Linear Regression for Advertising

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Overview

We're trying to decide whether or not companies should focus their efforts and capital more on either one of TV, radio or their newspaper ads to increase their sales. We've been hired on contract to help them figure it out! Let's get started!

Importing and loading dependencies

In [2]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
%matplotlib inline
```

Data Wrangling

We'll work with *Avertising* csv file. It has Advertising data with columns such as the sales made and expenditure on various ads:

- **TV**: Expenses on TV ads
- **Radio**: Expenses on Radio ads
- **Newspaper**: Expenses on Newspaper ads
- **Sales**: Total sales made

Reading the *Advertising csv* file as a DataFrame named *df*.

In [3]:

```
1 df = pd.read_csv("Advertising.csv")
```

Inspecting our data

In [4]:

```
1 df.head()
```

Out[4]:

	TV	Radio	Newspaper	Sales
0	230.1	37.8	69.2	22.1
1	44.5	39.3	45.1	10.4
2	17.2	45.9	69.3	12.0
3	151.5	41.3	58.5	16.5
4	180.8	10.8	58.4	17.9

In [5]:

```
1 df.shape
```

Out[5]:

```
(200, 4)
```

In [6]:

```
1 df.describe()
```

Out[6]:

	TV	Radio	Newspaper	Sales
count	200.000000	200.000000	200.000000	200.000000
mean	147.042500	23.264000	30.554000	15.130500
std	85.854236	14.846809	21.778621	5.283892
min	0.700000	0.000000	0.300000	1.600000
25%	74.375000	9.975000	12.750000	11.000000
50%	149.750000	22.900000	25.750000	16.000000
75%	218.825000	36.525000	45.100000	19.050000
max	296.400000	49.600000	114.000000	27.000000

In [7]:

```
1 df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 200 entries, 0 to 199
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: 6.4 KB
```

In [8]:

```
1 df.columns
```

Out[8]:

```
Index(['TV', 'Radio', 'Newspaper', 'Sales'], dtype='object')
```

Data Cleaning

*We check for **null** values*

In [9]:

```
1 df.isna().sum()
```

Out[9]:

```
TV           0
Radio        0
Newspaper    0
Sales        0
dtype: int64
```

*We check for **duplicate** values*

In [10]:

```
1 df.duplicated().sum()
```

Out[10]:

```
0
```

Exploratory Data Analysis

Setting a few style 'rules'

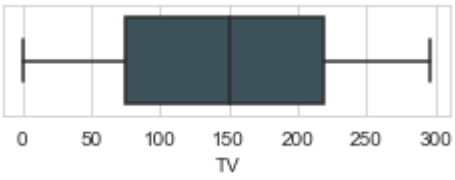
In [11]:

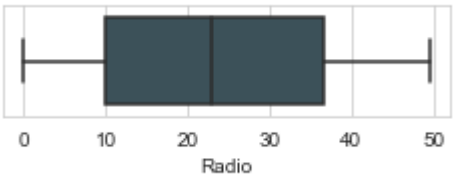
```
sns.set_palette("GnBu_d")
sns.set_style('whitegrid')
```

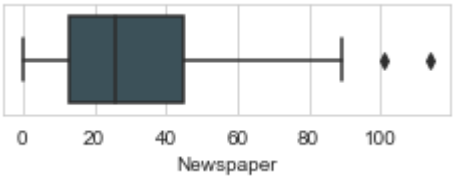
First, we check for outliers that can really affect our model

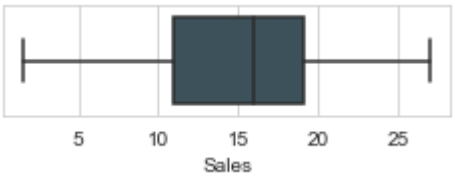
In [12]:

```
for i in df:
    plt.figure(figsize = (4,1))
    sns.boxplot(x = df[i])
    plt.show()
```









No such outliers observed

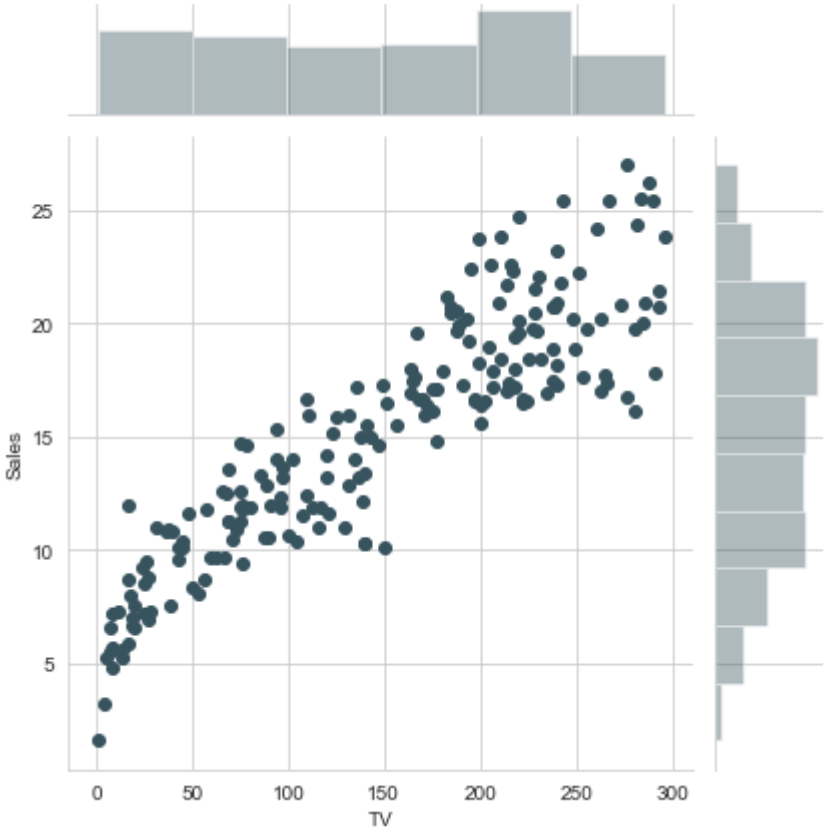
Next we'll create a jointplot to compare the TV and Sales columns.

In [13]:

```
1 sns.jointplot(x='TV',y='Sales',data=df)
```

Out[13]:

```
<seaborn.axisgrid.JointGrid at 0x260a2a92fa0>
```



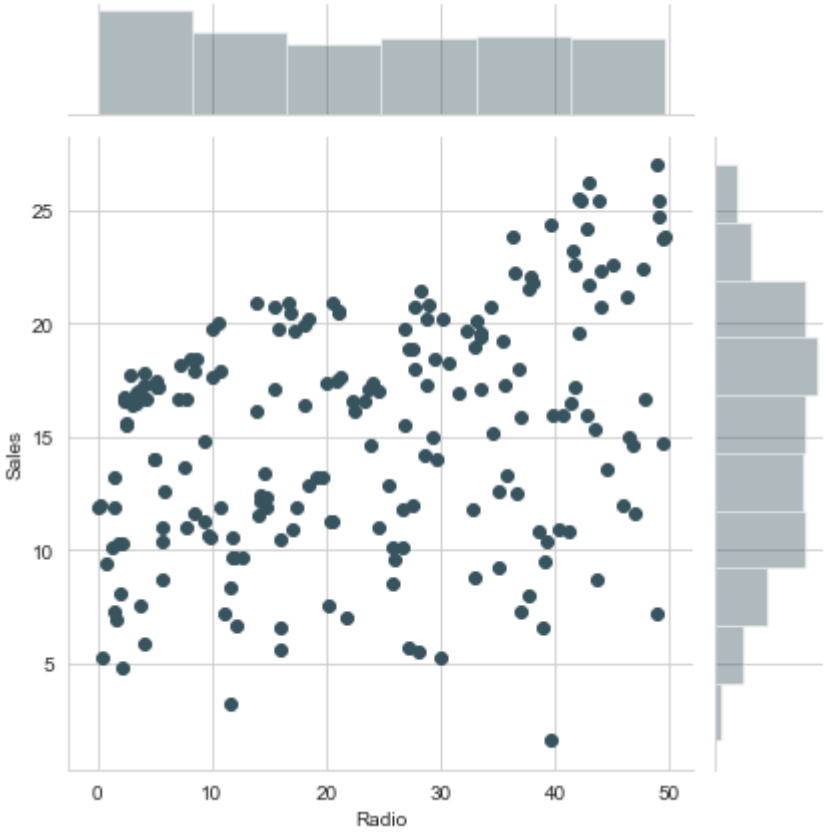
Doing the same, but with the Radio & Newspaper columns respectively.

In [14]:

```
1 sns.jointplot(x='Radio',y='Sales',data=df)
```

Out[14]:

```
<seaborn.axisgrid.JointGrid at 0x260a2bc8370>
```

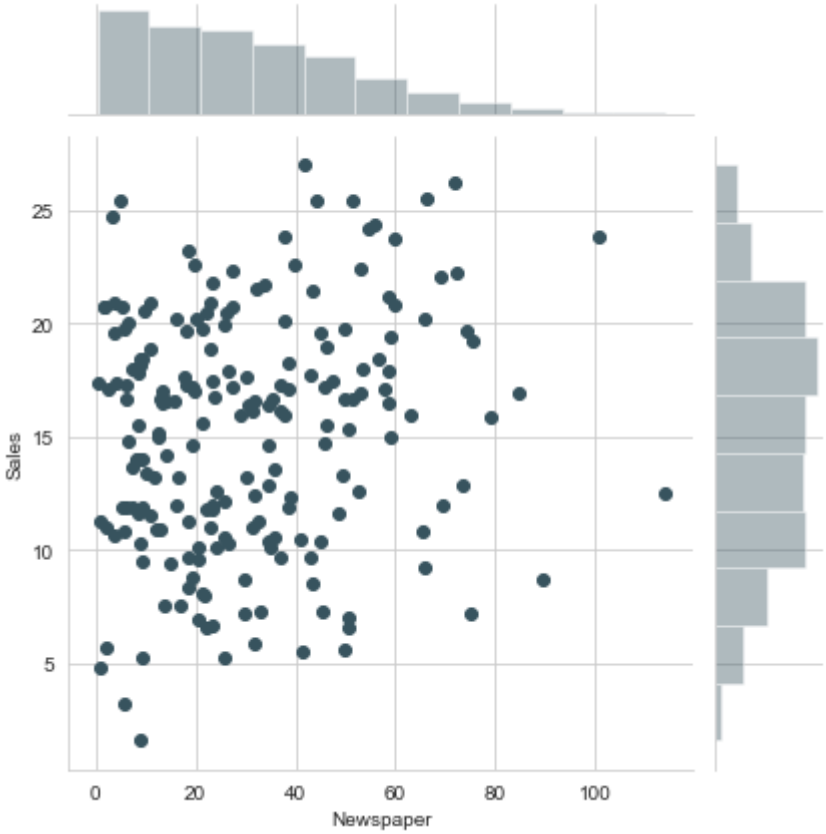


In [15]:

```
1 sns.jointplot(x='Newspaper',y='Sales',data=df)
```

Out[15]:

```
<seaborn.axisgrid.JointGrid at 0x260a2c58c70>
```



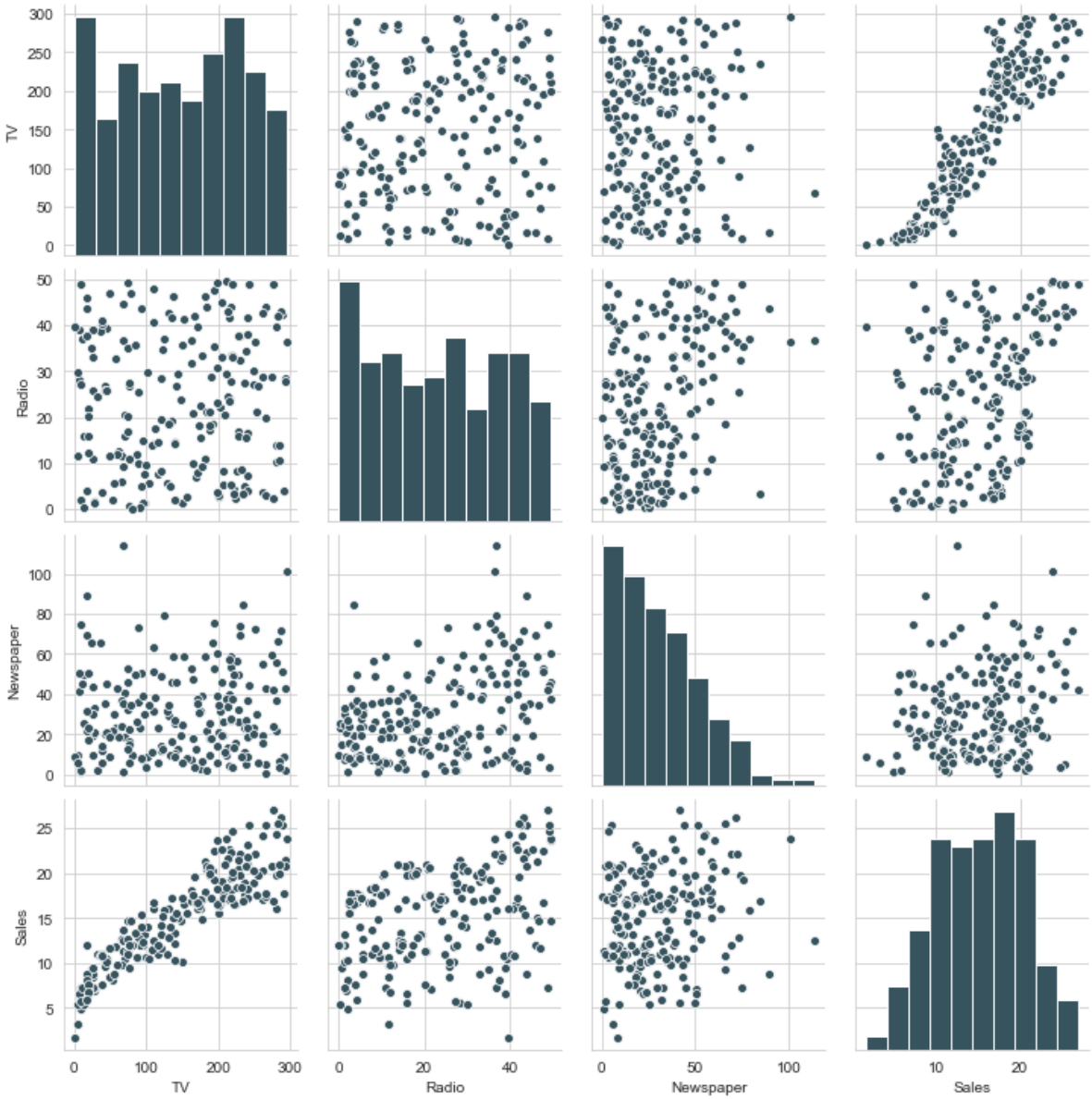
*Now to explore these features & relationships across the entire data set.

In [16]:

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

Out[16]:

```
<seaborn.axisgrid.PairGrid at 0x260a2d77070>
```



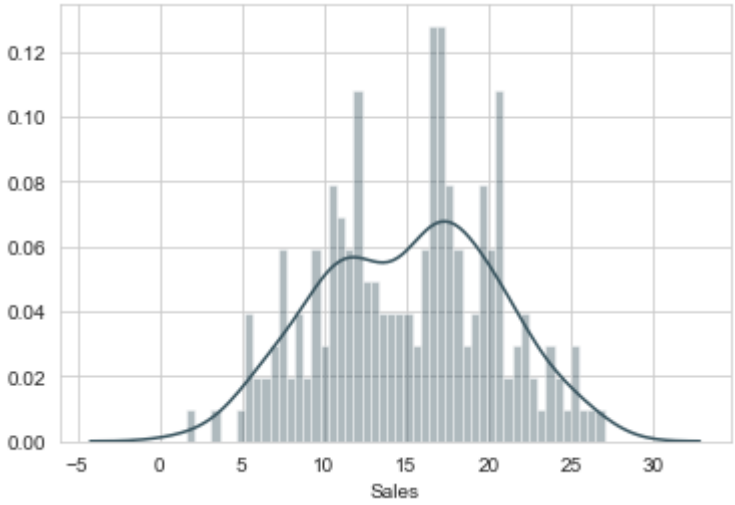
Plotting a univariate distribution of Sales made

In [17]:

```
1 sns.distplot(df['Sales'], bins=50)
```

Out[17]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x260a34029a0>
```



In [18]:

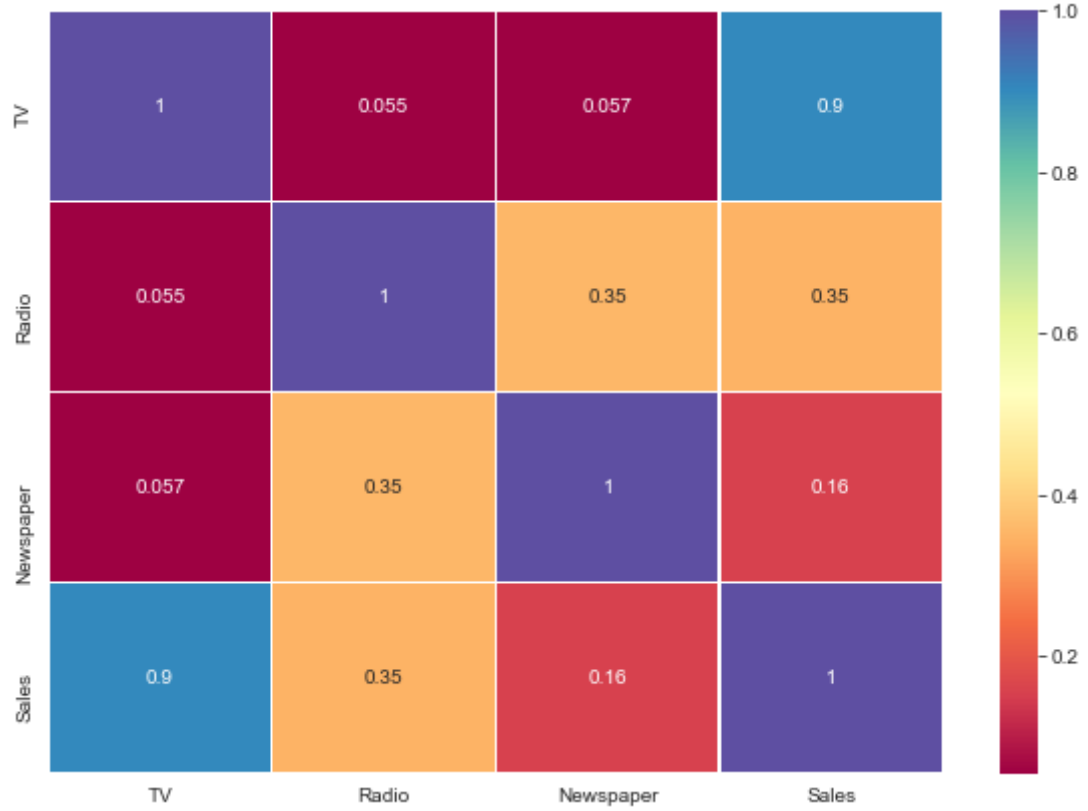
```
1 corr = df.corr()
```

In [19]:

```
plt.figure(figsize=(10,7))
sns.heatmap(corr, cmap='Spectral', linewidths = .2, annot=True)
```

Out[19]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x260a2ba7910>
```



Based off these plots what looks to be the most correlated feature with Sales?

In [20]:

```
# TV is the most correlated feature with Sales
```

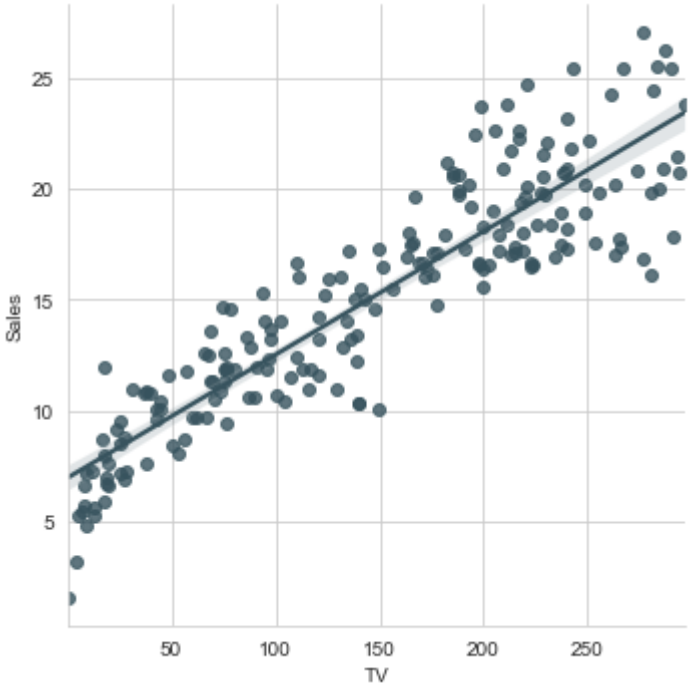
Creating a linear model plot (using seaborn's lmplot method) of Sale vs TV .

In [21]:

```
1 sns.lmplot(x='TV',y='Sales',data=df)
```

Out[21]:

```
<seaborn.axisgrid.FacetGrid at 0x260a3401f40>
```



Model

Dependent and Independent variables

Set a variable X equal to the amounts spent on different adverts (features) and a variable y equal to the "Sales" column.

In [22]:

```
1 X = df.iloc[:,0:3]
2 y = df['Sales'] #target variable
```

To look at the correlation between each variable

In [23]:

```
1 X.iloc[:,0:].corr()
```

Out[23]:

	TV	Radio	Newspaper
TV	1.000000	0.054809	0.056648
Radio	0.054809	1.000000	0.354104
Newspaper	0.056648	0.354104	1.000000

As we see; no exceptionally high correlation is observed, so won't be dropping any columns

Viewing the OLS model

Importing the api for statistical models

In [24]:

```
1 import statsmodels.api as sm
```

In [25]:

```
1 X_sm = sm.add_constant(X)
2 ols_model = sm.OLS(y, X_sm).fit()
3 ols_model.summary()
```

Out[25]:

OLS Regression Results

Dep. Variable:	Sales	**R-squared:**	0.903
Model:	OLS	**Adj. R-squared:**	0.901
Method:	Least Squares	**F-statistic:**	605.4
Date:	Mon, 19 Sep 2022	**Prob (F-statistic):**	8.13e-99
Time:	22:23:19	**Log-Likelihood:**	-383.34
No. Observations:	200	**AIC:**	774.7
Df Residuals:	196	**BIC:**	787.9
Df Model:	3		
Covariance Type:	nonrobust		

Observations:

A good R^2 value is observed.

The standard error values are low which indicates absence of a multi-colinearity relationship between the values

Training the Model

Now that we've explored the data a bit, we can go ahead and split the data into training and testing sets.

Importing model_selection.train_test_split from sklearn to split the data into training and testing sets.

In [26]:

```
1 from sklearn.model_selection import train_test_split
```

Setting the test_size as 30%

In [27]:

```
1 X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_sta
```

Importing the LinearRegression from sklearn.linear_model

In [28]:

```
1 from sklearn.linear_model import LinearRegression
```

Creating an instance of a LinearRegression() model named lm.

In [29]:

```
1 lr = LinearRegression()
```

Train/fit lr on the training data.

In [30]:

```
1 lr.fit(X_train,y_train)
```

Out[30]:

```
LinearRegression()
```

The coefficients of the model

In [31]:

```
1 coeff_df = pd.DataFrame(lr.coef_,X.columns,columns=['Coefficient'])
2 coeff_df
```

Out[31]:

	Coefficient
TV	0.054930
Radio	0.109558
Newspaper	-0.006194

Predicting Test Data

Now that we have fit/trained our model, we can evaluate its performance by predicting off the test values.

Use lr.predict() to predict off the X_test set of the data.

In [32]:

```
predictions = lr.predict(X_test)
```

Let's have some fun and try to predict the sales of a company with their expenditure on ads

In [33]:

```
lr_model = lr.fit(X, y)
# company A spends the following values on advertising on different platforms; 20,1
lr_model.predict([[20,10,11]])
```

Out[33]:

```
array([6.78774421])
```

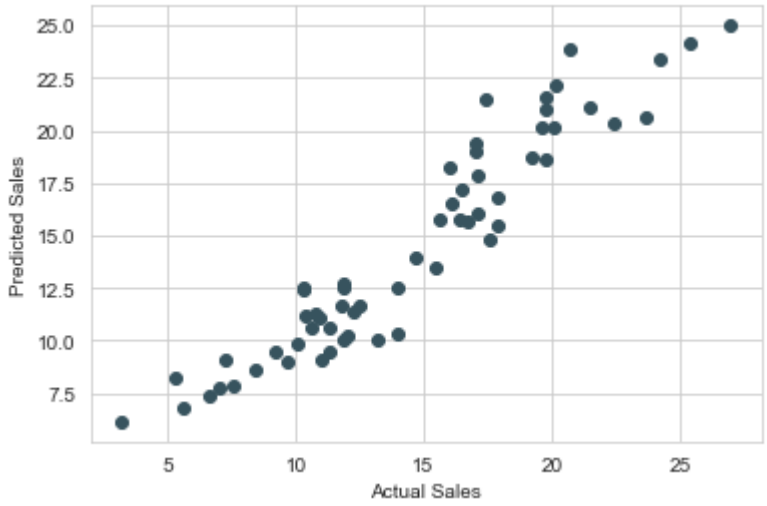
Create a scatterplot of the real test values versus the predicted values.

In [34]:

```
plt.scatter(y_test,predictions)
plt.xlabel('Actual Sales')
plt.ylabel('Predicted Sales')
```

Out[34]:

```
Text(0, 0.5, 'Predicted Sales')
```



Evaluating the Model

We will now evaluate model performance by calculating the residual sum of squares and the explained variance score (R^2).

In [35]:

```
from sklearn import metrics

print('MAE   : ', metrics.mean_absolute_error(y_test, predictions))
print('MSE   : ', metrics.mean_squared_error(y_test, predictions))
print('RMSE  : ', np.sqrt(metrics.mean_squared_error(y_test, predictions)))
print('R^2   : ', ols_model.rsquared)
```

```
MAE   :  1.3731200698367851
MSE   :  2.8685706338964976
RMSE  :  1.6936855180040058
R^2   :  0.9025912899684558
```

Residuals

Now we'll explore the residuals to make sure everything was okay with our data.

Plot a histogram of the residuals, if it looks normally distributed, we're on the right track!

In [36]:

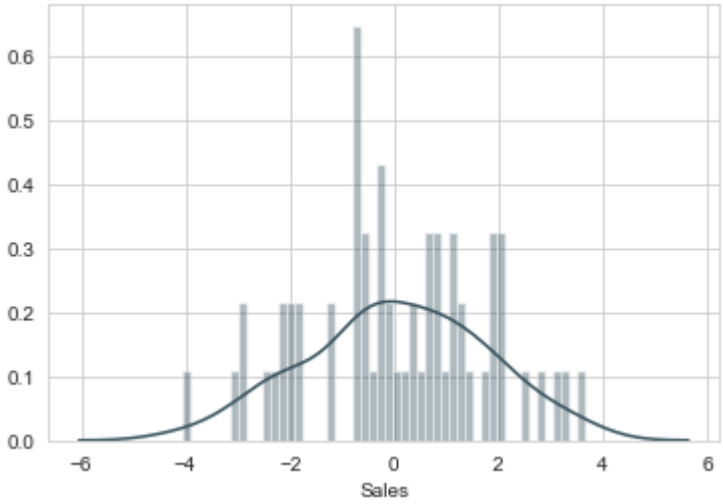
```
residuals = y_test-predictions
```

In [37]:

```
sns.distplot(residuals,bins=50)
```

Out[37]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x260a5bca550>
```



Conclusion

We still want to figure out the answer to the original question, do they focus on TV, radio or newspaper ads. We interpret the coefficients to get an idea.

In [38]:

```
1 coeff_df
```

Out[38]:

	Coefficient
TV	0.054930
Radio	0.109558
Newspaper	-0.006194

How can we interpret these coefficients?

Interpreting the coefficients, holding all other features fixed;

- a 1 unit increase in **TV ads** is associated with an **0.054930 increase in sales**.
- a 1 unit increase in **Radio ads** is associated with a **0.109558 increase in sales**.
- a 1 unit increase in **Newspaper** is associated with an **0.006194 decrease in sales**.

Should companies focus more on TV, radio, or newspaper ads?

The companies should focus a bit more on promoting radio ads to see a largaer increase in sales.

Nice Job :-)

We're done! The companies loved our insights! Let's move on*!!*

In [ ]:

```
1
```