2nd Hand Car Price Prediction

In this project we analyze the 'Used Cars' dataset from kaggle (https://www.kaggle.com/datasets/austinreese/craigslist-carstrucks-data?select=vehicles.csv).

The goal is to build a model that could estimate the price of second hand cars based on relevant features. We explore the data through cleanig and preprocessing, handling outliers, feature engineering and eventually testing different regression models to get the most accurate predictor.

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib
from matplotlib import pyplot as plt
import seaborn as sns
%matplotlib inline
matplotlib.rcParams['figure.figsize']= (20,10)
```

In [2]:
```
df1 = pd.read_csv("/Users/marwa/Desktop/2ndHCP/model/vehicles.csv")
```

Data Cleaning

In [4]:
```
df1.head()
```

Out[4]:

	id	url	region	
0	7222695916	https://prescott.craigslist.org/cto/d/prescott...	prescott	https://pres
1	7218891961	https://fayar.craigslist.org/ctd/d/bentonville...	fayetteville	https://f
2	7221797935	https://keys.craigslist.org/cto/d/summerland-k...	florida keys	https://
3	7222270760	https://worcester.craigslist.org/cto/d/west-br...	worcester / central MA	https://worce
4	7210384030	https://greensboro.craigslist.org/cto/d/trinit...	greensboro	https://greens

5 rows × 26 columns

In [5]:
```
df1.shape
```

Out[5]:
```
(426880, 26)
```

Examine the state feature so group by regions then aggregate by count

In [7]:
```
df1.groupby('state')['state'].agg("count")
```

Out[7]:
```
state
ak     3474
al     4955
ar     4038
az     8679
ca    50614
co    11088
ct     5188
dc     2970
de      949
fl    28511
ga     7003
hi     2964
ia     8632
id     8961
il    10387
in     5704
ks     6209
ky     4149
la     3196
ma     8174
md     4778
me     2966
mi    16900
mn     7716
mo     4293
ms     1016
mt     6294
nc    15277
nd      410
ne     1036
nh     2981
nj     9742
nm     4425
nv     3194
ny    19386
oh    17696
ok     6792
or    17104
pa    13753
ri     2320
sc     6327
sd     1302
tn    11066
tx    22945
ut     1150
va    10732
vt     2513
wa    13861
wi    11398
wv     1052
wy      610
Name: state, dtype: int64
```

Statistics

In [9]:
```
df1.describe()
```

Out [9]:

	id	price	year	odometer	county	
count	4.268800e+05	4.268800e+05	425675.000000	4.224800e+05	0.0	42033
mean	7.311487e+09	7.519903e+04	2011.235191	9.804333e+04	NaN	3
std	4.473170e+06	1.218228e+07	9.452120	2.138815e+05	NaN	
min	7.207408e+09	0.000000e+00	1900.000000	0.000000e+00	NaN	-8
25%	7.308143e+09	5.900000e+03	2008.000000	3.770400e+04	NaN	3
50%	7.312621e+09	1.395000e+04	2013.000000	8.554800e+04	NaN	3
75%	7.315254e+09	2.648575e+04	2017.000000	1.335425e+05	NaN	4
max	7.317101e+09	3.736929e+09	2022.000000	1.000000e+07	NaN	8

Drop irrelevant features:

Region can be removed since state wil suffice

Note that county has no values

Descirption and type can be removed since we are relying on manufacturer

In [11]:
```
df2= df1.drop(['id', 'url', 'region_url', 'image_url', 'description', 'la
              'long','region', 'VIN', 'title_status', 'type', 'cylinders
```

Handling missing values

In [13]:
```
#check columns with nan>50%

df2.isnull().mean()*100
```

Out[13]:
```
price            0.000000
year             0.282281
manufacturer     4.133714
model            1.236179
condition       40.785232
fuel             0.705819
odometer         1.030735
transmission     0.598763
drive           30.586347
size            71.767476
paint_color     30.501078
state            0.000000
posting_date     0.015930
dtype: float64
```

In [14]:
```
#since size feature as 71% NaN we will remove this feature
#and since our dataset is large it is efficiet enough to remove all rows
df2= df2.drop('size', axis='columns')
df3 = df2.dropna()
df3.shape
```

Out[14]: (152629, 12)

Feature Engineering

Checking categories of categorical variables

In [17]:
```
print("Manufacturer:\n" , df3['manufacturer'].unique(),
     "\n\nmodel:\n", df3['model'].unique(),
      "\n\ncondition:\n", df3['condition'].unique(),
      "\n\nFuel:\n", df3['fuel'].unique(),
      "\n\nodometer:\n", df3['odometer'].unique(),
      "\n\n transmission:\n", df3['transmission'].unique(),
      "\n\n drive: \n", df3['drive'].unique(),
      "\n\n paintcolour\n", df3['paint_color'].unique(),
      "\n\n state: \n", df3['state'].unique() )
```

```
Manufacturer:
 ['ford' 'gmc' 'chevrolet' 'toyota' 'jeep' 'nissan' 'cadillac' 'honda'
 'dodge' 'lexus' 'chrysler' 'volvo' 'hyundai' 'ram' 'lincoln'
 'mercedes-benz' 'infiniti' 'buick' 'acura' 'bmw' 'volkswagen' 'mazda'
 'porsche' 'ferrari' 'audi' 'mitsubishi' 'kia' 'pontiac' 'fiat' 'rover'
 'jaguar' 'alfa-romeo' 'saturn' 'subaru' 'mini' 'tesla' 'mercury'
 'harley-davidson' 'datsun' 'land rover' 'aston-martin']

model:
 ['f-150 xlt' 'sierra 2500 hd extended cab' 'silverado 1500 double' ...
 'cj 3a willys' 'rx& gls sport' 'gand wagoneer']

condition:
 ['excellent' 'good' 'like new' 'new' 'fair' 'salvage']

Fuel:
 ['gas' 'other' 'diesel' 'hybrid' 'electric']

odometer:
 [128000.  68696.  29499. ...  15113. 172511.  69550.]

 transmission:
 ['automatic' 'other' 'manual']

 drive:
 ['rwd' '4wd' 'fwd']

 paintcolour
 ['black' 'silver' 'grey' 'red' 'blue' 'white' 'brown' 'yellow' 'green'
 'custom' 'purple' 'orange']

 state:
 ['al' 'ak' 'az' 'ar' 'ca' 'co' 'ct' 'dc' 'de' 'fl' 'ga' 'hi' 'id' 'il'
 'in' 'ia' 'ks' 'ky' 'la' 'me' 'md' 'ma' 'mi' 'mn' 'ms' 'mo' 'mt' 'nc'
 'ne' 'nv' 'nj' 'nm' 'ny' 'nh' 'nd' 'oh' 'ok' 'or' 'pa' 'ri' 'sc' 'sd'
 'tn' 'tx' 'ut' 'vt' 'va' 'wa' 'wv' 'wi' 'wy']
```

In [18]:
```
#since model has a lot of different categories it can make interpretabili
#we will remove it since we assume that maufacturer provides enough info

df4=df3.drop(['model'], axis='columns')
```

In [19]:
```
#we will remove 'harley-davidson' from manufacturer as it is a motorcycle

df4= df4[~(df4.manufacturer== 'harley-davidson')]
```

In [20]:
```
#Checking count

# even though it isnt as many as 1000s it is still good to reduce it to p
#that arises when performing one-hot-encoding in high dimensional categor

#what we will do is check how many samples are present per category for a
#and state

manufacturer_count= df4.groupby('manufacturer')['manufacturer'].agg('coun
paint_count=df4.groupby('paint_color')['paint_color'].agg('count').sort_v
state_count= df4.groupby('state')['state'].agg('count').sort_values(ascen

print(manufacturer_count,
     '\n\n ',paint_count ,
     '\n\n', state_count)
```

```
manufacturer
ford             26172
chevrolet        21935
toyota           12902
honda             8599
nissan            7705
jeep              7345
gmc               5786
bmw               5223
dodge             5115
ram               4920
volkswagen        4293
hyundai           4030
mercedes-benz     3853
subaru            3340
kia               3206
lexus             3020
mazda             2382
chrysler          2368
cadillac          2365
buick             2163
acura             1977
lincoln           1828
infiniti          1811
audi              1755
mitsubishi        1450
volvo             1122
pontiac           1066
mini              1035
rover              681
jaguar             585
mercury            563
saturn             526
tesla              452
porsche            434
fiat               316
alfa-romeo         199
ferrari             25
datsun              24
land rover           9
aston-martin         8
Name: manufacturer, dtype: int64

  paint_color
white     37736
black     30835
silver    21870
blue      16865
red       16835
grey      14621
green      4473
brown      4035
custom     2759
yellow     1177
orange      980
purple      402
Name: paint_color, dtype: int64

 state
ca    17824
```

```
fl    10208
ny     8711
tx     7670
oh     7010
mi     6160
pa     5702
nc     5397
wi     5048
ma     3897
tn     3871
va     3665
or     3656
il     3641
co     3558
nj     3528
ia     3455
az     3285
mn     3274
in     2768
ok     2706
ga     2535
ks     2398
sc     2358
id     2241
ct     2062
ky     2056
wa     1867
nm     1698
mo     1677
al     1654
md     1530
vt     1512
ar     1497
mt     1423
nh     1171
ri     1138
me     1121
dc     1033
ak     1022
nv      965
la      912
hi      664
sd      505
de      444
wv      429
ms      402
ne      387
ut      354
wy      269
nd      230
Name: state, dtype: int64
```

In [21]:
```
manufacturer_less_than_100 = manufacturer_count[manufacturer_count<100]
len(df4['manufacturer'].unique())
```

Out[21]: 40

In [22]:
```
# we will group the manufacturers with counts <100 together as 'other'
```

```
df4.manufacturer= df4.manufacturer.apply(lambda x: 'other' if x in manufa

len(df4['manufacturer'].unique())
```

Out[22]: 37

Extracting age of each vehicle

In [24]:
```
# want the feature post_date to be a year only

#first we convert it to a date time for easier manipulation
#using to_datetime from pandas and setting utc=True for correct handling
df4['posting_date'] = pd.to_datetime(df4['posting_date'], utc=True)

df4['posting_date'].dtypes
```

Out[24]: datetime64[ns, UTC]

In [25]:
```
#then we extract the year out of it using dt.year and create a new column
df4['posting_year'] = df4['posting_date'].dt.year

#remove postiing date column
df4= df4.drop('posting_date', axis= 'columns')
df4.year.dtypes
```

Out[25]: dtype('float64')

In [26]:
```
#turn year into int32 to allow subtraction
df4['year']= df4['year'].astype('int32')
```

In [27]:
```
#now we want to create a column of age of the car since purchase

df5 = df4.copy()
df5['vehicle_age'] = df5['posting_year']-df5['year']
```

In [28]:
```
#clearly vehicle_age and year now are highly correlated and the posting_y
#2021 for all its entries which does not provide much information
#we will keep vehicle age as it provides enough info about the 2

df5=df5.drop(['year', 'posting_year'], axis= 'columns')
```

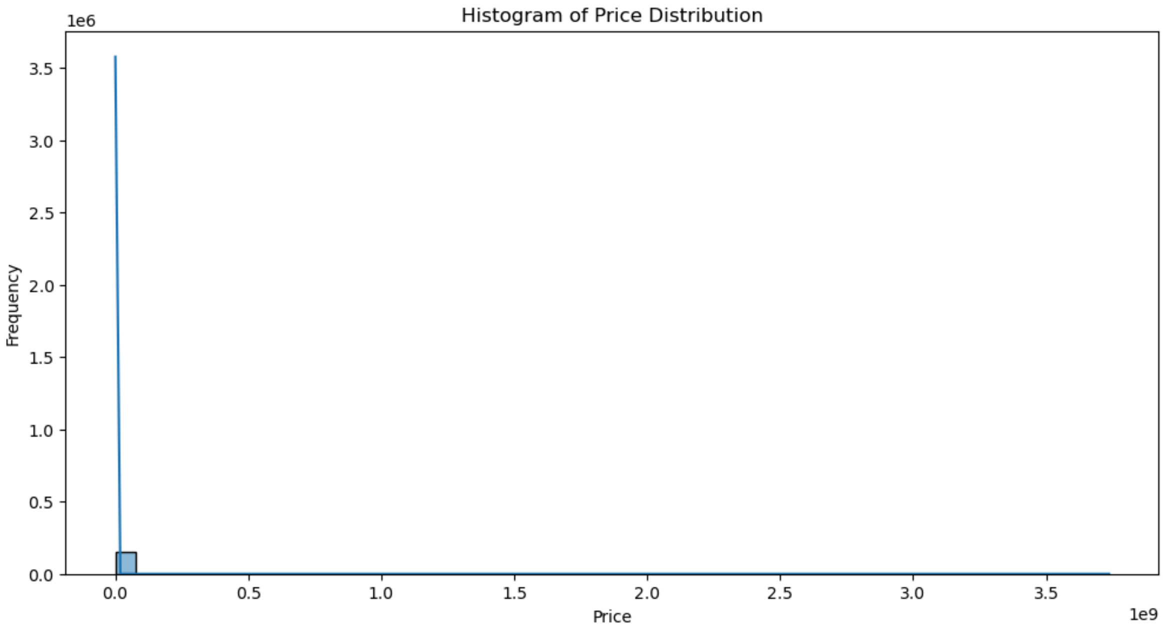
Outlier Removal

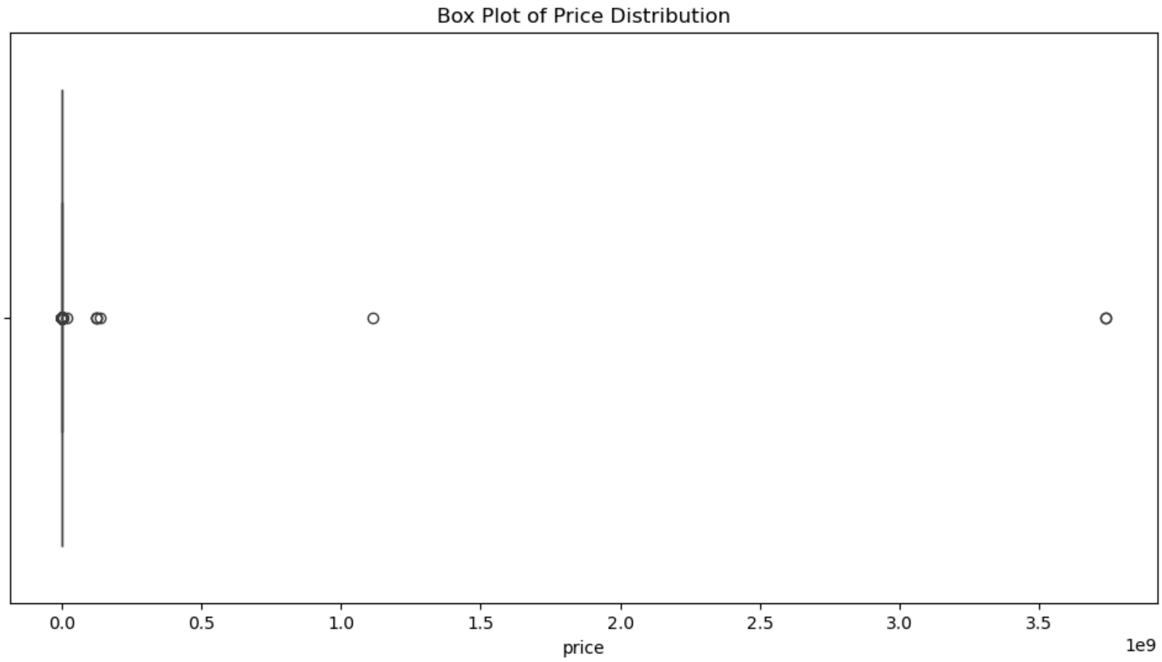
target variable price

In [32]:
```
#Visualising target variable price

plt.figure(figsize=(12, 6))
sns.histplot(df5['price'], bins=50, kde=True)
plt.title('Histogram of Price Distribution')
plt.xlabel('Price')
plt.ylabel('Frequency')
plt.show()
```

```
plt.figure(figsize=(12, 6))
sns.boxplot(x=df5['price'])
plt.title('Box Plot of Price Distribution')
plt.show()
```





In [33]:
```
# check price range

df5.price.describe(percentiles = [0.25,0.50,0.75,0.85,0.90,1])
```

Out[33]:
```
count     1.525880e+05
mean      7.598327e+04
std       1.383998e+07
min       0.000000e+00
25%       6.000000e+03
50%       1.290000e+04
75%       2.399500e+04
85%       3.099000e+04
90%       3.499500e+04
100%      3.736929e+09
max       3.736929e+09
Name: price, dtype: float64
```

mean price= 75,967 std dev= 13,838,120 which is extremely high relative to the mean. This indicates that there's a wide spread in the price and the possible presence of outliers.

min=0 indicates that there're samples with no price!! this can't be marketable. max= 3.74 billion! is extremely high for a car price! Could be an outlier

First Remove cars with price=0 since they are not marketable and dont provide any insight to our analysis

In [36]:
```
df6= df5[~(df5.price==0)]
df6[df5['price']==0]
```

```
/var/folders/s3/24r6s08x3pg9xyqf7659_57h0000gn/T/ipykernel_88375/52173903
3.py:2: UserWarning: Boolean Series key will be reindexed to match DataFra
me index.
  df6[df5['price']==0]
```

Out[36]:

price	manufacturer	condition	fuel	odometer	transmission	drive	paint_color

max price per state to check if differet states have more expensive cars

In [38]:
```
df6.groupby('state')['price'].max().reset_index()
```

Out[38]:

	state	price
0	ak	116000
1	al	140000
2	ar	149000
3	az	135000
4	ca	1111111111
5	co	164900
6	ct	106999
7	dc	89000
8	de	150000
9	fl	169999
10	ga	155000
11	hi	99990
12	ia	110000
13	id	123456789
14	il	123456
15	in	1234567
16	ks	124900
17	ky	123456
18	la	68000
19	ma	133995
20	md	95000
21	me	87500
22	mi	123456789
23	mn	123456
24	mo	69988
25	ms	1111111
26	mt	112500
27	nc	135008900
28	nd	82950
29	ne	124900
30	nh	114995
31	nj	125000
32	nm	120706
33	nv	120000

	state	price
34	ny	150000
35	oh	110000
36	ok	123456789
37	or	3736928711
38	pa	98772
39	ri	69500
40	sc	117995
41	sd	125000
42	tn	3736928711
43	tx	150000
44	ut	91500
45	va	81000
46	vt	85867
47	wa	225000
48	wi	125000
49	wv	51990
50	wy	74900

since prices vary in different states and the figures are highly right skewed it is best to perform the IQ method on price per state, so for every location we will get the bounds of the price in that location then remove outliers for each location

In [40]:
```
def remove_outliers(df):
    df_out= pd.DataFrame()
    #group by state
    for key, subdf in df.groupby('state'):

        Q1= subdf['price'].quantile(0.25)
        Q3= subdf['price'].quantile(0.75)
        IQR= Q3-Q1

        #define bounds
        lower= Q1 - 1.5 * IQR
        upper= Q3 + 1.5 * IQR

        #select prices per state within the bounds
        reduced_df= subdf[(subdf.price>= lower) & (subdf.price<= upper) ]
        df_out= pd.concat([df_out, reduced_df], ignore_index=True)

    return df_out

df7=remove_outliers(df6)
df7.shape
```

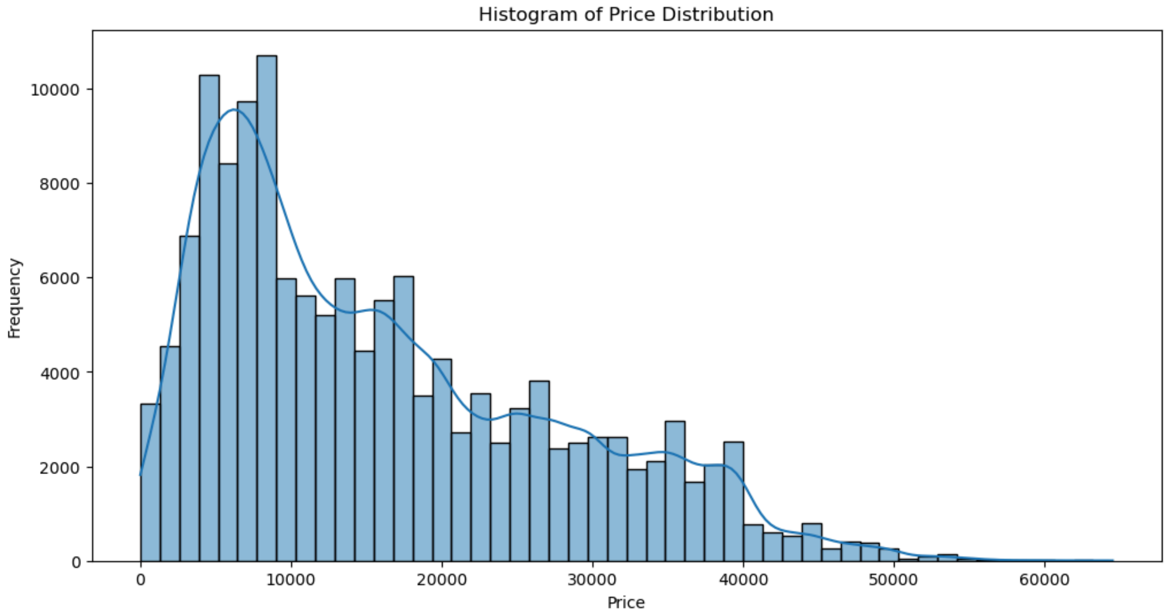
Out[40]: (144078, 10)

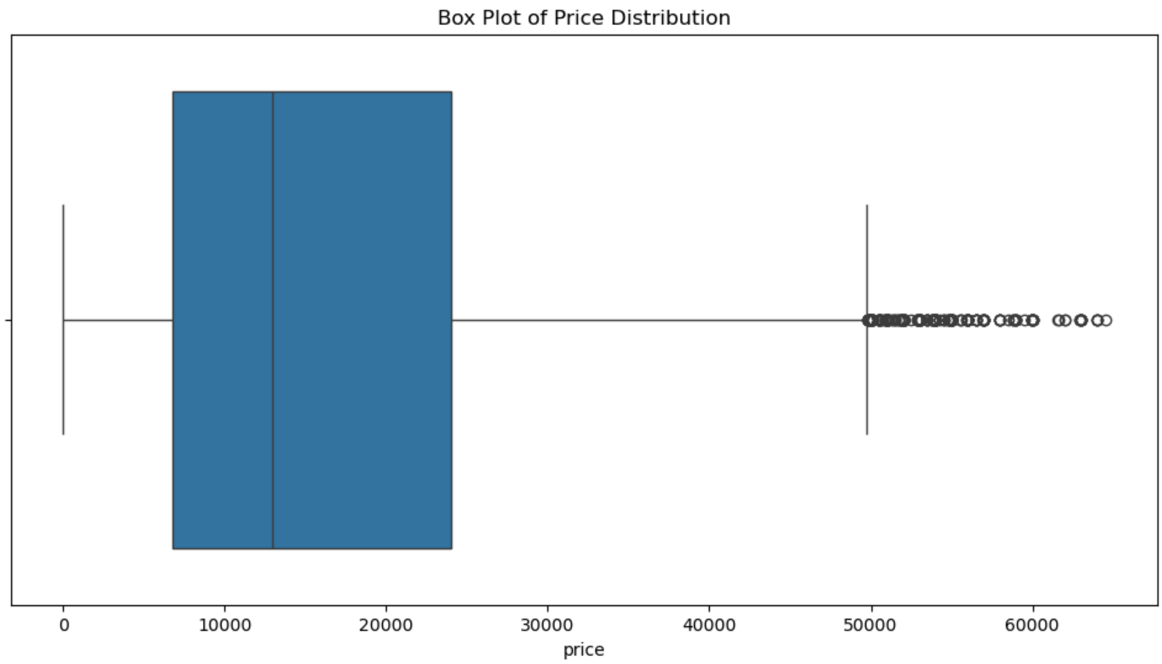
Price target variable

In [42]:
```
# visualise Price again

plt.figure(figsize=(12, 6))
sns.histplot(df7['price'], bins=50, kde=True)
plt.title('Histogram of Price Distribution')
plt.xlabel('Price')
plt.ylabel('Frequency')
plt.show()

plt.figure(figsize=(12, 6))
sns.boxplot(x=df7['price'])
plt.title('Box Plot of Price Distribution')
plt.show()
```





In [43]:
```
df7['price'].describe(percentiles = [0.25,0.50,0.75,0.85,0.90,1])
```

Out[43]:
```
count    144078.000000
mean      16103.381821
std       11566.195793
min           1.000000
25%        6795.000000
50%       12995.000000
75%       23990.000000
85%       29990.000000
90%       33990.000000
100%      64500.000000
max       64500.000000
Name: price, dtype: float64
```

The range looks better now it is still right skewed but that is to be expected in car prices

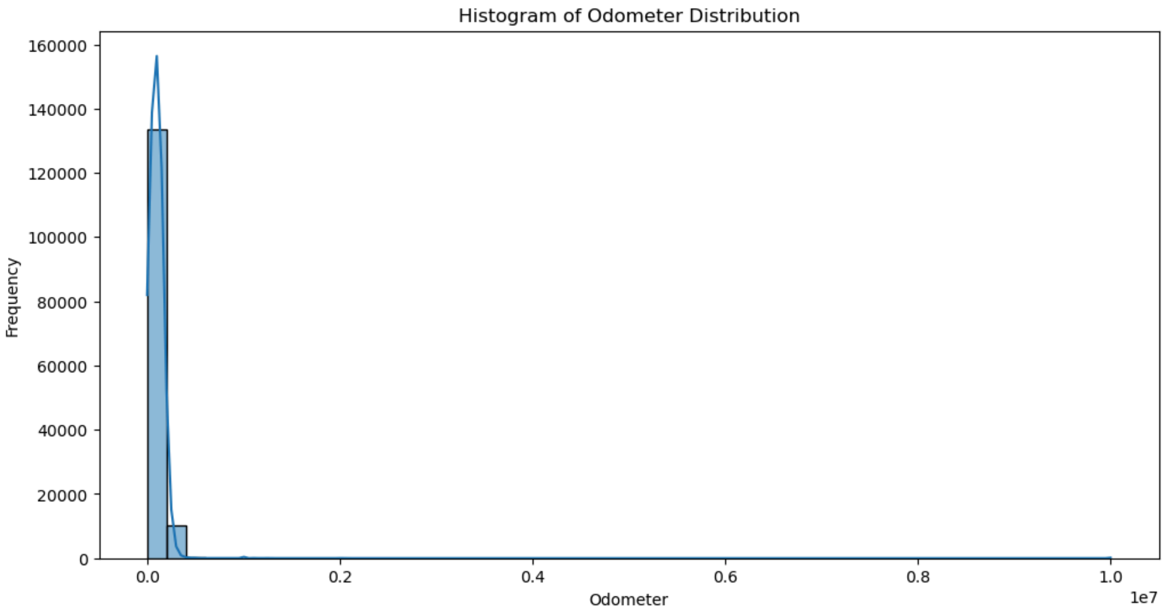
odometer/ mileage feature

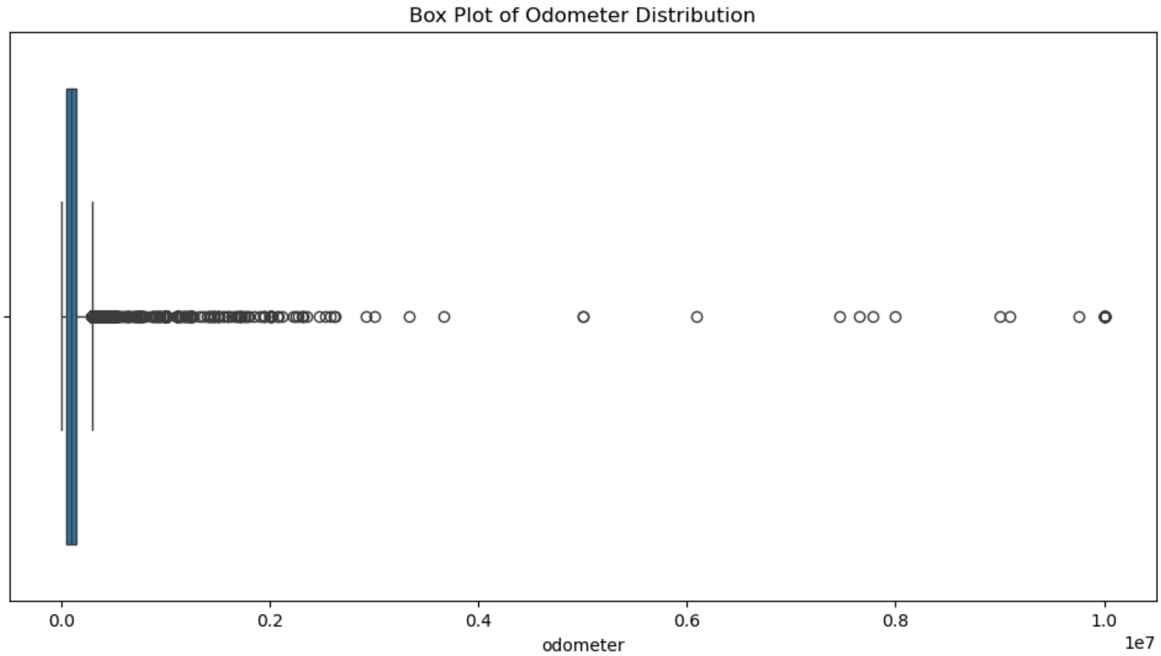
In [46]:
```
df7['odometer'].describe(percentiles = [0.25,0.50,0.75,0.85,0.90,1])
```

Out[46]:
```
count    1.440780e+05
mean     1.039443e+05
std      1.742401e+05
min      0.000000e+00
25%      4.397425e+04
50%      9.700000e+04
75%      1.435270e+05
85%      1.684450e+05
90%      1.860000e+05
100%     1.000000e+07
max      1.000000e+07
Name: odometer, dtype: float64
```

In [47]:
```
plt.figure(figsize=(12, 6))
sns.histplot(df7['odometer'], bins=50, kde=True)
plt.title('Histogram of Odometer Distribution')
plt.xlabel('Odometer')
plt.ylabel('Frequency')
plt.show()

plt.figure(figsize=(12, 6))
sns.boxplot(x=df7['odometer'])
plt.title('Box Plot of Odometer Distribution')
plt.show()
```





Notice the distribution is also highly right skewed. The odometer desciption shows minimum mileage=0 which is unlikely for second hand cars. Also the maximum= 10 million which is extremely high. According to the Guinness world record, the highest car mileage in history record is roughly around 3 mil!

In [49]:
```
# first we check for odometer = 0
df7[(df7['odometer']==0)]
```

Out[49]:

	price	manufacturer	condition	fuel	odometer	transmission	drive	pair
2173	4500	gmc	good	gas	0.0	automatic	rwd	
2269	4250	ford	good	gas	0.0	automatic	rwd	
2355	10500	chevrolet	good	gas	0.0	other	rwd	
2524	7000	ford	good	gas	0.0	automatic	4wd	
5916	9999	jeep	excellent	gas	0.0	automatic	fwd	
...	...	...	...	...	...	...	...	
134351	650	jeep	fair	gas	0.0	automatic	4wd	
137120	20998	mitsubishi	new	gas	0.0	automatic	fwd	
137640	4999	kia	excellent	gas	0.0	automatic	fwd	
139817	6250	chrysler	good	gas	0.0	automatic	rwd	
142597	3500	cadillac	good	gas	0.0	automatic	rwd	

226 rows × 10 columns

In [50]:

```
#even though some of those vehicles with odometer=0 are aged=0, our analy
#hence we will remove all samples with odometer<1000 as anything less tha
#considered a new car
# we will also remove all samples with odometer> 500,000 as they are unma
df8= df7[(df7.odometer>1000) & (df7.odometer<=500000)]

df8.odometer.describe()
```

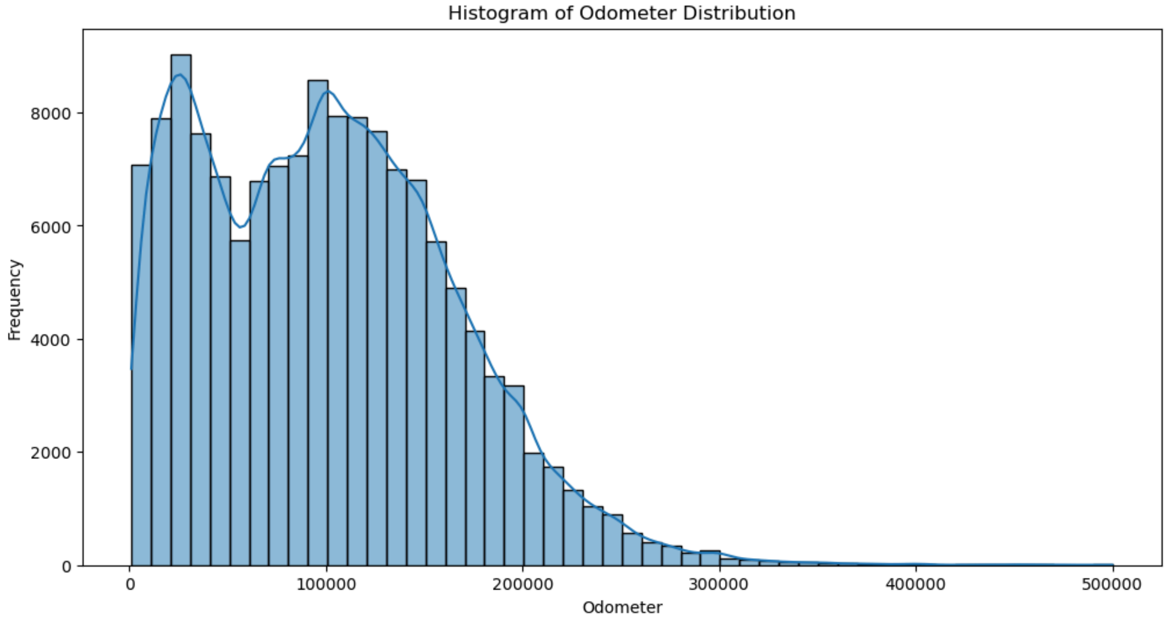
Out[50]:

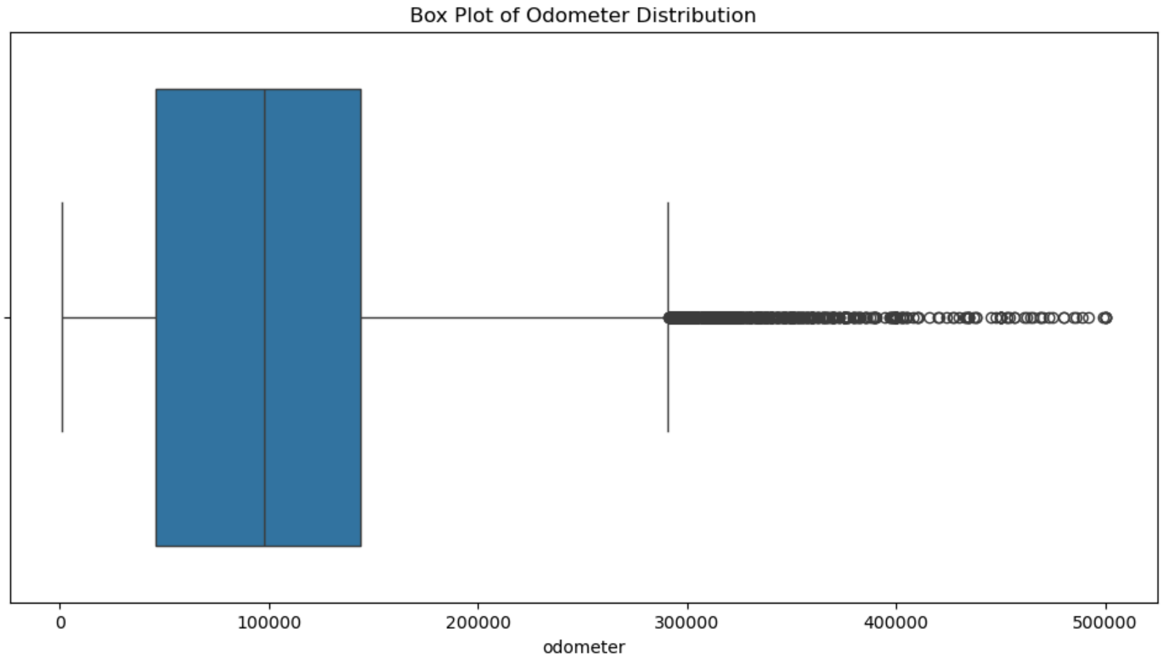
```
count     141853.000000
mean      100955.105074
std        64332.264191
min         1001.000000
25%        45996.000000
50%        98000.000000
75%       144000.000000
max       500000.000000
Name: odometer, dtype: float64
```

In [51]:

```
plt.figure(figsize=(12, 6))
sns.histplot(df8['odometer'], bins=50, kde=True)
plt.title('Histogram of Odometer Distribution')
plt.xlabel('Odometer')
plt.ylabel('Frequency')
plt.show()

plt.figure(figsize=(12, 6))
sns.boxplot(x=df8['odometer'])
plt.title('Box Plot of Odometer Distribution')
plt.show()
```





age of vehicle feature

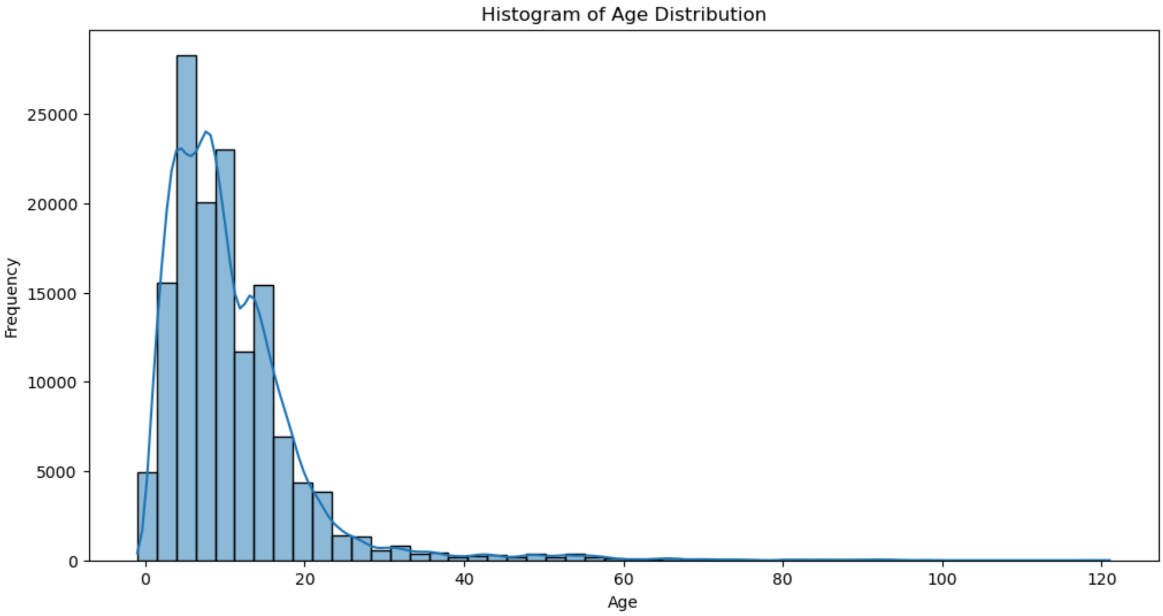
In [53]:
```
df8['vehicle_age'].describe(percentiles = [0.25,0.50,0.75,0.85,0.90,1])
```

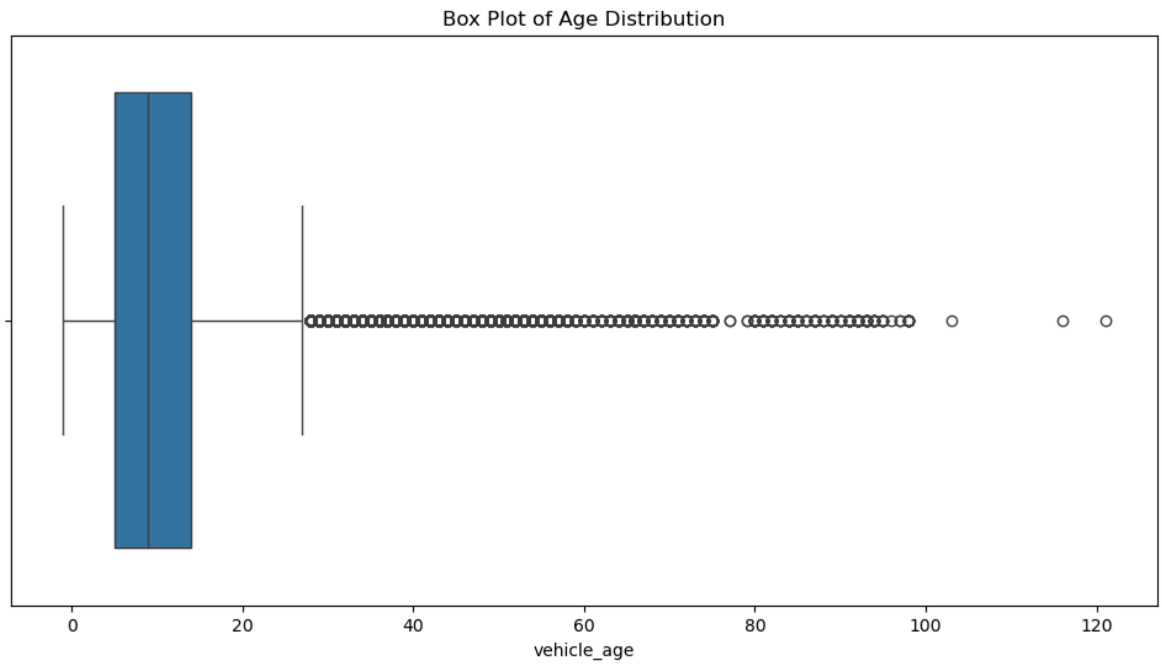
Out[53]:
```
count    141853.000000
mean         10.708184
std           8.918363
min          -1.000000
25%           5.000000
50%           9.000000
75%          14.000000
85%          17.000000
90%          19.000000
100%        121.000000
max         121.000000
Name: vehicle_age, dtype: float64
```

In [54]:
```
plt.figure(figsize=(12, 6))
sns.histplot(df8['vehicle_age'], bins=50, kde=True)
plt.title('Histogram of Age Distribution')
```

```
plt.xlabel('Age')
plt.ylabel('Frequency')
plt.show()

plt.figure(figsize=(12, 6))
sns.boxplot(x=df8['vehicle_age'])
plt.title('Box Plot of Age Distribution')
plt.show()
```





In [55]:
```
#remove cars with age<=0 as they can be errors or new cars and hence irre
# we will also split our data into vintage-classic cars (age>=30) and non

#non vintage
df_nonvintage= df8[(df8.vehicle_age>0) & (df8.vehicle_age<30)]

#vintage
df_vintage= df8[(df8.vehicle_age>=30) & (df8.vehicle_age<=100)]


df_nonvintage['vehicle_age'].describe(percentiles = [0.25,0.50,0.75,0.85,
```

Out[55]:
```
count    137114.000000
mean          9.555122
std           5.826401
min           1.000000
25%           5.000000
50%           8.000000
75%          13.000000
85%          16.000000
90%          18.000000
100%         29.000000
max          29.000000
Name: vehicle_age, dtype: float64
```

In [56]:
```
df_nonvintage.shape
```

Out[56]:
```
(137114, 10)
```

In [57]:
```
df_vintage.shape
```

Out[57]:
```
(4608, 10)
```

Checking for Duplicates

In [59]:
```
print('Duplicates in nonvintage data:\n ', df_nonvintage.duplicated().sum
      '\nDuplicates in vintage data:\n ', df_vintage.duplicated().sum())
```

```
Duplicates in nonvintage data:
  34681
Duplicates in vintage data:
  249
```

In [60]:
```
#removing duplicates
df_nonvintage= df_nonvintage.drop_duplicates()
df_vintage= df_vintage.drop_duplicates()

print('Duplicates in nonvintage data:\n ', df_nonvintage.duplicated().sum
      '\nDuplicates in vintage data:\n ', df_vintage.duplicated().sum())
```

```
Duplicates in nonvintage data:
  0
Duplicates in vintage data:
  0
```

In [61]:
```
df_nonvintage.shape
```

Out[61]:
```
(102433, 10)
```

In [62]:
```
df_vintage.shape
```

Out[62]:
```
(4359, 10)
```

In [63]:
```
df_nonvintage.dtypes
```

Out[63]:
```
price             int64
manufacturer     object
condition        object
fuel             object
odometer        float64
transmission     object
drive            object
paint_color      object
state            object
vehicle_age       int32
dtype: object
```

One hot encoding

In [66]:
```
manufacturer_count= df_nonvintage.groupby('manufacturer')['manufacturer']
paint_count=df_nonvintage.groupby('paint_color')['paint_color'].agg('coun
transmission_count= df_nonvintage.groupby('transmission')['transmission']
drive_count= df_nonvintage.groupby('drive')['drive'].agg('count').sort_va
fuel_count= df_nonvintage.groupby('fuel')['state'].agg('count').sort_valu
condition_count= df_nonvintage.groupby('condition')['condition'].agg('cou
state_count= df_nonvintage.groupby('state')['state'].agg('count').sort_va

print(manufacturer_count,
     '\n\n ',paint_count ,
     '\n\n', state_count,
     '\n\n', transmission_count,
     '\n\n ',drive_count ,
     '\n\n', fuel_count,
     '\n\n ',condition_count)
```

```
manufacturer
ford             16912
chevrolet        13273
toyota            9141
honda             6476
nissan            5416
jeep              4839
bmw               3602
gmc               3556
dodge             3296
ram               3120
volkswagen        2857
hyundai           2852
subaru            2693
mercedes-benz     2584
kia               2227
lexus             2203
chrysler          1743
mazda             1660
cadillac          1551
acura             1459
buick             1400
audi              1327
infiniti          1237
lincoln           1139
mitsubishi        1012
volvo              863
mini               795
pontiac            697
rover              452
jaguar             443
saturn             397
mercury            387
porsche            265
fiat               238
tesla              197
alfa-romeo         111
other               13
Name: manufacturer, dtype: int64

  paint_color
white     24876
black     20242
silver    15560
blue      11205
grey      10649
red       10643
green      3123
brown      2772
custom     1866
yellow      636
orange      567
purple      294
Name: paint_color, dtype: int64

 state
ca    10584
fl     6275
ny     5545
tx     5156
```

```
oh     4079
pa     3930
mi     3842
wi     3441
nc     3343
ma     2885
il     2752
co     2696
az     2600
mn     2581
nj     2540
or     2473
va     2455
tn     2384
ia     2312
in     1934
ga     1733
ks     1728
ok     1657
sc     1586
id     1506
wa     1465
ct     1451
nm     1385
ky     1314
mo     1115
md     1108
vt     1060
al     1058
mt     1003
dc      971
nh      926
ri      904
me      848
nv      842
ar      803
ak      626
la      576
hi      514
sd      421
de      386
wv      322
ms      321
ne      320
ut      309
wy      208
nd      160
Name: state, dtype: int64

 transmission
automatic    81592
other        14321
manual        6520
Name: transmission, dtype: int64

  drive
fwd    41258
4wd    39870
rwd    21305
Name: drive, dtype: int64
```

```
 fuel
gas         90945
diesel       4889
other        4501
hybrid       1657
electric      441
Name: state, dtype: int64

  condition
good         45784
excellent    42924
like new      9682
fair          3429
new            327
salvage        287
Name: condition, dtype: int64
```

In [67]:
```
#non vintage cars

#to ensure our dummies are not boolean (True/False) set dtype=int


df_nonvintage_encoded= pd.get_dummies(df_nonvintage, columns=['manufactur
                                      'paint_color', 'state'],  dtype=int



df_nonvintage_encoded.head()
```

Out[67]:

	price	odometer	vehicle_age	acura	alfa-romeo	audi	bmw	buick	cadillac	chev
0	55000	167000.0	8	0	0	0	0	0	0	
2	16000	53111.0	3	0	0	0	0	0	0	
4	29000	98000.0	11	0	0	0	0	0	0	
5	23000	94252.0	8	0	0	0	0	0	0	
7	13950	193121.0	14	0	0	0	0	0	0	

5 rows × 120 columns

In [68]:
```
#to avoide dummy variable trap, we will drop one of the columns from each
#we will choose columns with the least count

#for state= nd (least count), pain_color=custom, fuel= other, transmissio
#condition= salvage (least count), manufacturer= other
df_nonvintage_encoded.drop(['nd','other','custom','other','other','rwd','
```

In [ ]:

In [ ]:

In [69]:
```
manufacturer_count= df_vintage.groupby('manufacturer')['manufacturer'].ag
paint_count=df_vintage.groupby('paint_color')['paint_color'].agg('count')
transmission_count= df_vintage.groupby('transmission')['transmission'].ag
```

```
drive_count= df_vintage.groupby('drive')['drive'].agg('count').sort_value
fuel_count= df_vintage.groupby('fuel')['state'].agg('count').sort_values(
condition_count= df_vintage.groupby('condition')['condition'].agg('count'
state_count= df_vintage.groupby('state')['state'].agg('count').sort_value

print(manufacturer_count,
     '\n\n ',paint_count ,
     '\n\n', state_count,
     '\n\n', transmission_count,
     '\n\n ',drive_count ,
     '\n\n', fuel_count,
     '\n\n ',condition_count)
```

```
manufacturer
chevrolet        1223
ford             1026
jeep              247
mercedes-benz     208
toyota            190
volkswagen        182
pontiac           176
dodge             165
gmc               128
cadillac          114
buick             106
mercury            77
chrysler           66
lincoln            63
nissan             54
honda              49
mazda              41
bmw                35
porsche            33
volvo              30
jaguar             29
other              23
alfa-romeo         20
rover              17
ram                16
fiat               15
mitsubishi          7
lexus               6
mini                5
subaru              5
audi                2
acura               1
Name: manufacturer, dtype: int64

  paint_color
red       860
blue      732
white     690
black     525
green     329
custom    241
brown     234
grey      229
silver    193
yellow    186
orange    103
purple     37
Name: paint_color, dtype: int64

 state
ca    516
fl    249
tx    217
ny    210
co    177
pa    176
nc    173
or    166
oh    161
```

```
wi    132
az    131
wa    117
il    108
mi    103
va    102
nj     95
tn     95
ma     86
mn     85
mt     81
sc     80
nm     74
id     72
in     69
ks     67
ia     67
ct     60
md     57
ky     51
me     49
ga     48
al     45
ok     43
nh     40
ar     37
mo     35
vt     34
nv     32
ak     32
ri     29
la     25
sd     23
ut     18
ms     15
hi     15
wy     14
ne     13
dc     11
wv     11
de     10
nd      3
Name: state, dtype: int64

 transmission
automatic    2770
manual       1535
other          54
Name: transmission, dtype: int64

  drive
rwd    3176
4wd     831
fwd     352
Name: drive, dtype: int64

 fuel
gas         4186
diesel       166
other          5
```

```
electric      2
Name: state, dtype: int64

  condition
good         1938
excellent    1518
fair          615
like new      251
salvage        20
new            17
Name: condition, dtype: int64
```

In [70]:
```
# vintage cars




df_vintage_encoded= pd.get_dummies(df_vintage, columns=['manufacturer', '
                                  'paint_color', 'state'],   dtype=in

df_vintage_encoded.drop(['nd','other','custom','other','other','fwd','sal
```

Model

In [72]:
```
#split into x(input) and y (target/output)

#nonvintage
x_nonvintage=df_nonvintage_encoded.drop('price', axis='columns')
y_nonvintage= df_nonvintage_encoded.price

#vintage
x_vintage=df_vintage_encoded.drop('price', axis='columns')
y_vintage= df_vintage_encoded.price
```

In [73]:
```
x_nonvintage.shape
```

Out[73]:
```
(102433, 112)
```

In [74]:
```
x_vintage.shape
```

Out[74]:
```
(4359, 106)
```

split to train and test

In [76]:
```
from sklearn.model_selection import train_test_split

#since nonvintage cars dataset contains 102,433 samples an 80/20 split wi
x_nonvintage_train, x_nonvintage_test,y_nonvintage_train, y_nonvintage_te

#similarily the vintage cars dataset contains 4,359 samples an 80/20 spli
x_vintage_train, x_vintage_test,y_vintage_train, y_vintage_test= train_te
```

Linear regression

In [78]:
```
from sklearn.linear_model import LinearRegression

lr_nonvintage= LinearRegression()
lr_vintage= LinearRegression()

#fit for both vintage and nonvintage
lr_nonvintage.fit(x_nonvintage_train, y_nonvintage_train)
lr_vintage.fit(x_vintage_train, y_vintage_train)
```

Out[78]:
```
▾ LinearRegression
LinearRegression()
```

In [79]:
```
#evaluete the nonvintage model

lr_nonvintage.score(x_nonvintage_test, y_nonvintage_test)
```

Out[79]:
```
0.6904030226735173
```

69% is not bad but still need to improve the model

In [81]:
```
#evaluete the vintage model

lr_vintage.score(x_vintage_test, y_vintage_test)
```

Out[81]:
```
0.3941757946715474
```

39% is pretty low which is to be expected froom vintage cars since we have a smaller sample and it is harder to predict the prices of vintage cars

we will stick to modelling non vintage cars

k-fold Cross Validation

In [85]:
```
from sklearn.model_selection import ShuffleSplit
from sklearn.model_selection import cross_val_score

#shufflesplit will randomise the sample to ensure each fold will have equ
#of each of the data samples and is not targeted to one area
cv= ShuffleSplit(n_splits= 5, test_size=0.2, random_state=0)

cross_val_score(LinearRegression(), x_nonvintage, y_nonvintage, cv=cv)
```

Out[85]:
```
array([0.68721057, 0.69514816, 0.6933332 , 0.69261292, 0.69100681])
```

In each fold results remain roughly arond 69%

Testing different regression models

In [88]:
```
from sklearn.model_selection import GridSearchCV
from sklearn.linear_model import Lasso
```

```
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor
import xgboost as xgb
```

In [89]:
```
def find_best_model_using_gridsearchcv(X, y):
    algorithms = {
        'linear_regression': {
            'model': LinearRegression(),
            'params': {
                'fit_intercept': [True, False]
            }
        },
        'lasso': {
            'model': Lasso(),
            'params': {
                'alpha': [0.1, 1],  # Adjusted alpha values
                'selection': ['random', 'cyclic']
            }
        },
        'decision_tree': {
            'model': DecisionTreeRegressor(),
            'params': {
                'criterion': ['squared_error', 'friedman_mse'],
                'splitter': ['best', 'random']
            }
        },
    }

    scores = []
    cv = ShuffleSplit(n_splits=5, test_size=0.2, random_state=0)

    for algo_name, config in algorithms.items():
        try:
            gs = GridSearchCV(config['model'], config['params'], cv=cv,
                              return_train_score=False, n_jobs=-1)
            gs.fit(X, y)
            scores.append({
                'model': algo_name,
                'best_score_': gs.best_score_,
                'best_params_': gs.best_params_
            })
        except Exception as e:
            print(f"Error in {algo_name}: {e}")

    return pd.DataFrame(scores)

# Call the function with your data
results = find_best_model_using_gridsearchcv(x_nonvintage, y_nonvintage)
results
```

```
/opt/anaconda3/lib/python3.12/site-packages/sklearn/linear_model/_coordina
te_descent.py:697: ConvergenceWarning: Objective did not converge. You mig
ht want to increase the number of iterations, check the scale of the featu
res or consider increasing regularisation. Duality gap: 1.536e+12, toleran
ce: 9.964e+08
  model = cd_fast.enet_coordinate_descent(
/opt/anaconda3/lib/python3.12/site-packages/sklearn/linear_model/_coordina
te_descent.py:697: ConvergenceWarning: Objective did not converge. You mig
ht want to increase the number of iterations, check the scale of the featu
res or consider increasing regularisation. Duality gap: 1.463e+12, toleran
ce: 9.993e+08
  model = cd_fast.enet_coordinate_descent(
/opt/anaconda3/lib/python3.12/site-packages/sklearn/linear_model/_coordina
te_descent.py:697: ConvergenceWarning: Objective did not converge. You mig
ht want to increase the number of iterations, check the scale of the featu
res or consider increasing regularisation. Duality gap: 1.542e+12, toleran
ce: 1.002e+09
  model = cd_fast.enet_coordinate_descent(
/opt/anaconda3/lib/python3.12/site-packages/sklearn/linear_model/_coordina
te_descent.py:697: ConvergenceWarning: Objective did not converge. You mig
ht want to increase the number of iterations, check the scale of the featu
res or consider increasing regularisation. Duality gap: 1.533e+12, toleran
ce: 1.001e+09
  model = cd_fast.enet_coordinate_descent(
/opt/anaconda3/lib/python3.12/site-packages/sklearn/linear_model/_coordina
te_descent.py:697: ConvergenceWarning: Objective did not converge. You mig
ht want to increase the number of iterations, check the scale of the featu
res or consider increasing regularisation. Duality gap: 1.539e+12, toleran
ce: 1.002e+09
  model = cd_fast.enet_coordinate_descent(
/opt/anaconda3/lib/python3.12/site-packages/sklearn/linear_model/_coordina
te_descent.py:697: ConvergenceWarning: Objective did not converge. You mig
ht want to increase the number of iterations, check the scale of the featu
res or consider increasing regularisation. Duality gap: 1.861e+10, toleran
ce: 1.001e+09
  model = cd_fast.enet_coordinate_descent(
/opt/anaconda3/lib/python3.12/site-packages/sklearn/linear_model/_coordina
te_descent.py:697: ConvergenceWarning: Objective did not converge. You mig
ht want to increase the number of iterations, check the scale of the featu
res or consider increasing regularisation. Duality gap: 1.302e+12, toleran
ce: 9.964e+08
  model = cd_fast.enet_coordinate_descent(
/opt/anaconda3/lib/python3.12/site-packages/sklearn/linear_model/_coordina
te_descent.py:697: ConvergenceWarning: Objective did not converge. You mig
ht want to increase the number of iterations, check the scale of the featu
res or consider increasing regularisation. Duality gap: 1.285e+11, toleran
ce: 1.002e+09
  model = cd_fast.enet_coordinate_descent(
/opt/anaconda3/lib/python3.12/site-packages/sklearn/linear_model/_coordina
te_descent.py:697: ConvergenceWarning: Objective did not converge. You mig
ht want to increase the number of iterations, check the scale of the featu
res or consider increasing regularisation. Duality gap: 1.017e+12, toleran
ce: 9.993e+08
  model = cd_fast.enet_coordinate_descent(
/opt/anaconda3/lib/python3.12/site-packages/sklearn/linear_model/_coordina
te_descent.py:697: ConvergenceWarning: Objective did not converge. You mig
ht want to increase the number of iterations, check the scale of the featu
res or consider increasing regularisation. Duality gap: 1.539e+12, toleran
ce: 9.964e+08
  model = cd_fast.enet_coordinate_descent(
```

```
/opt/anaconda3/lib/python3.12/site-packages/sklearn/linear_model/_coordina
te_descent.py:697: ConvergenceWarning: Objective did not converge. You mig
ht want to increase the number of iterations, check the scale of the featu
res or consider increasing regularisation. Duality gap: 1.535e+12, toleran
ce: 1.001e+09
  model = cd_fast.enet_coordinate_descent(
/opt/anaconda3/lib/python3.12/site-packages/sklearn/linear_model/_coordina
te_descent.py:697: ConvergenceWarning: Objective did not converge. You mig
ht want to increase the number of iterations, check the scale of the featu
res or consider increasing regularisation. Duality gap: 8.169e+11, toleran
ce: 1.002e+09
  model = cd_fast.enet_coordinate_descent(
/opt/anaconda3/lib/python3.12/site-packages/sklearn/linear_model/_coordina
te_descent.py:697: ConvergenceWarning: Objective did not converge. You mig
ht want to increase the number of iterations, check the scale of the featu
res or consider increasing regularisation. Duality gap: 1.477e+12, toleran
ce: 1.002e+09
  model = cd_fast.enet_coordinate_descent(
/opt/anaconda3/lib/python3.12/site-packages/sklearn/linear_model/_coordina
te_descent.py:697: ConvergenceWarning: Objective did not converge. You mig
ht want to increase the number of iterations, check the scale of the featu
res or consider increasing regularisation. Duality gap: 1.544e+12, toleran
ce: 1.002e+09
  model = cd_fast.enet_coordinate_descent(
/opt/anaconda3/lib/python3.12/site-packages/sklearn/linear_model/_coordina
te_descent.py:697: ConvergenceWarning: Objective did not converge. You mig
ht want to increase the number of iterations, check the scale of the featu
res or consider increasing regularisation. Duality gap: 1.741e+12, toleran
ce: 1.249e+09
  model = cd_fast.enet_coordinate_descent(
```

Out[89]:

	model	best_score_	best_params_
0	linear_regression	0.691862	{'fit_intercept': True}
1	lasso	0.691769	{'alpha': 0.1, 'selection': 'cyclic'}
2	decision_tree	0.683318	{'criterion': 'friedman_mse', 'splitter': 'ran...

In [90]:

```
def find_best_model_using_gridsearchcv(X, y):
    algorithms = {

        'random_forest': {
            'model': RandomForestRegressor(),
            'params': {
                'n_estimators': [50,100]




            }
        }
        ,

        'xgboost': {
            'model': xgb.XGBRegressor(),
            'params':{
                'n_estimators': [100, 200],
                'max_depth': [3, 5]
            }
        }
```

```
    }

    scores = []
    cv = ShuffleSplit(n_splits=5, test_size=0.2, random_state=0)

    for algo_name, config in algorithms.items():
        try:
            gs = GridSearchCV(config['model'], config['params'], cv=cv,
                                  return_train_score=False, n_jobs=-1)
            gs.fit(X, y)
            scores.append({
                'model': algo_name,
                'best_score_': gs.best_score_,
                'best_params_': gs.best_params_
            })
        except Exception as e:
            print(f"Error in {algo_name}: {e}")

    return pd.DataFrame(scores)

# Call the function with your data
results = find_best_model_using_gridsearchcv(x_nonvintage, y_nonvintage)
results
```

Out[90]:

	model	best_score_	best_params_
0	random_forest	0.822767	{'n_estimators': 100}
1	xgboost	0.803931	{'max_depth': 5, 'n_estimators': 200}

Random Forest has the best performance with a score of 82%

Random Forest had the best performance

In [93]:

```
rf= RandomForestRegressor(n_jobs=-1)
rf.fit(x_nonvintage_train, y_nonvintage_train)
```

Out[93]:

```
▾ RandomForestRegressor
RandomForestRegressor(n_jobs=-1)
```

In [204…

```
rf.score(x_nonvintage_test, y_nonvintage_test)
```

Out[204… 0.8257530771207827

In [152…

```
imp=rf.feature_importances_

col= x_nonvintage_train.columns

imp_df= pd.DataFrame([imp], columns=col)
imp_df
```

Out[152…

	odometer	vehicle_age	acura	alfa-romeo	audi	bmw	buick	cadil
0	0.190751	0.418049	0.002148	0.000122	0.001265	0.002702	0.000931	0.0(

1 rows × 112 columns

In [202…

```
#we will sum all the levels within each category. since get_dummies arran
#in alphabetic order


#manufacturer starts with Acura and ends with Volvo
manufacturer= imp_df.loc[:,'acura':'volvo'].sum(axis=1).values[0]

#similarily for the rest of the features
paint_color= imp_df.loc[:,'black':'yellow'].sum(axis=1).values[0]
state= imp_df.loc[:,'ak':'wy'].sum(axis=1).values[0]
transmission= imp_df.loc[:,'automatic':'manual'].sum(axis=1).values[0]
drive= imp_df.loc[:,'4wd':'fwd'].sum(axis=1).values[0]
fuel= imp_df.loc[:,'diesel':'hybrid'].sum(axis=1).values[0]
condition= imp_df.loc[:,'excellent':'new'].sum(axis=1).values[0]

imp= pd.DataFrame({ 'manufacturer': [manufacturer], 'paint_color' : [pain
                   'drive': [drive], 'fuel': [fuel], 'condition': [condit

#add the first two columns from imp_df to include odometer and vehicle_ag
pd.concat([imp, imp_df.iloc[:,:2] ], axis=1)
```

Out[202…

	manufacturer	paint_color	state	transmission	drive	fuel	conditio
0	0.087551	0.030071	0.062539	0.014202	0.124431	0.050871	0.02153

We will remove features with less than 5% significancce: paint_color, transmission, condition

In [207…

```
#first select columns to be removed
trans= x_nonvintage_train.loc[:,'automatic':'manual'].columns.tolist()
color= x_nonvintage_train.loc[:,'black':'yellow'].columns.tolist()
cond= x_nonvintage_train.loc[:,'excellent':'new'].columns.tolist()

#combine those colums
col_remove= trans+color+cond

#modify both train and test sets

x_nonvintage_train_reduced =x_nonvintage_train.drop(columns= col_remove)
x_nonvintage_test_reduced= x_nonvintage_test.drop(columns= col_remove)
y_nonvintage_train_reduced =y_nonvintage_train.drop(columns= col_remove)
y_nonvintage_test_reduced= y_nonvintage_test.drop(columns= col_remove)
```

Implement Random Forest on the reduced data

In [253…

```
rf_reduced= RandomForestRegressor(n_jobs=-1)
rf_reduced.fit(x_nonvintage_train_reduced, y_nonvintage_train_reduced)
```

Out[253…

```
▾ RandomForestRegressor
RandomForestRegressor(n_jobs=-1)
```

In [254…

```
rf_reduced.score(x_nonvintage_test_reduced, y_nonvintage_test_reduced)
```

Out[254…

```
0.8046099029041316
```

Model performance did not improve. try with cross validation

In [216…

```
x_nonvintage_reduced =x_nonvintage.drop(columns= col_remove)
y_nonvintage_reduced =y_nonvintage.drop(columns= col_remove)
```

In [229…

```
cv= ShuffleSplit(n_splits= 5, test_size=0.2, random_state=0)

cross_val_score(RandomForestRegressor(n_jobs=-1), x_nonvintage_reduced, y
```

Out[229…

```
array([0.80388894, 0.80362325, 0.80208947, 0.79945176, 0.80429128])
```

In [230…

```
# try with the second best model: xgboost

cv= ShuffleSplit(n_splits= 5, test_size=0.2, random_state=0)

cross_val_score(xgb.XGBRegressor(n_jobs=-1), x_nonvintage_reduced, y_nonv
```

Out[230…

```
array([0.78439391, 0.78865314, 0.78627592, 0.78047609, 0.78332841])
```

Removing features did not improve our model. We will keep all features

In [233…

```
rf= RandomForestRegressor(n_jobs=-1)
rf.fit(x_nonvintage_train, y_nonvintage_train)
rf.score(x_nonvintage_test, y_nonvintage_test)
```

Out[233…

```
0.8258058553370891
```

In [305…

```
def predict_price(manufacturer, condition, fuel, odometer, transmission,
    # Initialize an array of the size of all the columns in x_nonvintage
    x = np.zeros(len(x_nonvintage.columns))

    #set first two indices to our numeric features
    x[0] = odometer
    x[1] = vehicle_age

    # list of categorical features
    features = [state, manufacturer, condition, fuel, transmission, paint

    # for all categores in a categorical feature, loop over the categorie
    for category in features:

        # Check if the category is in our data x_nonvintage
        if category in x_nonvintage.columns:
```

```
            # Get the index for the one hot encoded category in that data
            idx = np.where(x_nonvintage.columns == category)[0][0]

            #set that category index=1 (categories for that categorical f
            x[idx] = 1

    # prediction
    return rf.predict([x])[0]
```

In [307…

```
predict_price('bmw', 'like new', 'hybrid', 120000, 'automatic','fwd', 'gr
```

```
/opt/anaconda3/lib/python3.12/site-packages/sklearn/base.py:493: UserWarni
ng: X does not have valid feature names, but RandomForestRegressor was fit
ted with feature names
  warnings.warn(
```

Out[307… 9723.135

In [309…

```
predict_price('bmw', 'like new', 'hybrid', 100000, 'automatic','fwd', 'gr
```

```
/opt/anaconda3/lib/python3.12/site-packages/sklearn/base.py:493: UserWarni
ng: X does not have valid feature names, but RandomForestRegressor was fit
ted with feature names
  warnings.warn(
```

Out[309… 15187.78

In [311…

```
predict_price('bmw', 'good', 'hybrid', 100000, 'hybrid','fwd', 'grey','ny
```

```
/opt/anaconda3/lib/python3.12/site-packages/sklearn/base.py:493: UserWarni
ng: X does not have valid feature names, but RandomForestRegressor was fit
ted with feature names
  warnings.warn(
```

Out[311… 16578.1

In [320…

```
import pickle
with open('/Users/marwa/Desktop/2ndHCP/model/rf_model', 'wb') as f:
    pickle.dump(rf, f)
```

In [321…

```
import json
columns = {
    'data_columns' : [col.lower() for col in x_nonvintage.columns]
}

with open('/Users/marwa/Desktop/2ndHCP/model/columns', 'w') as f:
    f.write(json.dumps(columns))
```