In [1]:
```
import pandas as pd
import matplotlib.pyplot as plt
from sklearn import datasets
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.tree import  DecisionTreeClassifier
from sklearn import tree
from sklearn.metrics import classification_report
from sklearn import preprocessing
from sklearn.metrics import confusion_matrix
from scipy.special import boxcox1p
import warnings
warnings.filterwarnings("ignore")
from sklearn.preprocessing import LabelEncoder
from sklearn.preprocessing import StandardScaler
```

In [3]:
```
company = pd.read_csv("Company_Data .csv")
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	No
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

In [4]:
```
company.head()
```
Out[4]:

	Sales	CompPrice	Income	Advertising	Population	Price	ShelveLoc	Age	Education	Urban
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

In [6]:
```
company.shape
```
Out[6]:
```
(400, 11)
```

In [7]:
```
company.T
```
Out[7]:

	0	1	2	3	4	5	6	7	8	9	...	390
Sales	9.5	11.22	10.06	7.4	4.15	10.81	6.63	11.85	6.54	4.69	...	5.47
CompPrice	138	111	113	117	141	124	115	136	132	132	...	108
Income	73	48	35	100	64	113	105	81	110	113	...	75
Advertising	11	16	10	4	3	13	0	15	0	0	...	9
Population	276	260	269	466	340	501	45	425	108	131	...	61
Price	120	83	80	97	128	72	108	120	124	124	...	11
ShelveLoc	Bad	Good	Medium	Medium	Bad	Bad	Medium	Good	Medium	Medium	...	Medium
Age	42	65	59	55	38	78	71	67	76	76	...	67
Education	17	10	12	14	13	16	15	10	10	17	...	12
Urban	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	No	No	...	Yes
US	Yes	Yes	Yes	Yes	No	Yes	No	Yes	No	Yes	...	Yes

11 rows × 400 columns

In [8]:
```
company.describe()
```

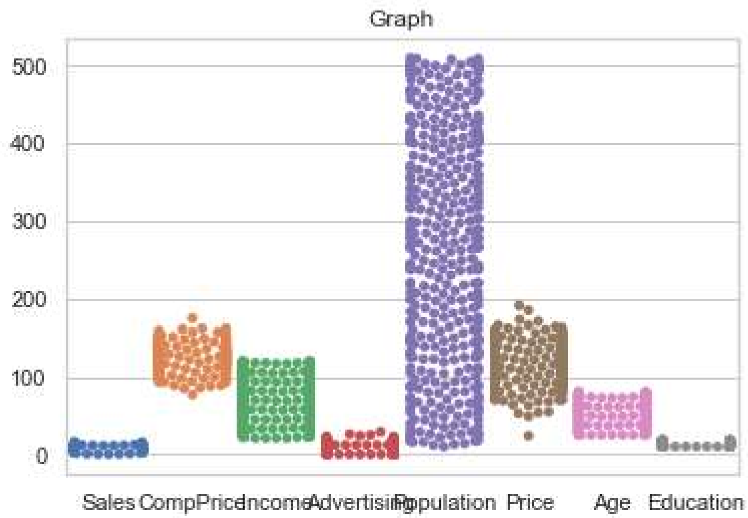
Out[8]:

	Sales	CompPrice	Income	Advertising	Population	Price	Age	Educ
count	400.000000	400.000000	400.000000	400.000000	400.000000	400.000000	400.000000	400.0(
mean	7.496325	124.975000	68.657500	6.635000	264.840000	115.795000	53.322500	13.9(
std	2.824115	15.334512	27.986037	6.650364	147.376436	23.676664	16.200297	2.62
min	0.000000	77.000000	21.000000	0.000000	10.000000	24.000000	25.000000	10.0(
25%	5.390000	115.000000	42.750000	0.000000	139.000000	100.000000	39.750000	12.0(
50%	7.490000	125.000000	69.000000	5.000000	272.000000	117.000000	54.500000	14.0(
75%	9.320000	135.000000	91.000000	12.000000	398.500000	131.000000	66.000000	16.0(
max	16.270000	175.000000	120.000000	29.000000	509.000000	191.000000	80.000000	18.0(

In [9]:
```
company.info()
```

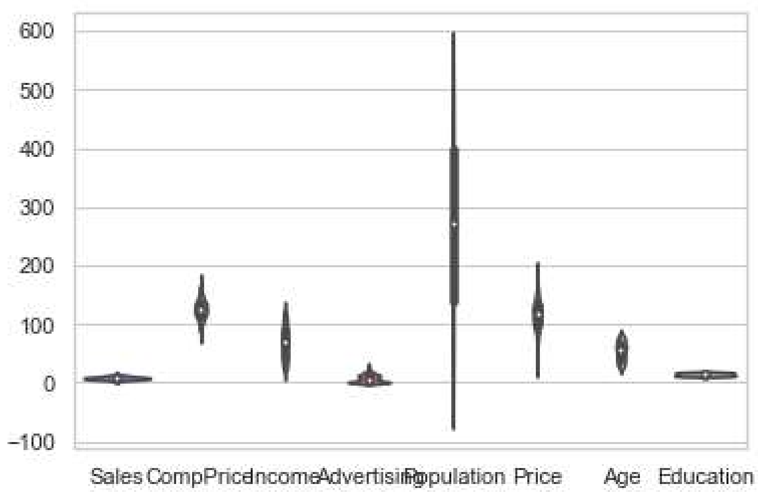
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 400 entries, 0 to 399
Data columns (total 11 columns):
 #   Column       Non-Null Count  Dtype  
---  ------       --------------  -----  
 0   Sales        400 non-null    float64
 1   CompPrice    400 non-null    int64  
 2   Income       400 non-null    int64  
 3   Advertising  400 non-null    int64  
 4   Population   400 non-null    int64  
 5   Price        400 non-null    int64  
 6   ShelveLoc    400 non-null    object 
 7   Age          400 non-null    int64  
 8   Education    400 non-null    int64  
 9   Urban        400 non-null    object 
 10  US           400 non-null    object 
dtypes: float64(1), int64(7), object(3)
memory usage: 34.5+ KB
```

In [10]:
```python
import seaborn as sns
sns.set(style="whitegrid")

ax = sns.swarmplot(data=company)

plt.title('Graph')

plt.show()
```



In [11]:
```python
sns.violinplot(data=company)
```

Out[11]: <AxesSubplot:>



In [12]:
```python
import seaborn as sns
plt.figure(figsize=(15,10))
sns.heatmap(company.corr(),annot=True)
```

Out[12]: <AxesSubplot:>

In [13]:
```python
numerical_feature = company.describe(include=["int64", "float64"]).columns

print(list(numerical_feature))
```

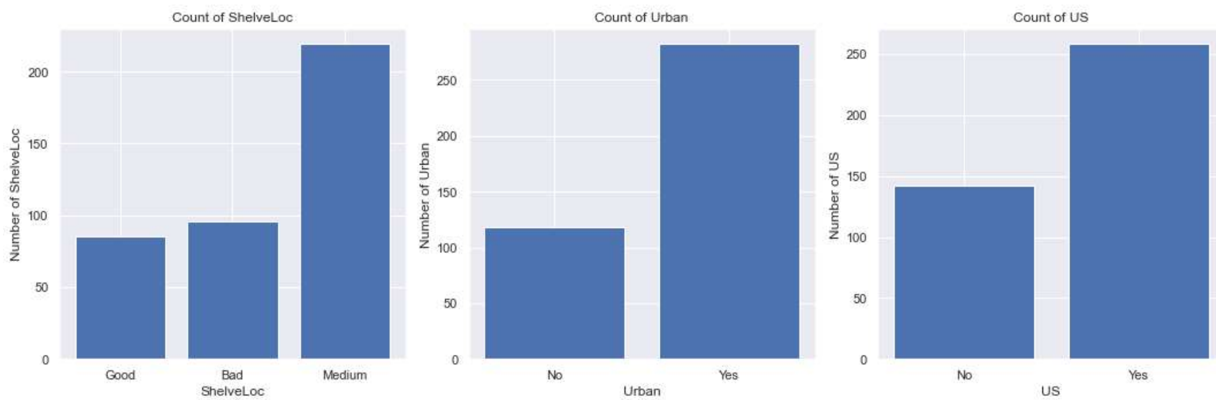
```
['Sales', 'CompPrice', 'Income', 'Advertising', 'Population', 'Price', 'Age', 'Education']
```

In [14]:
```python
sns.set_style('darkgrid')
sns.pairplot(company[numerical_feature])
plt.show()
```

In [15]:
```python
categorical_feature = company.describe(include=["object"]).columns

print(list(categorical_feature))
```

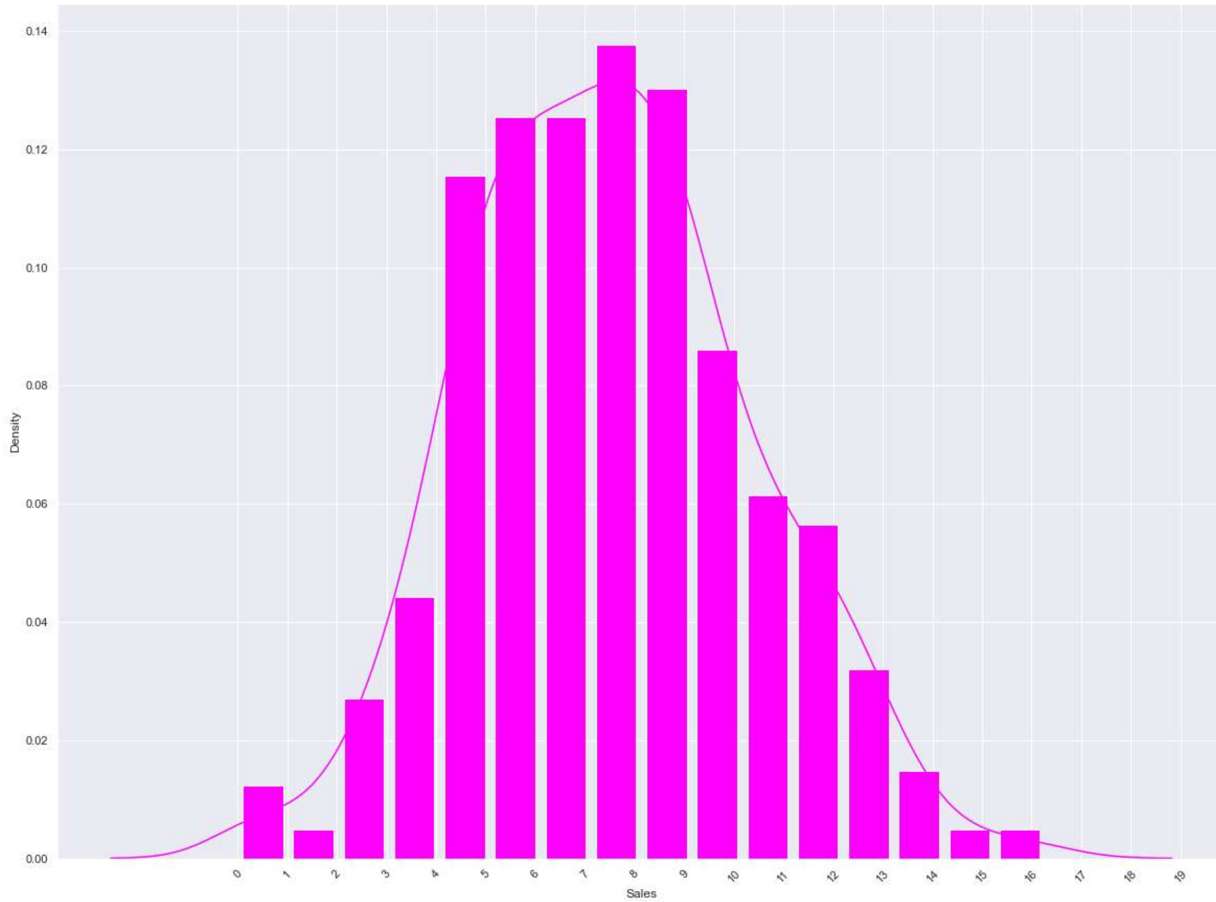
```
['ShelveLoc', 'Urban', 'US']
```

In [16]:
```
plt.figure(figsize=(15, 5))
for idx, column in enumerate(categorical_feature):
    df = company.copy()
    unique = df[column].value_counts(ascending=True);

    plt.subplot(1, 3, idx+1)
    plt.title("Count of "+ column)
    plt.bar(unique.index, unique.values);

    plt.xlabel(column, fontsize=12)
    plt.ylabel("Number of "+ column, fontsize=12)

plt.tight_layout()
plt.show()
```



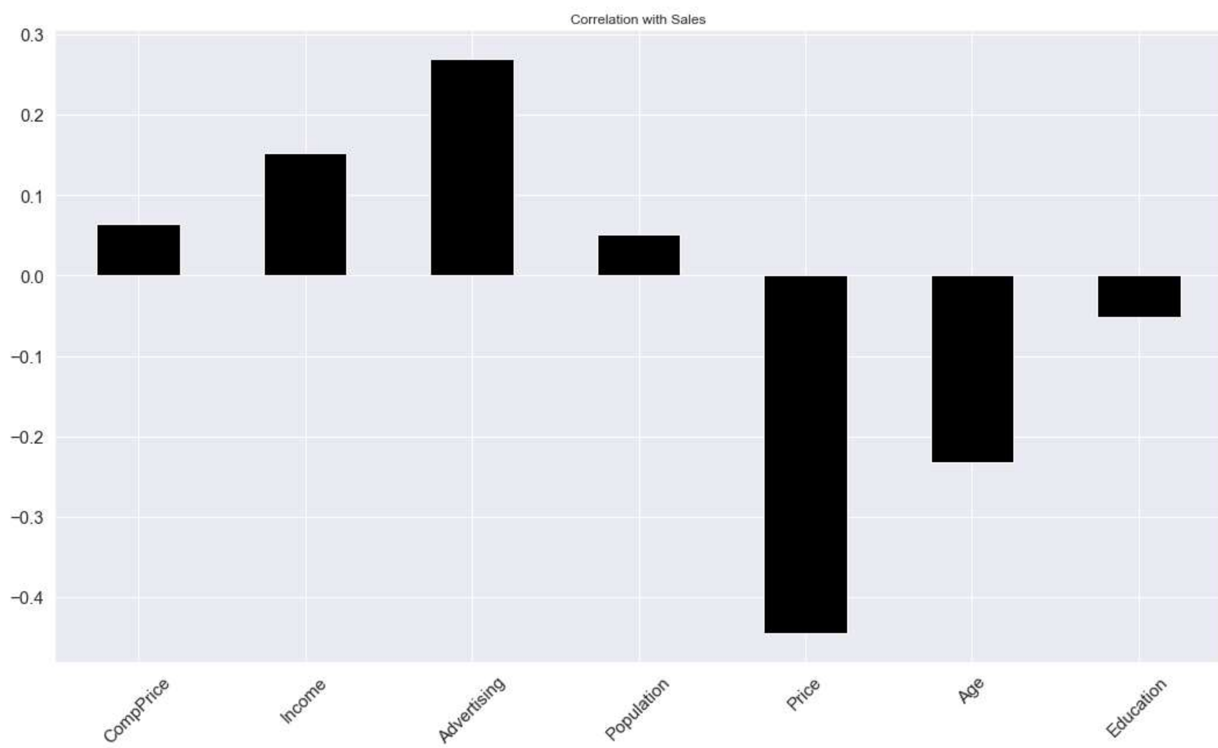
In [18]:
```
def distplot(param):
    plt.figure(figsize=(20,15))
    sns.distplot(company[param], color = "magenta", hist_kws={"rwidth":0.80, 'alp
    plt.xticks(np.arange(0,20,1),rotation=45)
    plt.show()
```

In [19]:
```
distplot('Sales')
```



In [20]:
```
company_1 = company.iloc[:,1:]

correlations = company_1.corrwith(company.Sales)
correlations = correlations[correlations!=1]
positive_correlations = correlations[correlations >0].sort_values(ascending = Fal
negative_correlations =correlations[correlations<0].sort_values(ascending = False

correlations.plot.bar(
        figsize = (18, 10),
        fontsize = 15,
        color = 'black',
        rot = 45, grid = True)
plt.title('Correlation with Sales')
```

Out[20]:
```
Text(0.5, 1.0, 'Correlation with Sales')
```



Changing the categorical variables into dummies.

In [21]:
```
company_1 = pd.get_dummies(company)
```

Converting the Target variable i.e. Sales into Categorical

In [22]:
```
company_1['Category'] = pd.cut(company_1['Sales'],
                        bins=[0,10, np.inf],
                        labels=['Average','High'],
                        include_lowest=True)
company_1
```

Out[22]:

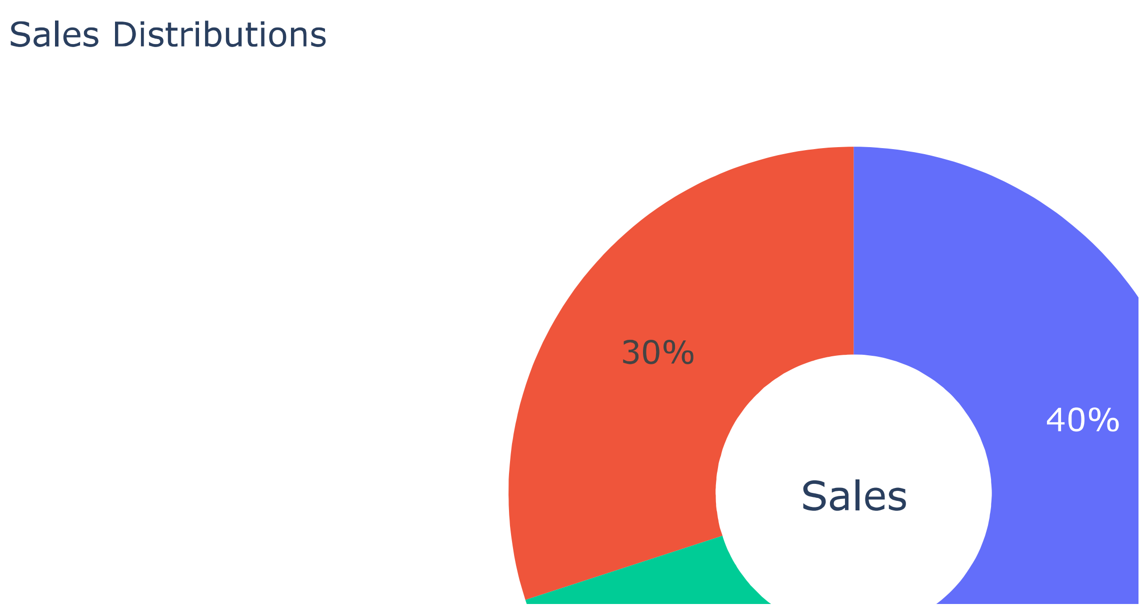
	Sales	CompPrice	Income	Advertising	Population	Price	Age	Education	ShelveLoc_Bad
0	9.50	138	73	11	276	120	42	17	1
1	11.22	111	48	16	260	83	65	10	0
2	10.06	113	35	10	269	80	59	12	0
3	7.40	117	100	4	466	97	55	14	0
4	4.15	141	64	3	340	128	38	13	1
...	...	...	...	...	...	...	...	...	...
395	12.57	138	108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

400 rows × 16 columns

In [30]:
```
!pip install plotly
```

```
Requirement already satisfied: plotly in c:\programdata\anaconda3\lib\site-pack
ages (5.5.0)
Requirement already satisfied: tenacity>=6.2.0 in c:\programdata\anaconda3\lib
\site-packages (from plotly) (8.0.1)
Requirement already satisfied: six in c:\programdata\anaconda3\lib\site-package
s (from plotly) (1.15.0)
```

In [31]:
```
from plotly.subplots import make_subplots
import plotly.graph_objects as go
type_ = ["Medium", "Low", "High"]
fig = make_subplots(rows=1, cols=1)

fig.add_trace(go.Pie(labels=type_, values=company['Sales'].value_counts(), name='

# Use `hole` to create a donut-like pie chart
fig.update_traces(hole=.4, hoverinfo="label+percent+name", textfont_size=16)

fig.update_layout(
    title_text="Sales Distributions",
    # Add annotations in the center of the donut pies.
    annotations=[dict(text='Sales', x=0.5, y=0.5, font_size=20, showarrow=False)]
fig.show()
```



Random Forest

In [32]:
```
from sklearn.model_selection import KFold
from sklearn.model_selection import cross_val_score
from sklearn.ensemble import RandomForestClassifier
```

In [33]:
```
array = company_1.values
X = array[:,1:15]
Y = array[:,15]
```

In [34]:
```
num_trees = 100
max_features = 4
kfold = KFold(n_splits = 10, random_state = 7, shuffle = True)
model = RandomForestClassifier(n_estimators = num_trees, max_features = max_featu
results = cross_val_score(model, X, Y, cv = kfold)
print(results.mean()*100)
```

```
87.25
```

Ensemble techniques

1. Bagging

In [35]:
```
from pandas import read_csv
from sklearn.model_selection import KFold
from sklearn.model_selection import cross_val_score
from sklearn.ensemble import BaggingClassifier
from sklearn.tree import DecisionTreeClassifier
```

In [36]:
```
seed = 10

cart = DecisionTreeClassifier()
num_trees = 100
```

In [37]:
```
model1 = BaggingClassifier(base_estimator=cart, n_estimators=num_trees, random_st
results1 = cross_val_score(model1, X, Y, cv=kfold)
print(results1.mean()*100)
```

```
86.75
```

2. Boosting

AdaBoost Classification

In [38]:
```
from pandas import read_csv
from sklearn.model_selection import KFold
from sklearn.model_selection import cross_val_score
from sklearn.ensemble import AdaBoostClassifier

model2 = AdaBoostClassifier(n_estimators=num_trees, random_state=seed)
results2 = cross_val_score(model2, X, Y, cv=kfold)
print(results2.mean()*100)
```

```
89.75
```

3. Stacking

In [39]:
```
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
from sklearn.ensemble import VotingClassifier
```

Iteration = 1

In [40]:
```
estimators = []
model3 = LogisticRegression(max_iter=500)
estimators.append(('logistic', model3))

model4 = DecisionTreeClassifier()
estimators.append(('cart', model4))

model5 = SVC()
estimators.append(('svm', model5))

model6 = BaggingClassifier(base_estimator=cart, n_estimators=num_trees, random_st
estimators.append(('bagging', model6))

model7 = AdaBoostClassifier(n_estimators=num_trees, random_state=seed)
estimators.append(('boosting', model7))

# create the ensemble modelIter
ensemble = VotingClassifier(estimators)
results3 = cross_val_score(ensemble, X, Y, cv=kfold)
print(results3.mean()*100)
```

```
89.25
```

Iteration = 2

In [41]:
```
estimators = []
model8 = LogisticRegression(max_iter=500)
estimators.append(('logistic', model8))

model9 = DecisionTreeClassifier()
estimators.append(('cart', model9))

model10 = BaggingClassifier(base_estimator=cart, n_estimators=num_trees, random_s
estimators.append(('bagging', model10))

model11 = AdaBoostClassifier(n_estimators=num_trees, random_state=seed)
estimators.append(('boosting', model11))

# create the ensemble model
ensemble = VotingClassifier(estimators)
results4 = cross_val_score(ensemble, X, Y, cv=kfold)
print(results4.mean()*100)
```

```
89.0
```

Iteration = 3

In [42]:
```
estimators = []
model12 = LogisticRegression(max_iter=500)
estimators.append(('logistic', model12))

model13 = DecisionTreeClassifier()
estimators.append(('cart', model13))

model14 = AdaBoostClassifier(n_estimators=num_trees, random_state=seed)
estimators.append(('boosting', model14))

# create the ensemble modSel
ensemble = VotingClassifier(estimators)
results5 = cross_val_score(ensemble, X, Y, cv=kfold)
print(results5.mean()*100)
```

```
90.0
```

Iteration = 4

In [43]:
```
estimators = []
model15 = DecisionTreeClassifier()
estimators.append(('cart', model15))

model16 = AdaBoostClassifier(n_estimators=num_trees, random_state=seed)
estimators.append(('boosting', model16))

# create the ensemble model
ensemble = VotingClassifier(estimators)
results6 = cross_val_score(ensemble, X, Y, cv=kfold)
print(results6.mean()*100)
```

```
86.75
```

Iteration = 5

In [44]:
```
estimators = []
model17 = LogisticRegression(max_iter=500)
estimators.append(('logistic', model17))

model18 = AdaBoostClassifier(n_estimators=num_trees, random_state=seed)
estimators.append(('boosting', model18))

# create the ensemble model
ensemble = VotingClassifier(estimators)
results6 = cross_val_score(ensemble, X, Y, cv=kfold)
print(results6.mean()*100)
```

```
91.5
```

In [ ]:
```

```