

CAR PRICE PREDICTION WITH MACHINE LEARNING

Car price prediction is one of the major research areas in machine learning. So, here I am going to train a model for car price prediction.

Steps to build the model

1.Import the libraries 2.Import Dataset 3.Exploratory Data Analysis 4.Training the model
5.Prediction 6.Model evaluation

1.Import the libraries

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_absolute_error
```

2.Import the dataset

```
sample = pd.read_csv('CarPrice_Assignment.csv')
```

```
sample.head()
```

	car_ID	symboling	CarName	fueltype	aspiration
0	1	3	alfa-romero giulia	gas	std
1	2	3	alfa-romero stelvio	gas	std
2	3	1	alfa-romero Quadrifoglio	gas	std
3	4	2	audi 100 ls	gas	std
4	5	2	audi 100ls	gas	std

	carbody	drivewheel	enginelocation	wheelbase	...	
0	convertible	rwd	front	88.6	...	130
1	convertible	rwd	front	88.6	...	130

2	hatchback	rwd	front	94.5	...	152
3	sedan	fwd	front	99.8	...	109
4	sedan	4wd	front	99.4	...	136

	fuelsystem	boreratio	stroke	compressionratio	horsepower	peakrpm
citympg \						
0	mpfi	3.47	2.68	9.0	111	5000
21						
1	mpfi	3.47	2.68	9.0	111	5000
21						
2	mpfi	2.68	3.47	9.0	154	5000
19						
3	mpfi	3.19	3.40	10.0	102	5500
24						
4	mpfi	3.19	3.40	8.0	115	5500
18						

	highwaympg	price
0	27	13495.0
1	27	16500.0
2	26	16500.0
3	30	13950.0
4	22	17450.0

[5 rows x 26 columns]

sample.tail()

	car_ID	symboling	CarName	fueltype	aspiration	doornumber
\						
200	201	-1	volvo 145e (sw)	gas	std	four
201	202	-1	volvo 144ea	gas	turbo	four
202	203	-1	volvo 244dl	gas	std	four
203	204	-1	volvo 246	diesel	turbo	four
204	205	-1	volvo 264gl	gas	turbo	four

	carbody	drivewheel	enginelocation	wheelbase	...	enginesize
fuelsystem \						
200	sedan	rwd	front	109.1	...	141
mpfi						
201	sedan	rwd	front	109.1	...	141

```

mpfi
202  sedan      rwd      front      109.1  ...      173
mpfi
203  sedan      rwd      front      109.1  ...      145
idi
204  sedan      rwd      front      109.1  ...      141
mpfi

```

```

      boreratio  stroke  compressionratio  horsepower  peakrpm  citympg  \
200      3.78    3.15              9.5          114    5400      23
201      3.78    3.15              8.7          160    5300      19
202      3.58    2.87              8.8          134    5500      18
203      3.01    3.40             23.0          106    4800      26
204      3.78    3.15              9.5          114    5400      19

```

```

      highwaympg  price
200           28 16845.0
201           25 19045.0
202           23 21485.0
203           27 22470.0
204           25 22625.0

```

[5 rows x 26 columns]

```
sample.head(10)
```

```

      car_ID  symboling      CarName  fueltype  aspiration
doornumber  \
0          1          3      alfa-romero giulia      gas      std
two
1          2          3      alfa-romero stelvio      gas      std
two
2          3          1  alfa-romero Quadrifoglio      gas      std
two
3          4          2          audi 100 ls      gas      std
four
4          5          2          audi 100ls      gas      std
four
5          6          2          audi fox      gas      std
two
6          7          1          audi 100ls      gas      std
four
7          8          1          audi 5000      gas      std
four
8          9          1          audi 4000      gas      turbo
four
9         10          0      audi 5000s (diesel)      gas      turbo
two

```

```
      carbody  drivewheel  enginelocation  wheelbase  ...

```

enginesize \						
0	convertible	rwd	front	88.6	...	130
1	convertible	rwd	front	88.6	...	130
2	hatchback	rwd	front	94.5	...	152
3	sedan	fwd	front	99.8	...	109
4	sedan	4wd	front	99.4	...	136
5	sedan	fwd	front	99.8	...	136
6	sedan	fwd	front	105.8	...	136
7	wagon	fwd	front	105.8	...	136
8	sedan	fwd	front	105.8	...	131
9	hatchback	4wd	front	99.5	...	131

	fuelsystem \	boreratio	stroke	compressionratio	horsepower	peakrpm
citympg						
0	mpfi	3.47	2.68	9.0	111	5000
21						
1	mpfi	3.47	2.68	9.0	111	5000
21						
2	mpfi	2.68	3.47	9.0	154	5000
19						
3	mpfi	3.19	3.40	10.0	102	5500
24						
4	mpfi	3.19	3.40	8.0	115	5500
18						
5	mpfi	3.19	3.40	8.5	110	5500
19						
6	mpfi	3.19	3.40	8.5	110	5500
19						
7	mpfi	3.19	3.40	8.5	110	5500
19						
8	mpfi	3.13	3.40	8.3	140	5500
17						
9	mpfi	3.13	3.40	7.0	160	5500
16						

	highwaympg	price
0	27	13495.000
1	27	16500.000
2	26	16500.000

3	30	13950.000
4	22	17450.000
5	25	15250.000
6	25	17710.000
7	25	18920.000
8	20	23875.000
9	22	17859.167

[10 rows x 26 columns]

sample.tail(10)

	car_ID	symboling	CarName	fueltype	aspiration	doornumber
\						
195	196	-1	volvo 144ea	gas	std	four
196	197	-2	volvo 244dl	gas	std	four
197	198	-1	volvo 245	gas	std	four
198	199	-2	volvo 264gl	gas	turbo	four
199	200	-1	volvo diesel	gas	turbo	four
200	201	-1	volvo 145e (sw)	gas	std	four
201	202	-1	volvo 144ea	gas	turbo	four
202	203	-1	volvo 244dl	gas	std	four
203	204	-1	volvo 246	diesel	turbo	four
204	205	-1	volvo 264gl	gas	turbo	four

	carbody	drivewheel	engine location	wheelbase	...	enginesize
fuelsystem \						
195	wagon	rwd	front	104.3	...	141
mpfi						
196	sedan	rwd	front	104.3	...	141
mpfi						
197	wagon	rwd	front	104.3	...	141
mpfi						
198	sedan	rwd	front	104.3	...	130
mpfi						
199	wagon	rwd	front	104.3	...	130
mpfi						
200	sedan	rwd	front	109.1	...	141
mpfi						

201	sedan	rwd	front	109.1	...	141
mpfi						
202	sedan	rwd	front	109.1	...	173
mpfi						
203	sedan	rwd	front	109.1	...	145
idi						
204	sedan	rwd	front	109.1	...	141
mpfi						

	boreratio	stroke	compressionratio	horsepower	peakrpm	citympg	\
195	3.78	3.15	9.5	114	5400	23	
196	3.78	3.15	9.5	114	5400	24	
197	3.78	3.15	9.5	114	5400	24	
198	3.62	3.15	7.5	162	5100	17	
199	3.62	3.15	7.5	162	5100	17	
200	3.78	3.15	9.5	114	5400	23	
201	3.78	3.15	8.7	160	5300	19	
202	3.58	2.87	8.8	134	5500	18	
203	3.01	3.40	23.0	106	4800	26	
204	3.78	3.15	9.5	114	5400	19	

	highwaympg	price
195	28	13415.0
196	28	15985.0
197	28	16515.0
198	22	18420.0
199	22	18950.0
200	28	16845.0
201	25	19045.0
202	23	21485.0
203	27	22470.0
204	25	22625.0

[10 rows x 26 columns]

sample.shape

(205, 26)

sample.info()

<class 'pandas.core.frame.DataFrame'>

RangeIndex: 205 entries, 0 to 204

Data columns (total 26 columns):

#	Column	Non-Null Count	Dtype
---	-----	-----	-----
0	car_ID	205 non-null	int64
1	symboling	205 non-null	int64
2	CarName	205 non-null	object
3	fueltype	205 non-null	object
4	aspiration	205 non-null	object

```

5  doornumber      205 non-null    object
6  carbody         205 non-null    object
7  drivewheel      205 non-null    object
8  enginelocation  205 non-null    object
9  wheelbase       205 non-null    float64
10 carlength       205 non-null    float64
11 carwidth        205 non-null    float64
12 carheight       205 non-null    float64
13 curbweight      205 non-null    int64
14 enginetype      205 non-null    object
15 cylindernumber  205 non-null    object
16 enginesize       205 non-null    int64
17 fuelsystem      205 non-null    object
18 boreratio       205 non-null    float64
19 stroke          205 non-null    float64
20 compressionratio 205 non-null    float64
21 horsepower      205 non-null    int64
22 peakrpm         205 non-null    int64
23 citympg         205 non-null    int64
24 highwaympg      205 non-null    int64
25 price           205 non-null    float64
dtypes: float64(8), int64(8), object(10)
memory usage: 41.8+ KB

```

```
sample.describe()
```

```

           car_ID  symboling  wheelbase  carlength  carwidth
carheight \
count  205.000000  205.000000  205.000000  205.000000  205.000000
205.000000
mean    103.000000    0.834146   98.756585   174.049268   65.907805
53.724878
std      59.322565    1.245307    6.021776   12.337289    2.145204
2.443522
min       1.000000   -2.000000   86.600000  141.100000   60.300000
47.800000
25%      52.000000    0.000000   94.500000  166.300000   64.100000
52.000000
50%     103.000000    1.000000   97.000000  173.200000   65.500000
54.100000
75%     154.000000    2.000000  102.400000  183.100000   66.900000
55.500000
max     205.000000    3.000000  120.900000  208.100000   72.300000
59.800000

           curbweight  enginesize  boreratio  stroke
compressionratio \
count  205.000000  205.000000  205.000000  205.000000
205.000000
mean   2555.565854  126.907317    3.329756    3.255415

```

```

10.142537
std      520.680204    41.642693    0.270844    0.313597
3.972040
min      1488.000000    61.000000    2.540000    2.070000
7.000000
25%      2145.000000    97.000000    3.150000    3.110000
8.600000
50%      2414.000000    120.000000   3.310000    3.290000
9.000000
75%      2935.000000    141.000000   3.580000    3.410000
9.400000
max      4066.000000    326.000000   3.940000    4.170000
23.000000

```

	horsepower	peakrpm	citympg	highwaympg	price
count	205.000000	205.000000	205.000000	205.000000	205.000000
mean	104.117073	5125.121951	25.219512	30.751220	13276.710571
std	39.544167	476.985643	6.542142	6.886443	7988.852332
min	48.000000	4150.000000	13.000000	16.000000	5118.000000
25%	70.000000	4800.000000	19.000000	25.000000	7788.000000
50%	95.000000	5200.000000	24.000000	30.000000	10295.000000
75%	116.000000	5500.000000	30.000000	34.000000	16503.000000
max	288.000000	6600.000000	49.000000	54.000000	45400.000000

```
sample.isnull().sum()
```

```

car_ID          0
symboling       0
CarName         0
fueltype        0
aspiration      0
doornumber      0
carbody         0
drivewheel      0
enginelocation  0
wheelbase       0
carlength       0
carwidth        0
carheight       0
curbweight      0
enginetype      0
cylindernumber  0
enginesize      0
fuelsystem      0
boreratio       0
stroke          0
compressionratio 0
horsepower      0
peakrpm         0
citympg         0

```



```
highwaympg      0
price           0
dtype: int64
```

```
sample['car_ID'].unique()
```

```
array([ 1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12,
13,
14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25,
26,
27, 28, 29, 30, 31, 32, 33, 34, 35, 36, 37, 38,
39,
40, 41, 42, 43, 44, 45, 46, 47, 48, 49, 50, 51,
52,
53, 54, 55, 56, 57, 58, 59, 60, 61, 62, 63, 64,
65,
66, 67, 68, 69, 70, 71, 72, 73, 74, 75, 76, 77,
78,
79, 80, 81, 82, 83, 84, 85, 86, 87, 88, 89, 90,
91,
92, 93, 94, 95, 96, 97, 98, 99, 100, 101, 102, 103,
104,
105, 106, 107, 108, 109, 110, 111, 112, 113, 114, 115, 116,
117,
118, 119, 120, 121, 122, 123, 124, 125, 126, 127, 128, 129,
130,
131, 132, 133, 134, 135, 136, 137, 138, 139, 140, 141, 142,
143,
144, 145, 146, 147, 148, 149, 150, 151, 152, 153, 154, 155,
156,
157, 158, 159, 160, 161, 162, 163, 164, 165, 166, 167, 168,
169,
170, 171, 172, 173, 174, 175, 176, 177, 178, 179, 180, 181,
182,
183, 184, 185, 186, 187, 188, 189, 190, 191, 192, 193, 194,
195,
196, 197, 198, 199, 200, 201, 202, 203, 204, 205], dtype=int64)
```

```
sample['CarName'].unique()
```

```
array(['alfa-romero giulia', 'alfa-romero stelvio',
'alfa-romero Quadrifoglio', 'audi 100 ls', 'audi 100ls',
'audi fox', 'audi 5000', 'audi 4000', 'audi 5000s (diesel)',
'bmw 320i', 'bmw x1', 'bmw x3', 'bmw z4', 'bmw x4', 'bmw x5',
'chevrolet impala', 'chevrolet monte carlo', 'chevrolet vega
2300',
'dodge rampage', 'dodge challenger se', 'dodge d200',
'dodge monaco (sw)', 'dodge colt hardtop', 'dodge colt (sw)',
'dodge coronet custom', 'dodge dart custom',
'dodge coronet custom (sw)', 'honda civic', 'honda civic cvcc',
'honda accord cvcc', 'honda accord lx', 'honda civic 1500 gl',
```

```

'honda accord', 'honda civic 1300', 'honda prelude',
'honda civic (auto)', 'isuzu MU-X', 'isuzu D-Max ',
'isuzu D-Max V-Cross', 'jaguar xj', 'jaguar xf', 'jaguar xk',
'mazda rx3', 'mazda glc deluxe', 'mazda rx2 coupe', 'mazda rx-
4',
'mazda glc deluxe', 'mazda 626', 'mazda glc', 'mazda rx-7 gs',
'mazda glc 4', 'mazda glc custom l', 'mazda glc custom',
'buick electra 225 custom', 'buick century luxus (sw)',
'buick century', 'buick skyhawk', 'buick opel isuzu deluxe',
'buick skylark', 'buick century special',
'buick regal sport coupe (turbo)', 'mercury cougar',
'mitsubishi mirage', 'mitsubishi lancer', 'mitsubishi
outlander',
'mitsubishi g4', 'mitsubishi mirage g4', 'mitsubishi montero',
'mitsubishi pajero', 'Nissan versa', 'nissan gt-r', 'nissan
rogue',
'nissan latiao', 'nissan titan', 'nissan leaf', 'nissan juke',
'nissan note', 'nissan clipper', 'nissan nv200', 'nissan dayz',
'nissan fuga', 'nissan otti', 'nissan teana', 'nissan kicks',
'peugeot 504', 'peugeot 304', 'peugeot 504 (sw)', 'peugeot
604sl',
'peugeot 505s turbo diesel', 'plymouth fury iii',
'plymouth cricket', 'plymouth satellite custom (sw)',
'plymouth fury gran sedan', 'plymouth valiant', 'plymouth
duster',
'porsche macan', 'porsche panamera', 'porsche cayenne',
'porsche boxster', 'renault 12tl', 'renault 5 gtl', 'saab 99e',
'saab 99le', 'saab 99gle', 'subaru', 'subaru dl', 'subaru brz',
'subaru baja', 'subaru rl', 'subaru r2', 'subaru trezia',
'subaru tribeca', 'toyota corona mark ii', 'toyota corona',
'toyota corolla 1200', 'toyota corolla hardtop',
'toyota corolla 1600 (sw)', 'toyota carina', 'toyota mark ii',
'toyota corolla', 'toyota corolla liftback',
'toyota celica gt liftback', 'toyota corolla tercel',
'toyota corona liftback', 'toyota starlet', 'toyota tercel',
'toyota cressida', 'toyota celica gt', 'toyota tercel',
'volkswagen rabbit', 'volkswagen 1131 deluxe sedan',
'volkswagen model 111', 'volkswagen type 3', 'volkswagen 411
(sw)',
'volkswagen super beetle', 'volkswagen dasher', 'vw dasher',
'vw rabbit', 'volkswagen rabbit', 'volkswagen rabbit custom',
'volvo 145e (sw)', 'volvo 144ea', 'volvo 244dl', 'volvo 245',
'volvo 264gl', 'volvo diesel', 'volvo 246'], dtype=object)

```

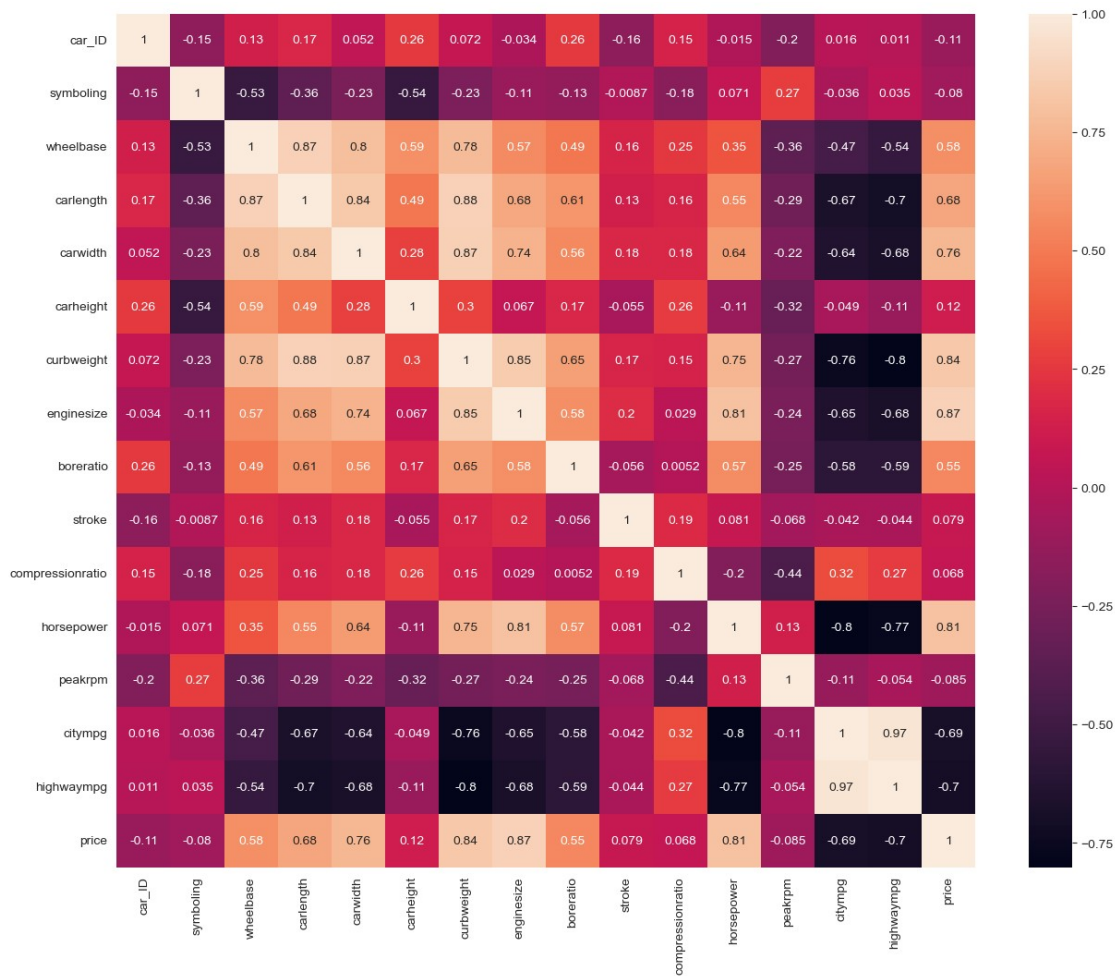
3.Exploratory Data Analysis

```

plt.figure(figsize=(15, 12))
sns.heatmap(sample.corr(),annot=True)

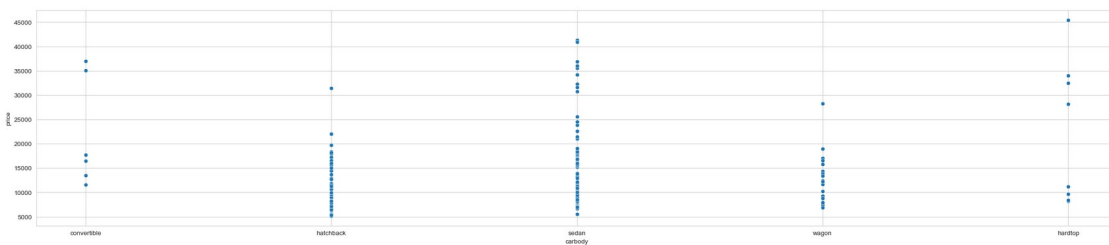
```

<AxesSubplot:>



```
plt.rcParams['figure.figsize']=(30,6)
sns.scatterplot(x='carbody', y='price', data=sample)

<AxesSubplot:xlabel='carbody', ylabel='price'>
```

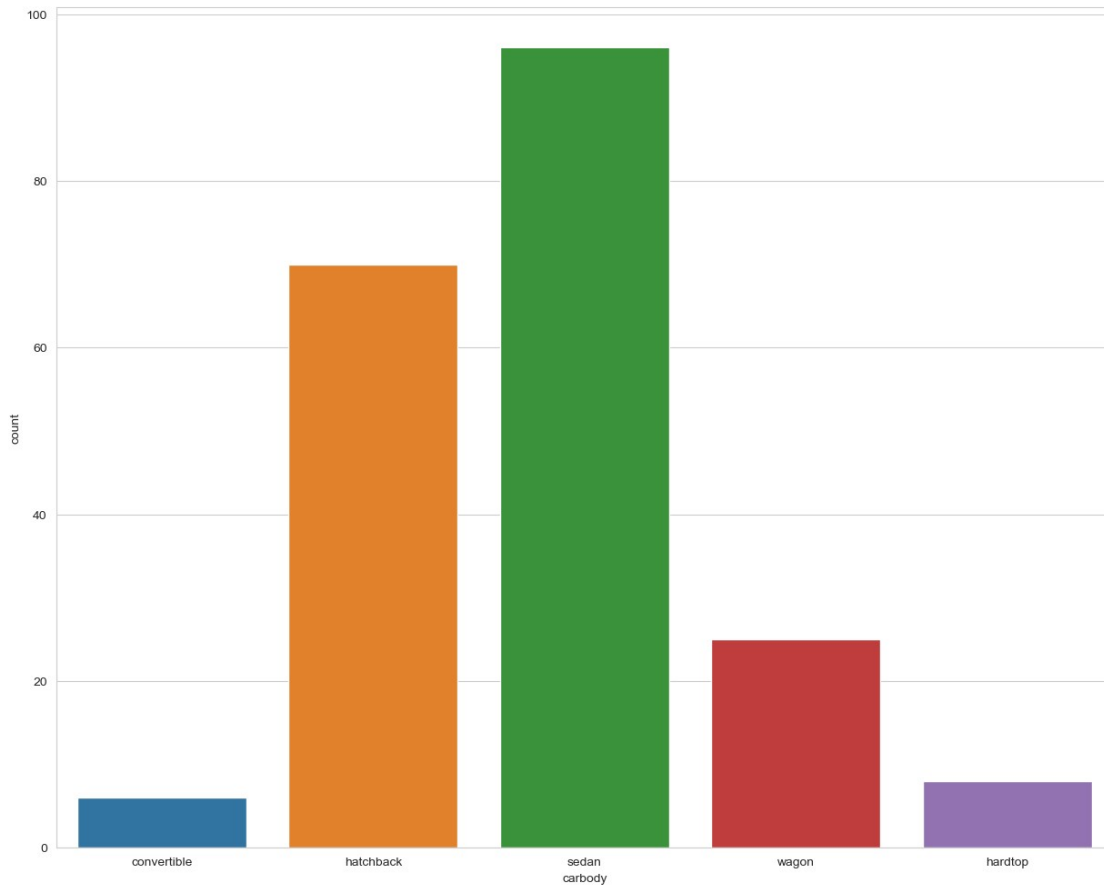


```
plt.figure(figsize=(15, 12))
sns.countplot(sample['carbody'])
```

C:\Users\priya\anaconda3\lib\site-packages\seaborn_decorators.py:36: FutureWarning: Pass the following variable as a keyword arg: x. From version 0.12, the only valid positional argument will be `data`, and passing other arguments without an explicit keyword will result in an error or misinterpretation.

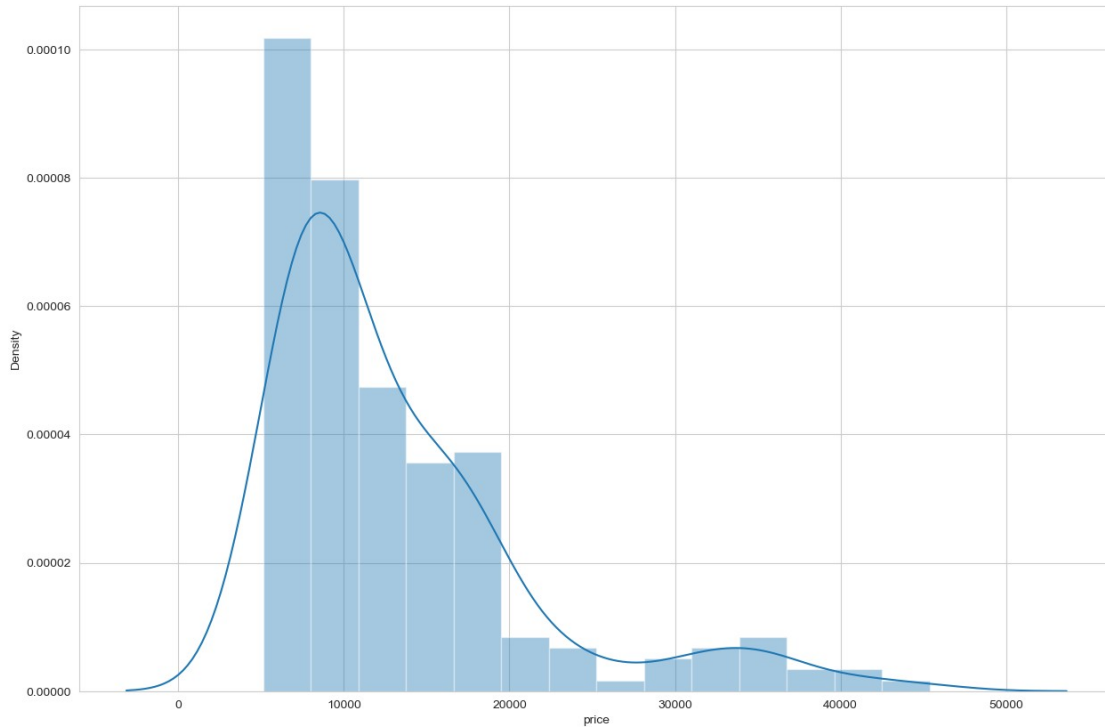
```
warnings.warn(
```

<AxesSubplot:xlabel='carbody', ylabel='count'>



```
sns.set_style("whitegrid")
plt.figure(figsize=(15, 10))
sns.distplot(sample.price)
plt.show()
```

```
C:\Users\priya\anaconda3\lib\site-packages\seaborn\
distributions.py:2619: FutureWarning: `distplot` is a deprecated
function and will be removed in a future version. Please adapt your
code to use either `displot` (a figure-level function with similar
flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```



4.Training the model

```
x =
sample.drop(columns=["price","CarName","fueltype","aspiration","doornu
mber","carbody","drivewheel","enginelocation","enginetype","cylindernu
mber","fuelsystem",])
y = sample["price"]
x_train,x_test,y_train,y_test =
train_test_split(x,y,test_size=0.2,random_state = 0)

print('Training X Shape:', x_train.shape)
print('Training Y Shape:', y_train.shape)
print('Testing X Shape:', x_test.shape)
print('Testing Y Shape:', y_test.shape)
```

Training X Shape: (164, 15)

Training Y Shape: (164,)

Testing X Shape: (41, 15)

Testing Y Shape: (41,)

```
model=RandomForestRegressor()
```

```
rfe = RandomForestRegressor(n_estimators=40,max_depth=20)
```

```
rfe = rfe.fit(x, y)
```

5.Predictions

```
predictions = rfe.predict(x_test)
```

```
errors = abs(predictions - y_test)
print('Mean Absolute Error:', round(np.mean(errors), 2), 'degrees.')
Mean Absolute Error: 675.3 degrees.
```

6. Model Evaluation

```
mape = 100 * (errors / y_test)
accuracy = 100 - np.mean(mape)
print('Accuracy using RandomForestRegressor:', round(accuracy, 2),
      '%.')
Accuracy using RandomForestRegressor: 95.14 %.
```

CONCLUSION:

Thus, created a car price prediction model using Random Forest Regressor with an accuracy of 95%