EDA on used cars

November 27, 2022

[1]:
```
import numpy as np
import pandas as pd
import os
import matplotlib.pyplot as plt
import seaborn as sns
```

[2]:
```
# Getting the current working directory
os.getcwd()
```

[2]:
```
'C:\\Users\\shoaib\\Desktop\\Revise Py-2022'
```

[3]:
```
#Reading the data from csv
cars_data=pd.read_csv("cars_sampled.csv")
```

[4]:
```
#Creating copy of cars_data
cars=cars_data.copy()  # deep copy
#Whatever changes made in cars will not be reflected in cars_data
```

[5]:
```
cars.head()
```

[5]:
```
        dateCrawled                                             name  \
0  30/03/2016 13:51                                     Zu_verkaufen
1     7/3/2016 9:54                           Volvo_XC90_2.4D_Summum
2     1/4/2016 0:57                                Volkswagen_Touran
3  19/03/2016 17:50                      Seat_Ibiza_1.4_16V_Reference
4  16/03/2016 14:51  Volvo_XC90_D5_Aut._RDesign_R_Design_AWD_GSHD_S...

    seller offerType  price   abtest vehicleType  yearOfRegistration  \
0  private     offer   4450     test   limousine                2003
1  private     offer  13299  control         suv                2005
2  private     offer   3200     test         bus                2003
3  private     offer   4500  control   small car                2006
4  private     offer  18750     test         suv                2008

     gearbox  powerPS    model  kilometer  monthOfRegistration fuelType  \
0     manual      150      3er     150000                    3   diesel
1     manual      163  xc_reihe     150000                    6   diesel
2     manual      101   touran     150000                   11   diesel
3     manual       86    ibiza      60000                   12   petrol
4  automatic      185  xc_reihe     150000                   11   diesel
```

```
        brand notRepairedDamage      dateCreated  postalCode          lastSeen
0         bmw               NaN  30/03/2016 0:00       20257     7/4/2016 4:44
1       volvo                no     7/3/2016 0:00       88045  26/03/2016 13:17
2  volkswagen               NaN  31/03/2016 0:00       27449     1/4/2016 8:40
3        seat                no  19/03/2016 0:00       34537     7/4/2016 4:44
4       volvo                no  16/03/2016 0:00       55270    1/4/2016 23:18
```

[6]:

```
cars.info()
#This gives the total entries in a column and its data type
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 50001 entries, 0 to 50000
Data columns (total 19 columns):
dateCrawled            50001 non-null object
name                   50001 non-null object
seller                 50001 non-null object
offerType              50001 non-null object
price                  50001 non-null int64
abtest                 50001 non-null object
vehicleType            44813 non-null object
yearOfRegistration     50001 non-null int64
gearbox                47177 non-null object
powerPS                50001 non-null int64
model                  47243 non-null object
kilometer              50001 non-null int64
monthOfRegistration    50001 non-null int64
fuelType               45498 non-null object
brand                  50001 non-null object
notRepairedDamage      40285 non-null object
dateCreated            50001 non-null object
postalCode             50001 non-null int64
lastSeen               50001 non-null object
dtypes: int64(6), object(13)
memory usage: 7.2+ MB
```

[7]:

```
pd.set_option('display.float_format',lambda x: '%.3f'%x) # Get the floating␣
↪point to 3 decimal places
pd.set_option('display.max_columns', 500) # To display maximum set of columns
cars.describe() #This gives the statistical info about the data- https://www.
↪mathsisfun.com/data/standard-deviation.html
# https://statisticsbyjim.com/basics/coefficient-variation/
```

[7]:

```
          price  yearOfRegistration   powerPS  kilometer  \
count 50001.000           50001.000 50001.000  50001.000
mean   6559.865            2005.544   116.496 125613.688
std   85818.470             122.992   230.568  40205.234
min       0.000            1000.000     0.000   5000.000
```

```
25%       1150.000            1999.000    69.000 125000.000
50%       2950.000            2003.000   105.000 150000.000
75%       7190.000            2008.000   150.000 150000.000
max   12345678.000            9999.000 19312.000 150000.000

       monthOfRegistration  postalCode
count            50001.000   50001.000
mean                 5.744   50775.217
std                  3.711   25743.702
min                  0.000    1067.000
25%                  3.000   30559.000
50%                  6.000   49504.000
75%                  9.000   71404.000
max                 12.000   99998.000
```

[8]:
```
print('---------------------------------------------')
print('           Data Cleaning                     ')
print('---------------------------------------------')
```

```
---------------------------------------------
           Data Cleaning
---------------------------------------------
```

[9]:
```
#Dropping unwanted columns as these variables are related ads
cars=cars.drop(['dateCrawled','name','dateCreated','lastSeen'],axis=1)
```

[10]:
```
#Removing the duplicates
cars.drop_duplicates(keep='first',inplace=True)
cars.info()
#16 duplicates removed from the cars dataset
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 49666 entries, 0 to 50000
Data columns (total 15 columns):
seller                 49666 non-null object
offerType              49666 non-null object
price                  49666 non-null int64
abtest                 49666 non-null object
vehicleType            44491 non-null object
yearOfRegistration     49666 non-null int64
gearbox                46855 non-null object
powerPS                49666 non-null int64
model                  46919 non-null object
kilometer              49666 non-null int64
monthOfRegistration    49666 non-null int64
fuelType               45177 non-null object
brand                  49666 non-null object
notRepairedDamage      39980 non-null object
```

```
postalCode             49666 non-null int64
dtypes: int64(6), object(9)
memory usage: 6.1+ MB
```

[11]:

```
#Checking the missing values from each variable
cars.isnull().sum()
```

[11]:

```
seller                    0
offerType                 0
price                     0
abtest                    0
vehicleType            5175
yearOfRegistration        0
gearbox                2811
powerPS                   0
model                  2747
kilometer                 0
monthOfRegistration       0
fuelType               4489
brand                     0
notRepairedDamage      9686
postalCode                0
dtype: int64
```

[12]:

```
#variable- year of registration
print(cars['yearOfRegistration'].value_counts().sort_index())
#There are some cars which are registered before 1900 and there are also cars␣
 ↪after 2019
```

```
1000      6
1255      1
1500      2
1910     15
1928      1
1929      1
1933      1
1934      1
1936      2
1938      1
1940      1
1941      1
1943      2
1945      2
1947      2
1950      4
1951      4
1952      3
1953      2
```

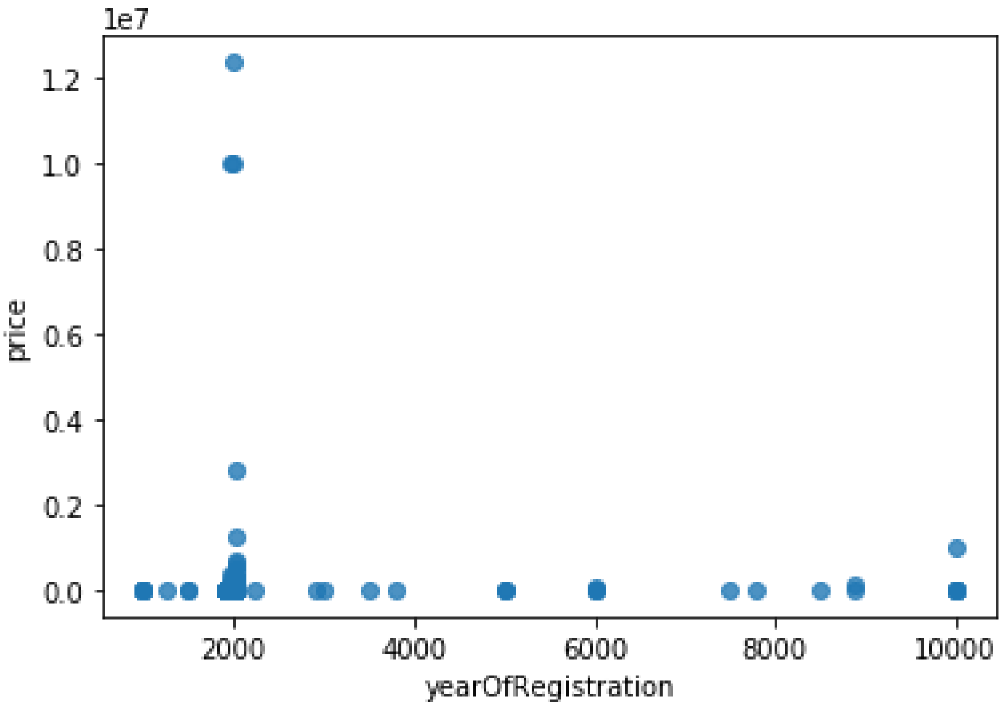
```
1954       1
1955       6
1956       7
1957       5
1958       4
1959       5
1960      33
1961       7
1962       6
1963      11
1964      16
        ...
2002    2560
2003    2742
2004    2614
2005    3109
2006    2668
2007    2357
2008    2190
2009    2018
2010    1645
2011    1548
2012    1235
2013     821
2014     624
2015     406
2016    1351
2017    1376
2018     528
2019       2
2222       1
2900       1
3000       1
3500       1
3800       1
5000       3
6000       4
7500       1
7800       1
8500       1
8888       2
9999       7
Name: yearOfRegistration, Length: 97, dtype: int64
```

[13]:
```python
print(cars['yearOfRegistration'].describe())
#There is no much difference b/w mean and median but std dev is differing from␣
↪mean by 123 years
```

```
sns.
 ↪regplot(x='yearOfRegistration',y='price',scatter=True,fit_reg=False,data=cars)
#Here we can't get any clear picture as there lot of outliers. so data is␣
 ↪concentrated at one point
```

```
count    49666.000
mean      2005.551
std        123.405
min       1000.000
25%       1999.000
50%       2003.000
75%       2008.000
max       9999.000
Name: yearOfRegistration, dtype: float64
```

[13]: <matplotlib.axes._subplots.AxesSubplot at 0x15fda7a3940>



[14]:
```
#After trial error, getting working range for year of registration
# Working range- 1950 and 2018
print(sum(cars['yearOfRegistration'] > 2018))
print(sum(cars['yearOfRegistration'] < 1950))
```

```
26
39
```

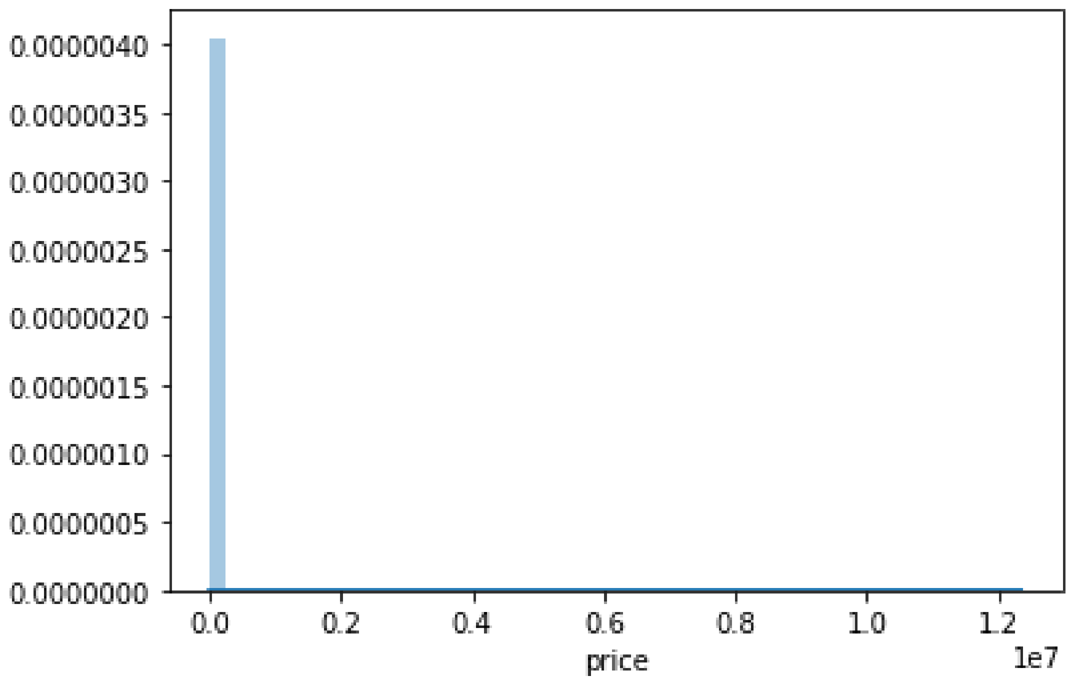
[15]:
```
#Variable - Price
cars['price'].value_counts().sort_index()
#There are 1437 cars at 0 dollar
```

[15]:
```
0         1437
1          172
2            1
3            1
5            4
7            1
8            2
10           5
11           1
12           1
14           1
15           8
20           6
21           1
25           5
26           1
30           7
35           4
39           1
40           3
45           6
50          41
55           3
60           7
65           1
70           2
75           9
77           1
80          12
85           3
          ...
163991       1
165000       1
169999       1
171000       1
175000       1
179999       1
189981       1
205000       1
214800       1
225000       1
230000       2
239000       1
```

```
249000         1
250000         1
257500         1
260000         1
270000         1
300000         1
370000         1
395000         1
485000         1
487000         1
619000         1
700000         1
999999         1
1250000        1
2795000        1
9999999        1
10010011       1
12345678       1
Name: price, Length: 2393, dtype: int64
```

[16]:
```
print(sns.distplot(cars['price']))
#Here the values are cluttered at zero
```

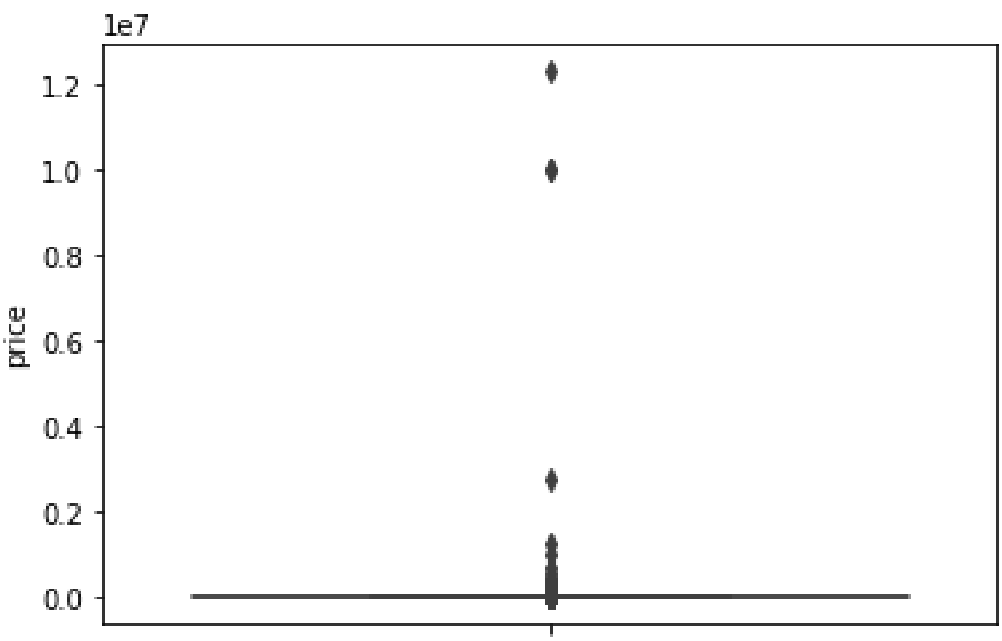
```
AxesSubplot(0.125,0.125;0.775x0.755)
```



[17]:
```python
print(sns.boxplot(y=cars['price']))
# similarly boxplot is not clearly visible due to outliers
cars['price'].describe()
# Std dev is 1300% of mean
```

```
AxesSubplot(0.125,0.125;0.775x0.755)
```

[17]:
```
count       49666.000
mean         6559.299
std         86105.705
min             0.000
25%          1150.000
50%          2950.000
75%          7100.000
max      12345678.000
Name: price, dtype: float64
```



[18]:
```python
#count
print(sum(cars['price'] > 150000))
print(sum(cars['price'] < 100))
# Working range- 100 and 150000 after trial and error
```

```
34
1770
```

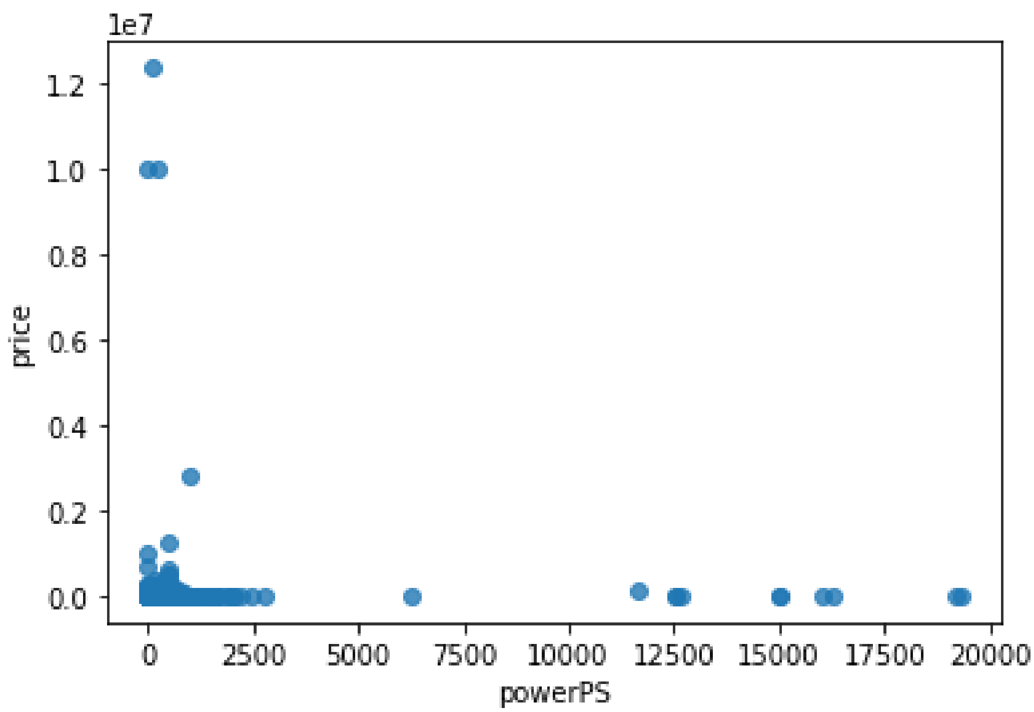
[19]:
```python
# Variable powerPS
cars['powerPS'].value_counts().sort_index()
#5581 cars have zero horse power
```

[19]:
```
0       5581
1          3
2          2
3          2
4          4
5         17
6          2
7          1
9          1
10         2
11         4
12         6
13         1
14         6
15         3
16         1
18         9
19         2
20         1
22         1
23         3
24         5
26        46
27         5
29         2
30         7
31         1
32         2
33         5
34        29
        ...
1223       1
1256       1
1363       1
1416       1
1502       1
1595       1
1598       1
1625       1
1653       1
1799       1
1910       1
1968       1
```

```
1992        1
1998        1
2004        1
2017        1
2172        1
2461        1
2789        1
6226        1
11620       1
12510       1
12512       1
12684       1
15017       1
15033       1
16011       1
16312       1
19211       1
19312       1
Name: powerPS, Length: 460, dtype: int64
```

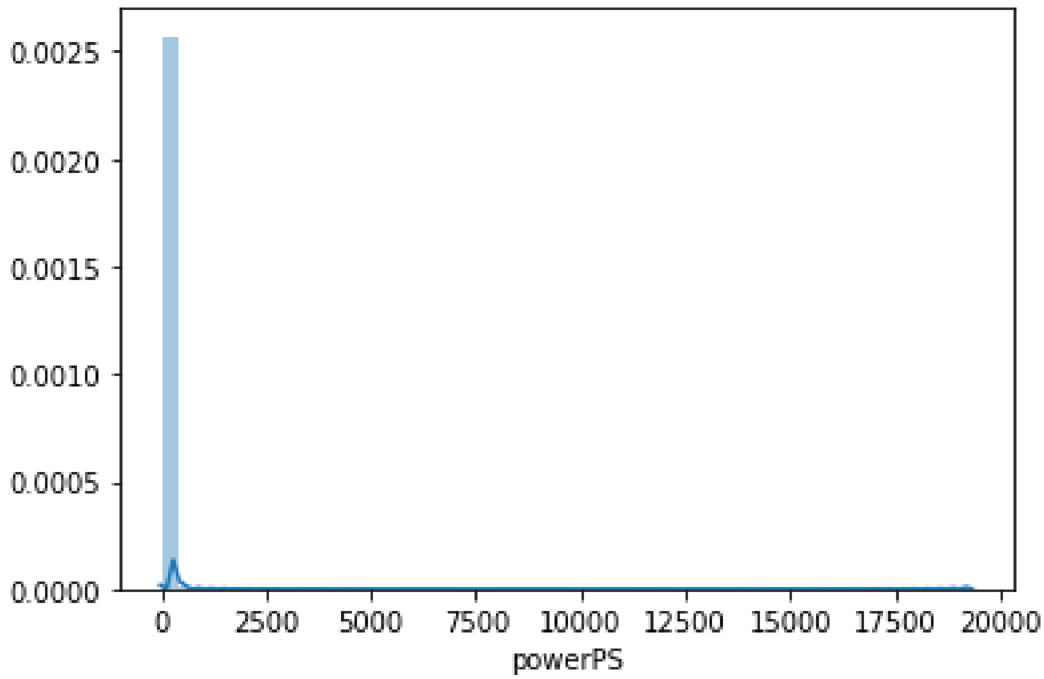
[20]:
```
sns.regplot(x='powerPS',y='price',scatter=True,fit_reg=False,data=cars)
#data is concentrated at zero power ps
```

[20]: <matplotlib.axes._subplots.AxesSubplot at 0x15fdbaf9d68>



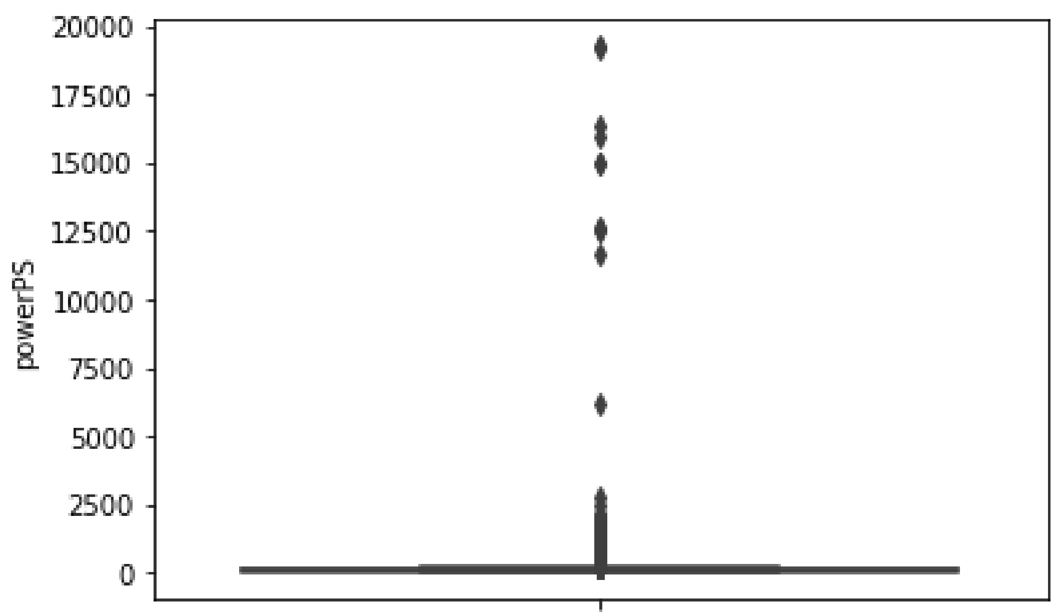
[21]:
```
sns.distplot(cars['powerPS'])
```

[21]: <matplotlib.axes._subplots.AxesSubplot at 0x15fdbbbe940>



[22]:
```
sns.boxplot(y=cars['powerPS'])
```

[22]: <matplotlib.axes._subplots.AxesSubplot at 0x15fdbcc5f60>



[23]:
```
cars['powerPS'].describe()
#std dev is 200% of mean
#minimum is zero but engine cannot start at that HP
```

[23]:
```
count    49666.000
mean       116.404
std        231.262
min          0.000
25%         69.000
50%        105.000
75%        150.000
max      19312.000
Name: powerPS, dtype: float64
```

[24]:
```
# Working range- 10 and 500
print(sum(cars['powerPS'] > 500))
print(sum(cars['powerPS'] < 10))
```

```
115
5613
```

[25]:
```
# ===============================================================================
# Working range of data
# ===============================================================================
cars=cars[
        (cars.yearOfRegistration <= 2018)
      & (cars.yearOfRegistration >= 1950)
      & (cars.price >= 100)
      & (cars.price <= 150000)
      & (cars.powerPS >= 10)
      & (cars.powerPS <= 500)]
cars.shape
#~7300 records are dropped
```

[25]:
```
(42855, 15)
```

[26]:
```
#Variable reduction
#Combining year of registration and month of registration to form new variable␣
 ↪Age
cars['monthOfRegistration']/=12
cars.head()
```

[26]:
```
    seller offerType  price   abtest vehicleType  yearOfRegistration  \
0  private     offer   4450     test   limousine                2003
1  private     offer  13299  control         suv                2005
2  private     offer   3200     test         bus                2003
3  private     offer   4500  control   small car                2006
4  private     offer  18750     test         suv                2008
```

```
     gearbox  powerPS     model  kilometer  monthOfRegistration fuelType  \
0     manual      150       3er     150000                0.250   diesel
1     manual      163  xc_reihe     150000                0.500   diesel
2     manual      101    touran     150000                0.917   diesel
3     manual       86     ibiza      60000                1.000   petrol
4  automatic      185  xc_reihe     150000                0.917   diesel

        brand notRepairedDamage  postalCode
0         bmw               NaN       20257
1       volvo                no       88045
2  volkswagen               NaN       27449
3        seat                no       34537
4       volvo                no       55270
```

[27]:
```
#new variable Age
cars['Age']=(2018-cars['yearOfRegistration']) + cars['monthOfRegistration']
cars['Age']= round(cars['Age'],2)
```

[28]:
```
cars['Age'].describe()
```

[28]:
```
count   42855.000
mean       14.872
std         7.090
min         0.000
25%        10.330
50%        14.830
75%        19.170
max        67.750
Name: Age, dtype: float64
```

[29]:
```
#dropping year of registration and month of registration
cars=cars.drop(['yearOfRegistration','monthOfRegistration'],axis=1)
```

[30]:
```
cars.head()
```

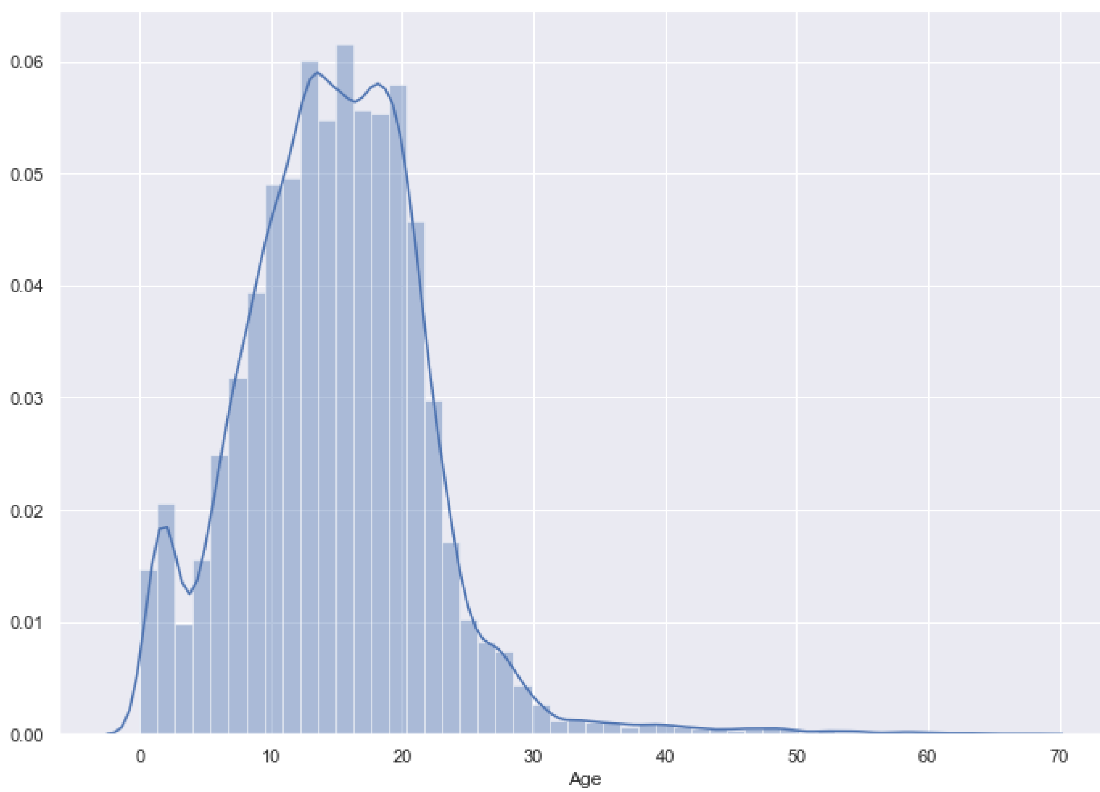
[30]:
```
    seller offerType  price   abtest vehicleType    gearbox  powerPS  \
0  private     offer   4450     test   limousine     manual      150
1  private     offer  13299  control         suv     manual      163
2  private     offer   3200     test         bus     manual      101
3  private     offer   4500  control   small car     manual       86
4  private     offer  18750     test         suv  automatic      185

      model  kilometer fuelType       brand notRepairedDamage  postalCode  \
0       3er     150000   diesel         bmw               NaN       20257
1  xc_reihe     150000   diesel       volvo                no       88045
2    touran     150000   diesel  volkswagen               NaN       27449
3     ibiza      60000   petrol        seat                no       34537
4  xc_reihe     150000   diesel       volvo                no       55270
```

```
     Age
0 15.250
1 13.500
2 15.920
3 13.000
4 10.920
```

[31]:
```
# ==============================================================================
# Visualizing Parameters
# ==============================================================================
sns.set(rc={'figure.figsize':(11.7,8.27)}) #A4 size dimension
```

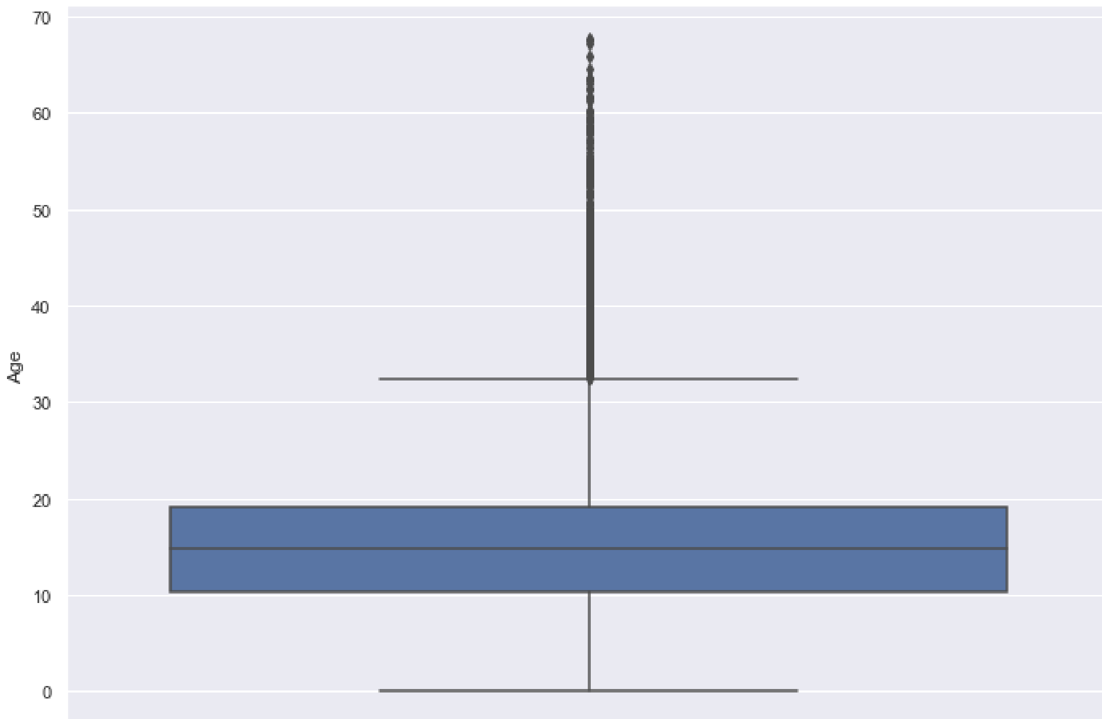
[32]:
```
#Age
sns.distplot(cars['Age'])
#data is slightly skewed towards right
```

[32]: <matplotlib.axes._subplots.AxesSubplot at 0x15fdbb5d2e8>



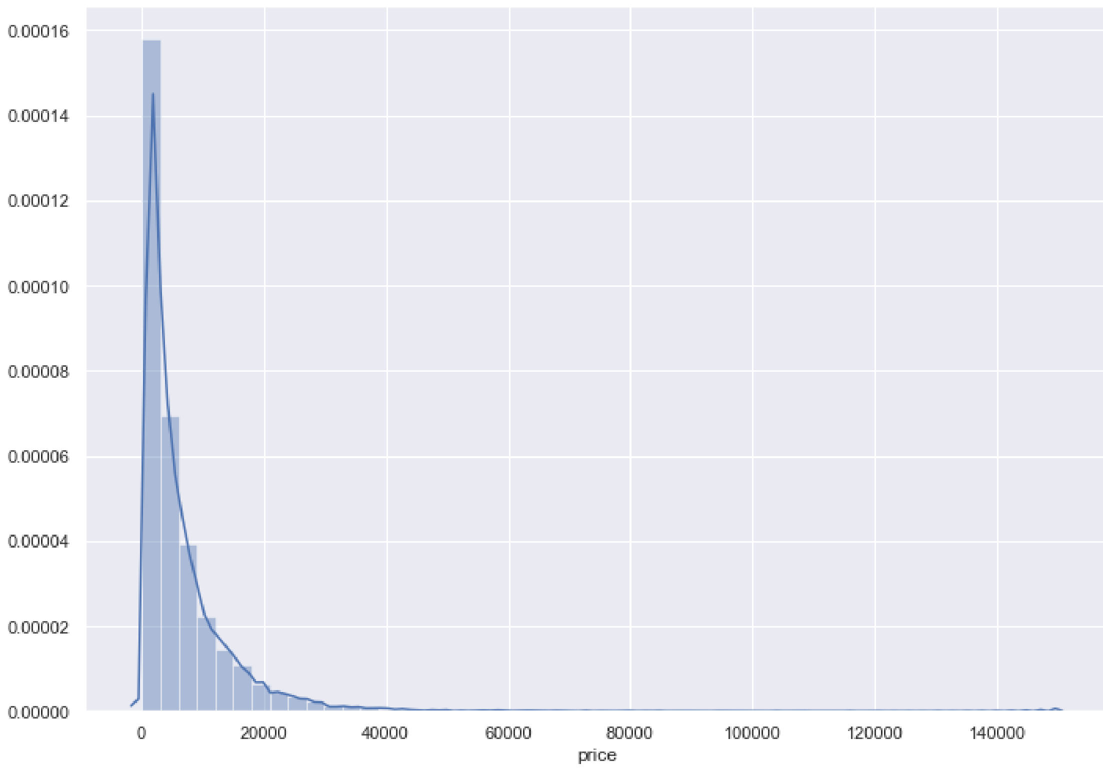
[33]:
```
sns.boxplot(y=cars['Age'])
#  Here it can be see that plots evenly distributed but still there are few␣
↪outliers
```

[33]: <matplotlib.axes._subplots.AxesSubplot at 0x15fdb0860b8>



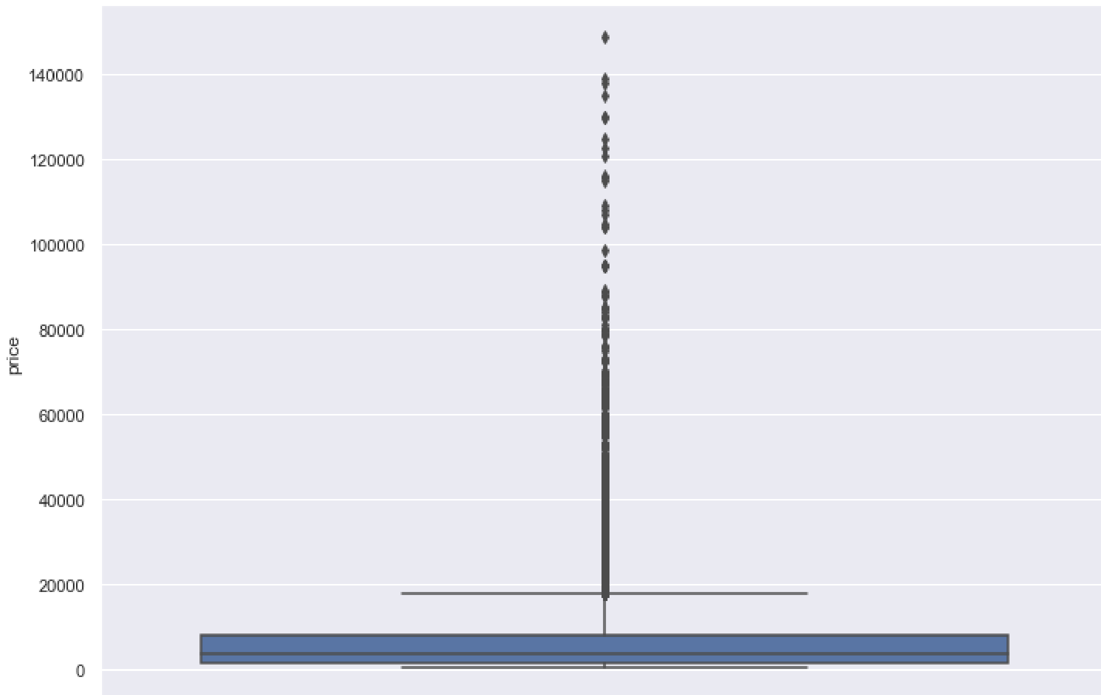
[34]:
```
#price
sns.distplot(cars['price'])
#plot is right skewed because of high end luxurious cars
```

[34]: <matplotlib.axes._subplots.AxesSubplot at 0x15fdb048cc0>



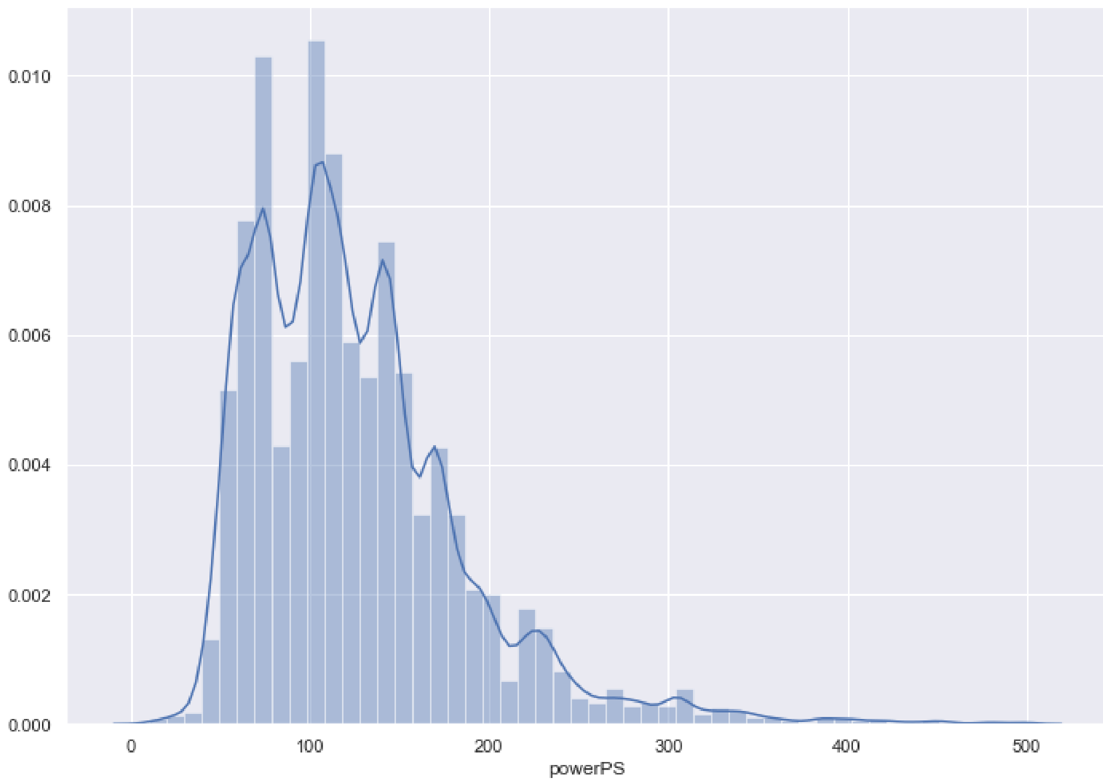
[35]:
```
sns.boxplot(y=cars['price'])
cars['price'].describe()
#std dev is still high due to luxurious cars
```

[35]:
```
count     42855.000
mean       6132.950
std        7944.135
min         100.000
25%        1450.000
50%        3499.000
75%        7900.000
max      149000.000
Name: price, dtype: float64
```



[36]:
```
#powerPS
sns.distplot(cars['powerPS'])
```

[36]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x15fdca838d0>
```



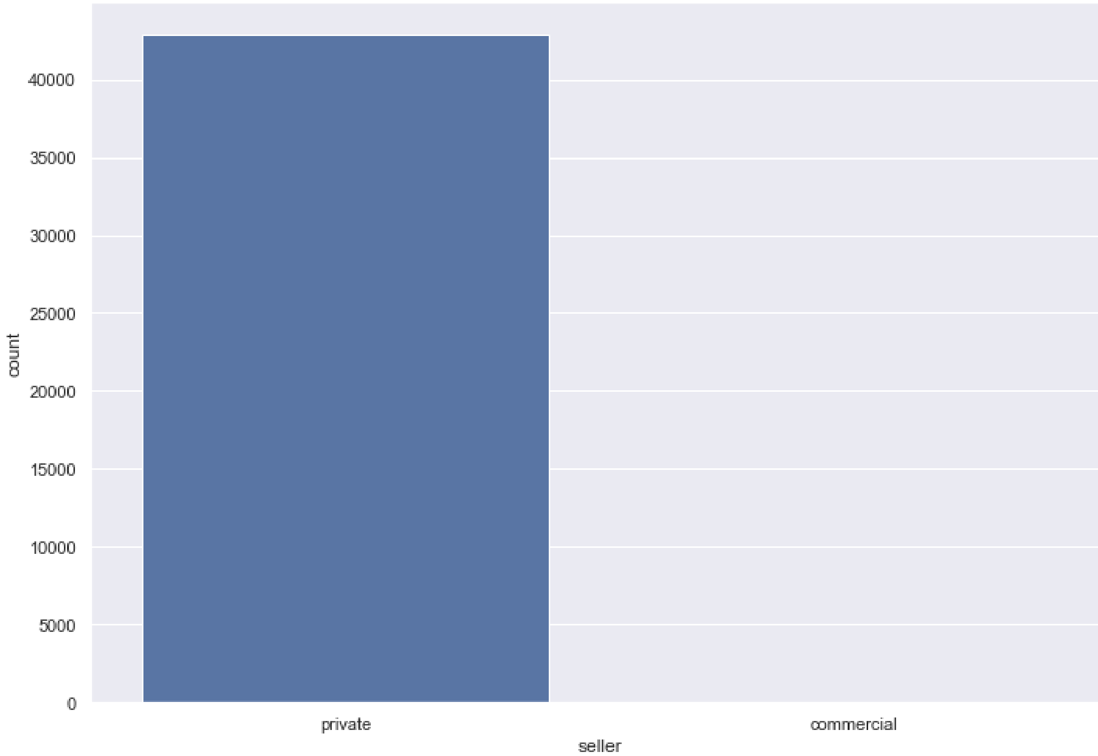
[37]:
```
sns.boxplot(y=cars['powerPS'])
cars['powerPS'].describe()
```

[37]:
```
count    42855.000
mean       126.054
std         60.525
min         10.000
25%         80.000
50%        116.000
75%        150.000
max        500.000
Name: powerPS, dtype: float64
```

[38]:
```
#Variable Age
print(cars['seller'].value_counts())
print(sns.countplot(cars['seller']))
pd.crosstab(cars['seller'],columns='count',normalize=True)
#almost all cars from private players; 99.99% of sellers at storm motors are␣
↪private persons not commercial businessess
```

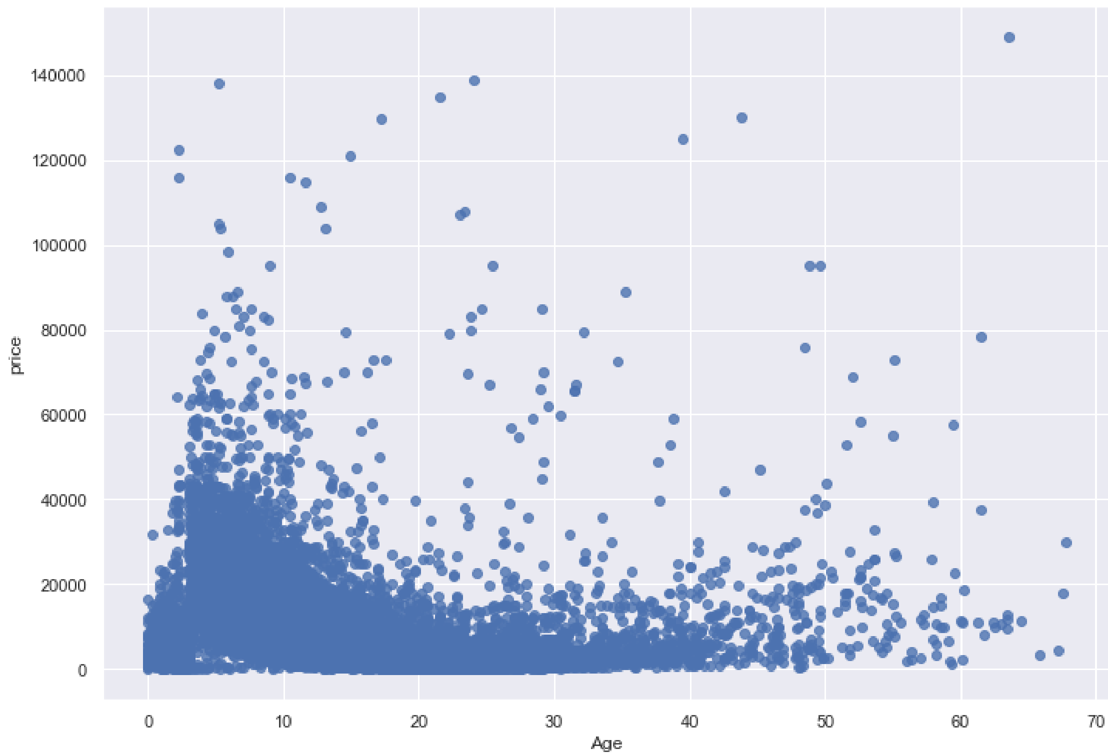
```
private       42854
commercial        1
Name: seller, dtype: int64
AxesSubplot(0.125,0.125;0.775x0.755)
```

[38]:
```
col_0       count
seller
commercial  0.000
private     1.000
```



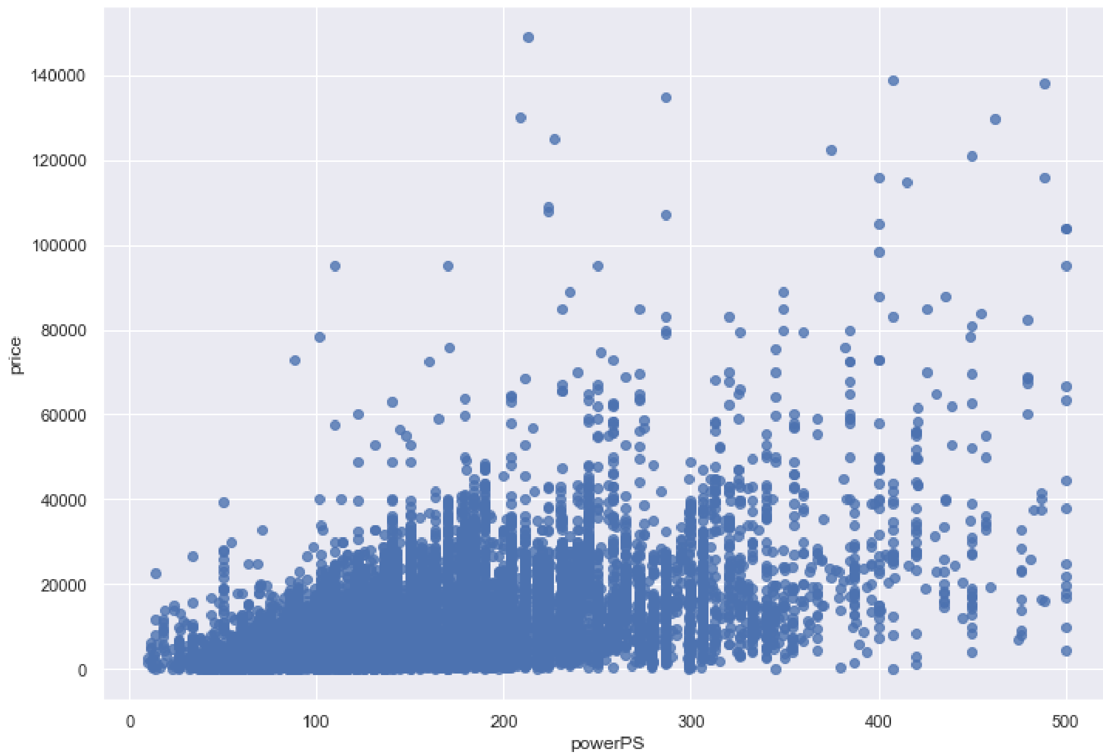
[39]:
```
# Age Vs Price
sns.regplot(x='Age',y='price',scatter=True,fit_reg=False,data=cars)
#As the Age of a vehicle increases, price starts to decrease
#but there are some cars whose price is higher despite increase in age
```

[39]: <matplotlib.axes._subplots.AxesSubplot at 0x15fdd22c1d0>



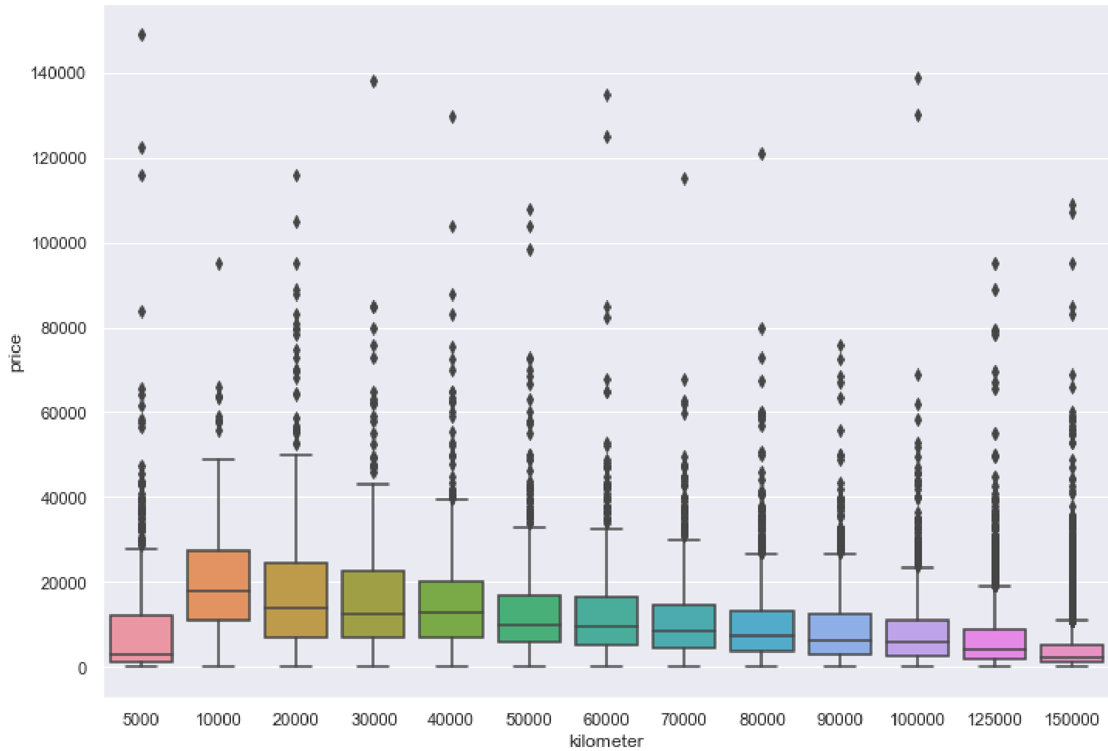
[40]:
```
# powerPS vs price
sns.regplot(x='powerPS', y='price', scatter=True,
            fit_reg=False, data=cars)
#as the power PS increases, price also increases
```

[40]: <matplotlib.axes._subplots.AxesSubplot at 0x15fdd296fd0>



[41]:
```
#Price Vs Kilometer
sns.boxplot(x='kilometer',y='price',data=cars)
#As running of a vehicle increases, price gets reduce except for vehicles below␣
↪5000 km running
#cars within 5000km running having low price because of high age
```

[41]: <matplotlib.axes._subplots.AxesSubplot at 0x15fdce94f60>



[42]:
```
cars_age=cars[(cars['kilometer']<= 5000)]
print(cars_age.shape)
cars_age.describe()
# The Average Age of 479 cars is same as the average age of 42000 cars
#which means cars which have running below 5000km have high aged cars due to␣
↪which price is lower
```

```
(479, 14)
```

[42]:

	price	powerPS	kilometer	postalCode	Age
count	479.000	479.000	479.000	479.000	479.000
mean	9950.616	124.649	5000.000	49691.161	14.844
std	15939.343	72.072	0.000	25925.783	12.320
min	101.000	14.000	5000.000	1069.000	0.170
25%	1100.000	75.000	5000.000	28540.500	3.750
50%	3000.000	110.000	5000.000	47269.000	15.170
75%	11949.500	150.000	5000.000	70702.000	20.500
max	149000.000	500.000	5000.000	99817.000	63.580

[43]:
```
cars_age1=cars[(cars['kilometer'] > 5000)]
print(cars_age1.shape)
cars_age1.describe()
```

```
(42376, 14)
```

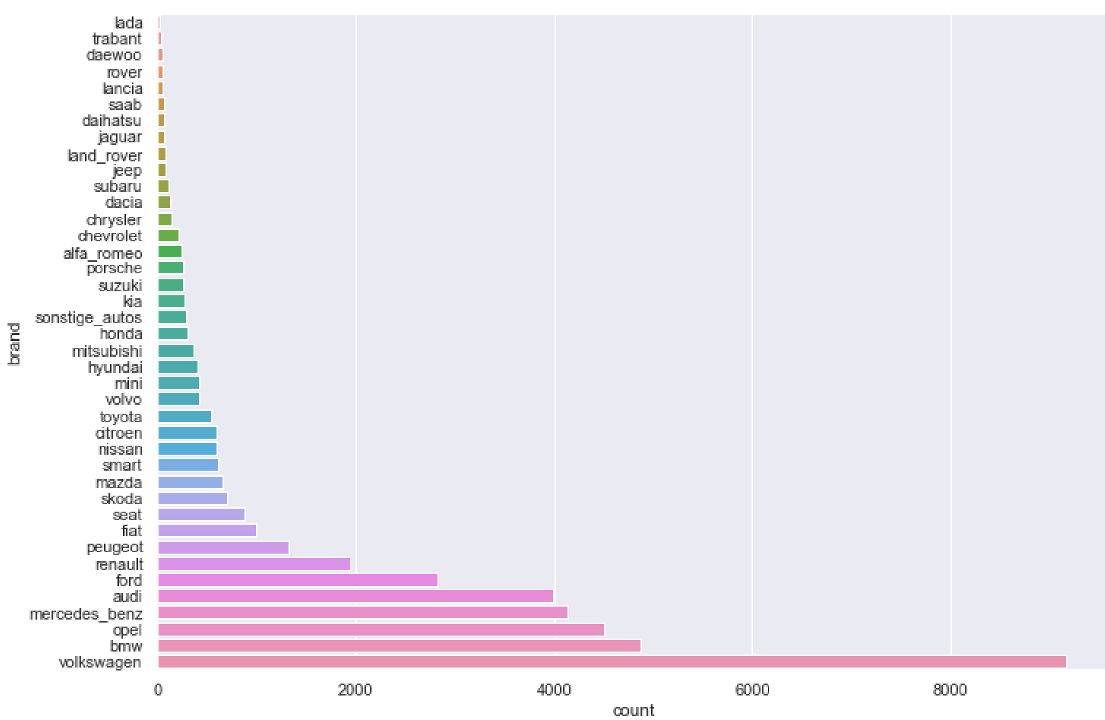
[43]:

	price	powerPS	kilometer	postalCode	Age
count	42376.000	42376.000	42376.000	42376.000	42376.000
mean	6089.797	126.070	127188.149	51576.149	14.872
std	7796.804	60.382	37106.044	25717.238	7.008
min	100.000	10.000	10000.000	1067.000	0.000
25%	1450.000	80.000	125000.000	31275.000	10.330
50%	3499.000	116.000	150000.000	50674.000	14.830
75%	7899.000	150.000	150000.000	72414.000	19.170
max	139000.000	500.000	150000.000	99998.000	67.750

[44]:
```
#cars[(cars['kilometer'] <= 5000) & (cars['Age'] > 10)]
# 293 cars among 500 cars have low price despite running lower than 5000 km but␣
↪age is high due to which price is low
```

[45]:
```
sns.countplot(y='brand',data=cars,order=cars['brand'].
↪value_counts(ascending=True).index)
# Volkswagen is highest sold brand and lada is least sold brand to the company
```

[45]: <matplotlib.axes._subplots.AxesSubplot at 0x15fdcacce80>



[46]:
```
pd.crosstab(cars['brand'],columns='count',normalize=True,colnames=['%']).
↪sort_values(by='count',ascending=False)*100
```

[46]:
```
%                count
brand
volkswagen      21.379
```

```
bmw              11.383
opel             10.498
mercedes_benz     9.665
audi              9.317
ford              6.583
renault           4.539
peugeot           3.089
fiat              2.324
seat              2.070
skoda             1.631
mazda             1.549
smart             1.454
nissan            1.402
citroen           1.395
toyota            1.279
mini              1.001
volvo             1.001
hyundai           0.947
mitsubishi        0.838
honda             0.700
sonstige_autos    0.698
kia               0.644
suzuki            0.616
porsche           0.607
alfa_romeo        0.572
chevrolet         0.497
chrysler          0.352
dacia             0.287
subaru            0.261
jeep              0.212
land_rover        0.189
jaguar            0.182
daihatsu          0.156
saab              0.152
lancia            0.131
daewoo            0.124
rover             0.124
trabant           0.100
lada              0.051
```

[47]:

```
print("Total Brands:",cars['brand'].unique().size)
print("Top 10 brands:")
cars.groupby(['brand',]).size().sort_values(ascending=False).nlargest(10)
#The top 10 most sold brands among 40 brands in the market
```

```
Total Brands: 40
Top 10 brands:
```

[47]:
```
brand
volkswagen       9162
bmw              4878
opel             4499
mercedes_benz    4142
audi             3993
ford             2821
renault          1945
peugeot          1324
fiat              996
seat              887
dtype: int64
```

[48]:
```
#Variable Model
print("Total Brands:",cars['model'].unique().size)
cars.groupby(['brand','model']).size().sort_values(ascending=False).nlargest(10)
#There are 248 models among them 10 most sold model by sellers are given below
```

```
Total Brands: 248
```

[48]:
```
brand          model
volkswagen     golf        3494
bmw            3er         2489
volkswagen     polo        1500
opel           corsa       1393
               astra       1278
audi           a4          1235
volkswagen     passat      1207
mercedes_benz  c_klasse    1046
bmw            5er         1013
mercedes_benz  e_klasse     908
dtype: int64
```

[49]:
```
luxury_cars=cars[(cars['price']>=40000) & (cars['Age'] >= 20)]
#working range based on observation
```

[50]:
```
summary=luxury_cars.groupby(['brand','model']).size().
 ↪sort_values(ascending=False)
summary.loc['Grand Total'] = summary.sum()
lux_cars=summary.to_frame('count')
lux_cars
#Luxury cars with age above 20 years and price above 40000 dollars
```

[50]:

brand	model	count
porsche	911	23
mercedes_benz	sl	3
jaguar	others	3
mercedes_benz	others	2

```
ford          mustang          2
alfa_romeo    spider           2
volkswagen    transporter      1
renault       others           1
mercedes_benz g_klasse         1
              c_klasse         1
fiat          others           1
bmw           m_reihe          1
Grand Total                   41
```

[51]:
```
porsche_car=cars[(cars['brand']=='porsche') & (cars['price']>=40000) &␣
 ↪(cars['Age'] >= 20)]
porsche_car.head(5)
#Porsche 911, a luxury cars, is main vehicle which is having high price despite␣
 ↪its increasing age
```

[51]:
```
       seller offerType   price   abtest vehicleType    gearbox  powerPS  \
3286  private     offer  139000     test       coupe     manual      408
4190  private     offer   80000  control      cabrio  automatic      286
5092  private     offer   69800     test       coupe     manual      272
5283  private     offer   52890     test      cabrio     manual      131
8650  private     offer   44300     test       coupe     manual      272

     model  kilometer fuelType    brand notRepairedDamage  postalCode    Age
3286   911     100000   petrol  porsche                no       10629 24.000
4190   911      80000   petrol  porsche                no       50858 23.830
5092   911     125000   petrol  porsche                no       80802 23.580
5283   911     150000   petrol  porsche                no       41812 38.580
8650   911     150000   petrol  porsche                no        9117 23.580
```

[52]:
```
luxury_cars.groupby(['vehicleType']).size()
#Coupe and Cabrio are the two most sought vehicle among luxury cars
```

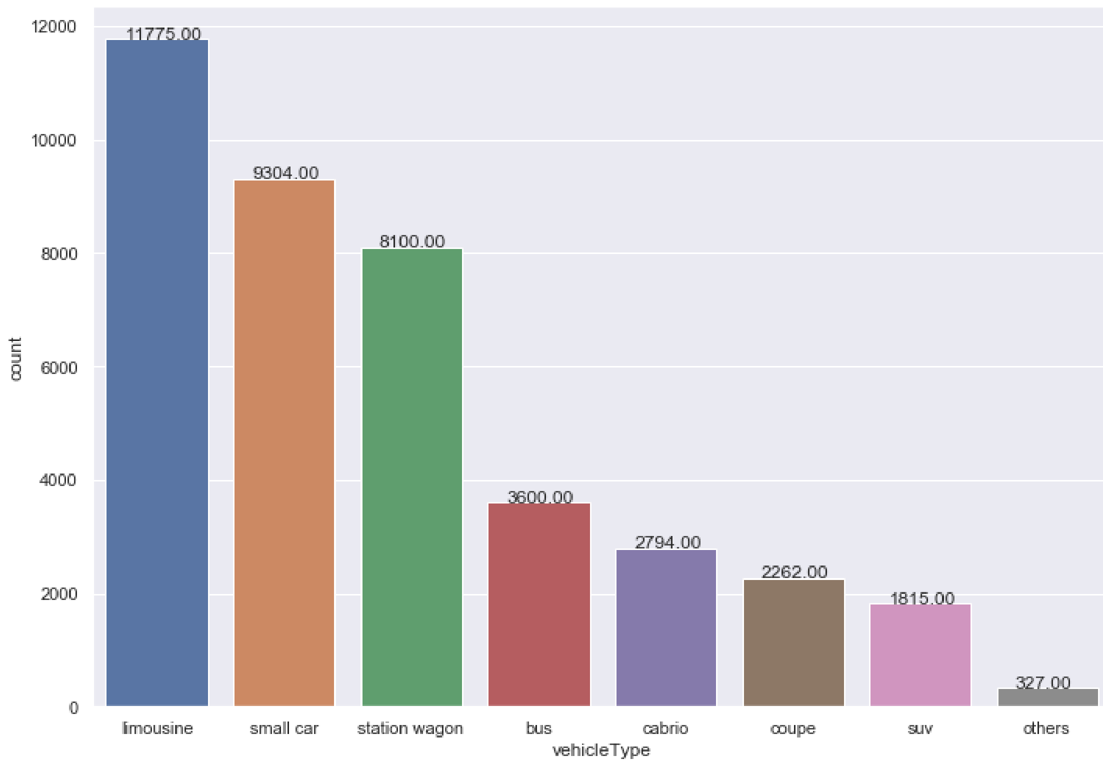
[52]:
```
vehicleType
bus            1
cabrio        20
coupe         24
limousine      1
suv            1
dtype: int64
```

[53]:
```
cars['vehicleType'].value_counts()
```

[53]:
```
limousine        11775
small car         9304
station wagon     8100
bus               3600
cabrio            2794
coupe             2262
suv               1815
```

```
others               327
Name: vehicleType, dtype: int64
```

[54]:
```
ax=sns.countplot(x='vehicleType',data=cars,order=cars['vehicleType'].
 ↪value_counts().index)
for p in ax.patches:
    ax.annotate('{:.2f}'.format(p.get_height()), (p.get_x()+0.15, p.
 ↪get_height()+1))
#Limusine is the highest sold vehicle type and least sold are SUV and others
```



[55]:
```
# Variable notRepairedDamage
# yes- car is damaged but not rectified
# no- car was damaged but has been rectified
print(cars['notRepairedDamage'].value_counts())
print("")
print(pd.
 ↪crosstab(cars['notRepairedDamage'],columns='count',normalize=True,colnames=['%'])*100)
# 90% of cars are damage rectified
```

```
no      32574
yes      3994
Name: notRepairedDamage, dtype: int64
```

```
%                  count
notRepairedDamage
no                89.078
yes               10.922
```

[56]:
```
print(cars['fuelType'].value_counts())
print("")
print(pd.
 ↪crosstab(cars['fuelType'],columns='count',normalize=True,colnames=['%'])*100)
# majority of cars are petrol engine followed by diesel engine cars
```

```
petrol     26549
diesel     12896
lpg          690
cng           70
hybrid        36
electro       10
other          6
Name: fuelType, dtype: int64

%          count
fuelType
cng        0.174
diesel    32.034
electro    0.025
hybrid     0.089
lpg        1.714
other      0.015
petrol    65.949
```

[57]:
```
print(cars['gearbox'].value_counts())
print("")
print(pd.
 ↪crosstab(cars['gearbox'],columns='count',normalize=True,colnames=['%'])*100)
# 77% of cars have manual gear box
```

```
manual       32650
automatic     9410
Name: gearbox, dtype: int64

%           count
gearbox
automatic 22.373
manual    77.627
```