In [1]:
```
import warnings
warnings.filterwarnings('ignore')
```

In [2]:
```
import numpy as np, pandas as pd, matplotlib.pyplot as plt, seaborn as sns
%matplotlib inline
```

In [3]:
```
cars_data = pd.read_csv(r'C:\Users\WNasir\Desktop\datasets\Car_sale_ads.csv')
```

In [4]:
```
cars_data.shape
```

Out[4]:
```
(208304, 25)
```

Quite enough data for ML standards

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

Out[5]:

	Index	Price	Currency	Condition	Vehicle_brand	Vehicle_model	Vehicle_version	Vehicle_g
0	0	86200	PLN	New	Abarth	595	NaN	
1	1	43500	PLN	Used	Abarth	Other	NaN	
2	2	44900	PLN	Used	Abarth	500	NaN	
3	3	39900	PLN	Used	Abarth	500	NaN	
4	4	97900	PLN	New	Abarth	595	NaN	

5 rows × 25 columns

In [6]:
```
cars_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 208304 entries, 0 to 208303
Data columns (total 25 columns):
 #   Column                  Non-Null Count   Dtype  
---  ------                  --------------   -----  
 0   Index                   208304 non-null  int64  
 1   Price                   208304 non-null  int64  
 2   Currency                208304 non-null  object 
 3   Condition               208304 non-null  object 
 4   Vehicle_brand           208304 non-null  object 
 5   Vehicle_model           208304 non-null  object 
 6   Vehicle_version         138082 non-null  object 
 7   Vehicle_generation      147860 non-null  object 
 8   Production_year         208304 non-null  int64  
 9   Mileage_km              207321 non-null  float64
 10  Power_HP                207661 non-null  float64
 11  Displacement_cm3        206338 non-null  float64
 12  Fuel_type               208304 non-null  object 
 13  CO2_emissions           94047 non-null   float64
 14  Drive                   193228 non-null  object 
 15  Transmission            207825 non-null  object 
 16  Type                    208304 non-null  object 
 17  Doors_number            206817 non-null  float64
 18  Colour                  208304 non-null  object 
 19  Origin_country          118312 non-null  object 
 20  First_owner             65094 non-null   object 
 21  First_registration_date 86445 non-null   object 
 22  Offer_publication_date  208304 non-null  object 
 23  Offer_location          208304 non-null  object 
 24  Features                208304 non-null  object 
dtypes: float64(5), int64(3), object(17)
memory usage: 39.7+ MB
```

In [7]:
```
cars_data.isna().sum()
```

Out[7]:
```
Index                          0
Price                          0
Currency                       0
Condition                      0
Vehicle_brand                  0
Vehicle_model                  0
Vehicle_version            70222
Vehicle_generation         60444
Production_year                0
Mileage_km                   983
Power_HP                     643
Displacement_cm3            1966
Fuel_type                      0
CO2_emissions             114257
Drive                      15076
Transmission                 479
Type                           0
Doors_number                1487
Colour                         0
Origin_country             89992
First_owner               143210
First_registration_date   121859
Offer_publication_date         0
Offer_location                 0
Features                       0
dtype: int64
```

In [8]:
```
cars_data.describe().T
```

Out[8]:

	count	mean	std	min	25%	50%	75'
Index	208304.0	104151.500000	6.013233e+04	0.0	52075.75	104151.5	156227.2
Price	208304.0	63053.833714	8.665967e+04	500.0	17800.00	35700.0	75990.0
Production_year	208304.0	2012.098241	6.998414e+00	1915.0	2008.00	2013.0	2017.0
Mileage_km	207321.0	150276.763960	2.937447e+06	1.0	53000.00	144566.0	206000.0
Power_HP	207661.0	151.836281	7.768355e+01	1.0	105.00	136.0	172.0
Displacement_cm3	206338.0	1882.567147	7.296097e+02	400.0	1461.00	1798.0	1997.0
CO2_emissions	94047.0	319156.381107	7.291396e+07	1.0	120.00	140.0	164.0
Doors_number	206817.0	4.637138	7.685590e-01	1.0	5.00	5.0	5.0

Standard deviations are quite large, mean data is very much skewed

Preprocessing other then numeric features

In [9]:
```python
cars_data.select_dtypes(include='object').nunique()
```

Out[9]:
```
Currency                      2
Condition                     2
Vehicle_brand               108
Vehicle_model              1203
Vehicle_version           19056
Vehicle_generation          569
Fuel_type                     8
Drive                         5
Transmission                  2
Type                          9
Colour                       14
Origin_country               37
First_owner                   1
First_registration_date    8441
Offer_publication_date       41
Offer_location            13635
Features                 177211
dtype: int64
```

- Take a bird's eye view on unique values

In [10]:
```python
for label, content in cars_data.items():
    if not pd.api.types.is_numeric_dtype(content):
        print(label)
        print(len(pd.unique(content)))
        print(pd.unique(content))
        print('*' * 100)
```

```
Currency
2
['PLN' 'EUR']
*************************************************************************
***************************
Condition
2
['New' 'Used']
*************************************************************************
***************************
Vehicle_brand
108
['Abarth' 'Acura' 'Aixam' 'Alfa Romeo' 'Alpine' 'Aston Martin' 'Audi'
 'Austin' 'Autobianchi' 'Baic' 'Bentley' 'BMW' 'Buick' 'Cadillac'
 'Casalini' 'Chatenet' 'Chevrolet' 'Chrysler' 'Citroën' 'Cupra' 'Dacia'
 'Daewoo' 'Daihatsu' 'DFSK' 'DKW' 'Dodge' 'DS Automobiles' 'FAW' 'Ferrar
i'
 'Fiat' 'Ford' 'Gaz' 'GMC' 'Grecav' 'Honda' 'Hummer' 'Hyundai' 'Infiniti'
 'Isuzu' 'Iveco' 'Jaguar' 'Jeep' 'Kia' 'Lada' 'Lamborghini' 'Lancia'
```

- As the above cell shows that some features have too many unique values so it is quite impossible to encode them
- Moreover some columns have extra information which make our model more complex

- So a better approach is to drop them before further preprocessing

creates a copy of data

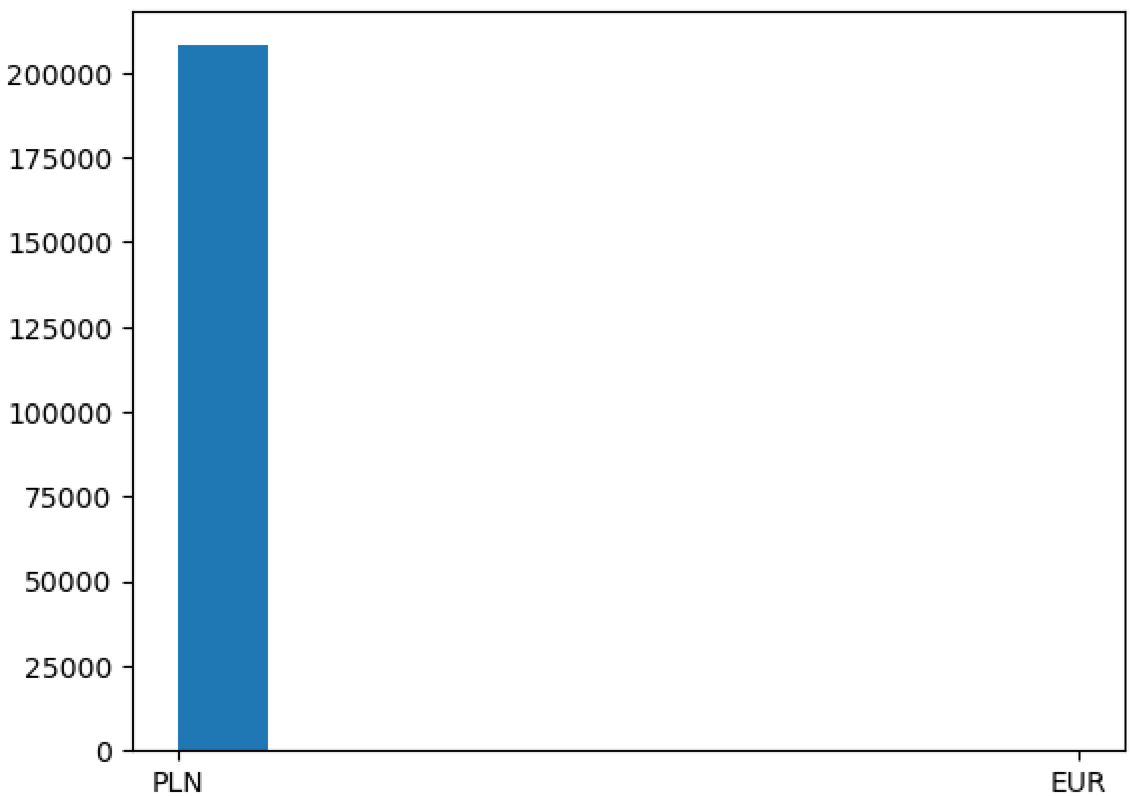
In [11]:
```
new_data = cars_data.copy()
```

In [12]:
```
cols = ['Index', 'Vehicle_model', 'Vehicle_version', 'Vehicle_generation', 'C
       'Offer_publication_date', 'Offer_location', 'Features', 'First_owner']
for i in cols:
    new_data.drop(i, axis=1, inplace=True)
```

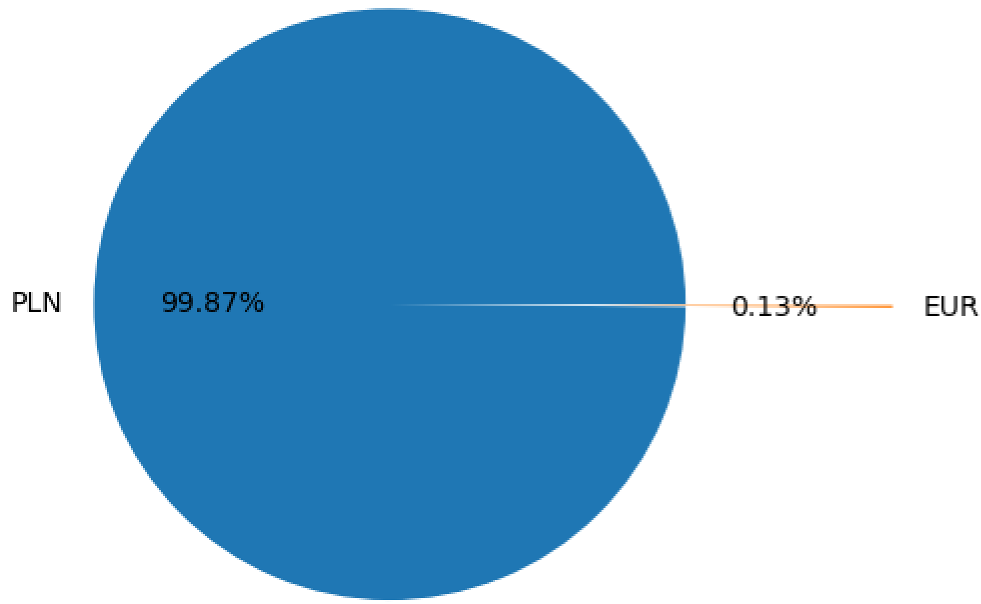
In [13]:
```
new_data.shape
```

Out[13]: (208304, 14)

In [14]:
```
plt.hist(new_data['Currency'])
plt.show()
```



In [15]:
```
plt.pie(x=new_data['Currency'].value_counts(), labels=pd.unique(new_data['Cur
plt.show()
```



In [16]:
```
new_data.loc[new_data['Currency'] == 'EUR']
```

Out[16]:

	Price	Currency	Condition	Vehicle_brand	Production_year	Mileage_km	Power_HP	D
141	18448	EUR	New	Aixam	2021	1.0	12.0	
142	17731	EUR	New	Aixam	2021	1.0	12.0	
143	14143	EUR	New	Aixam	2021	1.0	8.0	
144	13426	EUR	New	Aixam	2021	1.0	4.0	
152	9673	EUR	New	Aixam	2021	1.0	8.0	
...	...	...	...	...	...	...	...	
203703	28500	EUR	Used	Volvo	2017	18000.0	367.0	
208176	18900	EUR	Used	Volvo	2015	115000.0	235.0	
208205	7200	EUR	Used	Volvo	2017	54000.0	120.0	
208232	8900	EUR	Used	Volvo	2016	79000.0	163.0	
208281	12500	EUR	Used	Wartburg	1960	96000.0	38.0	

270 rows × 14 columns

Prices are mentioned in either currency, we can drop those currencies mentioned in Euros or we can convert them into PLNs and converting them is a good approach

In [17]:
```
new_data['Price_'] = new_data['Price'] * (new_data['Currency'].apply(lambda x
```

In [18]:
```
4.41 * 18448
```

Out[18]:
```
81355.68000000001
```

In [19]:
```

new_data['Price_'].loc[new_data['Currency'] == 'EUR']
```

Out[19]:
```
141        81355.68
142        78193.71
143        62370.63
144        59208.66
152        42657.93
             ...
203703    125685.00
208176     83349.00
208205     31752.00
208232     39249.00
208281     55125.00
Name: Price_, Length: 270, dtype: float64
```

Now drop the previous Price column and Currency column, because now they are useless

In [20]:
```
new_data.drop(['Price', 'Currency'], axis=1, inplace=True)
```

In [21]:
```
new_data.shape
```

Out[21]:
```
(208304, 13)
```

What cars' brands our data have

In [22]:
```
new_data['Vehicle_brand'].unique()
```

Out[22]:
```
array(['Abarth', 'Acura', 'Aixam', 'Alfa Romeo', 'Alpine', 'Aston Martin',
       'Audi', 'Austin', 'Autobianchi', 'Baic', 'Bentley', 'BMW', 'Buick',
       'Cadillac', 'Casalini', 'Chatenet', 'Chevrolet', 'Chrysler',
       'Citroën', 'Cupra', 'Dacia', 'Daewoo', 'Daihatsu', 'DFSK', 'DKW',
       'Dodge', 'DS Automobiles', 'FAW', 'Ferrari', 'Fiat', 'Ford', 'Gaz',
       'GMC', 'Grecav', 'Honda', 'Hummer', 'Hyundai', 'Infiniti', 'Isuzu',
       'Iveco', 'Jaguar', 'Jeep', 'Kia', 'Lada', 'Lamborghini', 'Lancia',
       'Land Rover', 'Lexus', 'Ligier', 'Lincoln', 'Lotus', 'MAN',
       'Warszawa', 'Maserati', 'Maybach', 'Mazda', 'McLaren',
       'Mercedes-Benz', 'Mercury', 'MG', 'Microcar', 'MINI', 'Mitsubishi',
       'Moskwicz', 'Nissan', 'NSU', 'Nysa', 'Oldsmobile', 'Opel', 'Inny',
       'Toyota', 'Tata', 'Uaz', 'Żuk', 'Trabant', 'Suzuki', 'Volvo',
       'Volkswagen', 'Subaru', 'Zastava', 'SsangYong', 'Saab', 'Plymouth',
       'Rolls-Royce', 'Renault', 'Peugeot', 'RAM', 'Triumph', 'Rover',
       'Porsche', 'Wołga', 'Tarpan', 'Zaporożec', 'Polonez', 'Pontiac',
       'Santana', 'Saturn', 'Scion', 'Seat', 'Škoda', 'Smart', 'Syrena',
       'Talbot', 'Tavria', 'Tesla', 'Vanderhall', 'Vauxhall', 'Wartburg'],
      dtype=object)
```

In [23]:
```
new_data.head()
```

Out[23]:

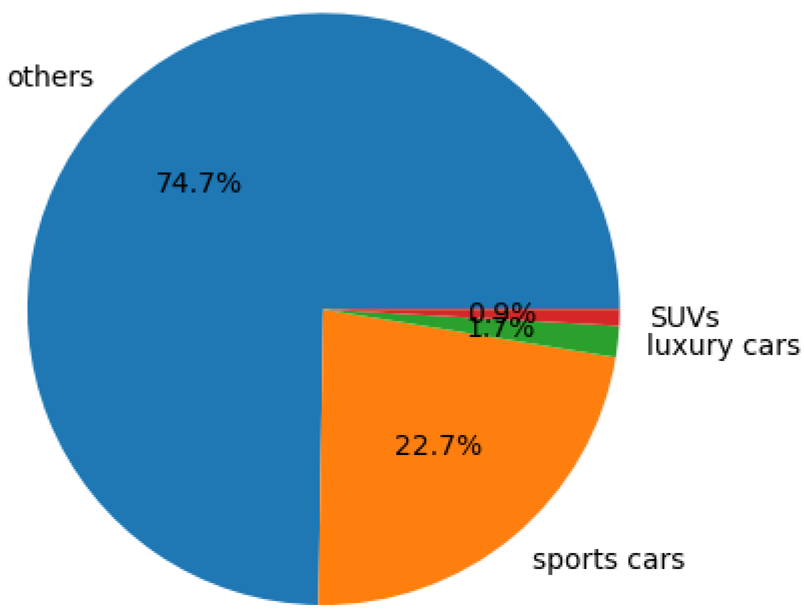
	Condition	Vehicle_brand	Production_year	Mileage_km	Power_HP	Displacement_cm3	Fuel_
0	New	Abarth	2021	1.0	145.0	1400.0	Gas
1	Used	Abarth	1974	59000.0	75.0	1100.0	Gas
2	Used	Abarth	2018	52000.0	180.0	1368.0	Gas
3	Used	Abarth	2012	29000.0	160.0	1368.0	Gas
4	New	Abarth	2021	600.0	165.0	1368.0	Gas

Vehicle Brands would definately impact our data but it has over one huundred values so an intutive approach is to recreate this column

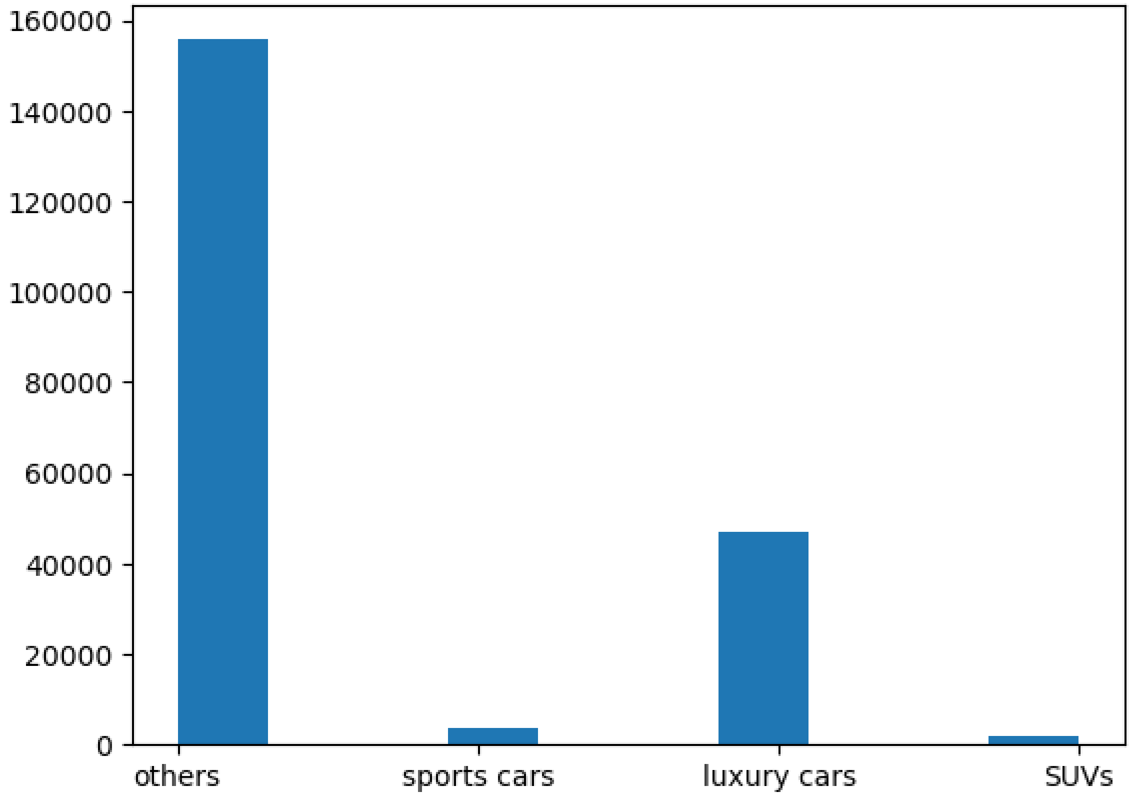
In [24]:
```
def model_sorter(brand_name):
    if brand_name in ['Alfa Romeo', 'Aston Martin', 'Autobianchi', 'Infiniti'
        return 'sports cars'
    elif brand_name in ['Audi', 'BMW', 'Buick', 'Cadillac', 'Rolls-Royce' 'Ja
        return 'luxury cars'
    elif brand_name in ['GMC', 'Hummer', 'Isuze', 'Jeep', 'MG', 'Skoda']:
        return 'SUVs'
    else:
        return 'others'

new_data['Vehicle_brand'] = new_data['Vehicle_brand'].apply(model_sorter)
```

In [25]:
```
plt.pie(x=new_data['Vehicle_brand'].value_counts(), labels=pd.unique(new_data
plt.show()
```



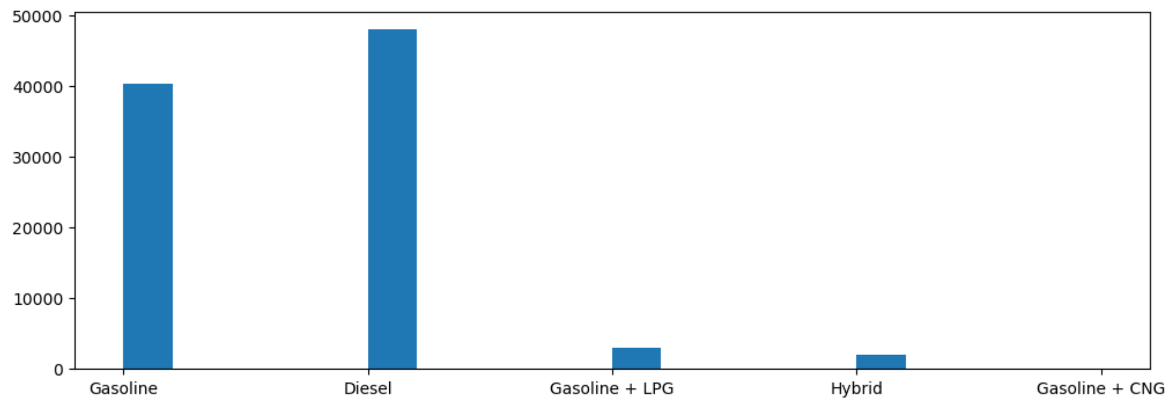
In [26]:
```
plt.hist(new_data['Vehicle_brand'])
plt.show()
```

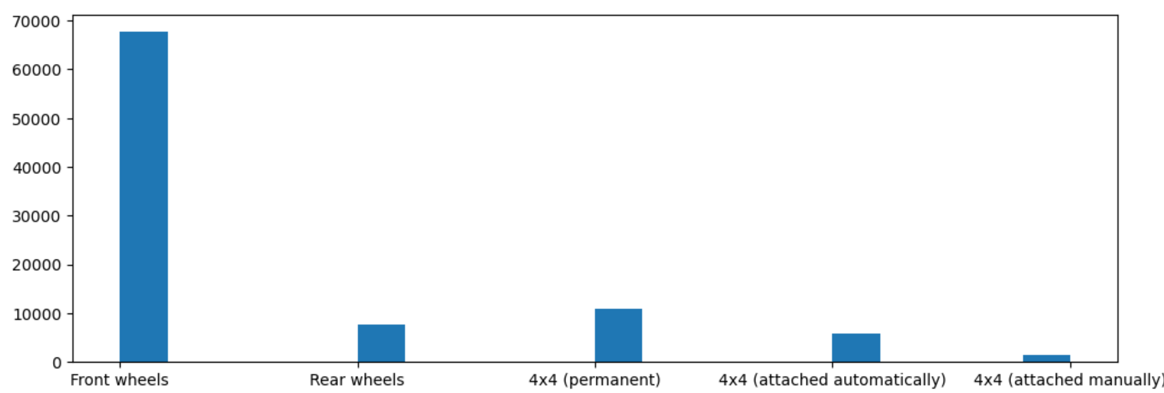


creating a new dataframe for ploting

In [27]:
```
plot_df = new_data.dropna()
```

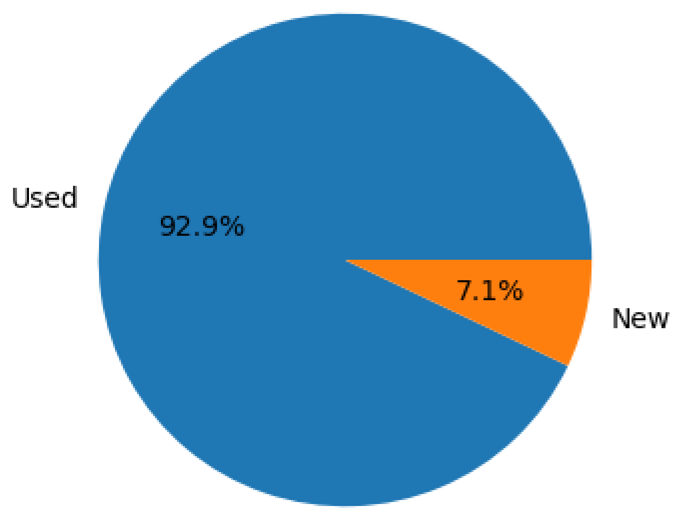
In [28]:
```
cols = ['Condition', 'Fuel_type', 'Drive', 'Transmission']
# fig, ax = plt.subplots(nrows=4, ncols=1, figsize=(30, 11))
# ax = ax.ravel()
for col in cols:
    plt.figure(figsize=(12, 4))
    plt.hist(x= plot_df[col], bins=20)
    plt.show()
#     sns.boxplot(data=cars_data, x=col, ax=ax[i], estimator = cars_data.mean,
```

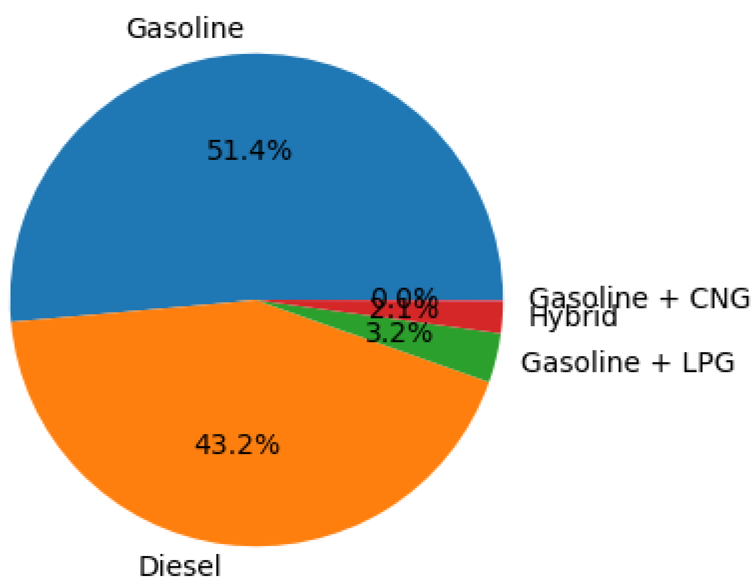


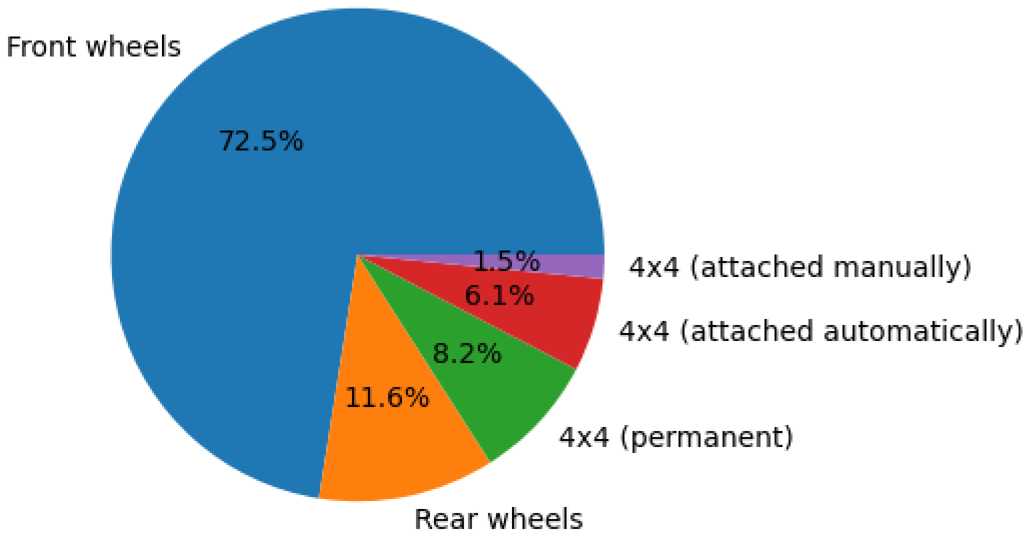


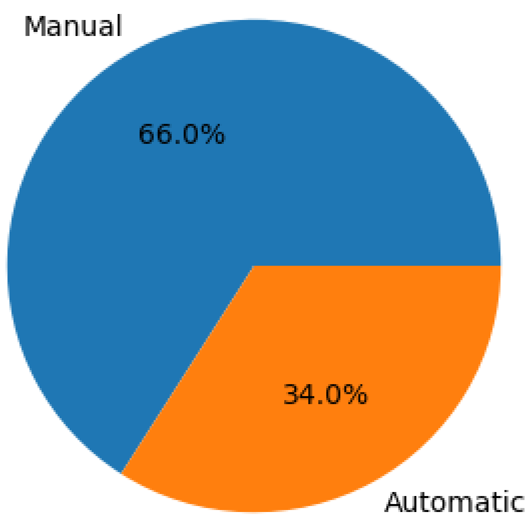

60000
50000
40000
30000
20000
10000
0
Manual
Automatic

In [29]:
```
cols = ['Condition', 'Fuel_type', 'Drive', 'Transmission']
for col in cols:
    plt.figure(figsize=(12, 4))
    plt.pie(x=plot_df[col].value_counts(), labels=pd.unique(plot_df[col]), au
    plt.show()
```



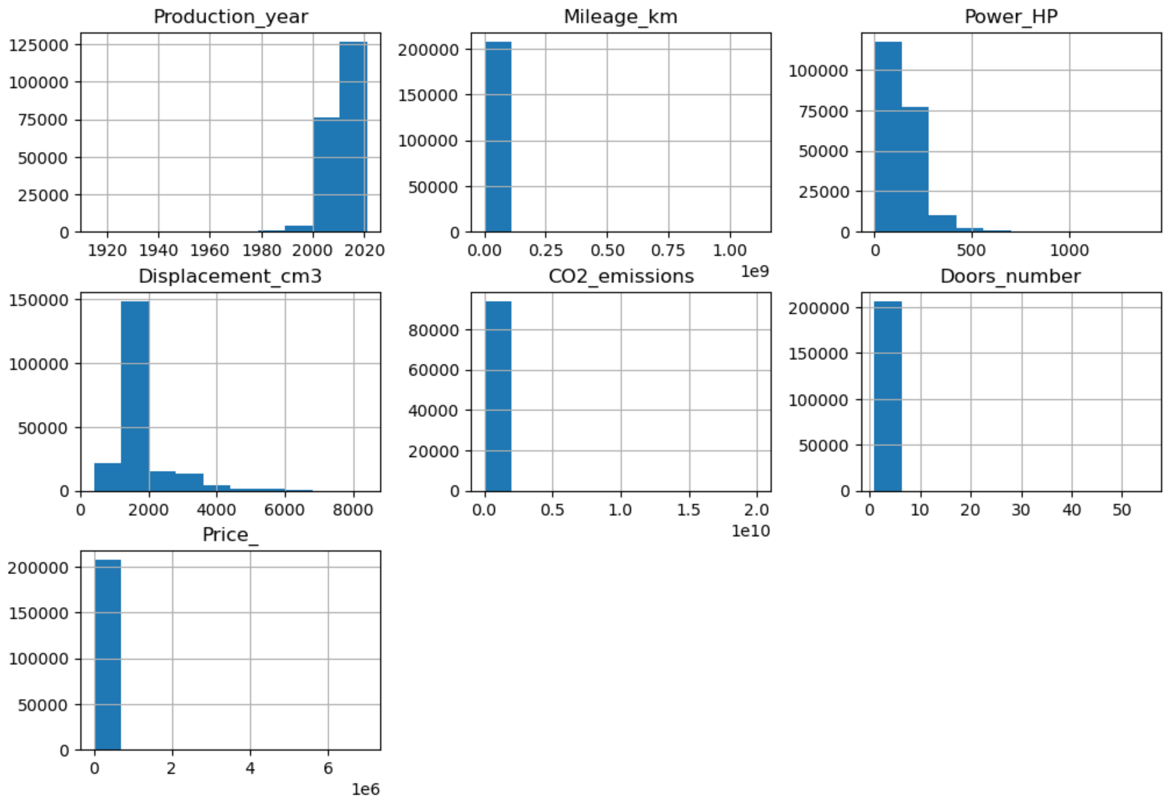




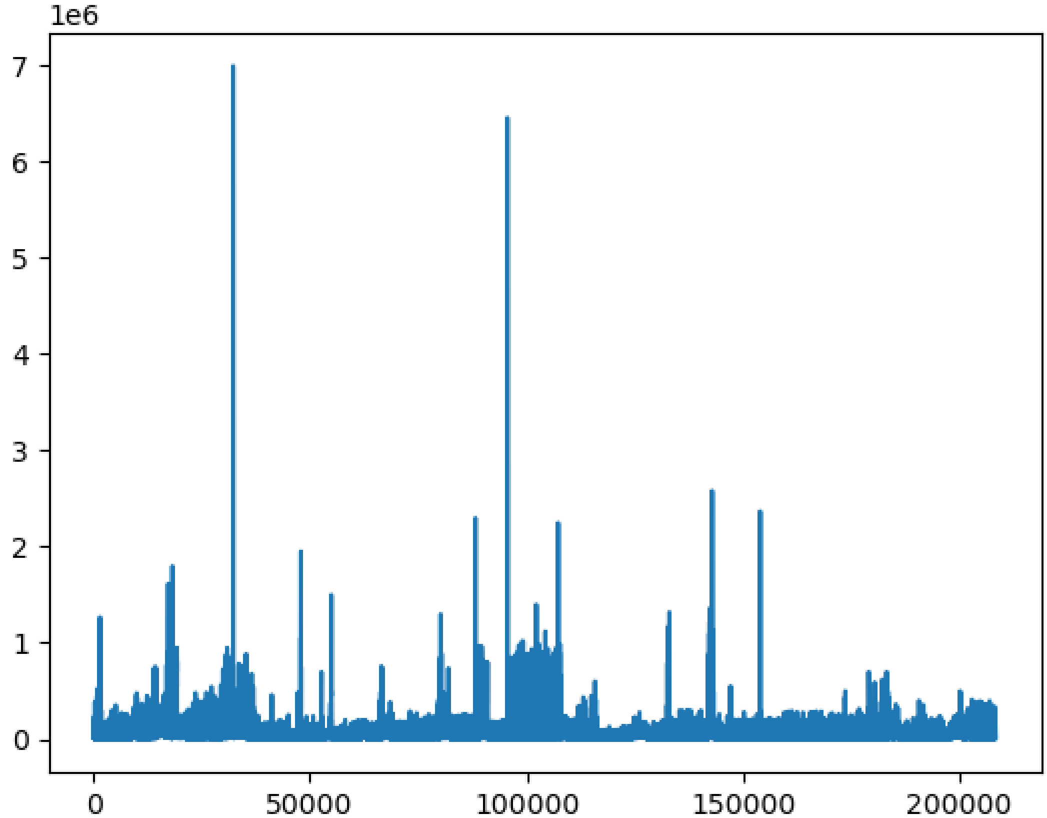


Now its time to dig deep numerical columns

In [30]:
```
new_data.hist(figsize=(12, 8))
plt.show()
```



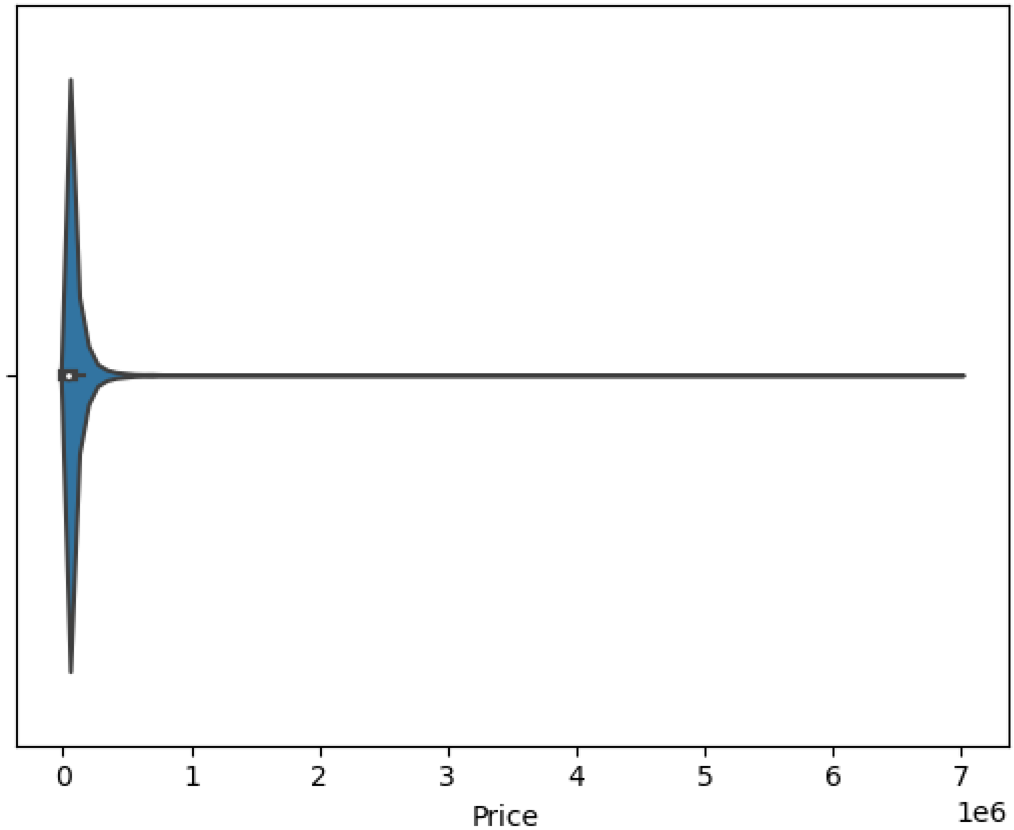
In [31]:
```
plt.plot(new_data['Price_'])
plt.show()
```



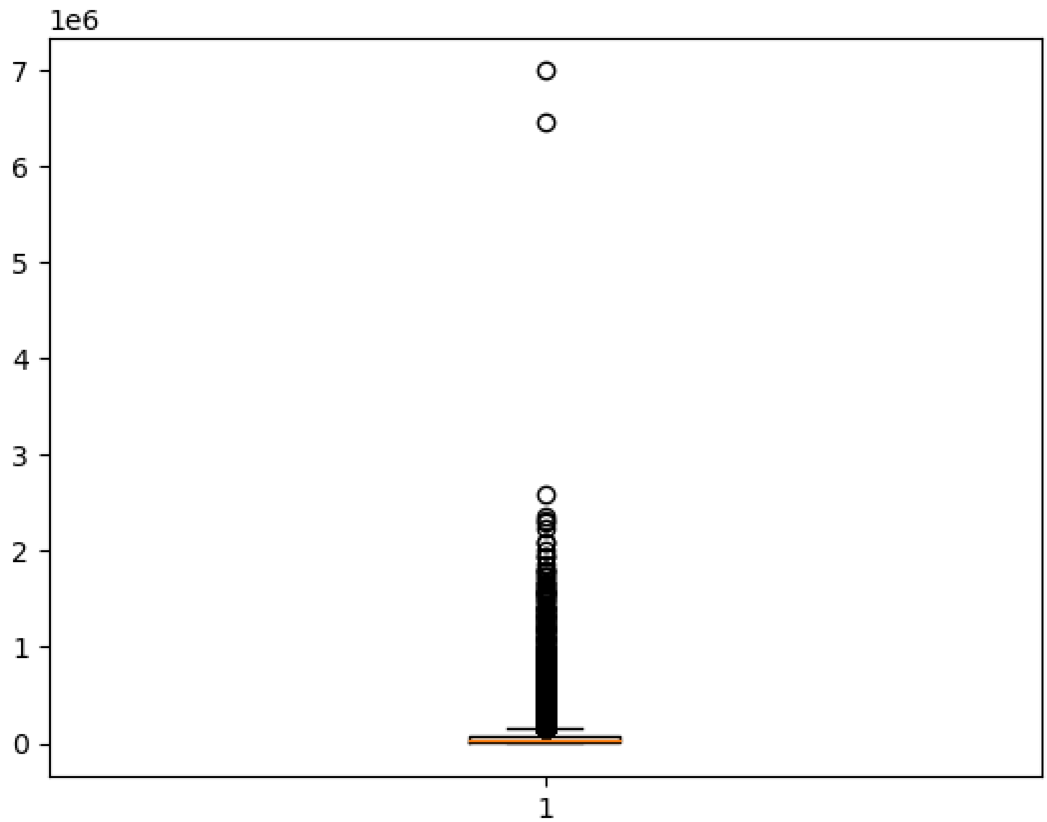
In [32]:
```
new_data['Price_'].describe().T
```

Out[32]:
```
count    2.083040e+05
mean     6.330202e+04
std      8.874514e+04
min      5.850000e+02
25%      1.780000e+04
50%      3.580000e+04
75%      7.600000e+04
max      6.999000e+06
Name: Price_, dtype: float64
```

In [33]:
```
sns.violinplot(data=new_data, x = 'Price_')
plt.show()
```



In [34]:
```
plt.boxplot(new_data['Price_'])
plt.show()
```



detecting outliers and removing them

In [35]:
```
np.std(new_data['Price_'])
```

Out[35]: 88744.93113590893

In [36]:
```
np.quantile(new_data['Price_'], (0.25, 0.75))
```

Out[36]: array([17800., 76000.])

In [37]:
```
np.percentile(new_data['Price_'], (10, 90))
```

Out[37]: array([9800. , 144245.2])

removing data between quartiles by using IQR

In [38]:
```
new = new_data.loc[(new_data['Price_'] >= 17800) & (new_data['Price_'] <= 760
```

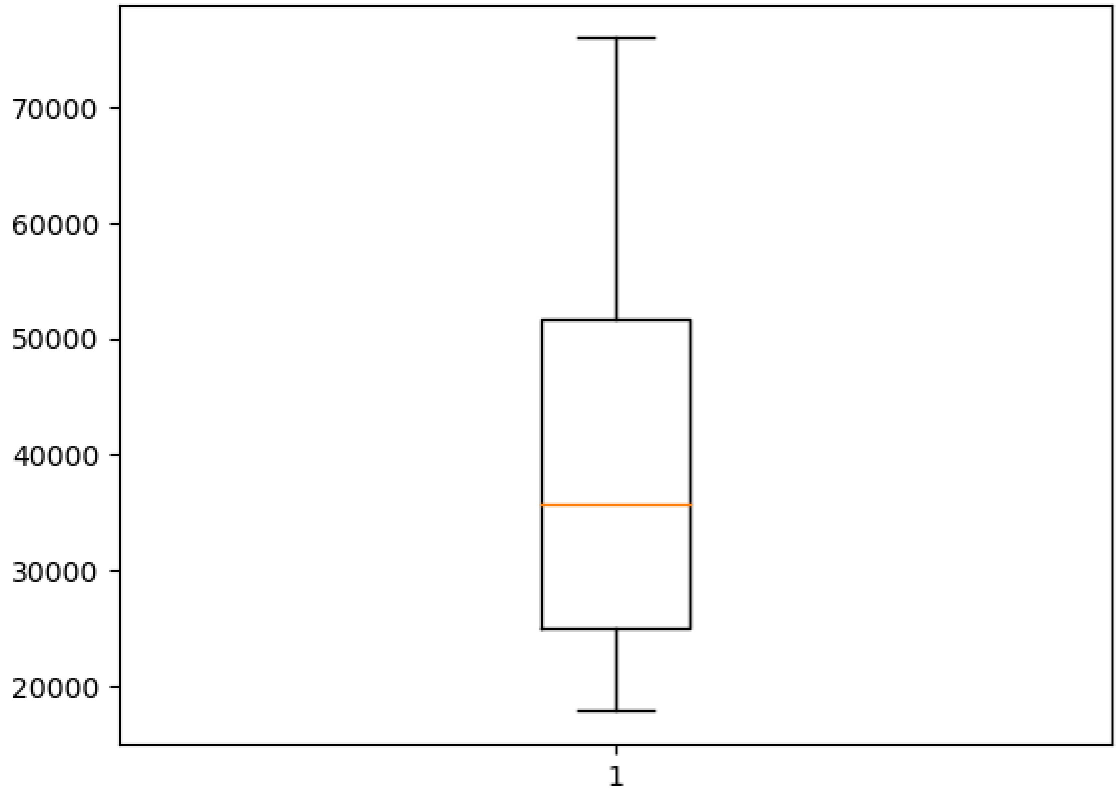
In [39]:
```
new
```

Out[39]:

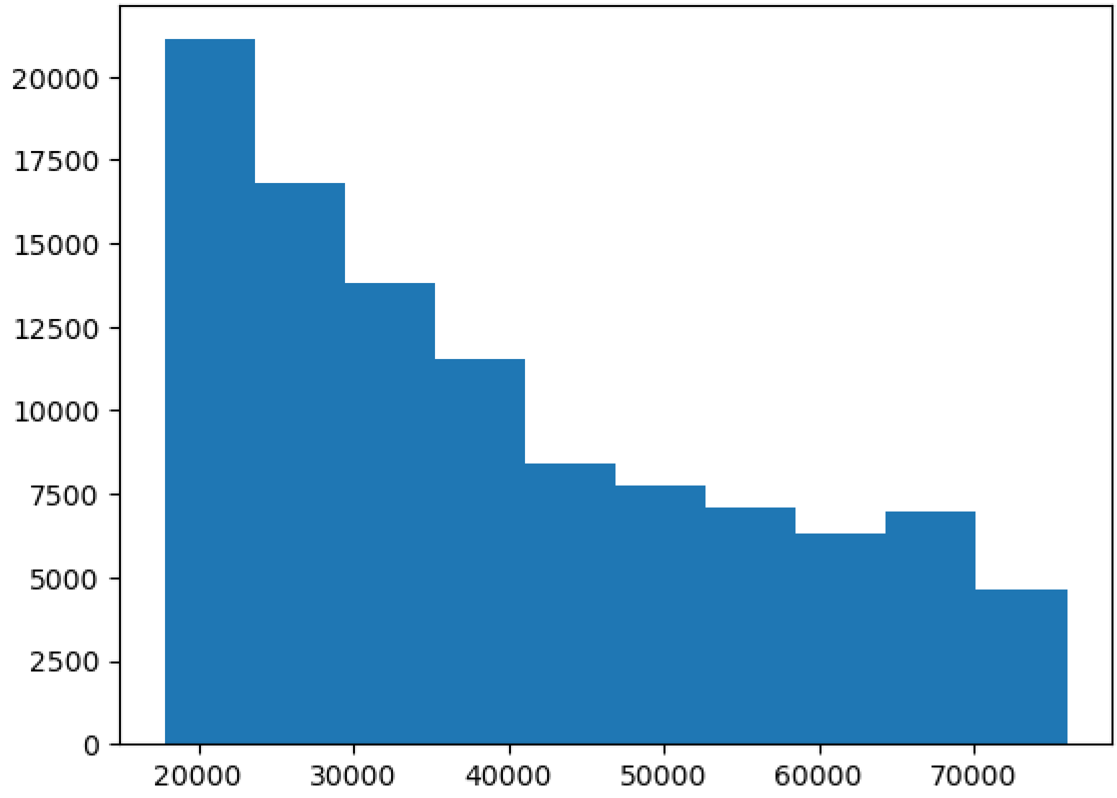
	Condition	Vehicle_brand	Production_year	Mileage_km	Power_HP	Displacement_cm3
1	Used	others	1974	59000.0	75.0	1100.0
2	Used	others	2018	52000.0	180.0	1368.0
3	Used	others	2012	29000.0	160.0	1368.0
5	Used	others	2016	46060.0	180.0	1368.0
6	Used	others	2021	2900.0	145.0	1368.0
...	...	...	...	...	...	...
208287	Used	others	1964	47109.0	75.0	2400.0
208293	Used	others	2020	500000000.0	333.0	3333.0
208297	Used	others	1981	18712.0	55.0	1116.0
208298	Used	others	1978	6000.0	NaN	750.0
208299	Used	others	2014	40000.0	173.0	1301.0

104429 rows × 13 columns

In [40]:
```
plt.boxplot(new['Price_'])
plt.show()
```



In [41]:
```
plt.hist(new['Price_'])
plt.show()
```

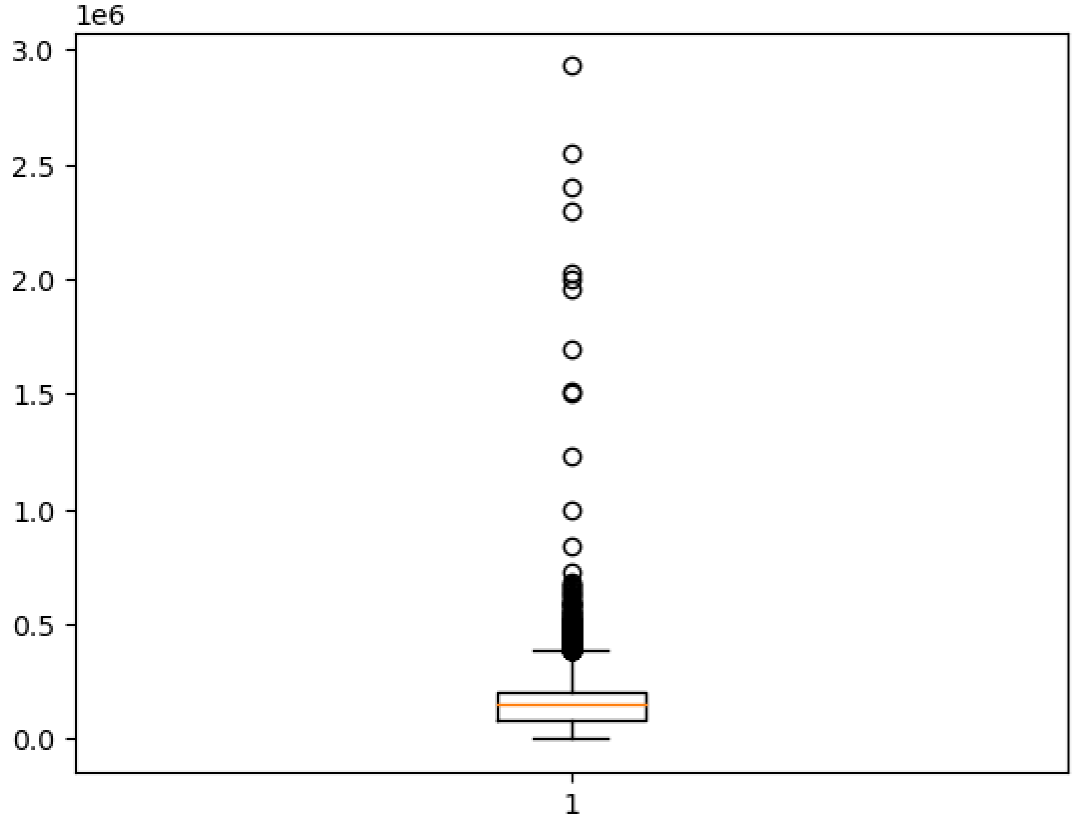


althouh it is still skewed to the right but way better then previous one. This hist and above mentioned boxplot clearly shows that transformed data is more dispersed

In [42]:
```
np.std(new['Price_'])
```

Out[42]:
```
16451.824159236352
```

In [43]:
```
plt.boxplot(plot_df['Mileage_km'])
plt.show()
```



In [44]:
```
np.quantile(plot_df['Mileage_km'], (0.15, 0.80))
```

Out[44]:
```
array([ 40817.55, 219000.  ])
```

In [45]:
```
new = new.loc[(new['Mileage_km'] >= 40817) & (new['Mileage_km'] <= 219000) ]
```

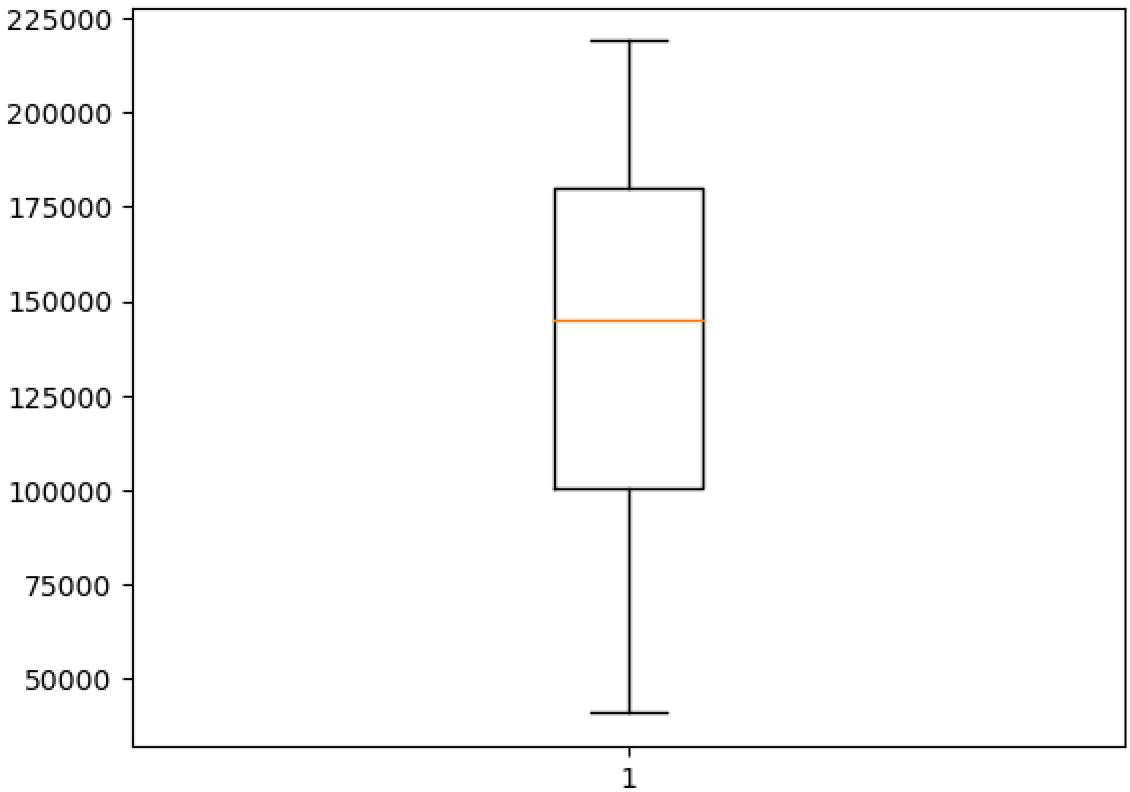
In [46]:
```
new
```

Out[46]:

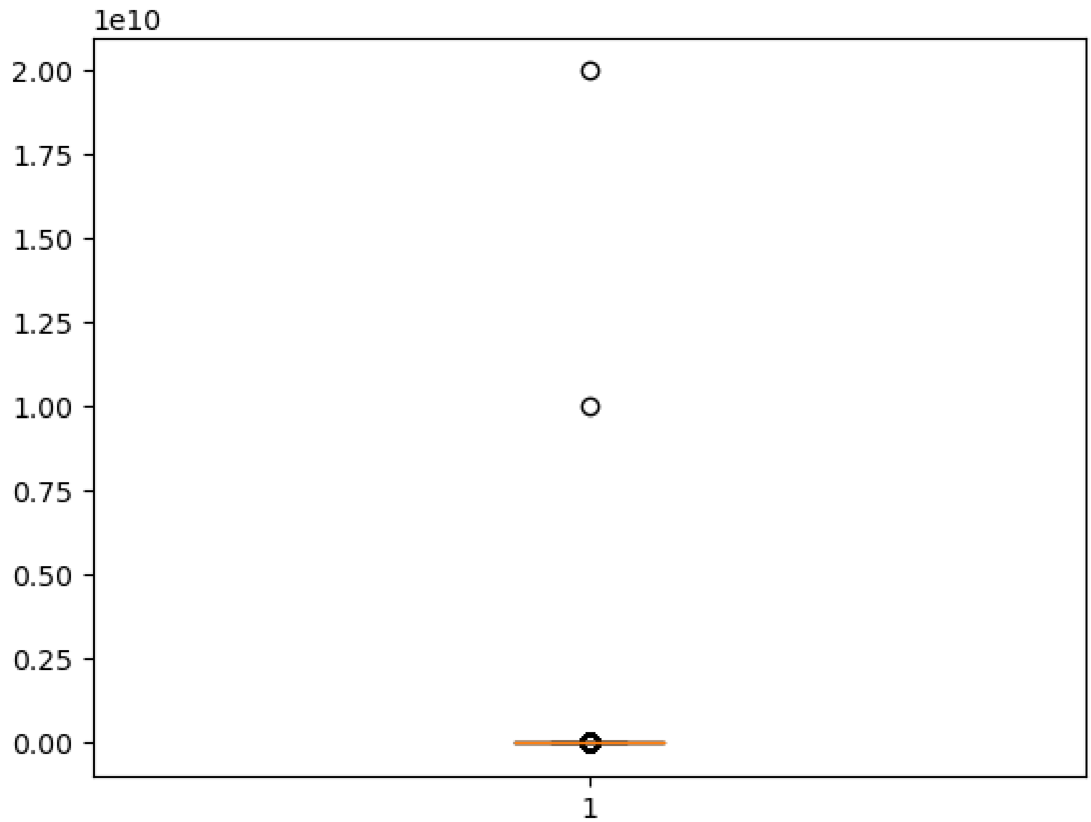
	Condition	Vehicle_brand	Production_year	Mileage_km	Power_HP	Displacement_cm3
1	Used	others	1974	59000.0	75.0	1100.0
2	Used	others	2018	52000.0	180.0	1368.0
5	Used	others	2016	46060.0	180.0	1368.0
11	Used	others	2010	179000.0	210.0	1368.0
13	Used	others	2015	117000.0	140.0	1400.0
...	...	...	...	...	...	...
208281	Used	others	1960	96000.0	38.0	900.0
208283	Used	others	1982	98600.0	100.0	2445.0
208284	Used	others	1983	190000.0	105.0	2445.0
208285	Used	others	1982	83000.0	95.0	2445.0
208287	Used	others	1964	47109.0	75.0	2400.0

71665 rows × 13 columns

In [47]:
```
plt.boxplot(new['Mileage_km'])
plt.show()
```



In [48]:
```
plt.boxplot(plot_df['CO2_emissions'])
plt.show()
```



It is too good to get rid off it

In [49]:
```
new.drop('CO2_emissions', axis=1, inplace=True)
```

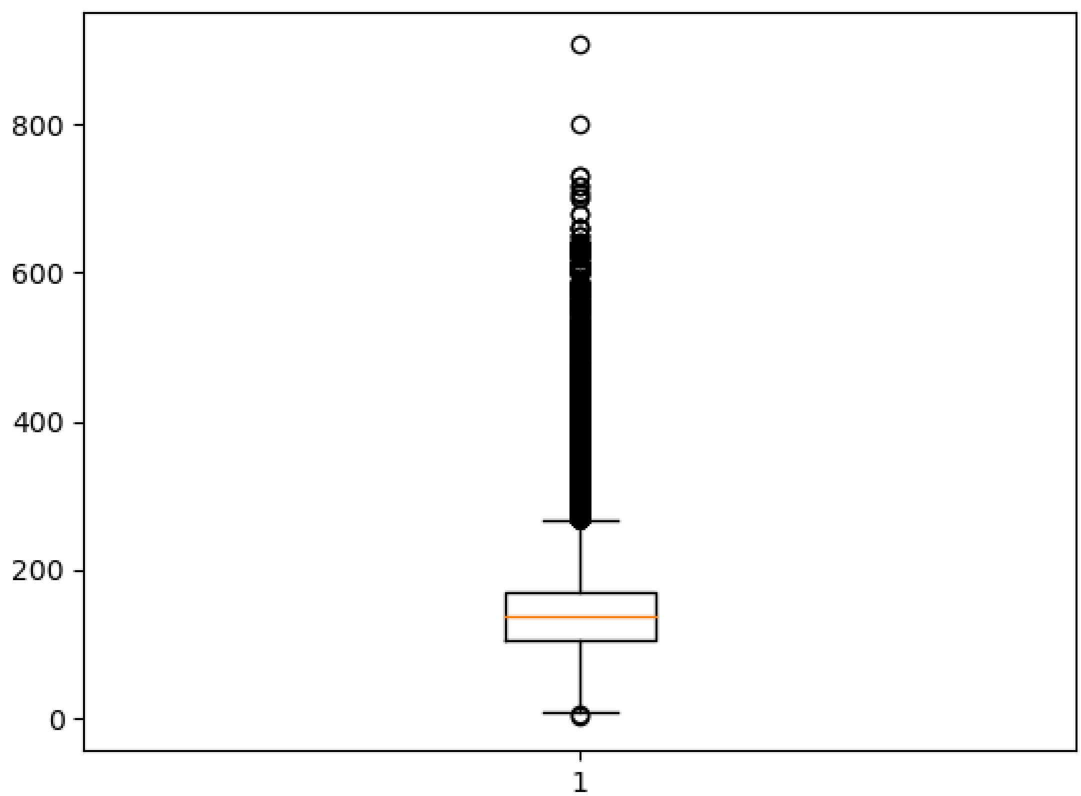
In [50]:
```
new.isna().sum()
```

Out[50]:
```
Condition              0
Vehicle_brand          0
Production_year        0
Mileage_km             0
Power_HP             192
Displacement_cm3     269
Fuel_type              0
Drive               4806
Transmission         147
Type                   0
Doors_number         405
Price_                 0
dtype: int64
```

In [51]:
```
new.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 71665 entries, 1 to 208287
Data columns (total 12 columns):
 #   Column            Non-Null Count  Dtype  
---  ------            --------------  -----  
 0   Condition         71665 non-null  object 
 1   Vehicle_brand     71665 non-null  object 
 2   Production_year   71665 non-null  int64  
 3   Mileage_km        71665 non-null  float64
 4   Power_HP          71473 non-null  float64
 5   Displacement_cm3  71396 non-null  float64
 6   Fuel_type         71665 non-null  object 
 7   Drive             66859 non-null  object 
 8   Transmission      71518 non-null  object 
 9   Type              71665 non-null  object 
 10  Doors_number      71260 non-null  float64
 11  Price_            71665 non-null  float64
dtypes: float64(5), int64(1), object(6)
memory usage: 7.1+ MB
```

In [52]:
```
plt.boxplot(plot_df['Power_HP'])
plt.show()
```



same as CO2_emissions column

In [53]:
```
new.drop('Power_HP', axis=1, inplace=True)
```

In [54]:
```
new.describe().T
```

Out[54]:

	count	mean	std	min	25%	50%	75%
Production_year	71665.0	2012.414121	5.111360	1922.0	2010.0	2013.0	2016.0
Mileage_km	71665.0	139316.170962	48184.513735	40828.0	100214.0	144860.0	180000.0
Displacement_cm3	71396.0	1806.723178	613.909968	400.0	1496.0	1600.0	1995.0
Doors_number	71260.0	4.699832	0.726179	2.0	5.0	5.0	5.0
Price_	71665.0	38854.420443	15765.689737	17800.0	25500.0	35899.0	49900.0

In [55]:
```
new = new.loc[new['Doors_number'] >= 2]
```

In [56]:
```
new.describe().T
```

Out[56]:

	count	mean	std	min	25%	50%	75%
Production_year	71260.0	2012.421232	5.088673	1922.0	2010.00	2013.0	2016.
Mileage_km	71260.0	139322.145102	48182.945049	40828.0	100250.75	144817.0	180000.
Displacement_cm3	71078.0	1806.074735	613.214301	400.0	1496.00	1600.0	1995.
Doors_number	71260.0	4.699832	0.726179	2.0	5.00	5.0	5.
Price_	71260.0	38848.656737	15762.095332	17800.0	25500.00	35833.5	49900.

now data processing part is almost complete

Getting data ready for model training

In [61]:
```
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import OneHotEncoder, OrdinalEncoder, StandardScal
from sklearn.compose import ColumnTransformer, TransformedTargetRegressor
from sklearn.pipeline import make_pipeline
from sklearn.model_selection import cross_val_score, train_test_split, learni
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_squared_error, mean_absolute_error, mean_abs
```

seperating columns based on object types

In [62]:
```
num_cols = [cname for cname, content in new.items() if pd.api.types.is_numeri
num_cols
```

Out[62]:
```
['Production_year', 'Mileage_km', 'Displacement_cm3', 'Doors_number', 'Price
_']
```

Some Object columns have relationship among itselfs so it is good approach to encode them either in HOT or Ordial

In [63]:
```
new.select_dtypes(include='object')
```

Out[63]:

	Condition	Vehicle_brand	Fuel_type	Drive	Transmission	Type
1	Used	others	Gasoline	Front wheels	Manual	coupe
2	Used	others	Gasoline	NaN	Automatic	small_cars
5	Used	others	Gasoline	Front wheels	Manual	small_cars
11	Used	others	Gasoline	Front wheels	Manual	city_cars
13	Used	others	Gasoline	Front wheels	Manual	city_cars
...	...	...	...	...	...	...
208281	Used	others	Gasoline	Front wheels	Manual	sedan
208283	Used	others	Gasoline	Front wheels	Manual	sedan
208284	Used	others	Gasoline	Rear wheels	Manual	sedan
208285	Used	others	Gasoline	NaN	Manual	sedan
208287	Used	others	Gasoline	Rear wheels	Manual	sedan

71260 rows × 6 columns

In [64]:
```
hot_cols = ['Condition', 'Transmission', 'Fuel_type']
ord_cols = ['Vehicle_brand', 'Drive', 'Type']
```

creating pipelines

In [65]:
```
num_pipe = make_pipeline(SimpleImputer(strategy='median'))
hot_pipe = make_pipeline(SimpleImputer(strategy='most_frequent'),
                         OneHotEncoder(handle_unknown='ignore', sparse=False))
ord_pipe = make_pipeline(SimpleImputer(strategy='most_frequent'),
                         OrdinalEncoder())
processed = ColumnTransformer([
    ('num', num_pipe, num_cols),
    ('hot', hot_pipe, hot_cols),
    ('ord', ord_pipe, ord_cols),
])
processed.set_output(transform='pandas')
processed_df = processed.fit_transform(new)
```

In [66]:
```
processed_df
```

Out[66]:

	num__Production_year	num__Mileage_km	num__Displacement_cm3	num__Doors_numb
1	1974.0	59000.0	1100.0	2
2	2018.0	52000.0	1368.0	3
5	2016.0	46060.0	1368.0	3
11	2010.0	179000.0	1368.0	3
13	2015.0	117000.0	1400.0	3
...	...	...	...	
208281	1960.0	96000.0	900.0	4
208283	1982.0	98600.0	2445.0	4
208284	1983.0	190000.0	2445.0	4
208285	1982.0	83000.0	2445.0	4
208287	1964.0	47109.0	2400.0	5

71260 rows × 17 columns

In [67]:
```
processed_df.isna().sum()
```

Out[67]:
```
num__Production_year            0
num__Mileage_km                 0
num__Displacement_cm3           0
num__Doors_number               0
num__Price_                     0
hot__Condition_Used             0
hot__Transmission_Automatic     0
hot__Transmission_Manual        0
hot__Fuel_type_Diesel           0
hot__Fuel_type_Electric         0
hot__Fuel_type_Gasoline         0
hot__Fuel_type_Gasoline + CNG   0
hot__Fuel_type_Gasoline + LPG   0
hot__Fuel_type_Hybrid           0
ord__Vehicle_brand              0
ord__Drive                      0
ord__Type                       0
dtype: int64
```

Spliting data into traing and testing

In [68]:
```
X = processed_df.drop('num__Price_', axis=1)
y = processed_df['num__Price_']
```

In [69]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y,  test_size = 0.2, r
```

Traing a model

In [70]:
```
%%time
rand_model = RandomForestRegressor()
rand_model.fit(X_train, y_train)
```

```
CPU times: total: 48.8 s
Wall time: 55.9 s
```

Out[70]:
```
RandomForestRegressor()
```

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In [71]:
```
rand_model.score(X_train, y_train)
```

Out[71]:
```
0.961124687810182
```

In [72]:
```
predicts = rand_model.predict(X_test)
```

In [73]:
```
r2_score(y_test, predicts)
```

Out[73]: 0.7552667911371554

In [74]:
```
mean_squared_error(y_test, predicts, squared=False)
```

Out[74]: 7811.351359673329

In [75]:
```
rand_model.feature_importances_
```

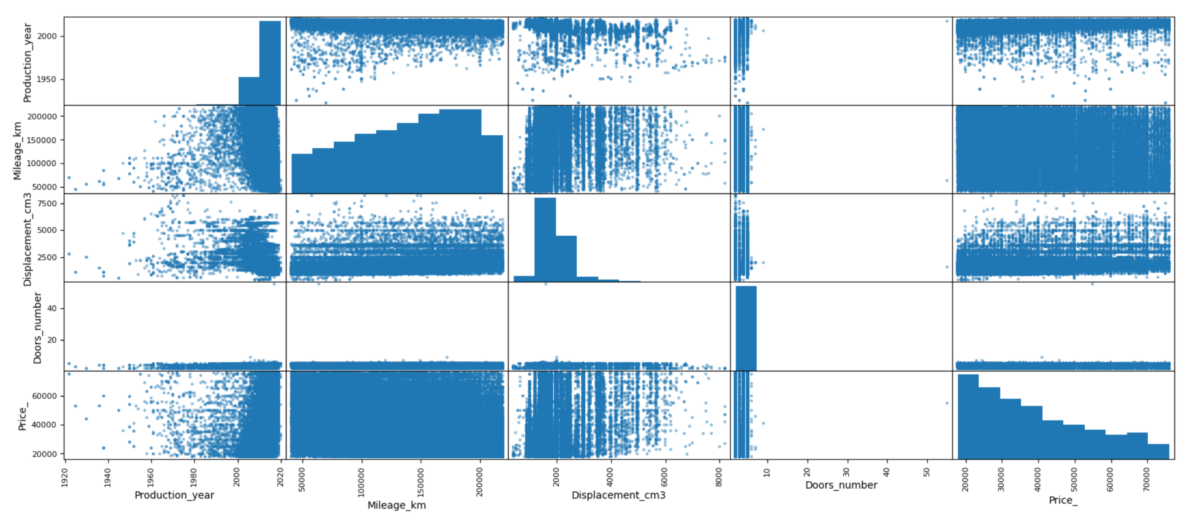
Out[75]:
```
array([3.74483103e-01, 1.39934406e-01, 2.31842829e-01, 1.50168829e-02,
       0.00000000e+00, 3.81681297e-02, 4.07220818e-02, 7.04669158e-03,
       6.03377080e-05, 1.53673060e-02, 3.99736761e-05, 1.89312334e-03,
       1.16977770e-03, 4.09336431e-02, 1.75575623e-02, 7.57641521e-02])
```

In [76]:
```
corr = new.corr()
corr
```

Out[76]:

	Production_year	Mileage_km	Displacement_cm3	Doors_number	Price_
Production_year	1.000000	-0.264078	-0.369691	0.302831	0.352128
Mileage_km	-0.264078	1.000000	0.212645	0.023999	-0.272404
Displacement_cm3	-0.369691	0.212645	1.000000	-0.249551	0.253871
Doors_number	0.302831	0.023999	-0.249551	1.000000	0.005931
Price_	0.352128	-0.272404	0.253871	0.005931	1.000000

In [77]:
```
from pandas.plotting import scatter_matrix
scatter_matrix(frame=new, figsize=(20, 8))
plt.show()
```



now set hyperparameters by using Grid Search, because data is not too large

In [78]:
```
from sklearn.model_selection import GridSearchCV
```

In [151]:
```
param = {'n_estimators' : [10, 20, 30, 40, 50, 60, 70, 80, 90, 100],
        'max_depth' : [1, 3, 5],
        'min_samples_split' : [2, 4, 6, 8],
        'max_features' : ['auto', 'sqrt', 'log2'],
         'bootstrap' : [True, False],
        }
grid_ser = GridSearchCV(estimator=RandomForestRegressor(n_jobs=-1, random_sta
grid_ser.fit(X_train, y_train)
```

```
C:\Users\WNasir\Desktop\sample_project_1\env\Lib\site-packages\sklearn\en
semble\_forest.py:413: FutureWarning: `max_features='auto'` has been depr
ecated in 1.1 and will be removed in 1.3. To keep the past behaviour, exp
licitly set `max_features=1.0` or remove this parameter as it is also the
default value for RandomForestRegressors and ExtraTreesRegressors.
  warn(
C:\Users\WNasir\Desktop\sample_project_1\env\Lib\site-packages\sklearn\en
semble\_forest.py:413: FutureWarning: `max_features='auto'` has been depr
ecated in 1.1 and will be removed in 1.3. To keep the past behaviour, exp
licitly set `max_features=1.0` or remove this parameter as it is also the
default value for RandomForestRegressors and ExtraTreesRegressors.
  warn(
C:\Users\WNasir\Desktop\sample_project_1\env\Lib\site-packages\sklearn\en
semble\_forest.py:413: FutureWarning: `max_features='auto'` has been depr
ecated in 1.1 and will be removed in 1.3. To keep the past behaviour, exp
licitly set `max_features=1.0` or remove this parameter as it is also the
default value for RandomForestRegressors and ExtraTreesRegressors.
  warn(
C:\Users\WNasir\Desktop\sample_project_1\env\Lib\site-packages\sklearn\en
```

In [152]:
```
grid_ser.best_params_
```

Out[152]:
```
{'bootstrap': True,
 'max_depth': 5,
 'max_features': 'auto',
 'min_samples_split': 2,
 'n_estimators': 80}
```

In [79]:
```
ideal = RandomForestRegressor(n_estimators=80, max_depth=5, max_features='auto
                             n_jobs=-1, random_state=42)
ideal.fit(X_train, y_train)
```

Out[79]:
```
RandomForestRegressor(max_depth=5, max_features='auto', n_estimators=80,
                      n_jobs=-1, random_state=42)
```

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In [80]:
```
pred = ideal.predict(X_test)
pred
```

Out[80]:
```
array([51693.75469945, 45765.03236222, 52473.93336489, ...,
       62184.58216824, 36651.4743255 , 23360.52938209])
```

In [81]:
```
print(r2_score(y_test, pred))
print(mean_squared_error(y_test, pred))
print(mean_absolute_error(y_test, pred))
print(mean_squared_error(y_test, pred, squared=False))
print(mean_absolute_percentage_error(y_test, pred))
```

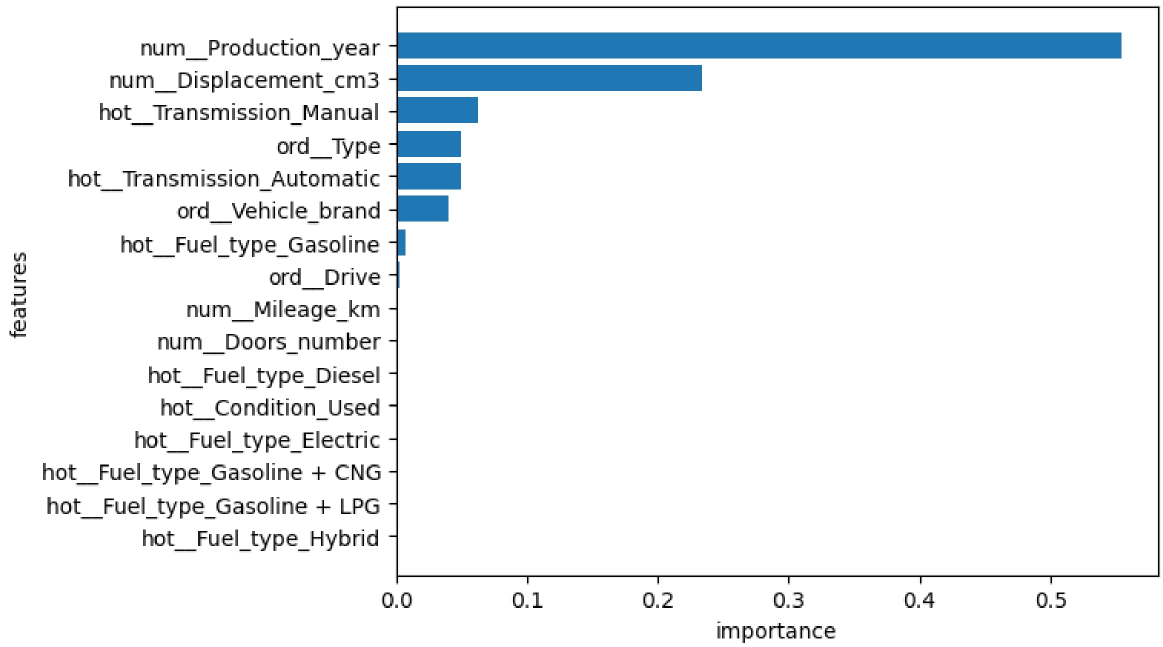
```
0.6337695849405809
91309055.56887065
7346.341313070408
9555.577197054641
0.2059394540164137
```

In [82]:
```
ideal.feature_importances_
```

Out[82]:
```
array([5.54582342e-01, 1.70498988e-03, 2.33423078e-01, 1.35928885e-04,
       0.00000000e+00, 4.91469098e-02, 6.17971905e-02, 3.40728464e-05,
       0.00000000e+00, 7.02921665e-03, 0.00000000e+00, 0.00000000e+00,
       0.00000000e+00, 4.06175465e-02, 2.19377242e-03, 4.93349527e-02])
```

In [83]:
```
def feature_imp(columns, importance):
    df = (pd.DataFrame({'features': columns,
                        'importance': importance}).sort_values("importance", a
    fig, ax = plt.subplots()
    plot = ax.barh(df['features'], df['importance'])
    ax.set_ylabel('features')
    ax.set_xlabel('importance')
    ax.invert_yaxis()
```

In [84]:
```
feature_imp(X_train.columns, ideal.feature_importances_)
```



In [85]:
```
ideal_df = processed_df.drop(['ord__Drive', 'num__Mileage_km', 'num__Doors_nu
```

In [86]:
```
ideal_df.columns
```

Out[86]:
```
Index(['num__Production_year', 'num__Displacement_cm3', 'num__Price_',
       'hot__Transmission_Automatic', 'hot__Transmission_Manual',
       'hot__Fuel_type_Diesel', 'hot__Fuel_type_Electric',
       'hot__Fuel_type_Gasoline', 'hot__Fuel_type_Gasoline + CNG',
       'hot__Fuel_type_Gasoline + LPG', 'hot__Fuel_type_Hybrid',
       'ord__Vehicle_brand', 'ord__Type'],
      dtype='object')
```

In [87]:
```
X, y = ideal_df.drop('num__Price_', axis=1), ideal_df['num__Price_']
```

In [88]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, rand
```

In [89]:
```
ideal_model = RandomForestRegressor(n_estimators=80, max_depth=5, max_feature
                             n_jobs=-1, random_state=42)
ideal_model.fit(X_train, y_train)
```

Out[89]:
```
RandomForestRegressor(max_depth=5, max_features='auto', n_estimators=80,
                      n_jobs=-1, random_state=42)
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
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In [90]:
```
pred1 = ideal_model.predict(X_test)
```

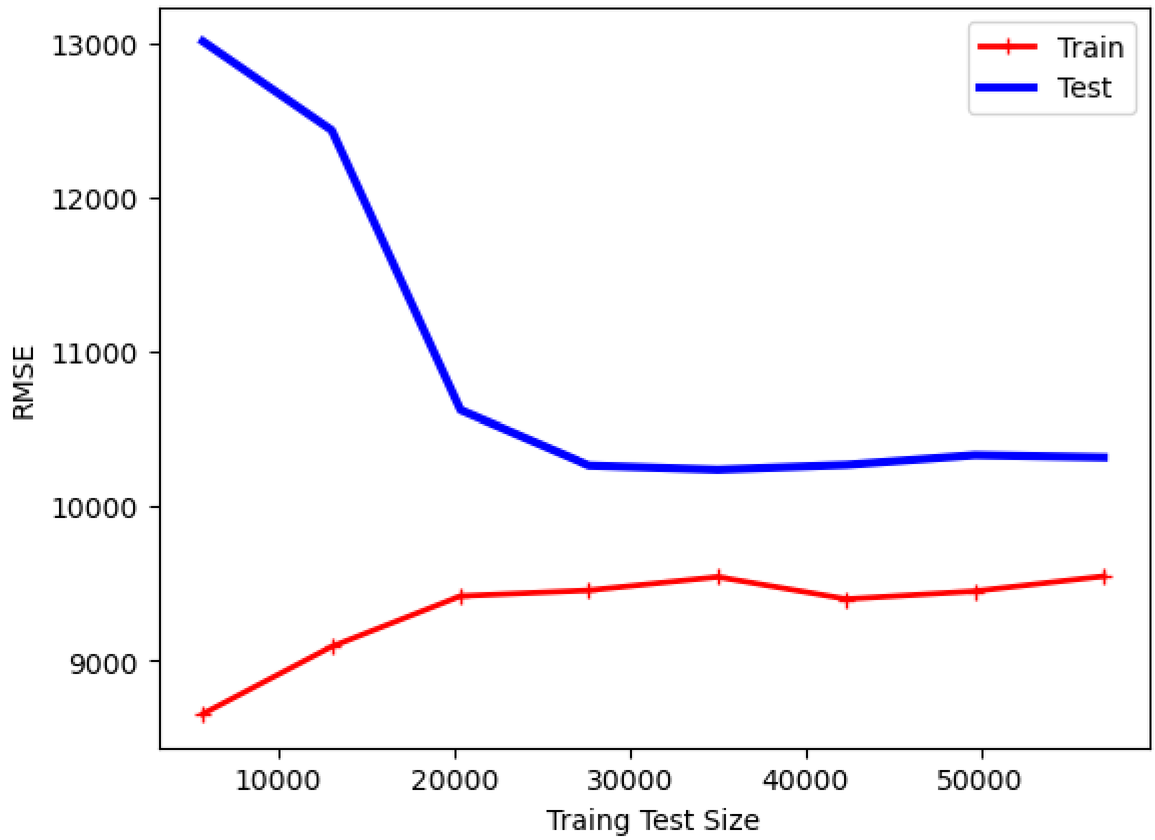
In [91]:
```
print(r2_score(y_test, pred1))
print(mean_squared_error(y_test, pred1))
print(mean_absolute_error(y_test, pred1))
print(mean_squared_error(y_test, pred1, squared=False))
print(mean_absolute_percentage_error(y_test, pred1))
```

```
0.6321655559588615
91708974.2140824
7364.086867378742
9576.480262292738
0.20623500612535237
```

In [92]:
```
mod = RandomForestRegressor(n_estimators=80, max_depth=5, max_features='auto'

                             n_jobs=-1, random_state=42)
```

In [93]:
```
train_sizes, train_scores, test_scores = learning_curve(mod, X, y, train_size
train_error = -train_scores.mean(axis=1)
test_error = -test_scores.mean(axis=1)
plt.plot(train_sizes, train_error, 'r-+', linewidth=2, label='Train')
plt.plot(train_sizes, test_error, 'b-', linewidth=3, label='Test')
plt.xlabel("Traing Test Size")
plt.ylabel('RMSE')
plt.legend()
plt.show()
```



In [94]:
```
print('R2_Score is ',r2_score(y_test, pred1))
print('MSE is ', mean_squared_error(y_test, pred1))
print('MAE is ', mean_absolute_error(y_test, pred1))
print('RMSE is ', mean_squared_error(y_test, pred1, squared=False))
print('MAPE is ', mean_absolute_percentage_error(y_test, pred1))
```

```
R2_Score is  0.6321655559588615
MSE is  91708974.2140824
MAE is  7364.086867378742
RMSE is  9576.480262292738
MAPE is  0.20623500612535237
```

In [ ]: