LAB 2

Exercise:

1) Perform all data preprocessing tasks and feature selection on “Exercise-CarData.csv”

In [1]:
```
# Import Libraries

import numpy as np
import pandas as pd
import seaborn as sns
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import MinMaxScaler, StandardScaler, LabelEncoder
, OneHotEncoder
```

In [2]:

```
# Load Data
# Replace "?,??,???....." to "NaN"
# Replace Doors value from string to corresponding numbers
# Convert Doors feature from object to int4

datasets = pd.read_csv('/home/nihar/Desktop/ML/Lab2/Exercise-CarData.csv',se
p=',\?*',engine='python')

numbers = { 'one': 1, 'two': 2, 'three': 3, 'four': 4, 'five': 5, 'six': 6,
'seven': 7, 'eight': 8, 'nine': 9,
            '1': 1, '2': 2,'3': 3, '4':4, '5': 5, '6': 6, '7': 7, '8': 8,
'9': 9 }
datasets.Doors = [numbers[item] for item in datasets.Doors]

datasets['Doors'] = pd.to_numeric(datasets['Doors'],errors='ignore')

print("\nData :\n",datasets.iloc[0:10,1:11])
```

```
Data :
    Price   Age       KM FuelType     HP  MetColor  Automatic    CC  Doors  \
0  13500  23.0  46986.0   Diesel   90.0       1.0          0  2000      3
1  13750  23.0  72937.0   Diesel   90.0       1.0          0  2000      3
2  13950  24.0  41711.0   Diesel   90.0       NaN          0  2000      3
3  14950  26.0  48000.0   Diesel   90.0       0.0          0  2000      3
4  13750  30.0  38500.0   Diesel   90.0       0.0          0  2000      3
5  12950  32.0  61000.0   Diesel   90.0       0.0          0  2000      3
6  16900  27.0      NaN   Diesel    NaN       NaN          0  2000      3
7  18600  30.0  75889.0      NaN   90.0       1.0          0  2000      3
8  21500  27.0  19700.0   Petrol  192.0       0.0          0  1800      3
9  12950  23.0  71138.0   Diesel    NaN       NaN          0  1900      3

   Weight
0    1165
1    1165
2    1165
3    1165
4    1170
5    1170
6    1245
7    1245
8    1185
9    1105
```

In [3]:
```python
# Statistics

print("\nData statistics :\n\n",datasets.describe())
print ("\n\nDataTypes of Features :\n\n",datasets.dtypes)
print("\n")
datasets.info()
```

```
Data statistics :

        Unnamed: 0         Price          Age             KM          HP  \
count  1436.000000   1436.000000  1336.000000    1421.000000  1430.000000
mean    717.500000  10730.824513    55.672156   68647.239972   101.478322
std     414.681806   3626.964585    18.589804   37333.023589    14.768255
min       0.000000   4350.000000     1.000000       1.000000    69.000000
25%     358.750000   8450.000000    43.000000   43210.000000    90.000000
50%     717.500000   9900.000000    60.000000   63634.000000   110.000000
75%    1076.250000  11950.000000    70.000000   87000.000000   110.000000
max    1435.000000  32500.000000    80.000000  243000.000000   192.000000

          MetColor    Automatic           CC        Doors      Weight
count  1286.000000  1436.000000  1436.000000  1436.000000  1436.00000
mean      0.674961     0.055710  1566.827994     4.033426  1072.45961
std       0.468572     0.229441   187.182436     0.952677    52.64112
min       0.000000     0.000000  1300.000000     2.000000  1000.00000
25%       0.000000     0.000000  1400.000000     3.000000  1040.00000
50%       1.000000     0.000000  1600.000000     4.000000  1070.00000
75%       1.000000     0.000000  1600.000000     5.000000  1085.00000
max       1.000000     1.000000  2000.000000     5.000000  1615.00000


DataTypes of Features :

 Unnamed: 0      int64
Price           int64
Age           float64
KM            float64
FuelType       object
HP            float64
MetColor      float64
Automatic       int64
CC              int64
Doors           int64
Weight          int64
dtype: object


<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1436 entries, 0 to 1435
Data columns (total 11 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   Unnamed: 0  1436 non-null   int64
 1   Price       1436 non-null   int64
 2   Age         1336 non-null   float64
 3   KM          1421 non-null   float64
 4   FuelType    1336 non-null   object
 5   HP          1430 non-null   float64
 6   MetColor    1286 non-null   float64
 7   Automatic   1436 non-null   int64
 8   CC          1436 non-null   int64
 9   Doors       1436 non-null   int64
 10  Weight      1436 non-null   int64
dtypes: float64(4), int64(6), object(1)
memory usage: 123.5+ KB
```

a) Data Transformation

In [4]:
```
# Create Data for Transformation
# Replace "Nan" with 0
# Replace FuelType with "NaN"

datasets = datasets.replace(np.nan, 0, regex=True)
X_new = datasets
X_new['FuelType'] = pd.to_numeric(X_new['FuelType'],errors='coerce')
X_new=X_new.values
print("\nData for transformation : \n\n", X_new[0:5,:])
```

```
Data for transformation :

 [[0.0000e+00 1.3500e+04 2.3000e+01 4.6986e+04        nan 9.0000e+01
  1.0000e+00 0.0000e+00 2.0000e+03 3.0000e+00 1.1650e+03]
 [1.0000e+00 1.3750e+04 2.3000e+01 7.2937e+04        nan 9.0000e+01
  1.0000e+00 0.0000e+00 2.0000e+03 3.0000e+00 1.1650e+03]
 [2.0000e+00 1.3950e+04 2.4000e+01 4.1711e+04        nan 9.0000e+01
  0.0000e+00 0.0000e+00 2.0000e+03 3.0000e+00 1.1650e+03]
 [3.0000e+00 1.4950e+04 2.6000e+01 4.8000e+04        nan 9.0000e+01
  0.0000e+00 0.0000e+00 2.0000e+03 3.0000e+00 1.1650e+03]
 [4.0000e+00 1.3750e+04 3.0000e+01 3.8500e+04        nan 9.0000e+01
  0.0000e+00 0.0000e+00 2.0000e+03 3.0000e+00 1.1700e+03]]
```

In [5]:
```
# Perform scaling on Data

scaler = MinMaxScaler()
X_scaled = scaler.fit_transform(X_new)
print("\nScaled Data : \n\n", X_scaled[0:5,:])
```

```
Scaled Data :

 [[0.00000000e+00 3.25044405e-01 2.87500000e-01 1.93358025e-01
              nan 4.68750000e-01 1.00000000e+00 0.00000000e+00
  1.00000000e+00 3.33333333e-01 2.68292683e-01]
 [6.96864111e-04 3.33925400e-01 2.87500000e-01 3.00152263e-01
              nan 4.68750000e-01 1.00000000e+00 0.00000000e+00
  1.00000000e+00 3.33333333e-01 2.68292683e-01]
 [1.39372822e-03 3.41030195e-01 3.00000000e-01 1.71650206e-01
              nan 4.68750000e-01 0.00000000e+00 0.00000000e+00
  1.00000000e+00 3.33333333e-01 2.68292683e-01]
 [2.09059233e-03 3.76554174e-01 3.25000000e-01 1.97530864e-01
              nan 4.68750000e-01 0.00000000e+00 0.00000000e+00
  1.00000000e+00 3.33333333e-01 2.68292683e-01]
 [2.78745645e-03 3.33925400e-01 3.75000000e-01 1.58436214e-01
              nan 4.68750000e-01 0.00000000e+00 0.00000000e+00
  1.00000000e+00 3.33333333e-01 2.76422764e-01]]
```

In [6]:
```
# Perform standardization on Data

std = StandardScaler()
X_std = std.fit_transform(X_new)
print("\nStandardized Data : \n\n", X_std[0:5,:])
```

```
Standardized Data :

 [[-1.73084506  0.76376268 -1.26023883 -0.55444821         nan -0.68571051
   0.80893626 -0.24289308  2.31497633 -1.08513865  1.75856113]
 [-1.72843274  0.83271485 -1.26023883  0.1325441          nan -0.68571051
   0.80893626 -0.24289308  2.31497633 -1.08513865  1.75856113]
 [-1.72602041  0.88787659 -1.21647334 -0.69409155         nan -0.68571051
  -1.23619133 -0.24289308  2.31497633 -1.08513865  1.75856113]
 [-1.72360808  1.16368529 -1.12894236 -0.52760492         nan -0.68571051
  -1.23619133 -0.24289308  2.31497633 -1.08513865  1.75856113]
 [-1.72119575  0.83271485 -0.95388041 -0.7790953          nan -0.68571051
  -1.23619133 -0.24289308  2.31497633 -1.08513865  1.853577  ]]
```

b) Handling Categorical Data

In [7]:
```
# Load Data
# Replace "?,??,???....." to "NaN"
# Replace Doors value from string to corresponding numbers
# Convert Doors feature from object to int64
# Replace FuelType from "NaN" to "Unknown"

datasets = pd.read_csv('/home/nihar/Desktop/ML/Lab2/Exercise-CarData.csv',se
p=',\?*',engine='python')
datasets.Doors = [numbers[item] for item in datasets.Doors]
datasets['Doors'] = pd.to_numeric(datasets['Doors'],errors='coerce')
datasets['FuelType'] = datasets['FuelType'].replace(np.nan, 'Unknown', regex
=True)
X_new = datasets.values
print("\nData for LabelEncoder : \n\n", X_new[0:10,:])
```

```
Data for LabelEncoder :

 [[0 13500 23.0 46986.0 'Diesel' 90.0 1.0 0 2000 3 1165]
 [1 13750 23.0 72937.0 'Diesel' 90.0 1.0 0 2000 3 1165]
 [2 13950 24.0 41711.0 'Diesel' 90.0 nan 0 2000 3 1165]
 [3 14950 26.0 48000.0 'Diesel' 90.0 0.0 0 2000 3 1165]
 [4 13750 30.0 38500.0 'Diesel' 90.0 0.0 0 2000 3 1170]
 [5 12950 32.0 61000.0 'Diesel' 90.0 0.0 0 2000 3 1170]
 [6 16900 27.0 nan 'Diesel' nan nan 0 2000 3 1245]
 [7 18600 30.0 75889.0 'Unknown' 90.0 1.0 0 2000 3 1245]
 [8 21500 27.0 19700.0 'Petrol' 192.0 0.0 0 1800 3 1185]
 [9 12950 23.0 71138.0 'Diesel' nan nan 0 1900 3 1105]]
```

In [8]:
```
# Convert FuelType into Numeric values

le = LabelEncoder()
X_new[ : ,4] = le.fit_transform(X_new[ : ,4])
print("\nNumeric FuelType : \n\n", X_new[0:100,4])
```

```
Numeric FuelType :

 [1 1 1 1 1 1 1 3 2 1 2 2 2 2 2 2 2 2 2 2 2 2 3 2 2 2 2 3 2 2 3 2 2 2 2 2 2 2
 2 2 2 2 2 2 1 3 1 1 2 1 2 1 2 2 2 2 2 2 2 2 2 3 2 2 2 2 2 2 2 1 2 2 2 2 2
 2 2 2 2 2 2 2 2 2 2 2 2 3 1 2 1 2 1 1 2 2 1 2 2 2 2]
```

In [9]:
```python
# Create one column for each FuelType

dummy = pd.get_dummies(datasets['FuelType'])
print("\n\nDummy :\n",dummy.iloc[0:10,:])
datasets = datasets.drop(['FuelType'],axis=1)
datasets = pd.concat([dummy,datasets],axis=1)
print("\n\nFinal Data :\n",datasets.iloc[0:17,:])
```

```
Dummy :
     CNG  Diesel  Petrol  Unknown
0    0       1       0        0
1    0       1       0        0
2    0       1       0        0
3    0       1       0        0
4    0       1       0        0
5    0       1       0        0
6    0       1       0        0
7    0       0       0        1
8    0       0       1        0
9    0       1       0        0


Final Data :
      CNG  Diesel  Petrol  Unknown  Unnamed: 0  Price   Age       KM     HP  \
0      0       1       0        0           0  13500  23.0  46986.0   90.0
1      0       1       0        0           1  13750  23.0  72937.0   90.0
2      0       1       0        0           2  13950  24.0  41711.0   90.0
3      0       1       0        0           3  14950  26.0  48000.0   90.0
4      0       1       0        0           4  13750  30.0  38500.0   90.0
5      0       1       0        0           5  12950  32.0  61000.0   90.0
6      0       1       0        0           6  16900  27.0      NaN    NaN
7      0       0       0        1           7  18600  30.0  75889.0   90.0
8      0       0       1        0           8  21500  27.0  19700.0  192.0
9      0       1       0        0           9  12950  23.0  71138.0    NaN
10     0       0       1        0          10  20950  25.0  31461.0  192.0
11     0       0       1        0          11  19950  22.0  43610.0  192.0
12     0       0       1        0          12  19600  25.0  32189.0  192.0
13     0       0       1        0          13  21500  31.0  23000.0  192.0
14     0       0       1        0          14  22500  32.0  34131.0  192.0
15     0       0       1        0          15  22000  28.0  18739.0    NaN
16     0       0       1        0          16  22750  30.0  34000.0  192.0

    MetColor  Automatic    CC  Doors  Weight
0        1.0          0  2000      3    1165
1        1.0          0  2000      3    1165
2        NaN          0  2000      3    1165
3        0.0          0  2000      3    1165
4        0.0          0  2000      3    1170
5        0.0          0  2000      3    1170
6        NaN          0  2000      3    1245
7        1.0          0  2000      3    1245
8        0.0          0  1800      3    1185
9        NaN          0  1900      3    1105
10       0.0          0  1800      3    1185
11       0.0          0  1800      3    1185
12       0.0          0  1800      3    1185
13       1.0          0  1800      3    1185
14       1.0          0  1800      3    1185
15       0.0          0  1800      3    1185
16       1.0          0  1800      3    1185
```

c) Handling the missing value

In [10]:
```
# Load Data
# Replace "?,??,???....." to "NaN"
# Replace Doors value from string to corresponding numbers
# Convert Doors feature from object to int64

datasets = pd.read_csv('/home/nihar/Desktop/ML/Lab2/Exercise-CarData.csv',se
p=',\?*',engine='python')
datasets.Doors = [numbers[item] for item in datasets.Doors]
datasets['Doors'] = pd.to_numeric(datasets['Doors'],errors='coerce')
X_new = datasets.values
print("\nData for LabelEncoder : \n\n", X_new[0:10,:])
```

```
Data for LabelEncoder :

 [[0 13500 23.0 46986.0 'Diesel' 90.0 1.0 0 2000 3 1165]
 [1 13750 23.0 72937.0 'Diesel' 90.0 1.0 0 2000 3 1165]
 [2 13950 24.0 41711.0 'Diesel' 90.0 nan 0 2000 3 1165]
 [3 14950 26.0 48000.0 'Diesel' 90.0 0.0 0 2000 3 1165]
 [4 13750 30.0 38500.0 'Diesel' 90.0 0.0 0 2000 3 1170]
 [5 12950 32.0 61000.0 'Diesel' 90.0 0.0 0 2000 3 1170]
 [6 16900 27.0 nan 'Diesel' nan nan 0 2000 3 1245]
 [7 18600 30.0 75889.0 nan 90.0 1.0 0 2000 3 1245]
 [8 21500 27.0 19700.0 'Petrol' 192.0 0.0 0 1800 3 1185]
 [9 12950 23.0 71138.0 'Diesel' nan nan 0 1900 3 1105]]
```

In [11]:
```
# Removing the row with all null values

datasets.dropna(how='all',inplace=True)
print("\nNew Data :\n\n",datasets.iloc[0:10,1:11])
```

```
New Data :

    Price   Age       KM FuelType     HP  MetColor  Automatic    CC  Doors  \
0  13500  23.0  46986.0   Diesel   90.0       1.0          0  2000      3
1  13750  23.0  72937.0   Diesel   90.0       1.0          0  2000      3
2  13950  24.0  41711.0   Diesel   90.0       NaN          0  2000      3
3  14950  26.0  48000.0   Diesel   90.0       0.0          0  2000      3
4  13750  30.0  38500.0   Diesel   90.0       0.0          0  2000      3
5  12950  32.0  61000.0   Diesel   90.0       0.0          0  2000      3
6  16900  27.0      NaN   Diesel    NaN       NaN          0  2000      3
7  18600  30.0  75889.0      NaN   90.0       1.0          0  2000      3
8  21500  27.0  19700.0   Petrol  192.0       0.0          0  1800      3
9  12950  23.0  71138.0   Diesel    NaN       NaN          0  1900      3

   Weight
0    1165
1    1165
2    1165
3    1165
4    1170
5    1170
6    1245
7    1245
8    1185
9    1105
```

In [12]:
```
# Imputation (Replacing null values with mean value of that attribute)

# Using Imputer function to replace NaN values with mean of that parameter v
alue
imputer = SimpleImputer(missing_values = np.nan,strategy = "mean")

# Fitting the data, function learns the stats
imputer = imputer.fit(X_new[:,[0,1,2,3,5,6,7,8,9,10]])

# fit_transform() will execute those stats on the input ie. X[:, 1:3]
X_new[:,[0,1,2,3,5,6,7,8,9,10]] = imputer.transform(X_new[:,[0,1,2,3,5,6,7,8
,9,10]])

# filling the missing value with mean
print("\n\nNew Data with Mean Value for NaN : \n\n", X_new[0:10,:])
```

```
New Data with Mean Value for NaN :

 [[0.0 13500.0 23.0 46986.0 'Diesel' 90.0 1.0 0.0 2000.0 3.0 1165.0]
 [1.0 13750.0 23.0 72937.0 'Diesel' 90.0 1.0 0.0 2000.0 3.0 1165.0]
 [2.0 13950.0 24.0 41711.0 'Diesel' 90.0 0.6749611197511665 0.0 2000.0
  3.0 1165.0]
 [3.0 14950.0 26.0 48000.0 'Diesel' 90.0 0.0 0.0 2000.0 3.0 1165.0]
 [4.0 13750.0 30.0 38500.0 'Diesel' 90.0 0.0 0.0 2000.0 3.0 1170.0]
 [5.0 12950.0 32.0 61000.0 'Diesel' 90.0 0.0 0.0 2000.0 3.0 1170.0]
 [6.0 16900.0 27.0 68647.23997185081 'Diesel' 101.47832167832168
  0.6749611197511665 0.0 2000.0 3.0 1245.0]
 [7.0 18600.0 30.0 75889.0 nan 90.0 1.0 0.0 2000.0 3.0 1245.0]
 [8.0 21500.0 27.0 19700.0 'Petrol' 192.0 0.0 0.0 1800.0 3.0 1185.0]
 [9.0 12950.0 23.0 71138.0 'Diesel' 101.47832167832168 0.6749611197511665
  0.0 1900.0 3.0 1105.0]]
```

d) Correlation

In [13]:
```
datasets.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1436 entries, 0 to 1435
Data columns (total 11 columns):
 #   Column      Non-Null Count  Dtype  
---  ------      --------------  -----  
 0   Unnamed: 0  1436 non-null   int64  
 1   Price       1436 non-null   int64  
 2   Age         1336 non-null   float64
 3   KM          1421 non-null   float64
 4   FuelType    1336 non-null   object 
 5   HP          1430 non-null   float64
 6   MetColor    1286 non-null   float64
 7   Automatic   1436 non-null   int64  
 8   CC          1436 non-null   int64  
 9   Doors       1436 non-null   int64  
 10  Weight      1436 non-null   int64  
dtypes: float64(4), int64(6), object(1)
memory usage: 134.6+ KB
```

In [14]:
```python
# Selecting features based on correlation
# Generating the correlation matrix

corr = datasets.iloc[:,1:11].corr()
corr.head(10)
```

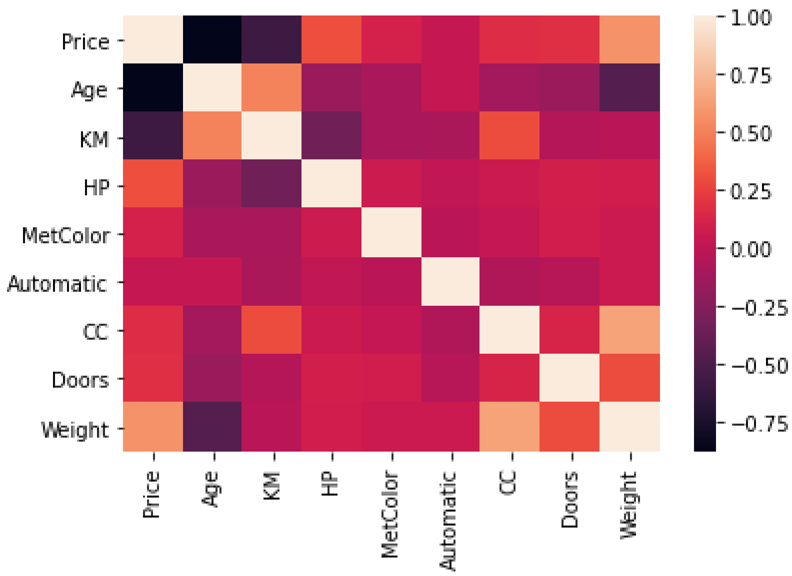
Out[14]:

	Price	Age	KM	HP	MetColor	Automatic	CC	Doors	Wei
Price	1.000000	-0.878407	-0.574720	0.309902	0.112041	0.033081	0.165067	0.185326	0.581
Age	-0.878407	1.000000	0.512735	-0.157904	-0.099659	0.032573	-0.120706	-0.157027	-0.464
KM	-0.574720	0.512735	1.000000	-0.335285	-0.093825	-0.081248	0.299993	-0.036191	-0.026
HP	0.309902	-0.157904	-0.335285	1.000000	0.064749	0.013755	0.053758	0.097162	0.086
MetColor	0.112041	-0.099659	-0.093825	0.064749	1.000000	-0.013973	0.029189	0.086203	0.057
Automatic	0.033081	0.032573	-0.081248	0.013755	-0.013973	1.000000	-0.069321	-0.027654	0.057
CC	0.165067	-0.120706	0.299993	0.053758	0.029189	-0.069321	1.000000	0.126768	0.651
Doors	0.185326	-0.157027	-0.036191	0.097162	0.086203	-0.027654	0.126768	1.000000	0.302
Weight	0.581198	-0.464299	-0.026271	0.086737	0.057142	0.057249	0.651450	0.302618	1.000

In [15]:
```python
# Generating the correlation heatmap

sns.heatmap(corr)
```

Out[15]: <AxesSubplot:>



In [16]:
```python
# Comparing the correlation between features and remove one of two features
 that have a correlation higher than 0.9

columns = np.full((corr.shape[0],), True, dtype=bool)
for i in range(corr.shape[0]):
    for j in range(i+1, corr.shape[0]):
        if corr.iloc[i,j] >= 0.9:
            if columns[j]:
                columns[j] = False

selected_columns = datasets.iloc[:,[1,2,3,5,6,7,8,9,10]].columns[columns]
selected_columns.shape
```

Out[16]: (9,)

In [17]:
```python
datasets = pd.concat([datasets['FuelType'],datasets[selected_columns]],axis=1)
print(datasets.iloc[0:10,:])
```

```
  FuelType  Price   Age       KM     HP  MetColor  Automatic    CC  Doors  \
0   Diesel  13500  23.0  46986.0   90.0       1.0          0  2000      3
1   Diesel  13750  23.0  72937.0   90.0       1.0          0  2000      3
2   Diesel  13950  24.0  41711.0   90.0       NaN          0  2000      3
3   Diesel  14950  26.0  48000.0   90.0       0.0          0  2000      3
4   Diesel  13750  30.0  38500.0   90.0       0.0          0  2000      3
5   Diesel  12950  32.0  61000.0   90.0       0.0          0  2000      3
6   Diesel  16900  27.0      NaN    NaN       NaN          0  2000      3
7      NaN  18600  30.0  75889.0   90.0       1.0          0  2000      3
8   Petrol  21500  27.0  19700.0  192.0       0.0          0  1800      3
9   Diesel  12950  23.0  71138.0    NaN       NaN          0  1900      3

   Weight
0    1165
1    1165
2    1165
3    1165
4    1170
5    1170
6    1245
7    1245
8    1185
9    1105
```

In [ ]: