main

April 9, 2022

1 Car prices prediction

[1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sb
import pickle
from sklearn.model_selection import train_test_split
from sklearn.pipeline import make_pipeline
from sklearn.preprocessing import StandardScaler
from sklearn.neural_network import MLPRegressor
```

1.1 Dataset Exploration :

[2]:
```
DataSet = pd.read_csv("DataSet.csv")

DataSet.head()
```

[2]:

	name	year	selling_price	km_driven	fuel	seller_type	transmission	owner	mileage	engine	max_power	torque	seats
0	Maruti Swift Dzire VDI	2014	450000	145500	Diesel	Individual	Manual	First Owner	23.4 kmpl	1248 CC	74 bhp	190Nm@ 2000rpm	5.0
1	Skoda Rapid 1.5 TDI Ambition	2014	370000	120000	Diesel	Individual	Manual	Second Owner	21.14 kmpl	1498 CC	103.52 bhp	250Nm@ 1500-2500rpm	5.0
2	Honda City 2017-2020 EXi	2006	158000	140000	Petrol	Individual	Manual	Third Owner	17.7 kmpl	1497 CC	78 bhp	12.7@ 2,700(kgm@ rpm)	5.0
3	Hyundai i20 Sportz Diesel	2010	225000	127000	Diesel	Individual	Manual	First Owner	23.0 kmpl	1396 CC	90 bhp	22.4 kgm at 1750-2750rpm	5.0
4	Maruti Swift VXI BSIII	2007	130000	120000	Petrol	Individual	Manual	First Owner	16.1 kmpl	1298 CC	88.2 bhp		

```
4     11.5@ 4,500(kgm@ rpm)    5.0
```

[3]:
```
DataSet.shape
```

[3]:
```
(8128, 13)
```

[4]:
```
DataSet.dtypes
```

[4]:
```
name              object
year               int64
selling_price      int64
km_driven          int64
fuel              object
seller_type       object
transmission      object
owner             object
mileage           object
engine            object
max_power         object
torque            object
seats            float64
dtype: object
```

[5]:
```
DataSet.isnull().sum()
```

[5]:
```
name              0
year              0
selling_price     0
km_driven         0
fuel              0
seller_type       0
transmission      0
owner             0
mileage         221
engine          221
max_power       215
torque          222
seats           221
dtype: int64
```

We can see that this dataset contains some rows that have empty cells (NaN), In this case we are going to get rid of those rows but we can for example replace those cells with their colmn's mean value

[6]:
```
DataSet = DataSet.dropna()
DataSet.isnull().sum().sum()
```

[6]:
```
0
```

Here, we create 2 functions : * Numerise : which will help us replace string columns with number (for example : for the transmission column manual is replaced with 0 and automatic is replaced with 1) * ExtractNum : which will help us extract numerical features from cell (for example : 32 kmpl becomes 32)

[7]:
```
def Numerise(DF, Column):
    x = pd.Series(DF[Column])
    col = pd.factorize(x)
    return col
```

[8]:
```
def ExtractNum(DF, Column):
    x = pd.Series(DF[Column])
    x = x.astype('str').str.extractall('(\d+)').unstack().fillna('').
 ↪sum(axis=1).astype(int)
    return np.array(x)
```

[9]:
```
DataSet.dtypes
```

[9]:
```
name              object
year               int64
selling_price      int64
km_driven          int64
fuel              object
seller_type       object
transmission      object
owner             object
mileage           object
engine            object
max_power         object
torque            object
seats            float64
dtype: object
```

And finally here we are creating a new DataFrame containing nothing but numerical values, some columns are discarded either because their features are inconsistent(Torque), or because they offer no use in our case(Name)

[10]:
```
NewDataSet = pd.DataFrame({"year" : np.array(DataSet["year"]),
                           "SellingPrice" : np.array(DataSet["selling_price"]),
                           "kmDriven" : np.array(DataSet["km_driven"]),
                           "fuel" : Numerise(DataSet, "fuel")[0],
                           "Seller" : Numerise(DataSet, "seller_type")[0],
                           "transmission" : Numerise(DataSet,␣
 ↪"transmission")[0],
                           "owner" : Numerise(DataSet, "owner")[0],
                           "mileage" : ExtractNum(DataSet, "mileage"),
                           "engine" : ExtractNum(DataSet, "engine"),
                           "maxPower" : ExtractNum(DataSet, "max_power"),
```

```
                          "Seats" : np.array(DataSet["seats"]),
                         })
NewDataSet
```

[10]:

	year	SellingPrice	kmDriven	fuel	Seller	transmission	owner
0	2014	450000	145500	0	0	0	0
1	2014	370000	120000	0	0	0	1
2	2006	158000	140000	1	0	0	2
3	2010	225000	127000	0	0	0	0
4	2007	130000	120000	1	0	0	0
…	…	…	…	…	…	…	…
7901	2013	320000	110000	1	0	0	0
7902	2007	135000	119000	0	0	0	3
7903	2009	382000	120000	0	0	0	0
7904	2013	290000	25000	0	0	0	0
7905	2013	290000	25000	0	0	0	0

	mileage	engine	maxPower	Seats
0	234	1248	74	5.0
1	2114	1498	10352	5.0
2	177	1497	78	5.0
3	230	1396	90	5.0
4	161	1298	882	5.0
…	…	…	…	…
7901	185	1197	8285	5.0
7902	168	1493	110	5.0
7903	193	1248	739	5.0
7904	2357	1396	70	5.0
7905	2357	1396	70	5.0

[7906 rows x 11 columns]

[11]:
```
NewDataSet.describe()
```

[11]:

	year	SellingPrice	kmDriven	fuel	Seller
count	7906.000000	7.906000e+03	7.906000e+03	7906.000000	7906.000000
mean	2013.983936	6.498137e+05	6.918866e+04	0.473817	0.199722
std	3.863695	8.135827e+05	5.679230e+04	0.545591	0.468575
min	1994.000000	2.999900e+04	1.000000e+00	0.000000	0.000000
25%	2012.000000	2.700000e+05	3.500000e+04	0.000000	0.000000
50%	2015.000000	4.500000e+05	6.000000e+04	0.000000	0.000000
75%	2017.000000	6.900000e+05	9.542500e+04	1.000000	0.000000
max	2020.000000	1.000000e+07	2.360457e+06	3.000000	2.000000

	transmission	owner	mileage	engine	maxPower
count	7906.000000	7906.000000	7906.000000	7906.000000	7906.000000
mean	0.131672	0.447255	947.702378	1458.708829	2766.125348

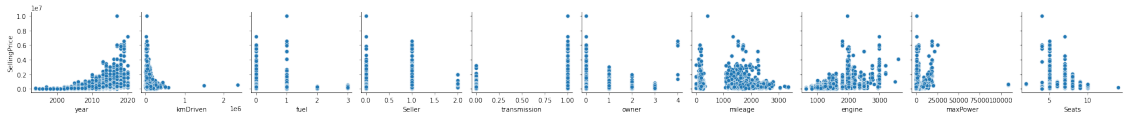
```
std         0.338155     0.710854   925.336832    503.893057    5162.123778
min         0.000000     0.000000     0.000000    624.000000      35.000000
25%         0.000000     0.000000   185.000000   1197.000000     100.000000
50%         0.000000     0.000000   240.000000   1248.000000     739.000000
75%         0.000000     1.000000  1944.000000   1582.000000    3748.000000
max         1.000000     4.000000  3344.000000   3604.000000  108495.000000
```

```
              Seats
count   7906.000000
mean       5.416393
std        0.959208
min        2.000000
25%        5.000000
50%        5.000000
75%        5.000000
max       14.000000
```

And here, we scatter plot the selling price with all the other parameters to inspect for relations between them.

[12]:
```
sb.pairplot(data=NewDataSet,
                 x_vars=['year', 'kmDriven', 'fuel', 'Seller', 'transmission',␣
 ↪'owner', 'mileage', 'engine', 'maxPower', 'Seats'],
                 y_vars=['SellingPrice'])
```

[12]:
```
<seaborn.axisgrid.PairGrid at 0x7f2e1dda2160>
```



We can see from the graph above, that some of the values just doesn't make sense or are just impossible in real life (for example: mileage > 200 or horsepower > 100000), this is very common in hand typed datasets where human caused error is present, especially with large datasets, we can just remove those values as shown below :

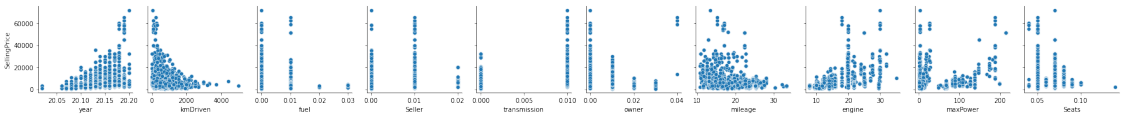
[13]:
```
NewDataSet = NewDataSet[NewDataSet["kmDriven"]<=700000]
NewDataSet = NewDataSet[NewDataSet["maxPower"]<=30000]
NewDataSet = NewDataSet[NewDataSet["mileage"]>1000]/100
NewDataSet.shape
```

[13]:
```
(3329, 11)
```

[14]:
```
sb.pairplot(data=NewDataSet,
                 x_vars=['year', 'kmDriven', 'fuel', 'Seller', 'transmission',␣
 ↪'owner', 'mileage', 'engine', 'maxPower', 'Seats'],
```

```
                    y_vars=['SellingPrice'])
```

[14]: <seaborn.axisgrid.PairGrid at 0x7f2e1bb31a30>



We can see from the graph below that the Selling price have some relation with the following columns : * Year * kmDriven * owner * mileage * engine * maxPower * Seats

1.2 Preparing for Training :

Before we train our model we first have to separate our dataset to 2 seperate DataFrames: * Features : which contains the input for the model * Labels : the expected output (in our case : * the features contains : Year, kmDriven, owner, mileage, engine, maxPower, seats * the label is the selling price)

[15]:
```
X = NewDataSet.drop(["SellingPrice", "fuel", "Seller", "transmission"], axis =␣
↪1)
Y = pd.DataFrame({"SellingPrice" : NewDataSet["SellingPrice"]})
```

[16]:
```
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, random_state=1)
```

Instansiating our neural network model inside a pipeline, this pipeline contains a StandardScaler which allows us to normalize the input for our model, it also contains an MLPRegressor (Multi-Layer Perceptron Regressor) with 2 hidden Layers each containing 64 nodes.

After that we fit our model.

[17]:
```
regressor = make_pipeline(
    StandardScaler(),
    MLPRegressor(
        hidden_layer_sizes = (64, 64),
        activation = "relu",
        solver = "adam",
        alpha = 0.0005,
        learning_rate='constant',
        learning_rate_init=0.005,
        max_iter = 10000
    )
)

regressor.fit(X_train, Y_train)
```

```
/home/chiheb/.local/lib/python3.8/site-
packages/sklearn/neural_network/_multilayer_perceptron.py:1599:
```

```
DataConversionWarning: A column-vector y was passed when a 1d array was
expected. Please change the shape of y to (n_samples, ), for example using
ravel().
  y = column_or_1d(y, warn=True)
```

[17]:
```
Pipeline(steps=[('standardscaler', StandardScaler()),
                ('mlpregressor',
                 MLPRegressor(alpha=0.0005, hidden_layer_sizes=(64, 64),
                              learning_rate_init=0.005, max_iter=10000))])
```

As we can see below our model has an over-all accuracy of 97.75% when tested with the test data we created earlier :

[18]:
```
(regressor.score(X_test, Y_test))**0.5
```

[18]:
```
0.9774887539186584
```

Here, we make a direct comparison between the expected selling price and the predicted selling price :

[19]:
```
results = pd.DataFrame({
    "Expected" : (Y_test["SellingPrice"]),
    "Predicted" :(regressor.predict(X_test))
})

results.head()
```

[19]:

	Expected	Predicted
7125	33500.00	35266.566733
1440	8500.00	7722.422296
2357	5000.00	4863.897270
2691	5099.99	5383.063916
1224	1250.00	2440.586752

All in all, the model is quite accurate for most cases, but is a bit hit-or-miss depending on the input, as we can see below, most of the time, the model will work as expected !

[20]:
```
results.describe()
```

[20]:

	Expected	Predicted
count	833.000000	833.000000
mean	7687.802737	7724.883712
std	9595.441682	9473.098670
min	600.000000	-4771.089065
25%	3200.000000	3240.470913
50%	5150.000000	5182.749003
75%	7400.000000	7467.591467
max	60000.000000	58983.081762

We Use Pickle to save the Model Object as a binary file that you can use in other projects as shown below :

[21]:
```
pickle.dump(regressor, open("Regressor", 'wb'))
```

[22]:
```
LoadedModel = pickle.load(open("Regressor", 'rb'))
LoadedModel.predict(X_test[:1])
```

[22]:
```
array([35266.56673323])
```