Advertising Budget

(Regression Problem)

To understand how mediums like TV, Radio & Newspaper influence Sales

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
import warnings
warnings.filterwarnings("ignore")
```

In [2]:
```
ad = pd.read_csv(r'Advertising Budget and Sales.csv', index_col=[0])
ad.head()
```

Out[2]:

	TV	radio	newspaper	sales
1	230.1	37.8	69.2	22.1
2	44.5	39.3	45.1	10.4
3	17.2	45.9	69.3	9.3
4	151.5	41.3	58.5	18.5
5	180.8	10.8	58.4	12.9

In [3]:
```
ad.info()
ad.describe().round()
ad.shape
ad.columns
ad.dtypes
ad.values
ad.size
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 200 entries, 1 to 200
Data columns (total 4 columns):
 #   Column     Non-Null Count  Dtype
---  ------     --------------  -----
 0   TV         200 non-null    float64
 1   radio      200 non-null    float64
 2   newspaper  200 non-null    float64
 3   sales      200 non-null    float64
dtypes: float64(4)
memory usage: 7.8 KB
```

Out[3]: 800

In [4]:
```
ad.isna().sum() # Check for null values
```

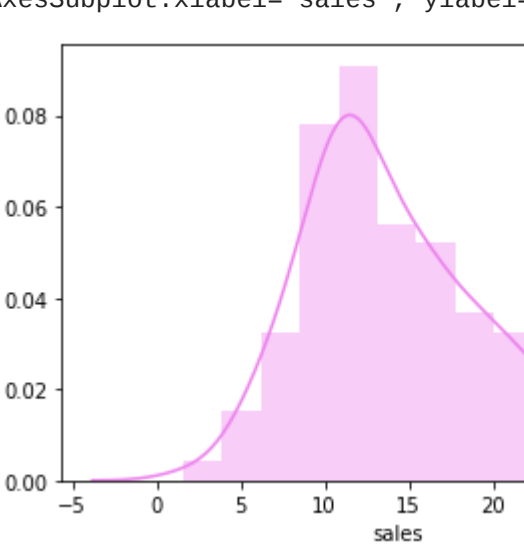
Out[4]:
```
TV           0
radio        0
newspaper    0
sales        0
dtype: int64
```

In [5]:
```
ad.dtypes
```

Out[5]:
```
TV           float64
radio        float64
newspaper    float64
sales        float64
dtype: object
```

In [6]:
```
sns.distplot(ad['sales'], color='violet', hist=True, rug=False)
```

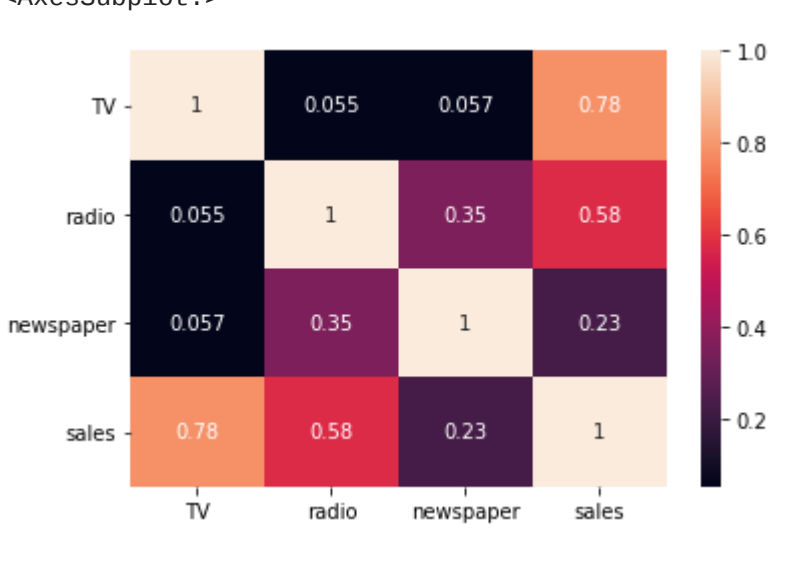
Out[6]: <AxesSubplot:xlabel='sales', ylabel='Density'>



Sales data seems to follow Gaussian/Normal Distribution

In [7]:
```
sns.heatmap(ad.corr(), annot=True)
```

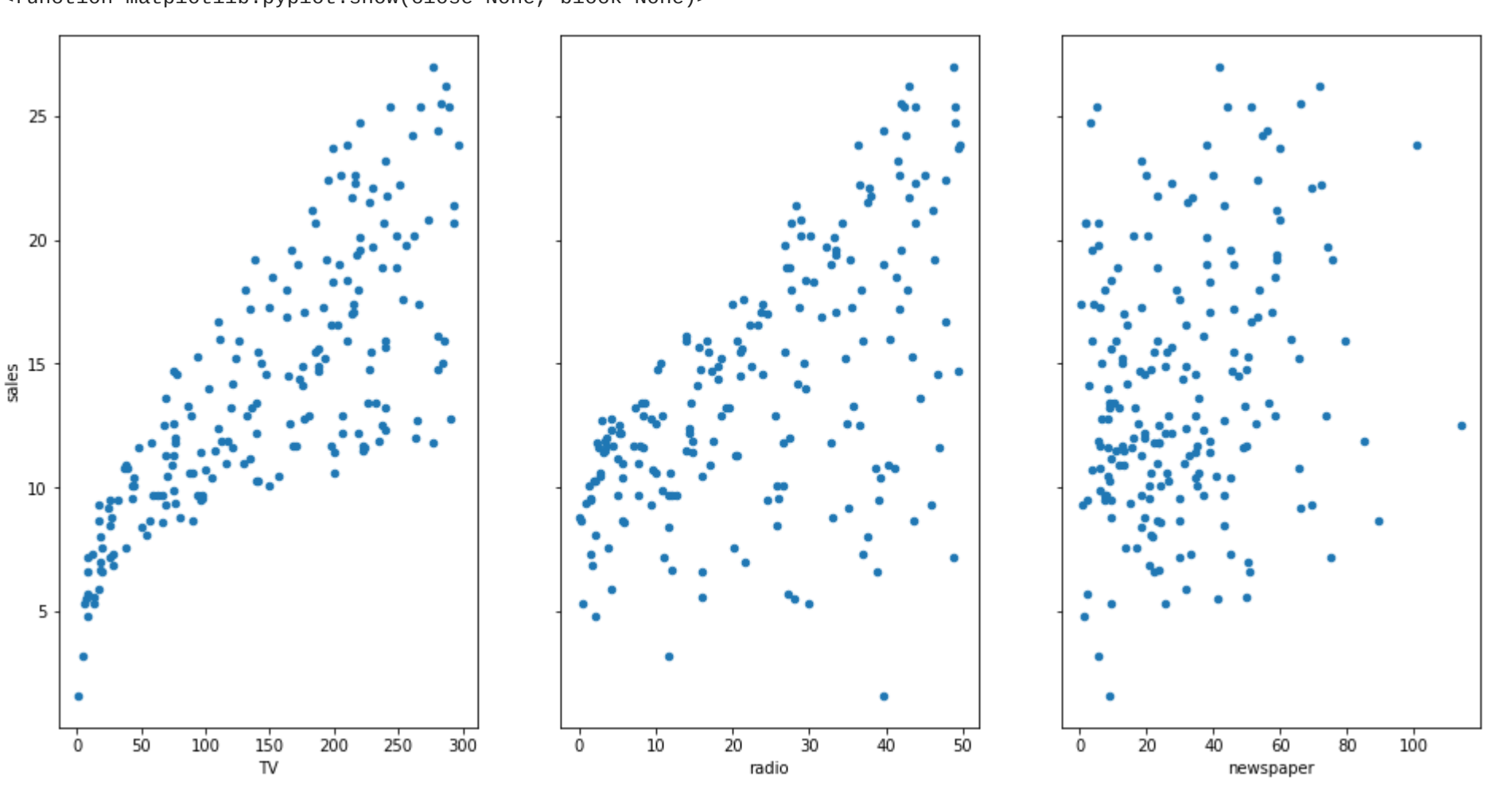
Out[7]: <AxesSubplot:>



The heatmap shows that 'sales' has a strong correlation with 'TV' relative to other features

In [8]:
```
fig,axs= plt.subplots(1,3,sharey=True) # sharey - share same y axis across the plot
ad.plot(kind="scatter",x='TV',y='sales',ax=axs[0],figsize=(16,8))
ad.plot(kind="scatter",x='radio',y='sales',ax=axs[1],figsize=(16,8))
ad.plot(kind="scatter",x='newspaper',y='sales',ax=axs[2],figsize=(16,8))
plt.show
```

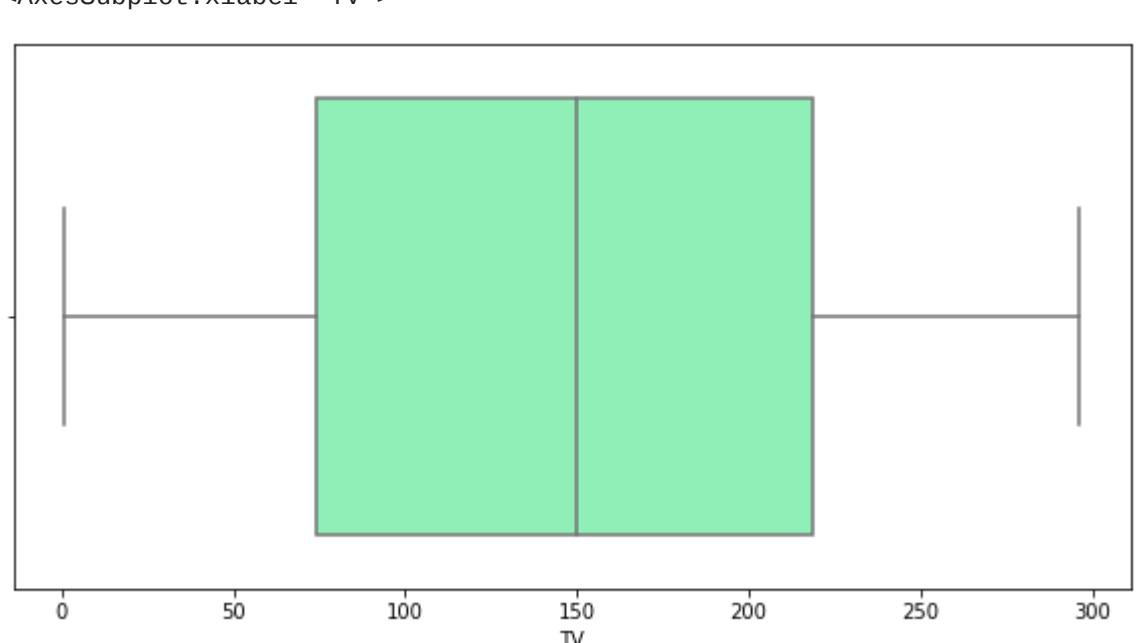
Out[8]: <function matplotlib.pyplot.show(close=None, block=None)>



There seems to be a few outliers in the newspaper plot

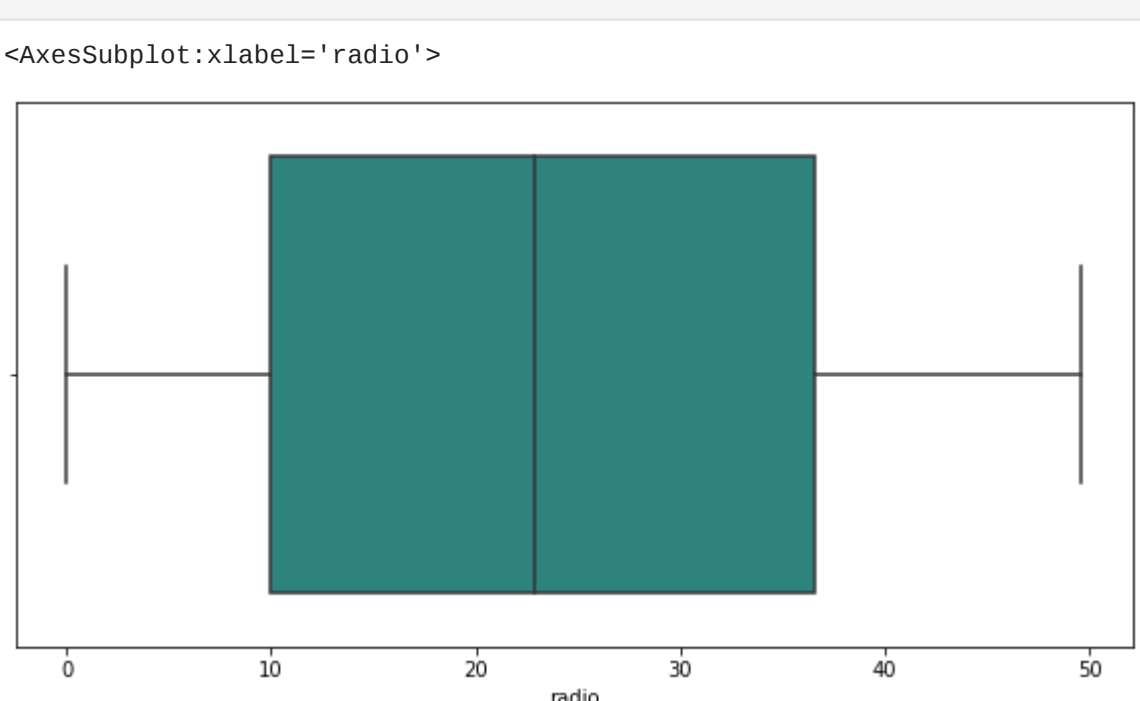
In [9]:
```
plt.rcParams["figure.figsize"] = [10.00, 5.00]
sns.boxplot(ad.TV, palette='rainbow')
```

Out[9]: <AxesSubplot:xlabel='TV'>



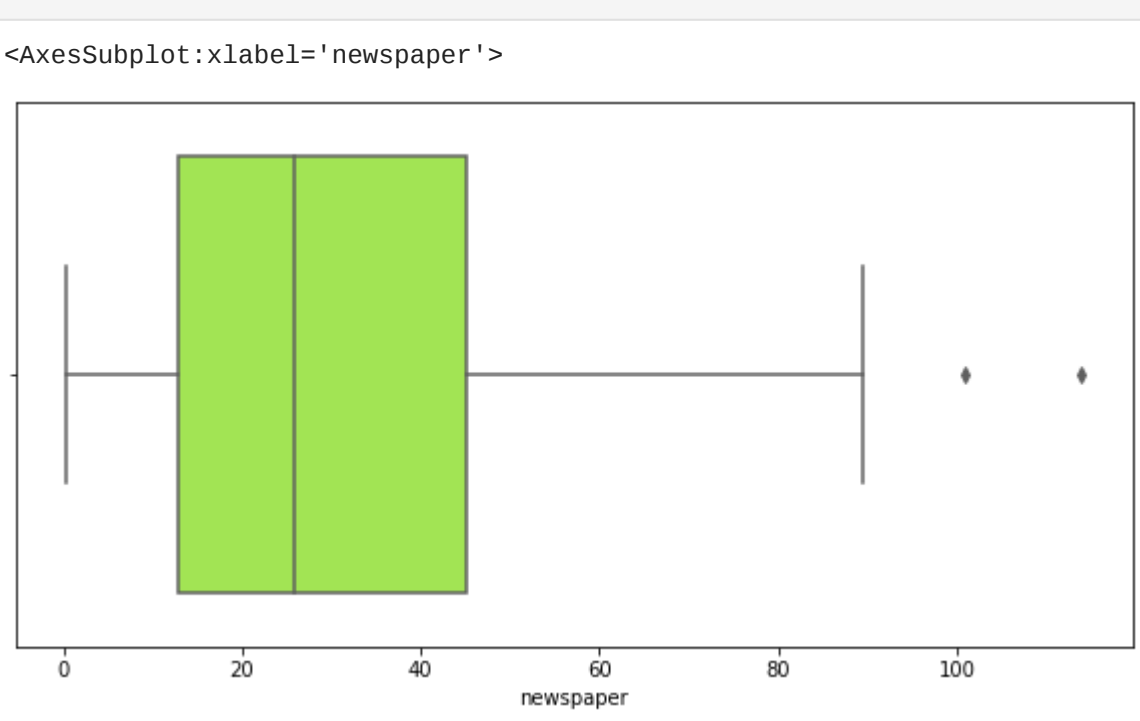
In [10]:
```
plt.rcParams["figure.figsize"] = [10.00, 5.00]
sns.boxplot(ad.radio,palette='viridis')
```

Out[10]: <AxesSubplot:xlabel='radio'>



In [11]:
```
plt.rcParams["figure.figsize"] = [10.00, 5.00]
sns.boxplot(ad.newspaper, palette='turbo')
```

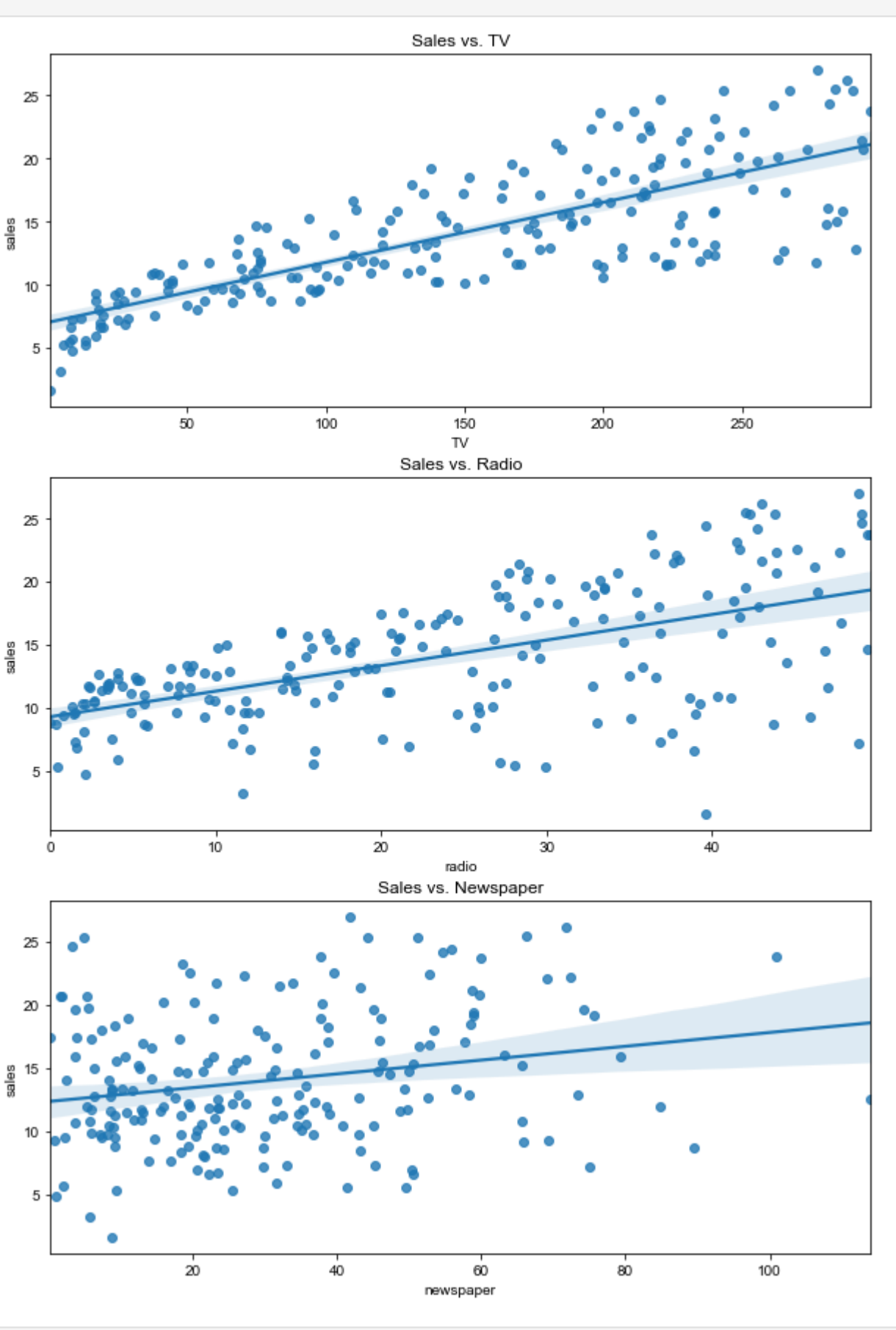
Out[11]: <AxesSubplot:xlabel='newspaper'>



Using boxplots we can confirm that there are indeed outliers in newspaper feature which need to be removed or they could affect the model prediction process

Combined regression plots of 'Sales' vs 'TV', 'radio' & 'newspaper'

In [12]:
```
figure, axes = plt.subplots(3, 1, sharey=True,figsize=(10, 15))
sns.set(style="darkgrid")
sns.regplot(data=ad, x='TV', y='sales', ax=axes[0]).set(title='Sales vs. TV')
sns.regplot(data=ad, x='radio', y='sales', ax=axes[1]).set(title='Sales vs. Radio')
sns.regplot(data=ad, x='newspaper', y='sales', ax=axes[2]).set(title='Sales vs. Newspaper')
plt.show()
```



In [13]:
```
# standard deviations of TV, radio & newspaper
np.std(ad.TV), np.std(ad.radio), np.std(ad.newspaper)
```

Out[13]: (85.63933175679269, 14.809645640595186, 21.724106057557353)

Observations

- *TV ads seem to have greater impact on sales with the steepest slope followed by Radio and Newspaper*
- *Spending on TV ads seems to have highest variance followed by Newspaper and Radio*

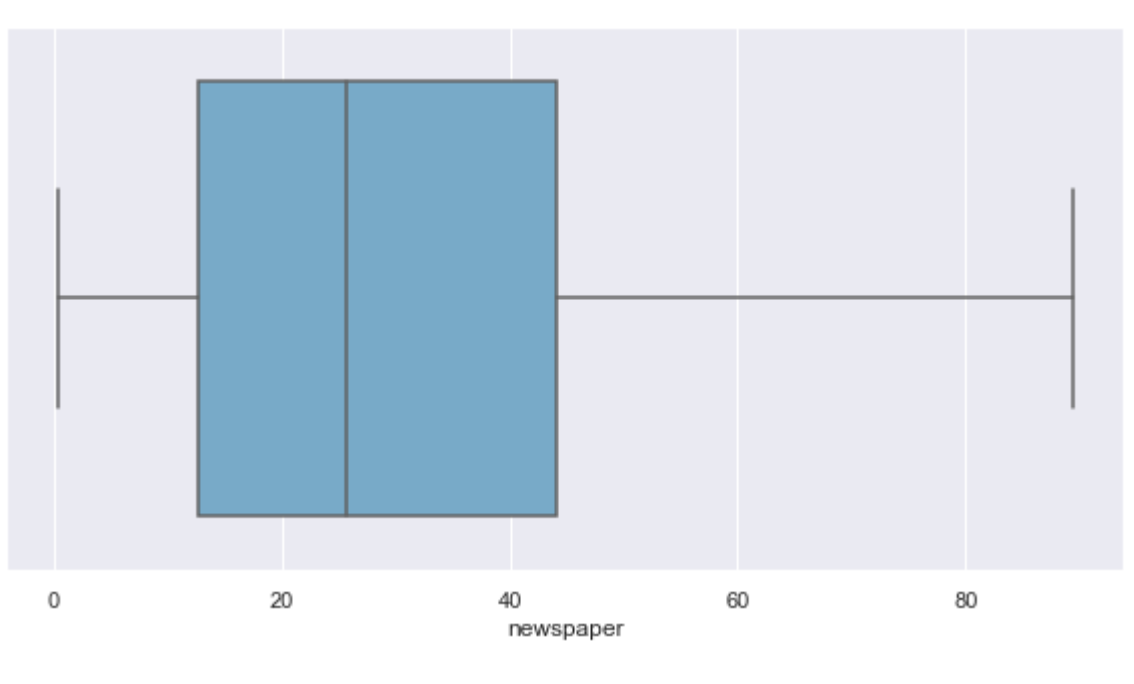
Removing Outliers

In [14]:
```
Q1 = ad['newspaper'].quantile(0.25)
Q3 = ad['newspaper'].quantile(0.75)
IQR = Q3-Q1
print("Old Shape: ", ad.shape)
upper = Q3+1.5*IQR # Upper bound
lower = Q1-1.5*IQR # Lower bound
ad=ad[~((ad['newspaper'] <= lower) | (ad['newspaper'] >= upper))]
print("New Shape: ", ad.shape)
```

```
Old Shape:  (200, 4)
New Shape:  (198, 4)
```

In [15]:
```
# Checking for removal of outliers
sns.boxplot(ad.newspaper, palette='Blues')
```

Out[15]: <AxesSubplot:xlabel='newspaper'>



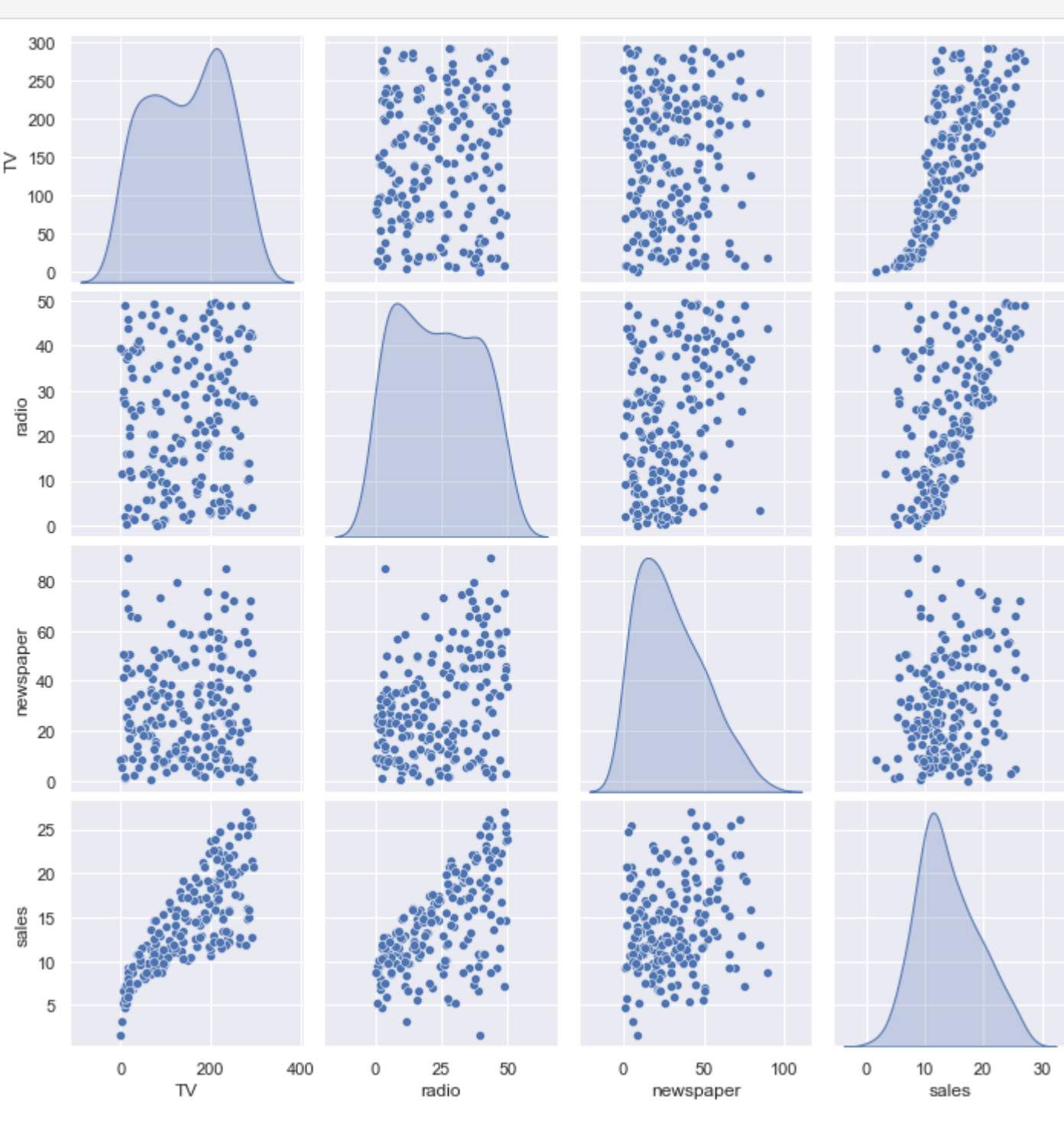
Newspaper feature has been cleared of outliers

Skewness in dataset

In [16]:
```
ad.skew()
```

Out[16]:
```
TV          -0.082332
radio        0.114842
newspaper    0.650112
sales        0.407130
dtype: float64
```

In [17]:
```
sns.pairplot(ad,x_vars=['TV','radio','newspaper','sales'],y_vars=['TV','radio','newspaper','sales'],diag_kind='kde')
plt.show()
```



Amongst all features it is clear that newspaper has a prononunced(positive) skew. We therefore apply sqrt to reduce it.

In [18]:
```
# Applying square root to normalize 'newspaper' feature.
ad['newspaper']=np.sqrt(ad['newspaper'])
```

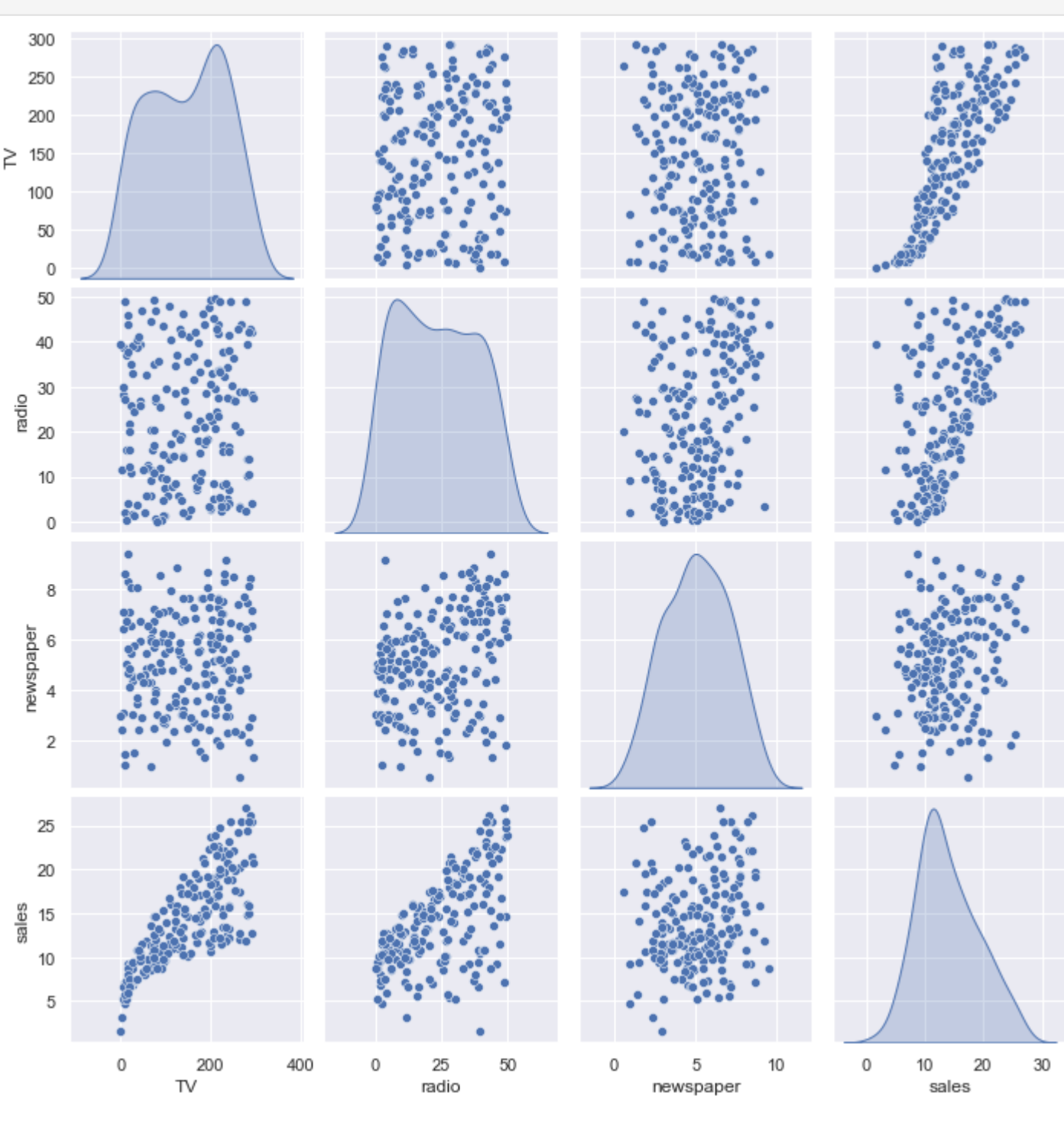
In [19]:
```
# import skew from scipy.stats
from scipy.stats import skew
skew(ad['newspaper'])
```

Out[19]: -0.040340871727186554

In [20]:
```
# Check to see skewness
ad.skew()
```

Out[20]:
```
TV          -0.082332
radio        0.114842
newspaper   -0.040649
sales        0.407130
dtype: float64
```

In [21]:
```
# verifying graphically
sns.pairplot(ad,x_vars=['TV','radio','newspaper','sales'],y_vars=['TV','radio','newspaper','sales'],diag_kind='kde')
plt.show()
```



Using pairplot we can see that newspaper is now normally distributed.

In [22]:
```
# Splitting the data for x features
x=ad[['TV','radio','newspaper']] # x variable is created as a model to train
x.head()
# x = ad.iloc[:,[0,1,2]].values
# x
```

Out[22]:

	TV	radio	newspaper
1	230.1	37.8	8.318654
2	44.5	39.3	6.715653
3	17.2	45.9	8.324662
4	151.5	41.3	7.648529
5	180.8	10.8	7.641989

In [23]:
```
# Splitting the data for y target
y=ad[['sales']] # y is created as the target variable, to be used to compare against x
y.head()
# y = ad.iloc[:,[3]].values
# y
```

Out[23]:

	sales
1	22.1
2	10.4
3	9.3
4	18.5
5	12.9

In [24]:
```
print(x.shape)
print(y.shape)
```

```
(198, 3)
(198, 1)
```

Model Testing

In [25]:
```
# Splitting the dataset into the Training set and Test set
from sklearn.model_selection import train_test_split
X_train,X_test,y_train,y_test = train_test_split(x,y,test_size=0.2,random_state=30)
```

In [26]:
```
print(X_train.shape)
print(y_train.shape)
print(X_test.shape)
print(y_test.shape)
```

```
(158, 3)
(158, 1)
(40, 3)
(40, 1)
```

Linear Regression

In [27]:
```
from sklearn.linear_model import LinearRegression
linereg=LinearRegression()
linereg.fit(X_train,y_train)
```

Out[27]: LinearRegression()

In [28]:
```
linereg.score(X_train, y_train)
```

Out[28]: 0.9124839582885386

In [29]:
```
linereg.score(X_test, y_test)
```

Out[29]: 0.8252542820487998

In [30]:
```
y_predict = linereg.predict(X_test)
y_predict
```

Out[30]:
```
array([[10.05678823],
       [ 5.53085232],
       [16.96971091],
       [14.16915841],
       [ 9.13210463],
       [15.41525653],
       [ 6.61941765],
       [ 8.66416973],
       [10.85730349],
       [18.64927391],
       [ 9.79231564],
       [15.34747738],
       [ 6.50374278],
       [19.06394167],
       [ 9.86360803],
       [ 9.68977996],
       [14.02253679],
       [17.18633556],
       [21.12732676],
       [11.93836113],
       [ 3.56747736],
       [16.30989321],
       [11.97164564],
       [ 9.48383474],
       [17.39873045],
       [15.1273564 ],
       [12.37851267],
       [17.47756203],
       [24.09021196],
       [10.78582867],
       [ 9.62788956],
       [22.05187182],
       [15.87364146],
       [11.13185438],
       [21.38184774],
       [15.16783038],
       [12.53390093],
       [ 4.43747282],
       [15.00100941],
       [18.839725  ]])
```

In [31]:
```
print(linereg.intercept_)
print(linereg.coef_)
```

```
[3.2076026]
[[ 0.04482975  0.19688873 -0.06050829]]
```

In [32]:
```
from sklearn import metrics
print(np.sqrt(metrics.mean_squared_error(y_test,y_predict)))
```

```
2.244524837134727
```