Untitled-Copy1

August 2, 2019

1 1. Load Required Packages

```
In [39]: import pandas as pd
         import matplotlib.pyplot as plt
         import seaborn as sns
         import numpy as np
         from sklearn.preprocessing import MinMaxScaler
         from sklearn.linear_model import LinearRegression
         from sklearn.metrics import mean_squared_error
         from sklearn.model_selection import train_test_split
         from sklearn.preprocessing import PolynomialFeatures
         from sklearn.linear_model import Ridge
         import sys
         import csv
         %matplotlib inline
```

```
In [ ]: try:
            if (sys.argv[1] == '-'):
                f = sys.stdin.read().splitlines()
            else:
                filename = sys.argv[1]
                f = open(filename, 'r')
            data = csv.reader(f)
        except Exception, e:
            print "Error Reading from file:"
```

2 2. Import the Data-Set

```
In [40]: cars  = pd.read_csv("data.csv")
```

```
In [41]: cars.head()
```

```
Out[41]:      car_company           model_ID  mileage  engine_power registration_date  \
         0  Edureka_motors   318 Gran Turismo   140245           105        01-10-2014
         1  Edureka_motors  218 Active Tourer    91512           100        01-06-2015
         2  Edureka_motors                318   113744           100        01-06-2012
         3  Edureka_motors   320 Gran Turismo   195063           135        01-05-2014
```

```
4   Edureka_motors                518   148943           100        01-11-2013

     fuel car_paint_color   car_type  feature1  feature2  feature3  feature4  \
0   diesel           white  hatchback     False      True     False     False
1   petrol           white        van     False      True      True     False
2   diesel            grey      sedan      True      True     False     False
3   diesel           black  hatchback     False      True      True     False
4   diesel           brown     estate      True      True      True     False

   feature5  feature6  feature7  feature8   sold_date  car_price
0      True      True      True      True  01-03-2018      19200
1     False     False      True     False  01-05-2018      14300
2     False     False      True     False  01-06-2018      14300
3      True     False      True      True  01-03-2018      16200
4      True     False      True      True  01-05-2018      17300
```

3 3. Data Pre-processing

a. (sold_date - registration_date) tells us how old the car is Let's add the column "car_age_days" to the data set.

```
In [42]: cars['sold_date'] = pd.to_datetime(cars['sold_date'])
         cars['registration_date'] = pd.to_datetime(cars['registration_date'])
```

```
In [43]: cars['car_age_days'] = cars['sold_date'] - cars['registration_date']
```

So, we have added the column 'car_age_days' to the dataset.

b. Let's convert car_age_days to categorical values to simplify analysys later.

```
In [44]: def simplify_car_age(element):
             if element <= pd.to_timedelta('365 days'):
                 return 'New'
             elif element >  pd.to_timedelta('365 days') and element <=  pd.to_timedelta('1460
                 return 'Little_Old'
             elif element >  pd.to_timedelta('1460 days') and element <=  pd.to_timedelta('2920
                 return "Old"
             elif element > pd.to_timedelta('2920 days'):
                 return 'Very_Old'
         cars['age_simplified'] = cars['car_age_days'].apply(simplify_car_age)
```

Now age_simplified column contains four categories which are: 1. New : < 1 Yr old 2. Little_old: 2-4 Yr old 3. old : 4-8 Yr old 4. Very_old : >8 Yr old

b. Let's Map model_ID column values to Four categories for easier analysis.

```
In [45]: def convert_to_cat(element):
             if element.isnumeric() :
                 return "Three_digit_model"
```

```
        elif 'Gran' in element:
            return "Gran_model"
        elif 'Active' in element:
            return "Active_model"
        elif 'X' in element:
            return "X_model"
    cars['model_cat'] = cars['model_ID'].apply(convert_to_cat)
    cars.drop(columns = 'model_ID',axis = 1 , inplace = True)
```

Now model_cat contains four categories which are: 1. "Three_digit_model" : if model_id is just 3 digit number 2. "Gran_model" : if model_id contains Gran in it. 3. "Active_model" : if model_id contains Active in it. 4. 'X_model' : id model_id contains X_model in it.

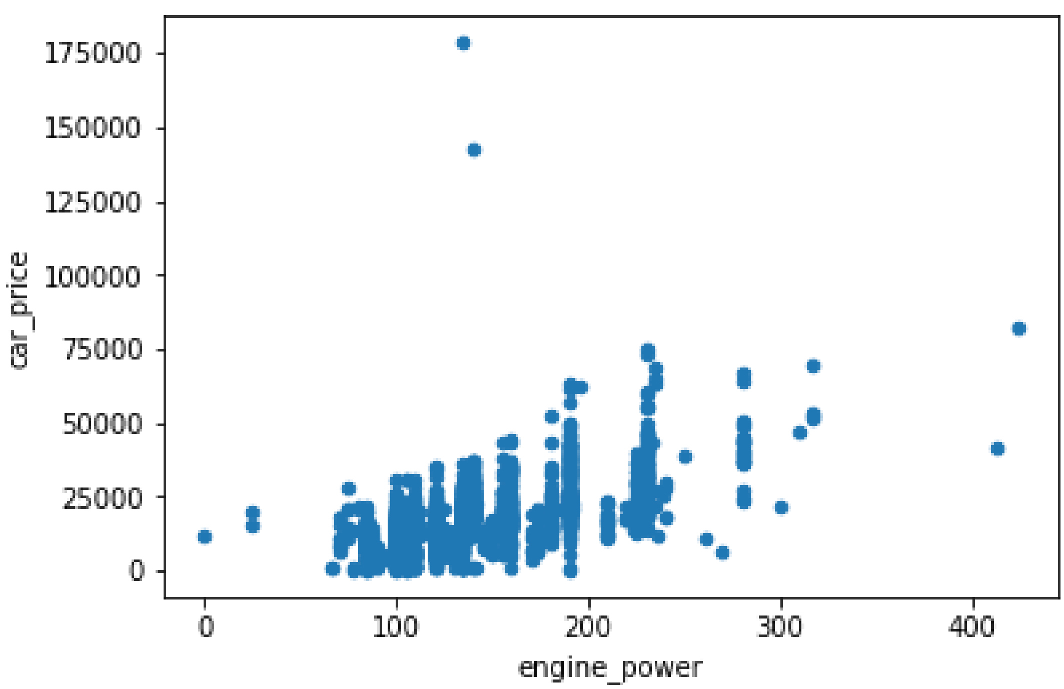
c. "car_company" is pretty redundant column we can drop it.

```
In [46]: cars.drop(columns = 'car_company',axis = 1 , inplace = True)
```

4 4. Data Exploration(EDA)

We will use Scatter plots to find any ouliers if present!
a.) car_price Vs engine_power

```
In [47]: cars['car_price'].astype('float')
         cars.plot(kind = 'scatter' , x = 'engine_power', y = 'car_price')

Out[47]: <matplotlib.axes._subplots.AxesSubplot at 0x2435784e208>
```

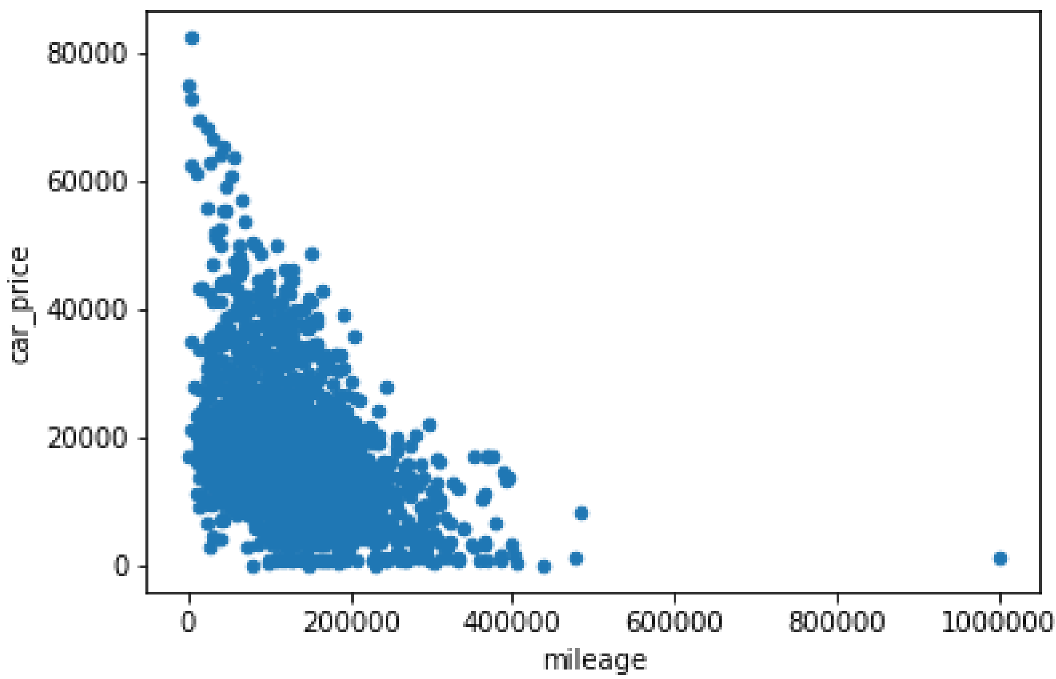


They are strongly correlated. we can see some outliers so we better drop those rows other wise they will effect our model performance.

```
In [48]: cars.loc[cars['car_price'] > 100000,'car_price'] = np.NaN
         cars.dropna(subset = ['car_price'],axis = 0,inplace = True)
```

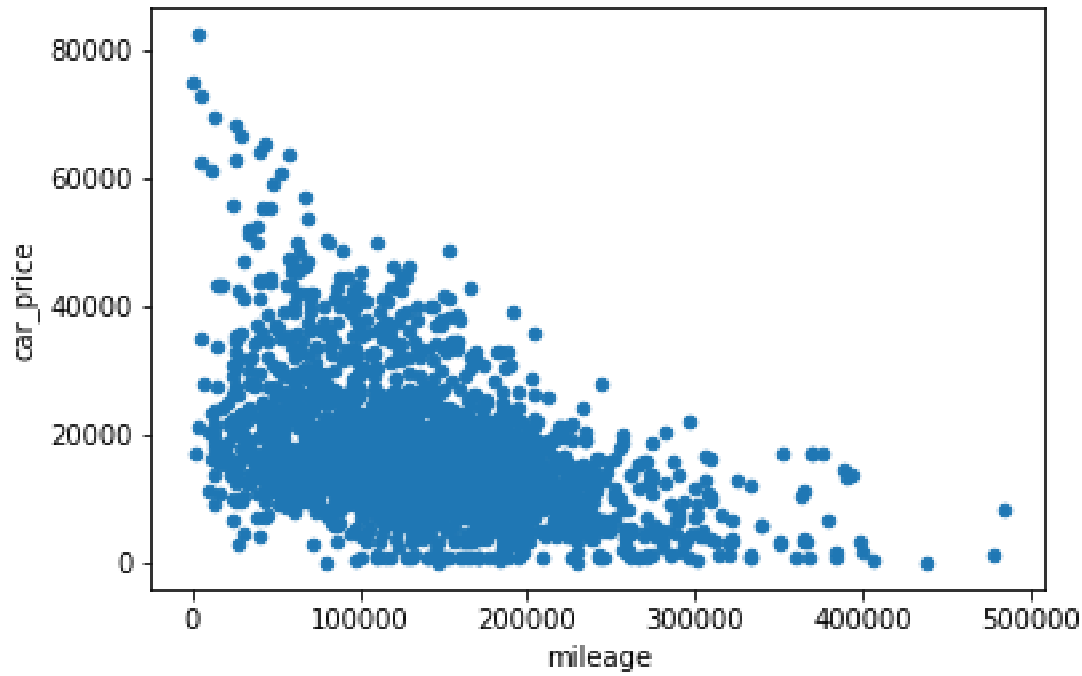
b.) car_price Vs mileage

```
In [49]: cars.plot(kind = 'scatter' , x = 'mileage', y = 'car_price')

Out[49]: <matplotlib.axes._subplots.AxesSubplot at 0x24357897d30>
```



There is an outlier here as well so we better drop that row as well.

```
In [50]: cars.loc[cars['mileage'] > 800000,'mileage'] = np.NaN
         cars.dropna(subset = ['mileage'], axis = 0, inplace = True)
         cars.plot(kind = 'scatter' , x = 'mileage', y = 'car_price')

Out[50]: <matplotlib.axes._subplots.AxesSubplot at 0x243575c5cc0>
```



Looks like we have a strong negative correleation between car_price and mileage.

Idea : if any feature has most of the values same then it is not a strong feature and dropping it will not have any effect on performance.

```
In [51]: f_list = ['feature1','feature2','feature3','feature4','feature5','feature6','feature7

         cars[f_list].sum()

Out[51]: feature1    1868
         feature2    2696
         feature3     669
         feature4     665
         feature5    1550
         feature6     820
         feature7    3157
         feature8    1803
         dtype: int64

In [52]: cars.shape

Out[52]: (3387, 19)
```

Feature7 seems redundant as it contains 3157 True values out of 3387 so its redundant so we drop that column.

```
In [53]: cars.drop(columns = ['feature7'],axis = 1,inplace = True)
```

5 Let's check out fuel,car_paint_color,car_type columns

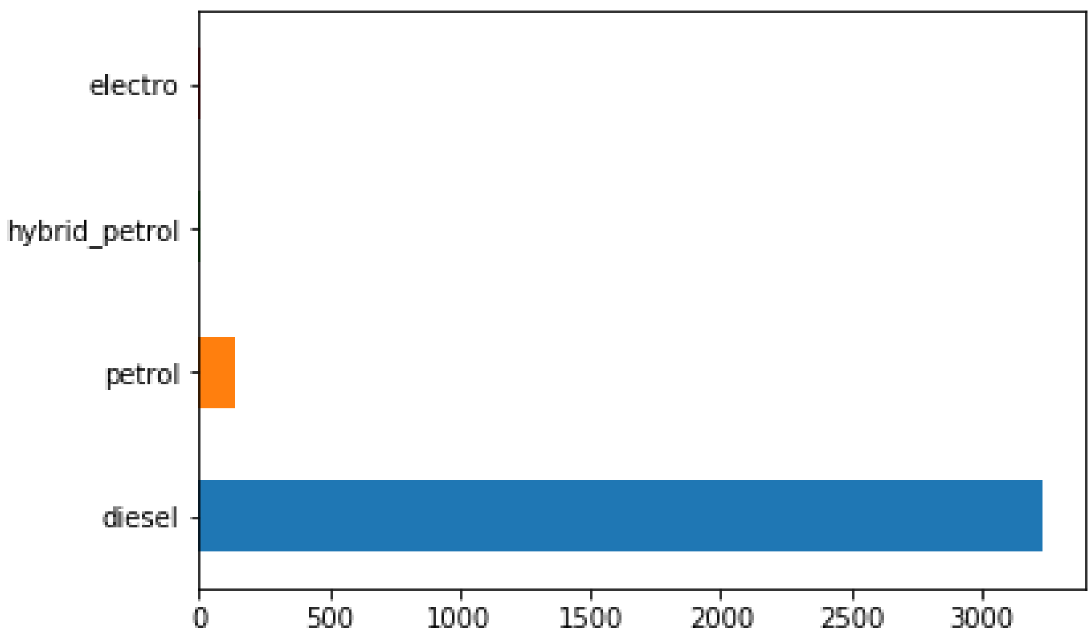
Question_1: which is the most popular fuel type ?

```
In [54]: cars['fuel'].value_counts()
```

```
Out[54]: diesel          3236
         petrol           142
         hybrid_petrol      6
         electro            3
         Name: fuel, dtype: int64
```

```
In [55]: cars['fuel'].value_counts().plot(kind = 'barh')
```

```
Out[55]: <matplotlib.axes._subplots.AxesSubplot at 0x24358902278>
```

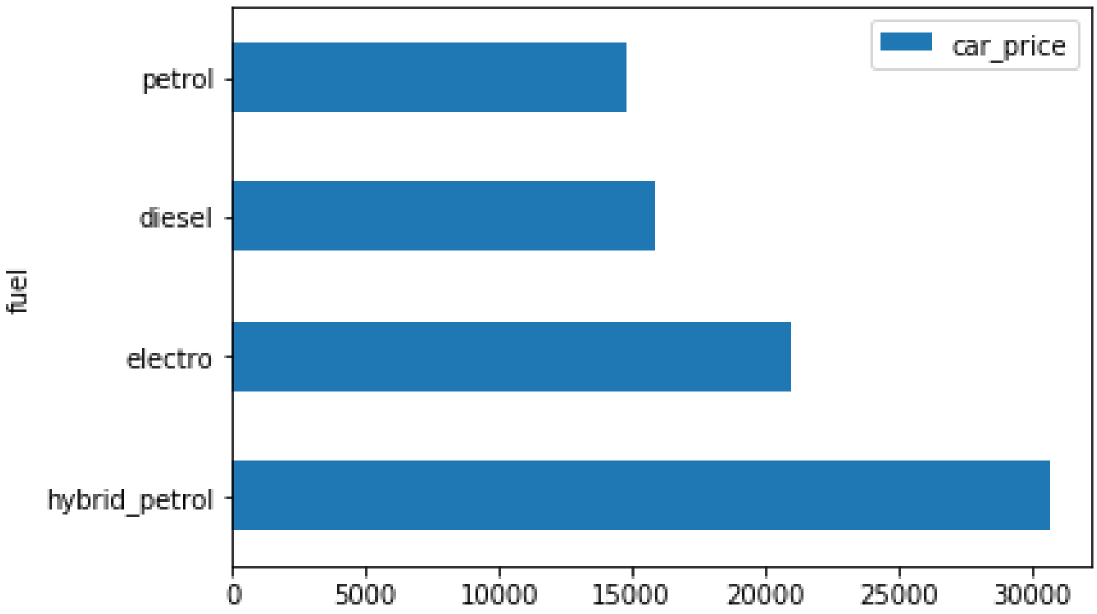


Ans_1: 95% of the car fuel types are diesel.

Question_2: which of the fuel type car is most expensive and which fuel type is lease expensive?

```
In [56]: mean_price_fuel = pd.pivot_table(cars, index = 'fuel' , values = 'car_price')
         mean_price_fuel.sort_values(by= 'car_price',ascending  = False).plot(kind = 'barh')
```

```
Out[56]: <matplotlib.axes._subplots.AxesSubplot at 0x24358946f28>
```



Ans_2 : Hybrid_petrol fuel type car is the most expensive car and petrol fuel type is least expensive.

Question_3 : Does colour of a car have any impact on the car_price?

In [57]:
```
cars['car_paint_color'].value_counts()
```

Out[57]:
```
black     1152
grey       794
blue       505
white      386
silver     234
brown      223
red         38
beige       36
green       14
orange       5
Name: car_paint_color, dtype: int64
```

Yes, May be an odd coloured car like pink go for a lesser price than normal colours like black,grey e.t.c

In [58]:
```
mean_colour_fuel = pd.pivot_table(cars, index = 'car_paint_color' , values = 'car_pri
mean_colour_fuel.sort_values(by= 'car_price',ascending  = False)
```

Out[58]:
```
                    car_price
car_paint_color
orange           17980.000000
white            17579.792746
```

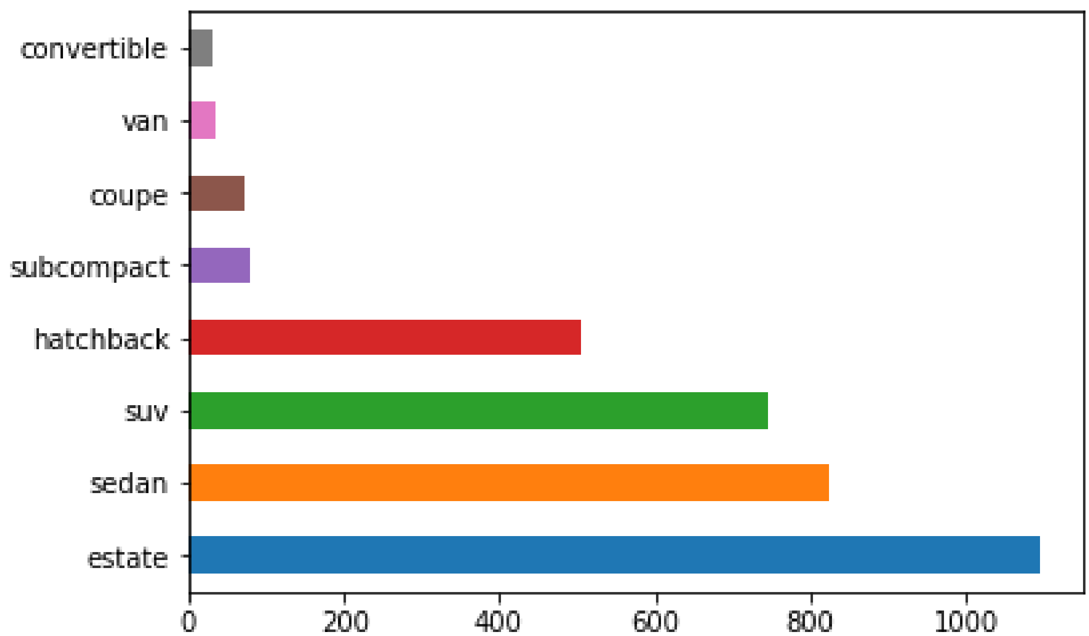
```
red         17018.421053
black       16258.940972
brown       15956.502242
beige       15380.555556
grey        15246.473552
silver      15164.957265
blue        14801.188119
green        5857.142857
```

Ans_3: According to the data orange coloured car is most expensive and green colored car is least expensive. But color does not impact car price strongly. For e.g You have same car but with different colour.The prices vary very little.

Question_4: Which car_type is most expensive and which is least on average?

```
In [59]: cars['car_type'].value_counts().plot('barh')
```

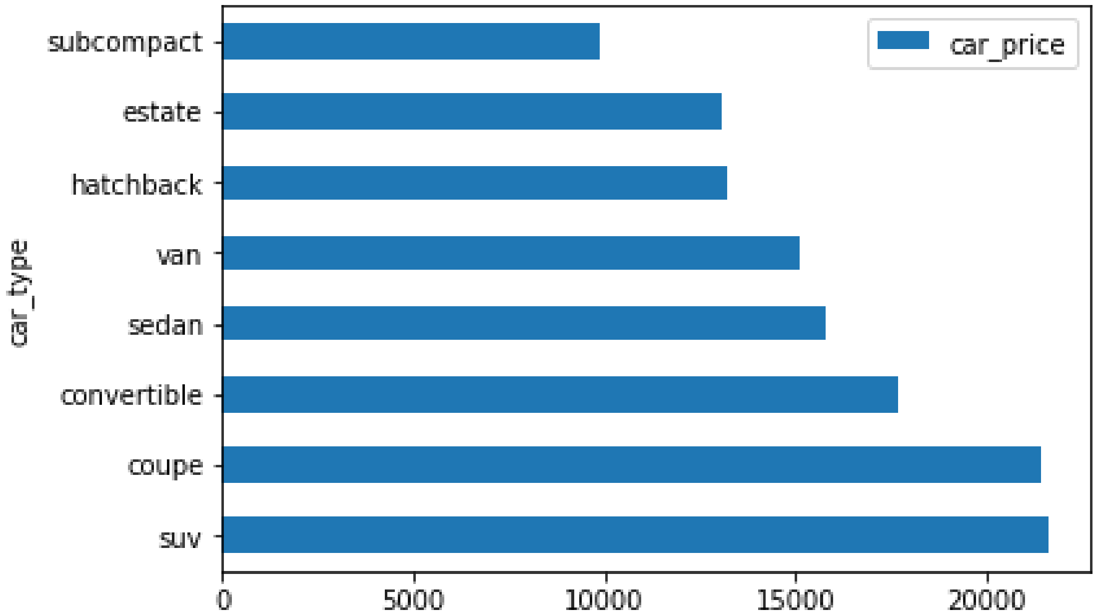
```
Out[59]: <matplotlib.axes._subplots.AxesSubplot at 0x243589b55c0>
```



Estate is the most popular car type!

```
In [60]: mean_car_type = pd.pivot_table(cars, index = 'car_type' , values = 'car_price')
         mean_car_type.sort_values(by= 'car_price',ascending  = False).plot(kind = 'barh')
```

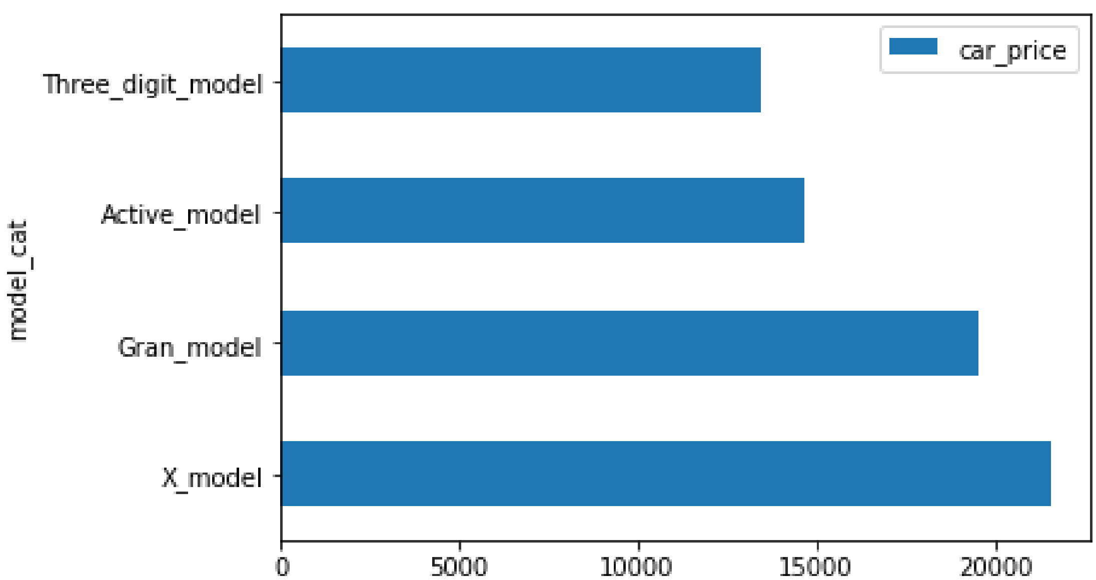
```
Out[60]: <matplotlib.axes._subplots.AxesSubplot at 0x24358a1f0b8>
```



Ans_4: On average an SUV costs most followed by coupe and convertible!
Question_5: Which car model costs the highest on average

```
In [61]: mean_car_model = pd.pivot_table(cars, index = 'model_cat' , values = 'car_price')
         mean_car_model.sort_values(by= 'car_price',ascending  = False).plot(kind = 'barh')
```

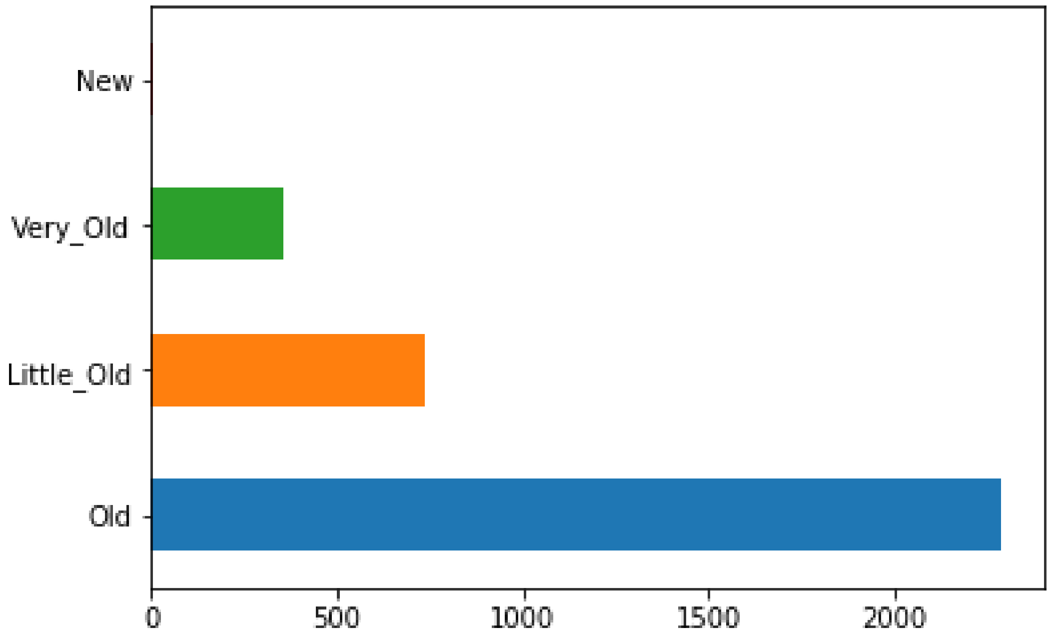
```
Out[61]: <matplotlib.axes._subplots.AxesSubplot at 0x24358a85ac8>
```



Ans_5: On average X_model costs most followed by Gran_model and Active_model
Question_6 : what is the age of most of the cars in the data?

```
In [62]: cars['age_simplified'].value_counts().plot(kind = 'barh')
```

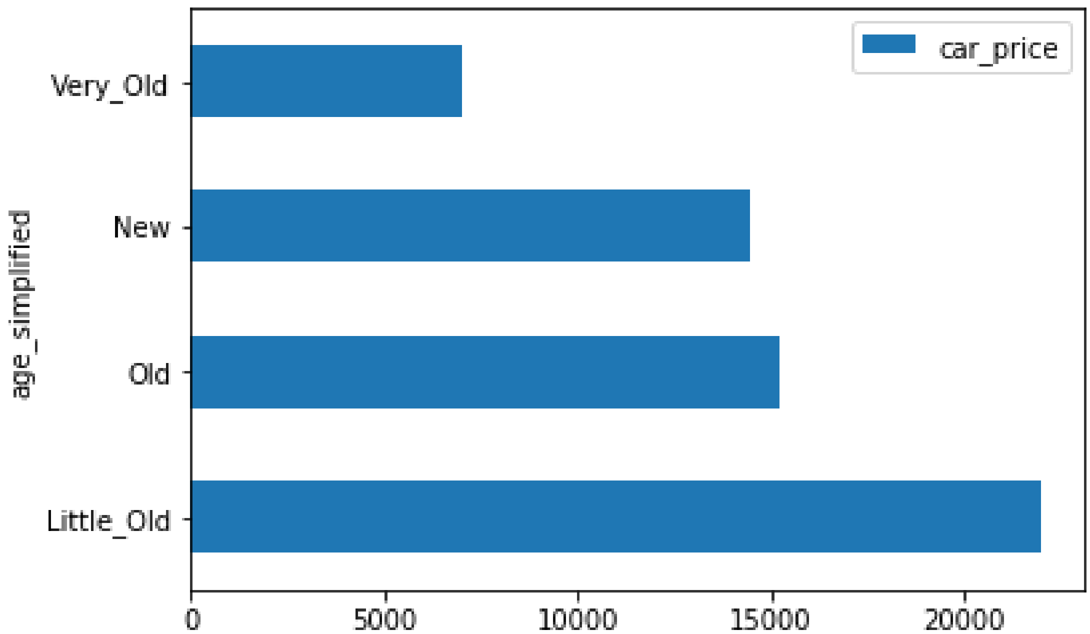
```
Out[62]: <matplotlib.axes._subplots.AxesSubplot at 0x24358aef080>
```



Ans_6 : Most of cars age is "Old" (2-4)Years old.
Question_7: What is the average price of each car_age category(New,little_old,old,very_old)

```
In [63]: mean_car_age_price = pd.pivot_table(cars, index = 'age_simplified' , values = 'car_pr
         mean_car_age_price.sort_values(by= 'car_price',ascending  = False).plot(kind = 'barh'
```

```
Out[63]: <matplotlib.axes._subplots.AxesSubplot at 0x24358b4b400>
```



Ans_7: On Averge a car that is 2-4 years old('Little_old') is the costs more and car which is greater than 8 years('Very_Old') costs least.

6 5. Data Modelling

Machine can understand only numbers so we have to convert those categorical values to numerical values.

Let's convert columns with categorical values to numerical using One-hot encoding.

```
In [64]: dummy_df = pd.get_dummies(cars,columns = ['car_type','fuel','model_cat','feature1','fe
```

we drop Non-numerical columns and prepare our data for modelling.

```
In [65]: model_df = dummy_df.drop(columns = ['car_paint_color','registration_date','sold_date'
```

```
In [66]: Y = model_df['car_price']
         X = model_df.drop(columns = ['car_price'],axis = 1)
```

Model_1: Linear Regression

```
In [78]: x_train, x_test, y_train, y_test = train_test_split(X, Y, test_size=0.15, random_state
         lm = LinearRegression()
         lm.fit(x_train,y_train)
```

```
Out[78]: LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None,
                  normalize=False)
```

7 6. Model Predictions(Linear Regression)

In [88]:
```
Yhat=lm.predict(x_train)
Yhat[0:5]
```

Out[88]:
```
array([ 8286.13664858,  9664.02544099,  -105.20664293, 19840.81099021,
        8873.92627532])
```

In [89]:
```
lm.intercept_
```

Out[89]:
```
10923.621840784128
```

In [90]:
```
lm.coef_
```

Out[90]:
```
array([-3.67349109e-02,  1.02146870e+02,  1.65871241e+03,  1.75460259e+03,
       -1.65086727e+03, -7.31009587e+02,  3.37988965e+02,  1.70358114e+02,
        2.11070429e+03, -3.65048950e+03, -2.59645044e+03,  1.70552976e+03,
        5.68106395e+03, -4.79014327e+03,  1.69875881e+02,  5.97291808e+02,
       -1.16496517e+03, -1.36577027e+03, -6.26211879e+02,  6.26211880e+02,
       -7.08832082e+02,  7.08832082e+02, -5.06294725e+02,  5.06294725e+02,
       -8.21398913e+02,  8.21398913e+02,  5.66280566e+01, -5.66280565e+01,
       -4.07230950e+02,  4.07230950e+02, -7.17344416e+02,  7.17344416e+02,
        4.29617895e+03, -1.40677487e+03,  9.77180712e+02, -3.86658480e+03])
```

In [91]:
```
print('The R-square of train data is: ', lm.score(x_train, y_train))
```

```
The R-square of train data is:  0.7456099370960487
```

In [92]:
```
mse = mean_squared_error(y_train, Yhat)
print('The mean square error of price and predicted value is: ', mse)
```

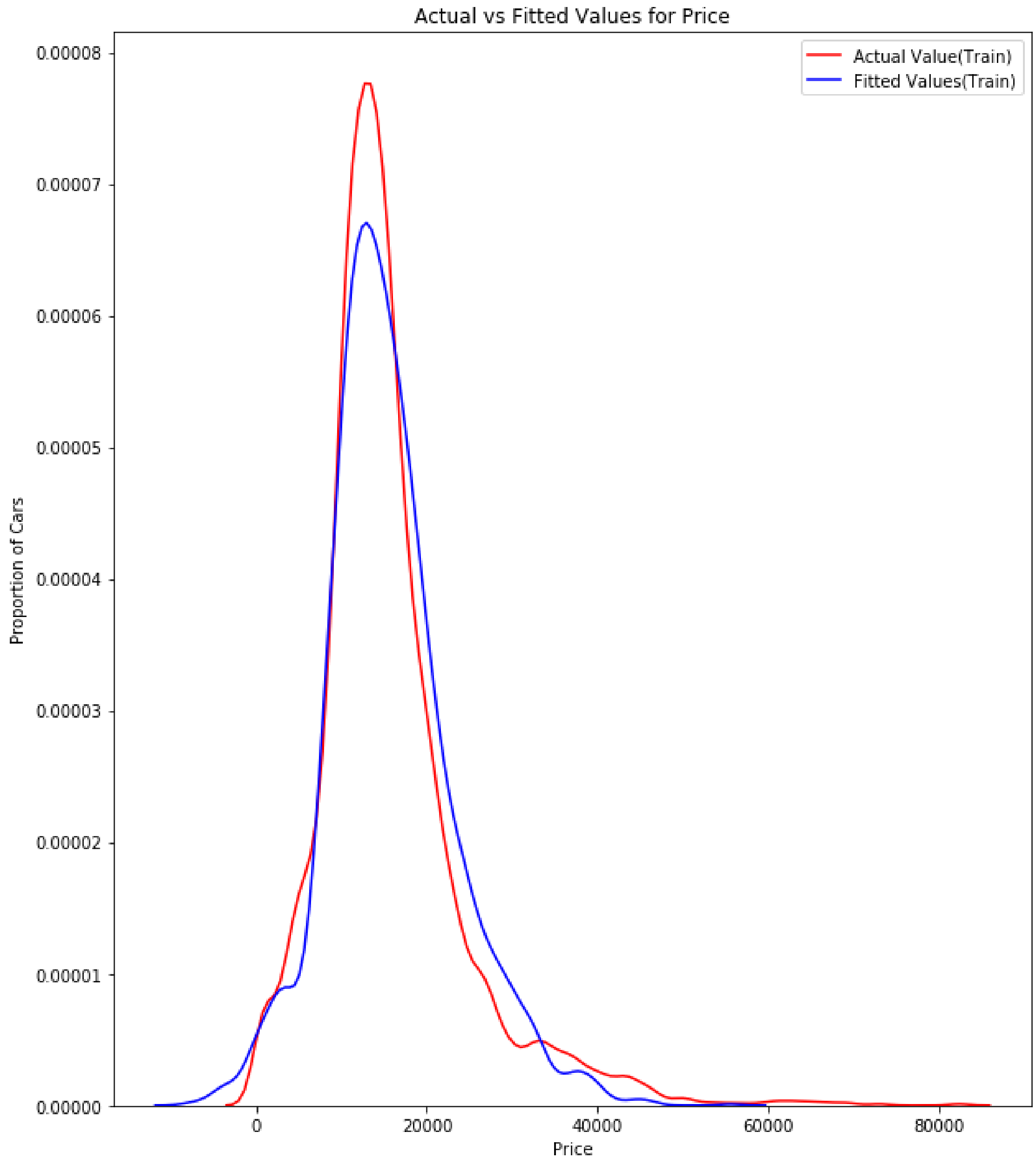
```
The mean square error of price and predicted value is:  18583009.992220502
```

8 7. Model Evaluation(Linear Regression)

Distribution plot between train data and predicted data

In [93]:
```
plt.figure(figsize=(10, 12))


ax1 = sns.distplot(y_train, hist=False, color="r", label="Actual Value(Train)")
sns.distplot(Yhat, hist=False, color="b", label="Fitted Values(Train)" , ax=ax1)


plt.title('Actual vs Fitted Values for Price')
plt.xlabel('Price')
plt.ylabel('Proportion of Cars')

plt.show()
plt.close()
```

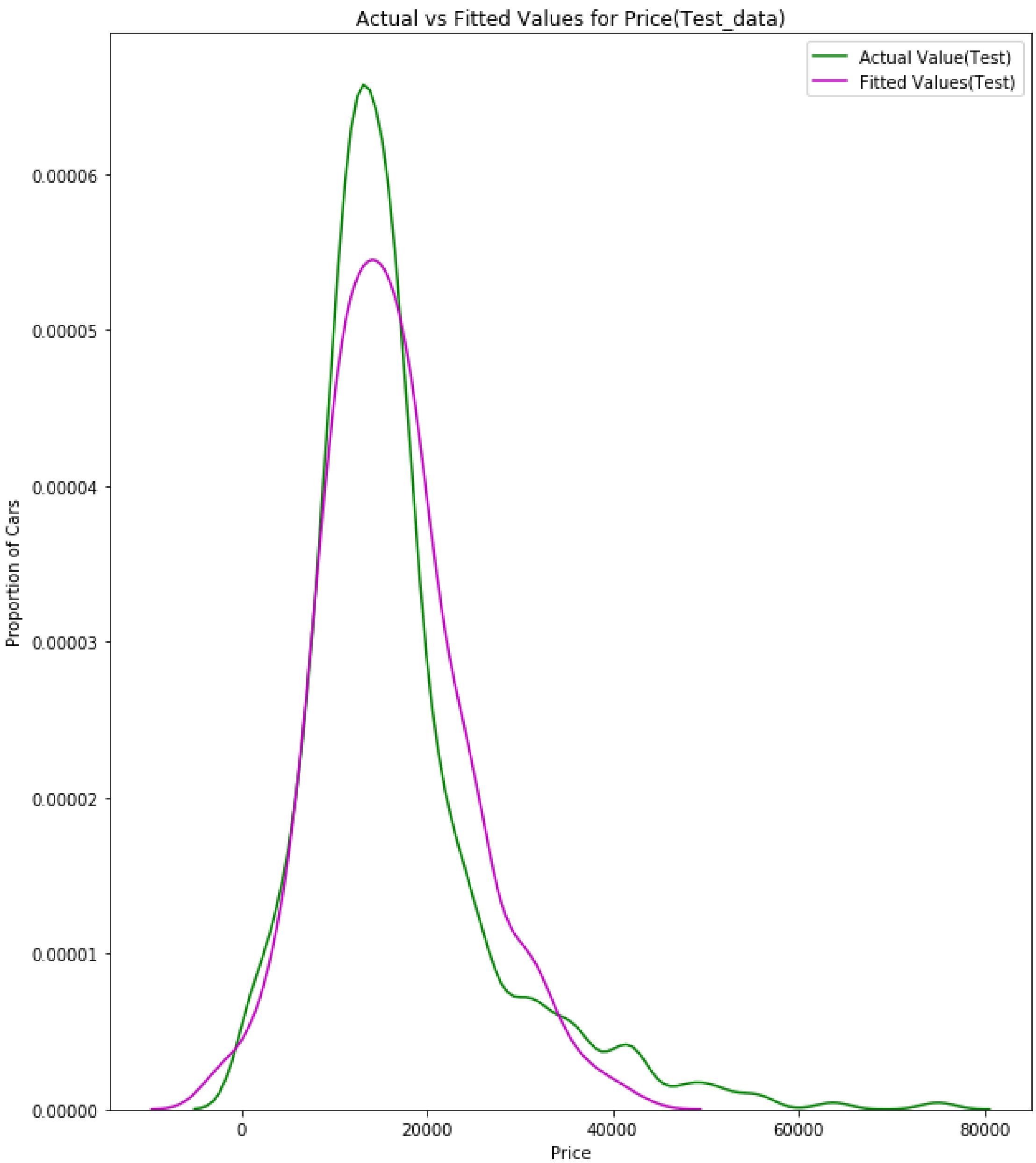
```
C:\Users\Welcome\Anaconda3\lib\site-packages\scipy\stats\stats.py:1713: FutureWarning: Using a
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```



Distribution plot between test data and predicted data

```
In [165]: plt.figure(figsize=(10, 12))


          ax2 = sns.distplot(y_test, hist=False, color="g", label="Actual Value(Test)")
          sns.distplot(yhat_test, hist=False, color="m", label="Fitted Values(Test)", ax=ax2)
```

```python
plt.title('Actual vs Fitted Values for Price(Test_data)')
plt.xlabel('Price')
plt.ylabel('Proportion of Cars')

plt.show()
plt.close()
```



The predicted values are more than expected for higher prices and that pattern kept on going.

model_2 : polynomial regression

```
In [94]: lm_2 = LinearRegression()
         pr = PolynomialFeatures(degree=2)
         x_train_pr = pr.fit_transform(x_train)
         x_test_pr = pr.fit_transform(x_test)
         lm_2.fit(x_train_pr, y_train)

         print('The R-square for prediction on test data: ', lm_2.score(x_test_pr,y_test))
```

```
The R-square for prediction on test data:  -48.24927413031234
```

R-squared value is negative which indicates the fit is actually worse than fitting a straight line so this is worse than linear regression.

model_3 : Ridge Regression

```
In [95]: pr=PolynomialFeatures(degree=2)
         x_train_pr_ridge=pr.fit_transform(x_train)
         x_test_pr_ridge=pr.fit_transform(x_test)
```

```
In [96]: RigeModel=Ridge(alpha=0.1)
         RigeModel.fit(x_train_pr, y_train)
```

```
C:\Users\Welcome\Anaconda3\lib\site-packages\sklearn\linear_model\ridge.py:125: LinAlgWarning:
Ill-conditioned matrix detected. Result is not guaranteed to be accurate.
Reciprocal condition number2.423100e-26
  overwrite_a=True).T
```

```
Out[96]: Ridge(alpha=0.1, copy_X=True, fit_intercept=True, max_iter=None,
            normalize=False, random_state=None, solver='auto', tol=0.001)
```

9 6. Model Predictions(Ridge Regression)

```
In [97]: yhat_rid = RigeModel.predict(x_test_pr)
```

```
In [102]: pd.DataFrame(yhat_rid).to_csv("Predicted_Values.csv")
```

```
In [98]: RigeModel.score(x_test_pr_ridge, y_test)
```

```
Out[98]: 0.8301400022156428
```

```
In [99]: RigeModel.score(x_train_pr_ridge, y_train)
```

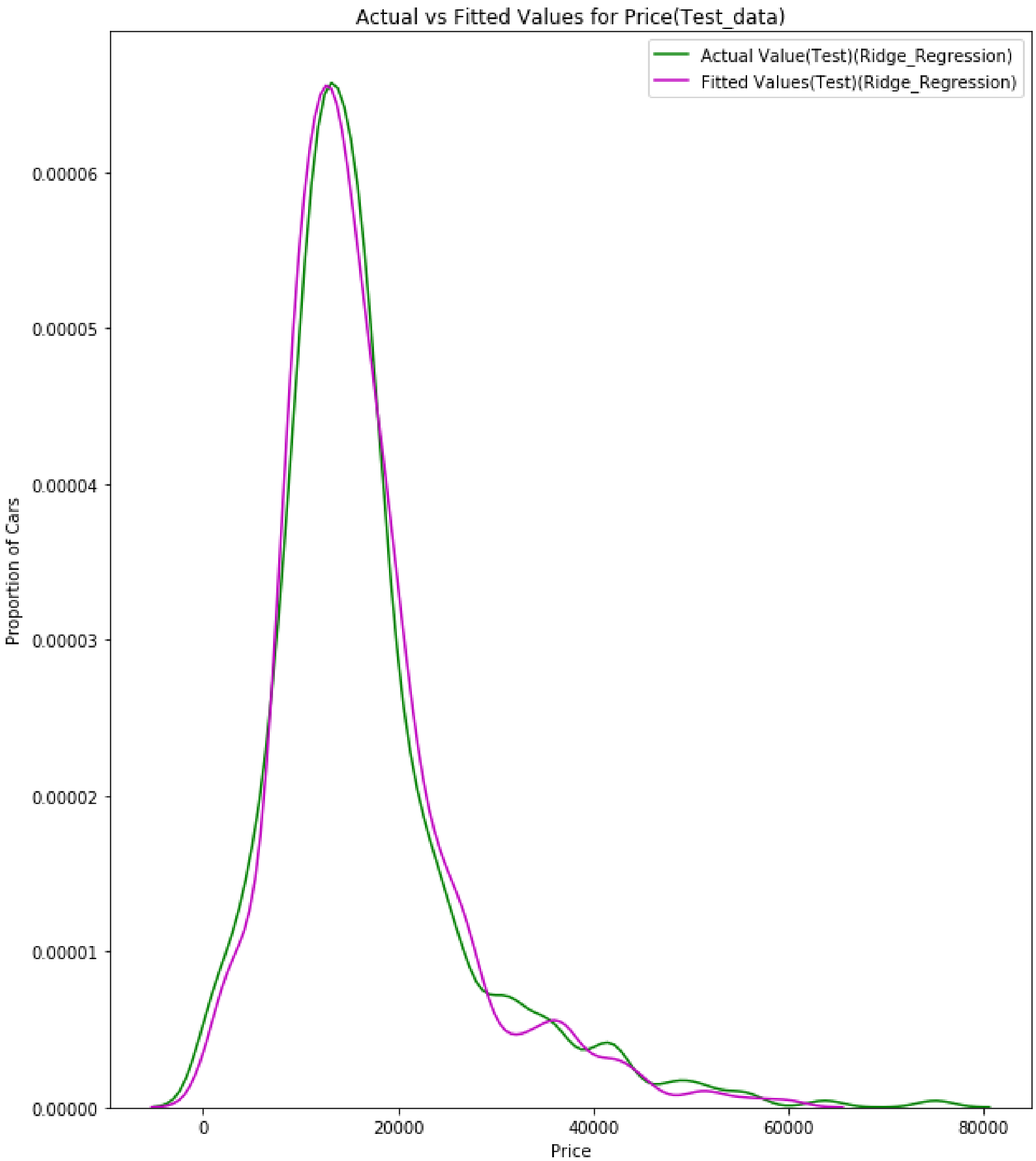
```
Out[99]: 0.8517594846848306
```

10 7.Model Evaluation(Ridge Regression)

Distribution plot between test data and predicted data

```
In [100]: plt.figure(figsize=(10, 12))


          ax3 = sns.distplot(y_test, hist=False, color="g", label="Actual Value(Test)(Ridge_Reg
          sns.distplot(yhat_rid, hist=False, color="m", label="Fitted Values(Test)(Ridge_Regres


          plt.title('Actual vs Fitted Values for Price(Test_data)')
          plt.xlabel('Price')
          plt.ylabel('Proportion of Cars')

          plt.show()
          plt.close()
```

```
C:\Users\Welcome\Anaconda3\lib\site-packages\scipy\stats\stats.py:1713: FutureWarning: Using a
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```


Actual vs Fitted Values for Price(Test_data)
Actual Value(Test)(Ridge_Regression)
Fitted Values(Test)(Ridge_Regression)
Proportion of Cars
0.00006
0.00005
0.00004
0.00003
0.00002
0.00001
0.00000
0
20000
40000
60000
80000
Price

```
In [ ]:
```