```
In [1]: #Import the libraries
        import pandas as pd
        import numpy as np
        import matplotlib.pyplot as plt
        from sklearn import preprocessing
        from sklearn.model_selection import train_test_split
        from sklearn import datasets, tree
        from sklearn.tree import export graphviz
        from sklearn import externals
        from io import StringIO
        import pydotplus
        import seaborn as sns
        from sklearn.ensemble import RandomForestClassifier as RF
        from sklearn.metrics import accuracy_score
        from sklearn.metrics import confusion matrix
        import matplotlib.image as mpimg
        import matplotlib.pyplot as plt
```

PROBLEM: A cloth manufacturing company is interested to know about the segment or attributes causes high sale.

```
In [2]: # import the dataset
company=pd.read_csv("C:\\Users\\nishi\\Desktop\\Assignments\\Random_Forests\\Company
```

## In [3]: company

#### Out[3]:

	Sales	CompPrice	Income	Advertising	Population	Price	ShelveLoc	Age	Education	Urbar
0	9.50	138	73	11	276	120	Bad	42	17	Yes
1	11.22	111	48	16	260	83	Good	65	10	Yes
2	10.06	113	35	10	269	80	Medium	59	12	Yes
3	7.40	117	100	4	466	97	Medium	55	14	Yes
4	4.15	141	64	3	340	128	Bad	38	13	Yes
395	12.57	138	108	17	203	128	Good	33	14	Yes
396	6.14	139	23	3	37	120	Medium	55	11	Nc
397	7.41	162	26	12	368	159	Medium	40	18	Yes
398	5.94	100	79	7	284	95	Bad	50	12	Yes
399	9.71	134	37	0	27	120	Good	49	16	Yes

400 rows × 11 columns

4

```
In [4]: company.head()
Out[4]:
                     CompPrice
                                          Advertising
                                                      Population Price
                                                                                          Education
              Sales
                                 Income
                                                                         ShelveLoc
                                                                                    Age
                                                                                                     Urban
           0
               9.50
                            138
                                                             276
                                                                                                 17
                                      73
                                                  11
                                                                    120
                                                                               Bad
                                                                                      42
                                                                                                        Yes
           1
              11.22
                            111
                                      48
                                                  16
                                                             260
                                                                     83
                                                                              Good
                                                                                      65
                                                                                                 10
                                                                                                        Yes
           2
              10.06
                                                             269
                            113
                                      35
                                                  10
                                                                     80
                                                                            Medium
                                                                                      59
                                                                                                 12
                                                                                                        Yes
               7.40
                            117
                                     100
                                                   4
                                                             466
                                                                     97
                                                                            Medium
                                                                                      55
                                                                                                 14
                                                                                                        Yes
               4.15
                            141
                                      64
                                                   3
                                                             340
                                                                    128
                                                                               Bad
                                                                                      38
                                                                                                 13
                                                                                                        Yes
          company1=company.copy()
In [5]:
In [6]:
          company1.describe()
Out[6]:
                       Sales CompPrice
                                              Income
                                                      Advertising
                                                                   Population
                                                                                    Price
                                                                                                  Age
                                                                                                        Educ
                                                                                                       400.00
           count
                  400.000000
                              400.000000
                                          400.000000
                                                       400.000000
                                                                   400.000000
                                                                               400.000000
                                                                                           400.000000
           mean
                    7.496325
                              124.975000
                                           68.657500
                                                         6.635000
                                                                   264.840000
                                                                               115.795000
                                                                                            53.322500
                                                                                                        13.90
                    2.824115
                               15.334512
                                           27.986037
                                                         6.650364
                                                                   147.376436
                                                                                23.676664
                                                                                            16.200297
                                                                                                         2.62
             std
             min
                    0.000000
                               77.000000
                                           21.000000
                                                         0.000000
                                                                    10.000000
                                                                                24.000000
                                                                                            25.000000
                                                                                                        10.00
            25%
                    5.390000
                                                                   139.000000
                              115.000000
                                           42.750000
                                                         0.000000
                                                                               100.000000
                                                                                            39.750000
                                                                                                        12.00
            50%
                    7.490000
                              125.000000
                                           69.000000
                                                         5.000000
                                                                   272.000000
                                                                               117.000000
                                                                                            54.500000
                                                                                                        14.00
            75%
                    9.320000
                              135.000000
                                           91.000000
                                                        12.000000
                                                                   398.500000
                                                                               131.000000
                                                                                            66.000000
                                                                                                        16.00
                   16.270000 175.000000
                                          120.000000
                                                        29.000000
                                                                   509.000000
                                                                               191.000000
                                                                                            80.000000
                                                                                                        18.00
            max
In [7]: company1.isnull().sum()
Out[7]: Sales
                            0
          CompPrice
                            0
          Income
                            0
          Advertising
                            0
          Population
                            0
          Price
                            0
                            0
          ShelveLoc
                            0
          Age
          Education
                            0
          Urban
                            0
          US
                            0
```

dtype: int64

### In [8]: company1.dtypes

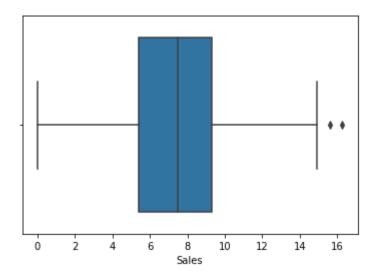
Out[8]: Sales float64 CompPrice int64 Income int64 Advertising int64 Population int64 Price int64 ShelveLoc object int64 Age Education int64 Urban object US object dtype: object

#### **CHECK FOR OUTLIERS**

## In [9]: | outL=sns.boxplot(company1['Sales'])

C:\Users\nishi\anaconda3\lib\site-packages\seaborn\\_decorators.py:36: FutureWar ning: Pass the following variable as a keyword arg: x. From version 0.12, the o nly valid positional argument will be `data`, and passing other arguments witho ut an explicit keyword will result in an error or misinterpretation.

warnings.warn(

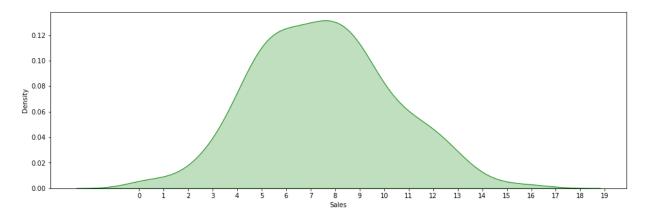


There are two ouliers.

```
In [10]: plt.rcParams["figure.figsize"] = 9,5
```

```
In [11]: plt.figure(figsize=(16,5))
    print("Skew: {}".format(company1['Sales'].skew()))
    print("Kurtosis: {}".format(company1['Sales'].kurtosis()))
    ax = sns.kdeplot(company1['Sales'],shade=True,color='g')
    plt.xticks([i for i in range(0,20,1)])
    plt.show()
```

Skew: 0.18556036318721578 Kurtosis: -0.08087736743346197



The data is skewed to the right.

```
In [12]: obj_colum = company1.select_dtypes(include='object').columns.tolist()
```

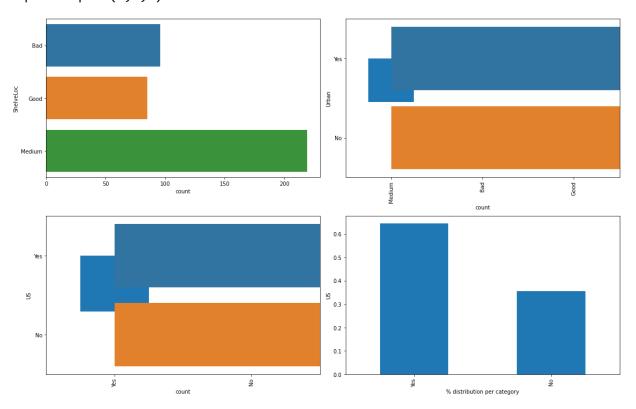
```
In [13]: plt.figure(figsize=(16,10))
    for i,col in enumerate(obj_colum,1):
        plt.subplot(2,2,i)
        sns.countplot(data=company1,y=col)
        plt.subplot(2,2,i+1)
        company1[col].value_counts(normalize=True).plot.bar()
        plt.ylabel(col)
        plt.xlabel('% distribution per category')
    plt.tight_layout()
    plt.show()
```

<ipython-input-13-971a39a9eccf>:3: MatplotlibDeprecationWarning: Adding an axes
using the same arguments as a previous axes currently reuses the earlier instan
ce. In a future version, a new instance will always be created and returned.
Meanwhile, this warning can be suppressed, and the future behavior ensured, by
passing a unique label to each axes instance.

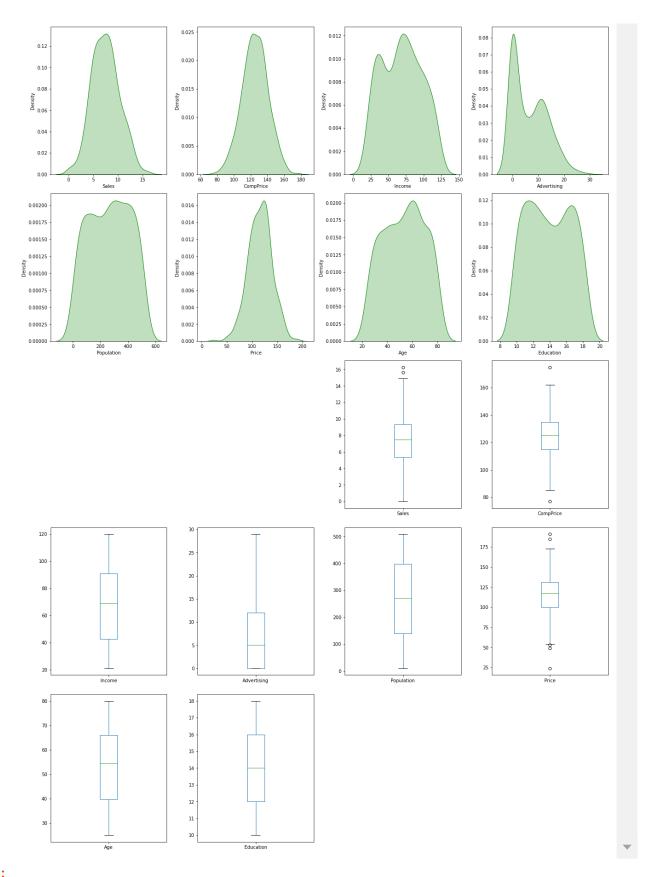
plt.subplot(2,2,i)

<ipython-input-13-971a39a9eccf>:3: MatplotlibDeprecationWarning: Adding an axes
using the same arguments as a previous axes currently reuses the earlier instan
ce. In a future version, a new instance will always be created and returned.
Meanwhile, this warning can be suppressed, and the future behavior ensured, by
passing a unique label to each axes instance.

plt.subplot(2,2,i)



```
In [14]: num_columns = company1.select_dtypes(exclude='object').columns.tolist()
```



### Out[15]:

	Sales	CompPrice	Income	Advertising	Population	Price	Age	Education
skewness	0.185560	-0.042755	0.049444	0.639586	-0.051227	-0.125286	-0.077182	0.0440(
kurtosis	-0.080877	0.041666	-1.085289	-0.545118	-1.202318	0.451885	-1.134392	-1.2983

4

```
In [16]: | corr = company1.corr()
In [17]: company1 = pd.get_dummies(company1, columns = ['ShelveLoc', 'Urban', 'US'])
In [18]: | corr = company1.corr()
In [19]: |plt.figure(figsize=(10,10))
                              sns.heatmap(corr,annot=True)
Out[19]: <AxesSubplot:>
                                                                                                                                                                                                                                                                              -1.00
                                                                                    0.064 0.15 0.27 0.05 -0.44 -0.23-0.052-0.39 0.5 -0.0740.015-0.015-0.18 0.18
                                                  CompPrice -0.064
                                                                                                -0.081-0.024-0.095 0.58 -0.1 0.025-0.0350.0260.00870.0670.067-0.0170.017
                                                                                                                                                                                                                                                                              - 0.75
                                                        Income - 0.15 -0.081 1 0.0590.00790.0570.00470.0570.072-0.0130.051-0.0380.038 -0.09 0.09
                                                                                                                         0.27 0.0450.00460.0340.0350.056-0.016-0.0420.042 -0.68 0.68
                                                Advertising - 0.27 -0.0240.059
                                                                                                                                                                                                                                                                              - 0.50
                                                  Population - 0.05 -0.0950.00790.27 1 -0.0120.043 -0.11 0.04 0.00780.0410.052 -0.052-0.0610.061
                                                                          -0.44 0.58 -0.0570.045-0.012 1 -0.1 0.012-0.0360.0460.00660.0470.047-0.0580.058
                                                                                                                                                                                                                                                                              - 0.25
                                                                          -0.23 -0.1-0.004\(\textit{0}.004\(\text{60}.043\) -0.1 1 0.00650.0440.0230.057-0.0280.0280.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\text{0}.008\(\tex
                                                   Education -0.0520.025-0.057-0.034-0.11 0.0120.0065 1 0.013-0.0290.013 0.033-0.0330.078-0.078
                                                                                                                                                                                                                                                                              - 0.00
                                         ShelveLoc_Bad --0.39 -0.0350.072-0.035 0.04 -0.0360.0440.013 1 -0.29 -0.62 -0.0810.0810.000980009
                                                                                                                                                                                                                                                                              - -0.25
                                                                            0.5 0.026-0.0130.0560.00780.046-0.023-0.029-0.29 1
                                                                                                                                                                                             -0.57 0.039-0.039-0.0790.079
                                       ShelveLoc_Good -
                                 ShelveLoc_Medium -0.0740.00870.051-0.016-0.0410.00660.057 0.013 -0.62 -0.57
                                                                                                                                                                                                         0.037-0.0370.066-0.066
                                                                                                                                                                                                                                                                                -0.50
                                                    Urban No -0.015-0.067-0.038-0.0420.052-0.047-0.0280.033-0.0810.0390.037
                                                   Urban Yes -0.0150.0670.0380.042-0.0520.0470.028-0.0330.081-0.0390.037
                                                                                                                                                                                                                                                                              - -0.75
                                                          US No --0.18-0.017-0.09 -0.68-0.061-0.0580.00870.0780.00098.0790.066 0.047-0.047
                                                         US_Yes - 0.18 0.017 0.09 0.68 0.061 0.0580.00870.078.000980.079-0.066-0.0470.047
                                                                                                                                                                                                                                                                               -1.00
                                                                                                                                                                                                                                                 US Yes
                                                                                                    Income
                                                                                                                                                                                                 ShelveLoc_Medium
                                                                                        CompPrice
                                                                                                                                                              Education
                                                                                                                                                                                     ShelveLoc_Good
                                                                                                                                                                                                             Urban_No
                                                                                                               Advertising
                                                                                                                           Population
```

# RANDOM FOREST MODEL

Since the target variable is continious, we create a class of the value based on the mean <= 7.49 == "Small" and > 7.49 == "large"

```
In [20]: company1["sales"]="small"
         company1.loc[company1["Sales"]>7.49,"sales"]="large"
         company1.drop(["Sales"],axis=1,inplace=True)
In [21]: | X = company1.iloc[:,0:14]
         y = company1.iloc[:,14]
In [22]: |x_train,x_test,y_train,y_test = train_test_split(X,y,test_size = 0.2)
In [23]: |y_train.value_counts()
Out[23]: small
                  163
         large
                  157
         Name: sales, dtype: int64
In [24]: model =RF(n jobs=4,n estimators = 150, oob score =True,criterion ='entropy')
         model.fit(x_train,y_train)
         model.oob_score_
Out[24]: 0.809375
In [25]: pred_train = model.predict(x_train)
In [26]: | accuracy_score(y_train,pred_train)
Out[26]: 1.0
In [27]: confusion_matrix(y_train,pred_train)
Out[27]: array([[157,
                        0],
                [ 0, 163]], dtype=int64)
In [28]: pred_test = model.predict(x_test)
In [29]: | accuracy_score(y_test,pred_test)
Out[29]: 0.75
In [30]: confusion_matrix(y_test,pred_test)
Out[30]: array([[31, 11],
                [ 9, 29]], dtype=int64)
```

```
In [31]: | df_t=pd.DataFrame({'Actual':y_test, 'Predicted':pred_test})
In [32]: df_t
Out[32]:
                Actual Predicted
            86
                           small
                 large
           345
                 small
                          small
           394
                 small
                          small
           251
                 small
                          small
            39
                 small
                           small
           118
                 large
                           small
           257
                 large
                          small
            15
                 large
                          small
             6
                 small
                           small
            52
                 large
                           small
          80 rows × 2 columns
In [33]: | cols = list(company1.columns)
In [34]: predictors = cols[0:14]
          target = cols[14]
In [35]: | tree1 = model.estimators_[20]
In [36]: dot_data = StringIO()
In [37]: export_graphviz(tree1, out_file = dot_data, feature_names = predictors, class_name
In [38]: graph = pydotplus.graph_from_dot_data(dot_data.getvalue())
In [39]: graph.write_png('company_full.png')
Out[39]: True
```

# **CONCLUSION**

Since the accuracy of the Training set is 100% we test the accurancy on the test data which is 75%

As seen in the confusion matrix of Test data 60 instances are presdicted correctly and 20 instances are not.

```
In [40]: rf_small = RF(n_estimators=10, max_depth = 3)
In [41]: rf_small.fit(x_train,y_train)
Out[41]: RandomForestClassifier(max_depth=3, n_estimators=10)
In [42]: | tree_small = rf_small.estimators_[5]
In [43]: export_graphviz(tree_small, out_file = dot_data, feature_names = predictors, rour
In [44]: graph_small = pydotplus.graph_from_dot_data(dot_data.getvalue())
In [45]: graph.write_png('company_small.png')
Out[45]: True
In [46]: from PIL import Image
         graph = pydotplus.graph_from_dot_data(dot_data.getvalue())
         image=Image.open('company_small.png')
In [47]: | image
Out[47]:
```

#### Out[50]:

	feature	importance
4	Price	0.253447
5	Age	0.117588
0	CompPrice	0.105676
2	Advertising	0.102578
1	Income	0.093680
3	Population	0.089862
8	ShelveLoc_Good	0.074884
6	Education	0.057032
7	ShelveLoc_Bad	0.036101
9	ShelveLoc_Medium	0.023204
10	Urban_No	0.012137
11	Urban_Yes	0.012017
12	US_No	0.010921
13	US_Yes	0.010871

PRICE is the most important feature.