Project-1

Data Set - http://www.stat.ufl.edu/~winner/data/airq402.dat

Data Description - http://www.stat.ufl.edu/~winner/data/airq402.txt

Assignment Expectations/Steps -

1. Import and store the data in a data frame. (2.5 points)
2. Remove the outliers from the data (5 points)
3. Treat "Average Fare" – 3rdColumn as your Dependent Variable and Rest of the columns as Independent Variat
4. Drop the independent variables which has less than 0.1 correlation with the dependent variable (5 points)
5. Create scatter Plot of Independent Variable vs Dependent Variable. (2.5 points)
6. Divide the data set into training and test data set and build a Multiple Linear Regression model. (5 points)
7. Print the coefficients & intercepts of the linear regression model (5 points)
8. Print the accuracy of the overall model (2.5 points)

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

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1. Import and store the data in a data frame.

```
# Assign new, compressed names to the columns
cols=['cityFrom','cityTo','avgFare','distance','avgWeekPsgrs',
      'mktLeadArLn','mktShare','avgFareLead','lowPriceArLn','mktShareLow','price']

#df = pd.read_fwf('airq402.dat', names=colnames)
df = pd.read_fwf('http://users.stat.ufl.edu/~winner/data/airq402.dat', names=cols)
df.head()
```

	cityFrom	cityTo	avgFare	distance	avgWeekPsgrs	mktLeadArLn	mktShare	avgFa
0	CAK	ATL	114.47	528	424.56	FL	70.19	
1	CAK	MCO	122.47	860	276.84	FL	75.10	
2	ALB	ATL	214.42	852	215.76	DL	78.89	
3	ALB	BWI	69.40	288	606.84	WN	96.97	
4	ALB	ORD	158.13	723	313.04	UA	39.79	

Exploratory Data Analysis

```
print(df.isnull().values.any())
#The dataset has no missing values and 4 columns with object values,, these could be treated
```

```
False
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 11 columns):
cityFrom        1000 non-null object
cityTo          1000 non-null object
avgFare         1000 non-null float64
distance        1000 non-null int64
avgWeekPsgrs    1000 non-null float64
mktLeadArLn     1000 non-null object
mktShare        1000 non-null float64
avgFareLead     1000 non-null float64
lowPriceArLn    1000 non-null object
mktShareLow     1000 non-null float64
price           1000 non-null float64
dtypes: float64(6), int64(1), object(4)
memory usage: 86.0+ KB
```

```
df.select_dtypes(include=['object']).nunique()
```

```
cityFrom        90
cityTo          85
mktLeadArLn     16
lowPriceArLn    19
dtype: int64
```

```
cityStack = df.cityFrom.append(df.cityTo)
airlnStack = df.mktLeadArLn.append(df.lowPriceArLn)
print('unique locations: {} | unique airlines: {}'.format(cityStack.nunique(), airlnStack.nu
```

```
unique locations: 104 | unique airlines: 19
```

```
#What can be experimented with is a simple categorical encoding, wherein each unique entry i
cats = ['cityFrom','cityTo','mktLeadArLn','lowPriceArLn']
df[cats] = df[cats].astype('category')
df.head()
```

	cityFrom	cityTo	avgFare	distance	avgWeekPsgrs	mktLeadArLn	mktShare	avgFa
0	CAK	ATL	114.47	528	424.56	FL	70.19	
1	CAK	MCO	122.47	860	276.84	FL	75.10	
2	ALB	ATL	214.42	852	215.76	DL	78.89	
3	ALB	BWI	69.40	288	606.84	WN	96.97	
4	ALB	ORD	158.13	723	313.04	UA	39.79	

```
df.dtypes
```

```
cityFrom         category
cityTo           category
avgFare           float64
distance            int64
avgWeekPsgrs      float64
mktLeadArLn      category
mktShare          float64
avgFareLead       float64
lowPriceArLn     category
mktShareLow       float64
price             float64
dtype: object
```

```
#In order to actually use the numeric representation, we need to get the underlying cat.code
df = df.apply(lambda x: x.cat.codes if x.dtype.name == 'category' else x)
df.head()
```

	cityFrom	cityTo	avgFare	distance	avgWeekPsgrs	mktLeadArLn	mktShare	avgFa
0	16	0	114.47	528	424.56	6	70.19	
1	16	40	122.47	860	276.84	6	75.10	
2	2	0	214.42	852	215.76	4	78.89	
3	2	7	69.40	288	606.84	14	96.97	
4	2	52	158.13	723	313.04	12	39.79	

2.Remove the outliers from the data

```
#calculating the IQR
Q1 = df.quantile(0.25)
Q3 = df.quantile(0.75)
IQR = Q3 - Q1
print(IQR)
#print the df before exoluding the outlier
print(df.shape)
df_out = df[~((df < (Q1 - 1.5 * IQR)) |(df > (Q3 + 1.5 * IQR))).any(axis=1)]
#print the df before after the outlier
print(df_out.shape)
```

```
avgFare          71.4175
distance        899.0000
avgWeekPsgrs    512.7150
mktShare         27.0000
avgFareLead      78.8925
mktShareLow      39.7775
price            54.7625
dtype: float64
(1000, 11)
(885, 11)
```

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3. Treat "Average Fare" – 3rdColumn as your Dependent Variable and Rest of the columns as Independent Variable

=====I have done the same execrise in step 6.====

4. Drop the independent variables which has less than 0.1 correlation with the dependent variable

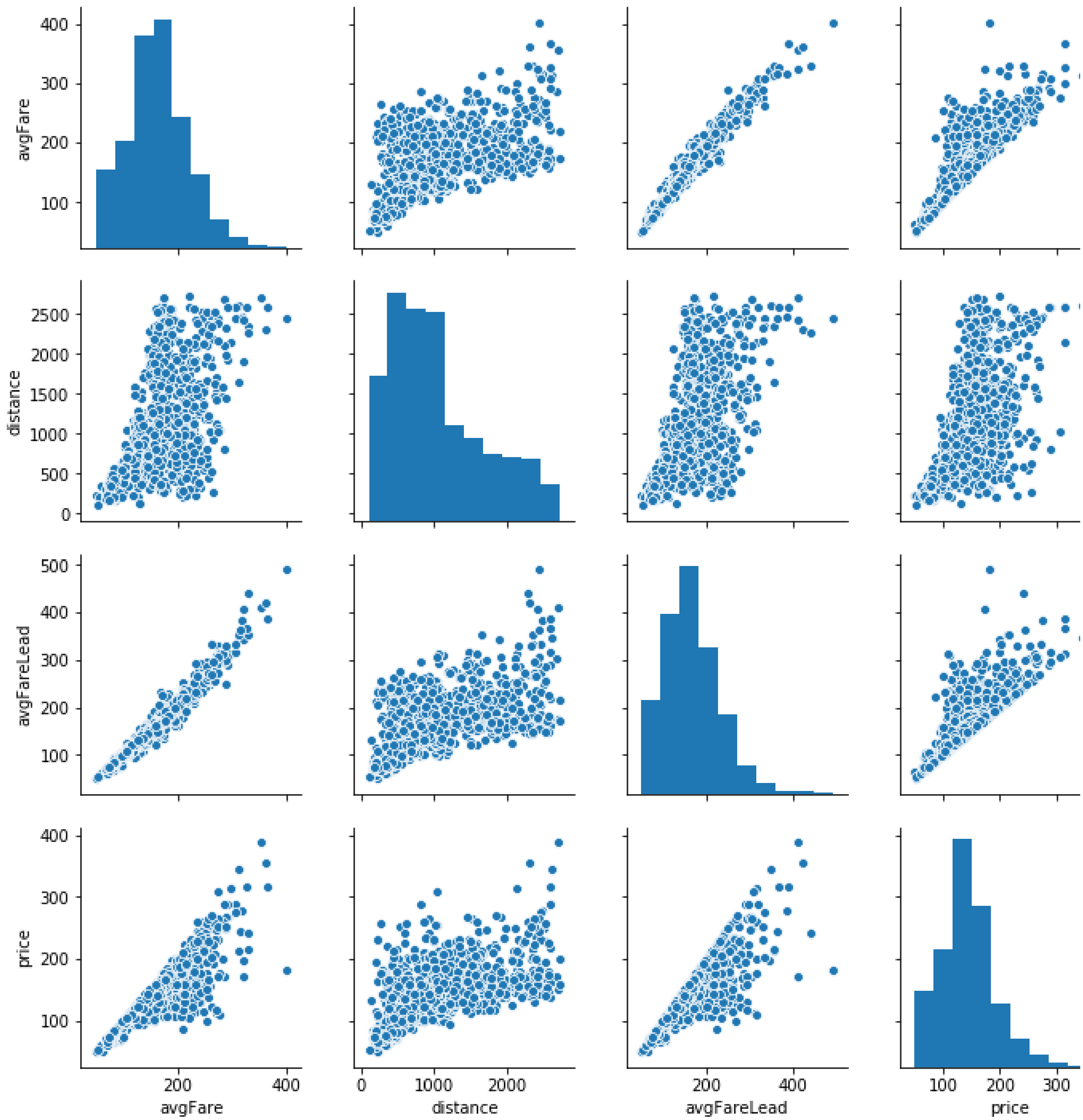
```
df.corr()
#there are cityFrom,cityTo,avgWeekPsgrs,mktLeadArLn,mktShare,lowPriceArLn,mktShareLow are nc
df.drop(['cityFrom','cityTo','avgWeekPsgrs','mktLeadArLn','mktShare','lowPriceArLn','lowPric
df.head()
```

	avgFare	distance	avgFareLead	price
0	114.47	528	111.03	111.03
1	122.47	860	123.09	118.94
2	214.42	852	223.98	167.12
3	69.40	288	68.86	68.86
4	158.13	723	161.36	145.42

5. Create scatter Plot of Independent Variable vs Dependent Variable.

```
sns.pairplot(df)
```

```
<seaborn.axisgrid.PairGrid at 0x7f0d0efc1ba8>
```



6. Divide the data set into training and test data set and build a Multiple Linear Regression model.

```
from sklearn.linear_model import LinearRegression
x = df.drop(['avgFare'], axis=1)

y = df[['avgFare']]

X_train, X_test, y_train, y_test = train_test_split(x, y, test_size=0.2, random_state=1)
y_train = y_train.values.ravel()

regressor = LinearRegression()
model = regressor.fit(X_train, y_train)
y_pred = regressor.predict(X_test)
```

```
print(y_pred)
```

```
[111.4775088  188.28132609 171.52125184 229.40564722 236.96570567
 116.04528994 186.26949058 109.241131   142.37481857 138.08442651
 178.38256747 231.11136286 144.72242786  86.32664677 102.97735587
 125.56457699 139.83148906 153.0289888  215.80200427  86.14716129
 125.42868461 148.97911943 166.21743831 231.18147803 178.72088731
 124.63957342 130.28179057 143.53191155 137.32476346 145.32010943
 114.22727777 157.76676896 152.81183041 220.24928765 110.91871348
  92.31541314 121.60383672  76.16139171  80.53214921  91.65407819
 102.07631881 107.15337032 131.89420999 157.41713114 132.04862576
  85.3985872  177.03959826 194.65742867 266.17820884 135.9532829
 185.33287174 228.8620569  215.2835798  152.70221997 182.27408974
 224.58452854 152.88568171  75.67624517 129.00474153  91.8574831
 208.26008277 150.05889977 251.03142857 137.79768532 192.34317707
 166.96892231 200.31885261 165.5009478  129.81637586 133.74710176
 315.43746481 111.6375333  137.88178409  79.63673968 142.57208944
 225.21586745 147.28820798 225.11063178 170.39224358 148.87619736
 196.671222   130.08641009 169.40602595 159.98918641 200.01540763
 151.28072791 185.47503369  85.17215411 127.55776538 125.05731819
 162.25457792 216.86617588  81.74549954 117.95046574 231.04245751
  99.53040376  84.17326755 118.48331099 218.91332094  83.63768183
 220.45727477 121.31719117 150.58814241 137.88795084 199.82121172
 121.64291551 187.94402639 174.63748839 131.09984542 208.80240786
 172.90781359 203.05615557 130.36693625 140.50514423 184.62604688
 103.90628246 220.23075485 147.67776144  92.65810614 207.34120548
  92.58002281 167.77778337  76.03253903 143.40785844 168.67439955
 101.32339536  97.78952388 226.97220219 105.98942219 132.37753876
 156.26579839 223.84068243 182.69239429 209.41730023 160.92319357
 110.88719003 181.2476173   91.43294171 169.49865523 187.96028442
 110.15655383 176.81384262 182.04710119 143.31437463 153.83143105
  76.36634879 136.19657718 111.70732042 167.72895773 171.76594661
 159.14816533 115.19613044 131.81928359 121.62268984 108.73090381
 153.4899982  127.01280707  77.68645493 306.54759202 104.14653499
 176.59943202 203.04983134  87.66135183  86.82960164 148.76488612
 131.63522002 238.28363614 250.25897803 170.78977412 171.49549903
 155.89903348 234.58159554 194.36623666 281.61697181 146.08693999
 262.16078724 181.97361076 120.22315011 218.34674993 145.84025824
 246.24042556 190.46219929 209.78002212 165.91979264 135.22502544
 187.80602957 176.71154155 148.7146692  118.11615355 123.8476599
  68.86462544 170.09637573 130.94408745 108.66315656 171.77479858
 256.46799815 110.06225867 157.75034076 202.79160218 188.95707701]
```

7. Print the coefficients & intercepts of the linear regression model

```
r_sq = model.score(X_train, y_train)
print('coefficient of determination:', r_sq)
print('intercept:', model.intercept_)
print('slope:', model.coef_)
```

```
coefficient of determination: 0.9727704708097619
intercept: 11.725921665575669
slope: [0.00157137 0.72778308 0.19951958]
```

8. Print the accuracy of the overall model

```
# show accuracy
from sklearn.metrics import r2_score
r2 = regressor.score(X_train, y_train)

# adjusted r2 using formula adj_r2 = 1 - (1- r2) * (n-1) / (n - k - 1)
# k = number of predictors = X_train_scaled.shape[1] - 1
adj_r2 = 1 - (1-r2)*(len(X_train) - 1) / (len(X_train) - (X_train.shape[1] - 1) - 1)
print(r2, adj_r2)
```

```
0.9727704708097619 0.9727021407490586
```