In [2]:	import pandas as pd import seaborn as sns from matplotlib import pyplot as plt from sklearn.model_selection import train_test_split from sklearn.ensemble import RandomForestClassifier as RF from sklearn.metrics import accuracy_score from sklearn.metrics import accuracy_score from in import StringIO import pydotplus from sklearn.tree import export_graphviz import matplotlib.image as mpimg
In [3]: In [4]: In [5]:	<pre>company = df.copy() company.head()</pre>
In [6]: Out[6]:	1 11.22
In [7]: Out[7]:	Advertising 400.0 6.635000 6.650364 0.0 0.00 5.00 12.00 29.00 Population 400.0 264.840000 147.376436 10.0 139.00 272.00 398.50 509.00 Price 400.0 115.795000 23.676664 24.0 100.00 117.00 131.00 191.00 Age 400.0 53.322500 16.200297 25.0 39.75 54.50 66.00 80.00 Education 400.0 13.900000 2.620528 10.0 12.00 14.00 16.00 18.00 company.isnull().sum() Sales 0 Comprice 0 Income 0 Advertising 0 Population 0 Price Price 0 Price Pri
	ShelveLoc 0 Age 0 Education 0 Urban 0 US 0 dtype: int64 company.dtypes
	Age int64 Education int64 Urban object US object dtype: object
n [11]:	ax = sns.boxplot(company['Sales'])
n [12]: n [13]:	
n [14]:	0.10 - 0.08 - 0.06 - 0.04 - 0.02 - 0.00 - 0.01 - 0.02 - 0.00 - 0.02 - 0.00 - 0.01 - 0.02 - 0.00 - 0.
n [16]:	<pre>plt.figure(figsize=(16,10)) for i,col in enumerate(obj_colum,1): plt.subplot(2,2,i) sns.countplot(data=company,y=col) plt.subplot(2,2,i+1) company[col].value_counts(normalize=True).plot.bar() plt.ylabel(col) plt.xlabel('% distribution per category') plt.tight_layout() plt.show()</pre>
	Medium - Sount See - Sound See
	No - 0.6 - 0.5 - 0.4 - 95 0.3 - 0.2 - 0.1 - 0.1 -
n [17]: n [18]:	num_columns = company.select_dtypes(exclude='object').columns.tolist() plt.figure(figsize=(18,40)) for i,col in enumerate(num_columns,1): plt.subplot(8,4,i) sns.kdeplot(df[col],color='g',shade=True) plt.subplot(8,4,i+10) df[col],plt.box() plt.tight_layout() plt.tight_layout() plt.show() num_data = df[num_columns] pd.DataFrame(data=[num_data.skew(),num_data.kurtosis()],index=['skewness','kurtosis'])
	0.012 - 0.010 - 0.008 - 0.007 - 0.006 - 0.005 - 0.006
	0.00 0 15 10 15 0.000 60 80 100 120 140 160 180 0.000 0 25 50 75 100 125 150 0.00 0 10 20 30 Advertising 0.00200 0.00175 0.00150 0.00
	0.0075 0.00050 0.00025 0.00000 0 200 400 600 0 000 0 50 100 150 200 40 60 80 0 000 0 40 400 60 80 0 160 18 20 0 16
	120 - 100 -
	80 - 125 - 100 - 100 - 100 - 75 - 100 - 200 - 100 - 25 - 0 - 25 -
	70 - 16 - 15 - 14 - 13 - 12 - 11 - 10 - 10 - 1
ut[18]: n [19]: n [20]:	Sales CompPrice Income Advertising Population Price Age Education skewness 0.185560 -0.042755 0.049444 0.639586 -0.051227 -0.125286 -0.077182 0.044007 kurtosis -0.080877 0.041666 -1.085289 -0.545118 -1.202318 0.451885 -1.134392 -1.298332 corr = company.corr() pd.get_dummies(company, columns = ['ShelveLoc', 'Urban', 'US']) plt.figure(figsize=(10,10)) sns.heatmap(corr, annot=True)
	9 - 0.064
	9 - 0.05
In []: n [23]: n [24]:	
n [27]:	<pre>large 162 small 158 Name: sales, dtype: int64 model =RF(n_jobs=4, n_estimators = 150, oob_score =True, criterion ='entropy') model.fit(x_train,y_train) model.oob_score_</pre> 0.80625
n [29]: ut[29]: n [30]: ut[30]: n [31]:	<pre>1.0 confusion_matrix(y_train, pred_train) array([[162, 0],</pre>
ut[32]: n [33]:	<pre>confusion_matrix(y_test,pred_test) array([[26, 11],</pre>
	325 large large 230 small small 135 small large 365 small small 71 small small 119 small small 326 small large 131 small small 158 large large 170 large large
n [37]: n [38]: n [39]:	<pre>predictors = cols[0:14] target = cols[14] tree1 = model.estimators_[20] dot_data = StringIO()</pre>
1 [42]: 1 [43]: 1 [44]: 1 [44]: 1 [45]:	<pre>graph = pydotplus.graph_from_dot_data(dot_data.getvalue()) graph.write_png('company_full.png')</pre> True
1 [46]: 1 [46]: 1 [47]: 1 [48]: 1 [49]: 1 [50]:	RandomForestClassifier(max_depth=3, n_estimators=10) tree_small = rf_small.estimators_[5]
ut[50]: n [51]: n [52]: ut[52]:	<pre>img = mpimg.imread('company_full.png') plt.imshow(img)</pre>
n [53]: ut[53]: n [54]:	model.feature_importances_ array([0.11424132, 0.10155598, 0.1023964 , 0.09280051, 0.21688652, 0.11391961, 0.0524279 , 0.04248318, 0.08823116, 0.03113596, 0.0111756 , 0.01213655, 0.01063965, 0.00996967])
n [55]: ut[55]:	feature importance 4 Price 0.216887 0 CompPrice 0.114241 5 Age 0.113920 2 Advertising 0.102396 1 Income 0.101556 3 Population 0.092801 8 ShelveLoc_Good 0.088231 6 Education 0.052428