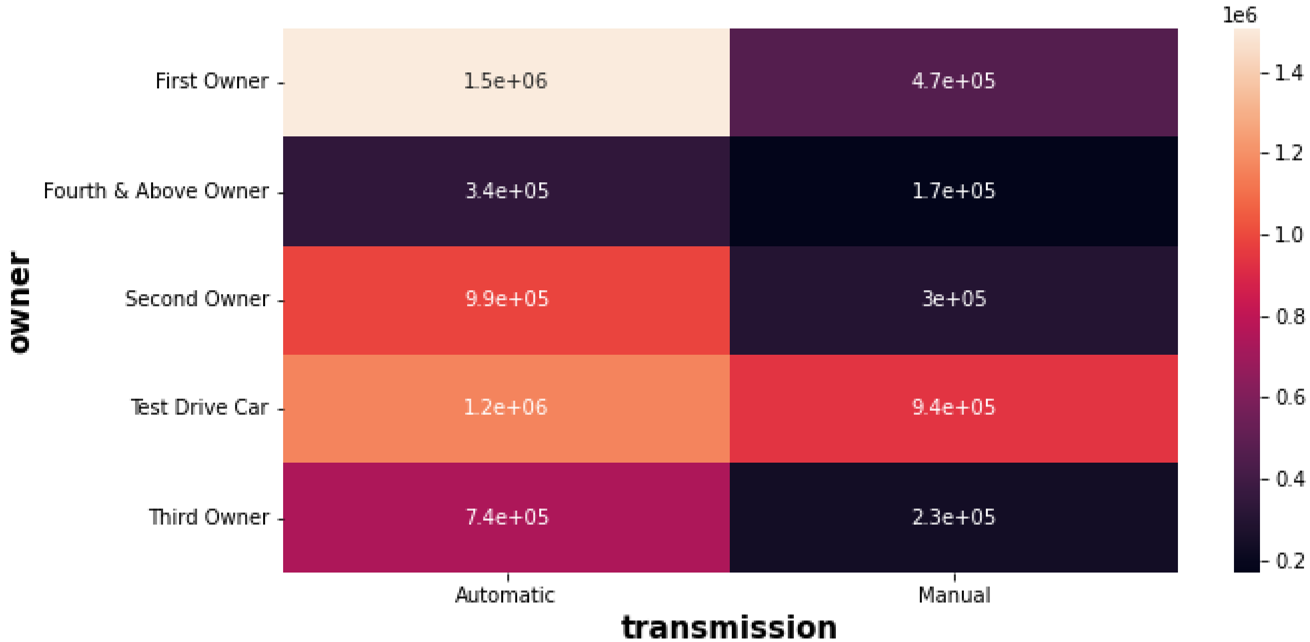
- Inference: Selling Price is inversly propotional to the age of vehicle.

In [20]:
```
plt.figure(figsize=(10,5))
sns.distplot(df[df['seller_type']=='Individual']['selling_price'],hist=False)
sns.distplot(df[df['seller_type']=='Dealer']['selling_price'],hist=False)
plt.xlabel("selling_price", fontdict={'fontsize':18, 'color':'green', 'fontweight':'bold'})

plt.show()
```



- Inference: From the above graph we can say that the density of individual seller_type is more than dealer.

In [21]:
```
df_1 =df.pivot_table(values='selling_price',index='owner',columns='transmission')
plt.figure(figsize=(10,5))
sns.heatmap(df_1,annot= True)
plt.xlabel("transmission", fontdict={'fontsize':15, 'color':'Black', 'fontweight':'bold'})
plt.ylabel("owner", fontdict={'fontsize':15, 'color':'Black', 'fontweight':'bold'})
plt.show()
```



- Inference :automatic & first owner has higher prices and manual & Fourth and above owners have least price.

In [22]:
```
df_2=df.pivot_table(values='selling_price',index='owner',columns='seller_type')
plt.figure(figsize=(10,5))
sns.heatmap(df_2,annot= True)
plt.xlabel("seller_type", fontdict={'fontsize':15, 'color':'Black', 'fontweight':'bold'})
plt.ylabel("owner", fontdict={'fontsize':15, 'color':'Black', 'fontweight':'bold'})
plt.show()
```

- Inference :

```
  1)we can clearly see from the above map that, trustmark dealer has more price than individual and
dealer.
  2)Test drive car has high price in every seller type
  3)for dealer and individual only fourth & above owner car price is low
```

In [23]:

```
# encode the categorical variable columns:
df.replace({'fuel':{'Petrol':0,'Diesel':1,'CNG':2,'LPG':3,'Electric':4}},inplace=True)

df.replace({'seller_type':{'Dealer':0,'Individual':1,'Trustmark Dealer':2}},inplace=True)

df.replace({'owner':{"Test Drive Car":0,"First Owner":1,"Second Owner":2,"Third Owner":3,"Fourth & Above Owner":

df.rename(columns={'transmission':'is_automatic'}, inplace=True)
df.replace({'is_automatic':{'Manual':0,'Automatic':1}},inplace=True)
```

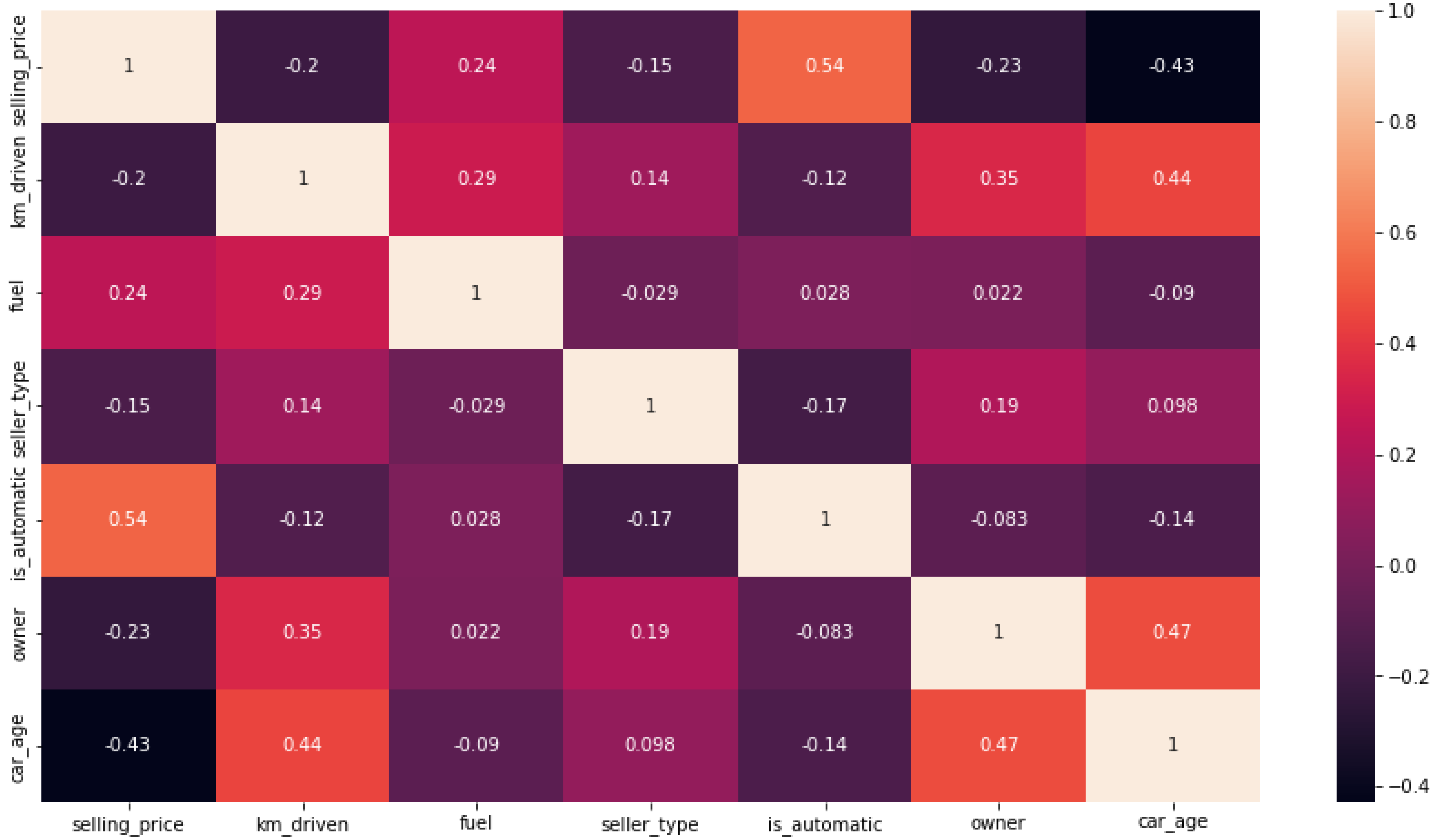
In [24]:

```
# Let's check the replacement
df.head()
```

Out[24]:

	name	selling_price	km_driven	fuel	seller_type	is_automatic	owner	car_age
0	Maruti 800 AC	60000	70000	0	1	0	1	15
1	Maruti Wagon R LXI Minor	135000	50000	0	1	0	1	15
2	Hyundai Verna 1.6 SX	600000	100000	1	1	0	1	10
3	Datsun RediGO T Option	250000	46000	0	1	0	1	5
4	Honda Amaze VX i-DTEC	450000	141000	1	1	0	2	8

In [25]:
```
# Check the correlation of variables
plt.figure(figsize=(15,8))
sns.heatmap(df.corr(), annot= True)
plt.show()
```



- Inference: There is high inverse correlation between
  - selling price and car age
  - selling price and owner
  - selling price and km driven
- https://www.investopedia.com/terms/i/inverse-correlation.asp (https://www.investopedia.com/terms/i/inverse-correlation.asp)

In [26]:

```
# shorten the length of name of car to get some uniformity.
df['name']=df['name'].str.split().str.slice(0,3).str.join(' ')
df['name']
```

Out[26]:

```
0           Maruti 800 AC
1          Maruti Wagon R
2       Hyundai Verna 1.6
3         Datsun RediGO T
4          Honda Amaze VX
              ...
4330    Hyundai i20 Magna
4331    Hyundai i20 Magna
4332        Maruti 800 AC
4333    Hyundai Creta 1.6
4334     Renault KWID RXT
Name: name, Length: 4335, dtype: object
```

Model Building

In [27]:

```
# split the data into X and Y
X=df.drop(columns='selling_price')
Y=df['selling_price']
```

In [28]:
```
# import necessary liberaries
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.preprocessing import OneHotEncoder
from sklearn.metrics import mean_squared_error
from sklearn.pipeline import make_pipeline
from sklearn.compose import make_column_transformer
from sklearn import metrics
```

In [29]:
```
# manage the categorical data using one hot encoder
ohe=OneHotEncoder()
ohe.fit(X[['name','fuel','seller_type','is_automatic','owner']])
```

Out[29]: OneHotEncoder()

In [30]:
```
col_transform=make_column_transformer((OneHotEncoder(categories=ohe.categories_),['name','fuel','seller_type','i
```

In [46]:
```
X_train,X_test,Y_train,Y_test=train_test_split(X,Y,test_size=0.2,random_state=13)
reg=LinearRegression()
pipe=make_pipeline(col_transform,reg)
pipe.fit(X_train,Y_train)
y_pred=pipe.predict(X_test)
error=mean_squared_error(Y_test,y_pred)
rmse=np.sqrt(error)
```

In [47]:
```
rmse
```

Out[47]: 236872.96691171892

In [57]:
```
# find r2 score
regressor = LinearRegression()
pipe=make_pipeline(col_transform,reg)
pipe.fit(X_train, Y_train)
test_pred = pipe.predict(X_test)
err_score = metrics.r2_score(Y_test,test_pred)
err_score
```

Out[57]:
```
0.8364054187663195
```

In [58]:
```
pipe.predict(pd.DataFrame([['Datsun RediGO T',46000,0,1,0,1,5]],columns=['name','km_driven','fuel','seller_type'
```

Out[58]:
```
array([234537.54459636])
```

- predicted price : 234537
- Expected price is 250000

- The difference in predicted price and expected price is due to the less accuracy of model

I apply Linear Regression algorithm to this model for assignment purpose only.