★ Machine Learning Project - Ad Budget Estimation ★

Description:

The advertising dataset captures the sales revenue generated with respect to advertisement costs across multiple channels like radio, tv, and newspapers. It is required to understand the impact of ad budgets on the overall sales.

Objective:

- Understand the Dataset & cleanup (if required).
- Build Regression models to predict the sales w.r.t a single & multiple feature.
- Also evaluate the models & compare thier respective scores like R2, RMSE, etc.

1. Data Exploration

In [214]:
```
#Importing the basic librarires

import numpy as np
import pandas as pd
import seaborn as sns
from IPython.display import display

import matplotlib.pyplot as plt
plt.rcParams['figure.figsize'] = [10,6]

import warnings
warnings.filterwarnings('ignore')
```

In [215]:
```
#Importing the dataset

df = pd.read_csv('Advertising Budget and Sales.csv', index_col=0, names=['TV','Radio','Newspaper','Sales'], skiprows=1)
df.reset_index(drop=True, inplace=True)
original_dataset = df.copy(deep=True)
display(df.head())

print('\n\033[1mInference:\033[0m The Datset consists of {} features & {} samples.'.format(df.shape[1], df.shape[0]))
```

	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	9.3
3	151.5	41.3	58.5	18.5
4	180.8	10.8	58.4	12.9

Inference: The Datset consists of 4 features & 200 samples.

In [216]:
```
#Checking the dtypes of all the columns

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
```

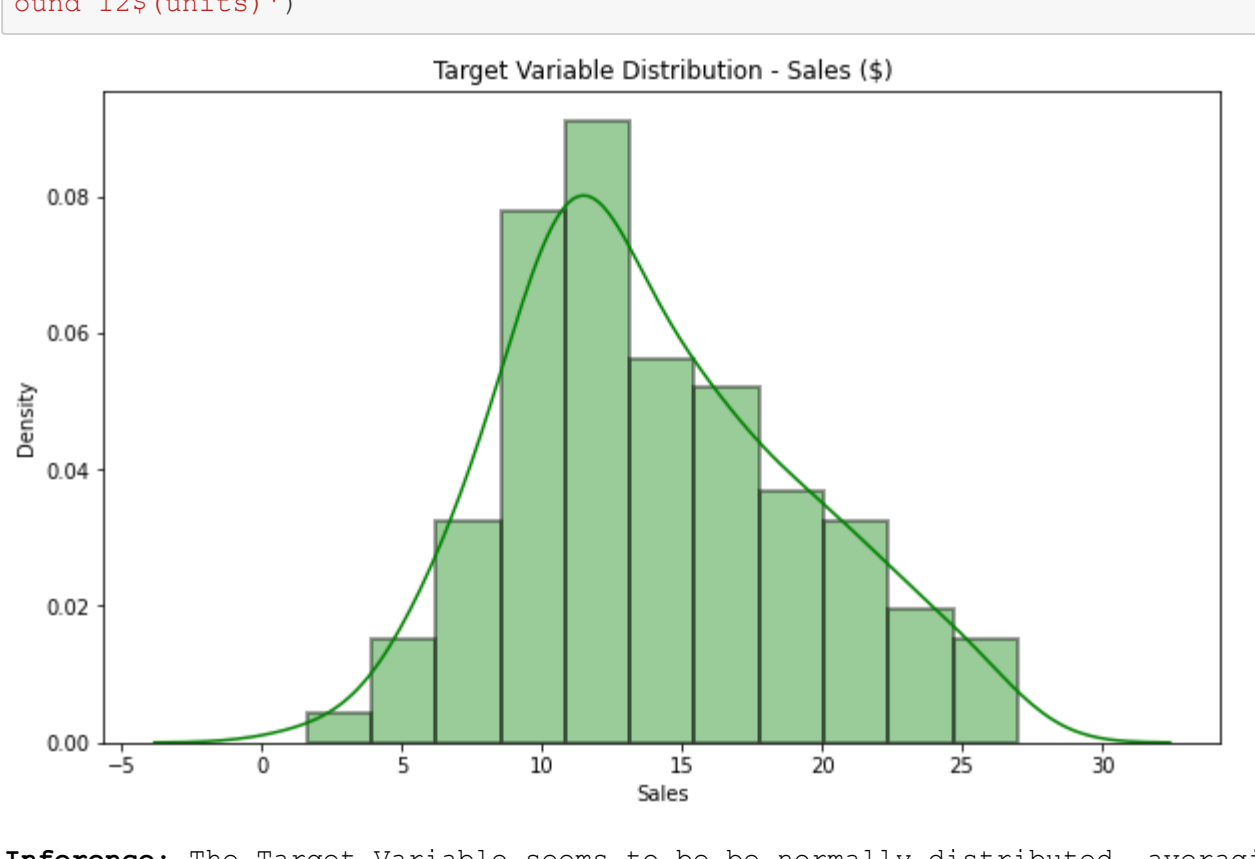
In [217]:
```
#Checking the stats of all the columns

display(df.describe())
print('\n \033[1mInference:\033[0m The stats seem to be fine, let us do further analysis on the Dataset')
```

	TV	Radio	Newspaper	Sales
count	200.000000	200.000000	200.000000	200.000000
mean	147.042500	23.264000	30.554000	14.022500
std	85.854236	14.846809	21.778621	5.217457
min	0.700000	0.000000	0.300000	1.600000
25%	74.375000	9.975000	12.750000	10.375000
50%	149.750000	22.900000	25.750000	12.900000
75%	218.825000	36.525000	45.100000	17.400000
max	296.400000	49.600000	114.000000	27.000000

Inference: The stats seem to be fine, let us do further analysis on the Dataset

2. Exploratory Data Analysis (EDA)

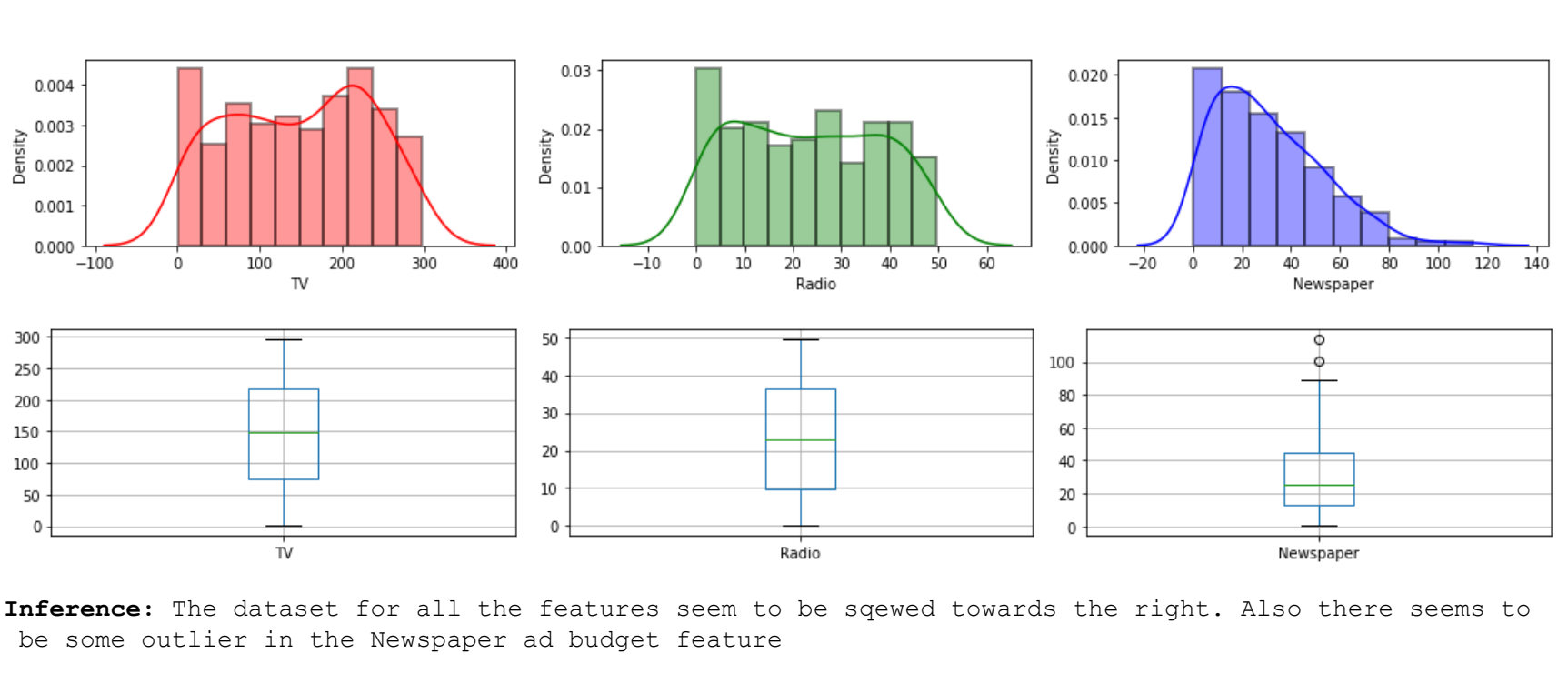
In [218]:
```
#Let us first analyze the distribution of the target variable

c = df.columns
sns.distplot(df[c[3]], color='g',hist_kws=dict(edgecolor="black", linewidth=2))
plt.title('Target Variable Distribution - Sales ($)')
plt.show()

print('\n\033[1mInference:\033[0m The Target Variable seems to be be normally distributed, averaging around 12$(units)')
```



Inference: The Target Variable seems to be be normally distributed, averaging around 12$(units)

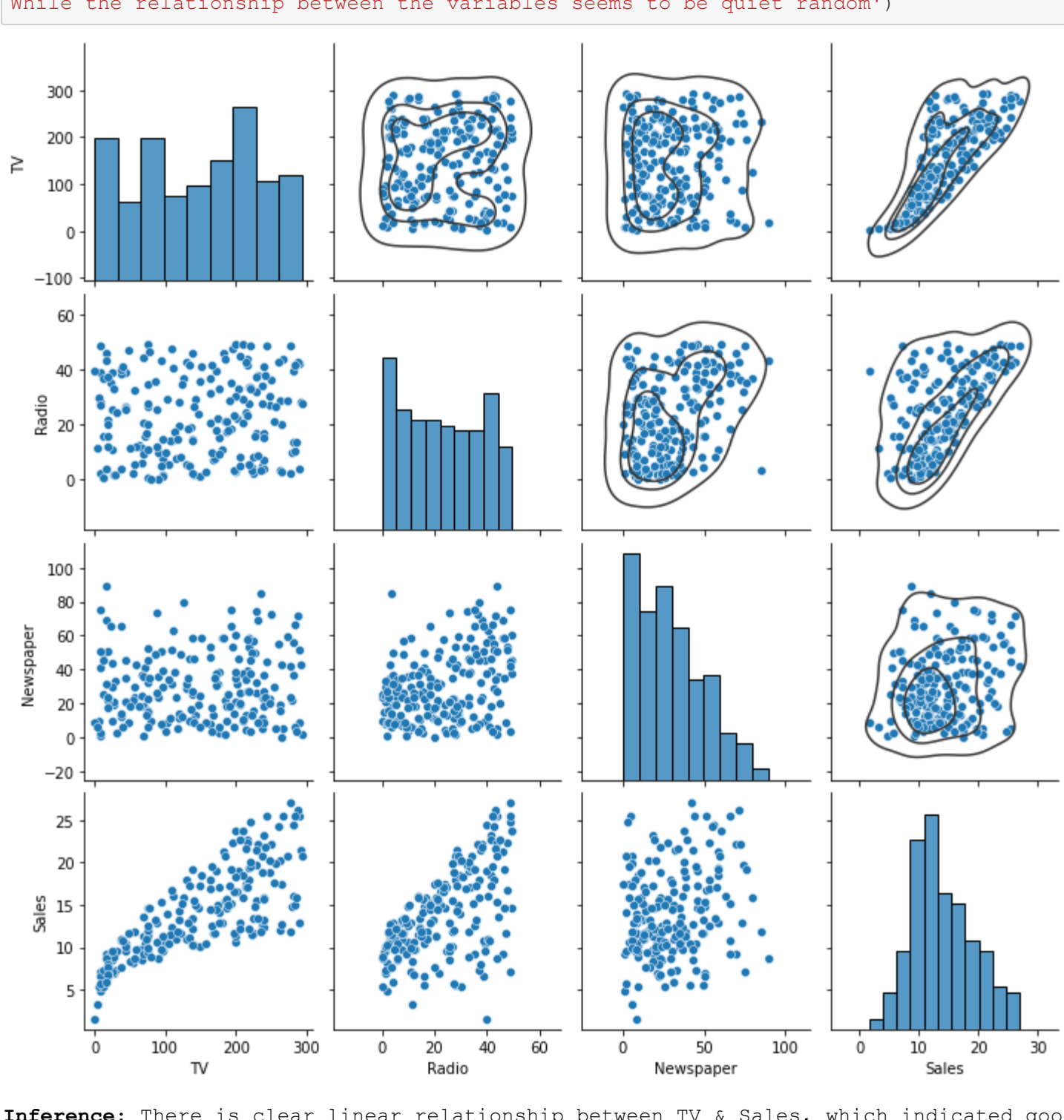
In [219]:
```
#Understanding the features set

print('\033[1mFeatures Distribution'.center(130))

clr=['r','g','b']

plt.figure(figsize=[15,2.5])
for i in range(3):
    plt.subplot(1,3,i+1)
    sns.distplot(df[c[i]],hist_kws=dict(edgecolor="black", linewidth=2), bins=10, color=clr[i])
plt.tight_layout()
plt.show()

plt.figure(figsize=[15,2.5])
for i in range(3):
    plt.subplot(1,3,i+1)
    df.boxplot(df.columns[i])
plt.tight_layout()
plt.show()

print('\n\033[1mInference:\033[0m The dataset for all the features seem to be sqewed towards the right. Also there \
seems to be some outlier in the Newspaper ad budget feature')
```

Features Distribution



Inference: The dataset for all the features seem to be sqewed towards the right. Also there seems to be some outlier in the Newspaper ad budget feature

In [357]:
```
#Understanding the relationship between all the features

g = sns.pairplot(df)
g.map_upper(sns.kdeplot, levels=4, color=".2")
plt.show()

print('\n\033[1mInference:\033[0m There is clear linear relationship between TV & Sales, which indicated good explainability.\
While the relationship between the variables seems to be quiet random')
```



Inference: There is clear linear relationship between TV & Sales, which indicated good explainability.While the relationship between the variables seems to be quiet random

3. Data Preprocessing

In [221]:
```
#Check for empty elements

print(df.isnull().sum())
print('\n\033[1mInference:\033[0m The dataset doesn\'t have any null elements')
```

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

Inference: The dataset doesn't have any null elements

In [222]:
```
#Removal of any Duplicate rows (if any)

counter = 0
rs,cs = df.shape

df.drop_duplicates(inplace=True)

if df.shape==(rs,cs):
    print('\n\033[1mInference:\033[0m The dataset doesn\'t have any duplicates')
else:
    print(f'\n\033[1mInference:\033[0m Number of duplicates dropped/fixed ---> {r-df.shape[0]}')
```

Inference: The dataset doesn't have any duplicates

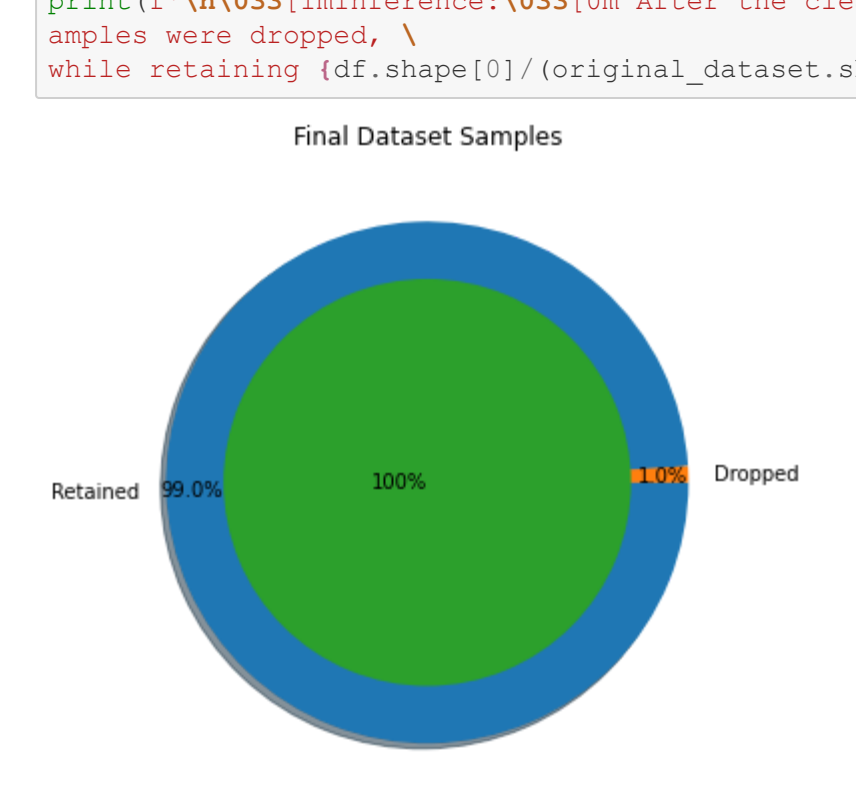
In [223]:
```
#Removal of outlier:

for i in df.columns:
    Q1 = df[i].quantile(0.25)
    Q3 = df[i].quantile(0.75)
    IQR = Q3 - Q1
    df = df[df[i] <= (Q3+(1.5*IQR))]
    df = df[df[i] >= (Q1-(1.5*IQR))]
    df = df.reset_index(drop=True)
display(df)
print('\n\033[1mInference:\033[0m After removal of outliers, The dataset now has {} features & {} samples.'.format(df.shape[1], df.shape[0]))
```

	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	9.3
3	151.5	41.3	58.5	18.5
4	180.8	10.8	58.4	12.9
...	...	...	...	...
193	38.2	3.7	13.8	7.6
194	94.2	4.9	8.1	9.7
195	177.0	9.3	6.4	12.8
196	283.6	42.0	66.2	25.5
197	232.1	8.6	8.7	13.4

198 rows × 4 columns

Inference: After removal of outliers, The dataset now has 4 features & 198 samples.

In [224]:
```
#Final Dataset size after performing Preprocessing

plt.title('Final Dataset Samples')
plt.pie([df.shape[0], original_dataset.shape[0]-df.shape[0]], radius = 1, labels=['Retained','Dropped'], counterclock=False,
        autopct='%1.1f%%', pctdistance=0.9, explode=[0,0], shadow=True)
plt.pie([df.shape[0]], labels=['100%'], labeldistance=-0, radius=0.78)
plt.show()

print(f'\n\033[1mInference:\033[0m After the cleanup process, {original_dataset.shape[0]-df.shape[0]} samples were dropped, \
while retaining {df.shape[0]/(original_dataset.shape[0]-df.shape[0])}% of the data.')
```

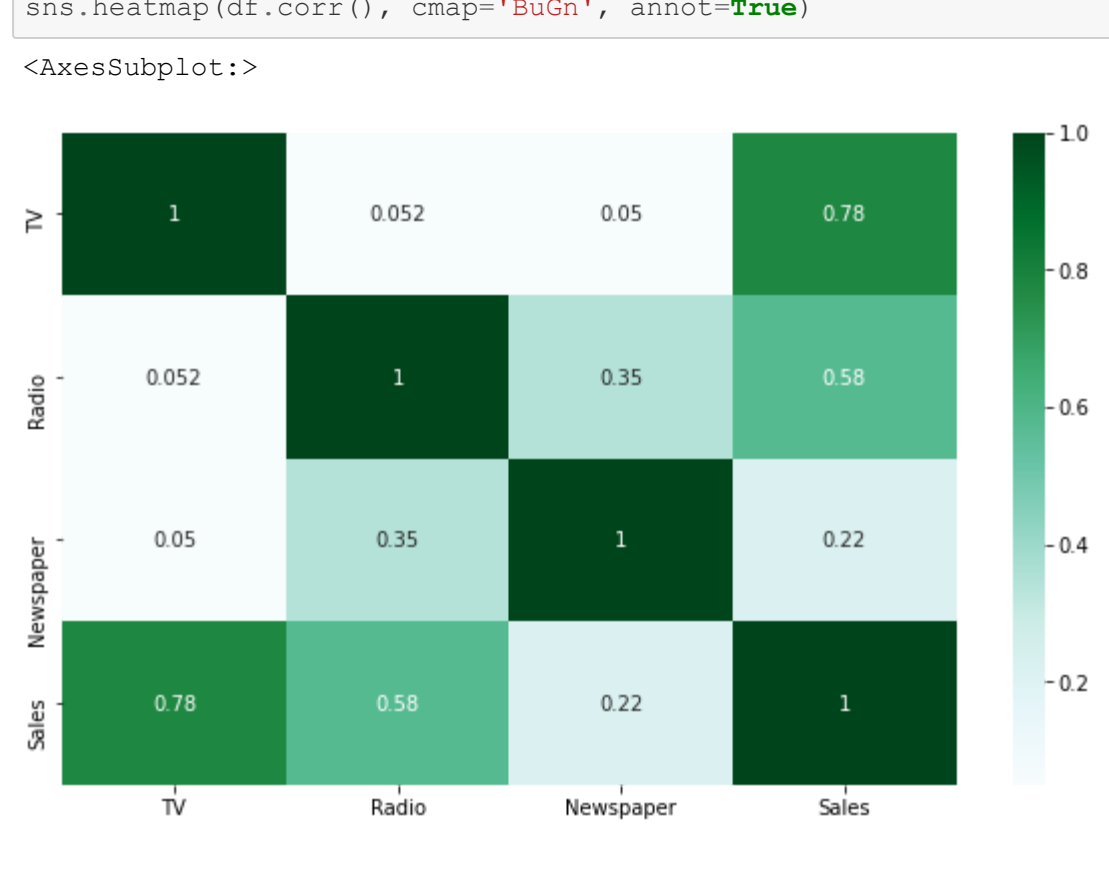


Inference: After the cleanup process, 2 samples were dropped, while retaining 99.0% of the data.

4. Feature Selection/Extraction

In [225]:
```
sns.heatmap(df.corr(), cmap='BuGn', annot=True)
```

Out[225]: <AxesSubplot:>



5. Data Manipulation

In [226]:
```
#Splitting the data intro training & testing sets

from sklearn.model_selection import train_test_split

X = df.drop(['Sales'],axis=1)
Y = df.Sales
Train_X, Test_X, Train_Y, Test_Y = train_test_split(X, Y, train_size=0.8, test_size=0.2, random_state=100)

print('Original set  ---> ',X.shape,Y.shape,'\nTraining set  ---> ',Train_X.shape,Train_Y.shape,'\nTesting set   ---> ', Test_X.shape,'', Test_Y.shape)
```

```
Original set  --->  (198, 3) (198,)
Training set  --->  (158, 3) (158,)
Testing set   --->  (40, 3)  (40,)
```

In [227]:
```
#Feature Scaling (Standardization)

from sklearn.preprocessing import StandardScaler

std = StandardScaler()

Train_X_std = std.fit_transform(Train_X)
Train_X_std = pd.DataFrame(Train_X_std, columns=X.columns)
Test_X_std = std.transform(Test_X)
Test_X_std = pd.DataFrame(Test_X_std, columns=X.columns)
```

6. Linear Regression Model

In [228]:
```
#Creating a Linear Regression model with statsmodels

from statsmodels.formula import api
API = api.ols(formula=f'{c[3]} ~ {c[0]}', data=df).fit()
#print(API.conf_int())
#print(API.pvalues)
API.summary()
```

Out[228]:

OLS Regression Results

Dep. Variable:	Sales	R-squared:	0.607
Model:	OLS	Adj. R-squared:	0.605
Method:	Least Squares	F-statistic:	302.8
Date:	Mon, 08 Nov 2021	Prob (F-statistic):	1.29e-41
Time:	19:35:15	Log-Likelihood:	-514.27
No. Observations:	198	AIC:	1033.
Df Residuals:	196	BIC:	1039.
Df Model:	1		
Covariance Type:	nonrobust		

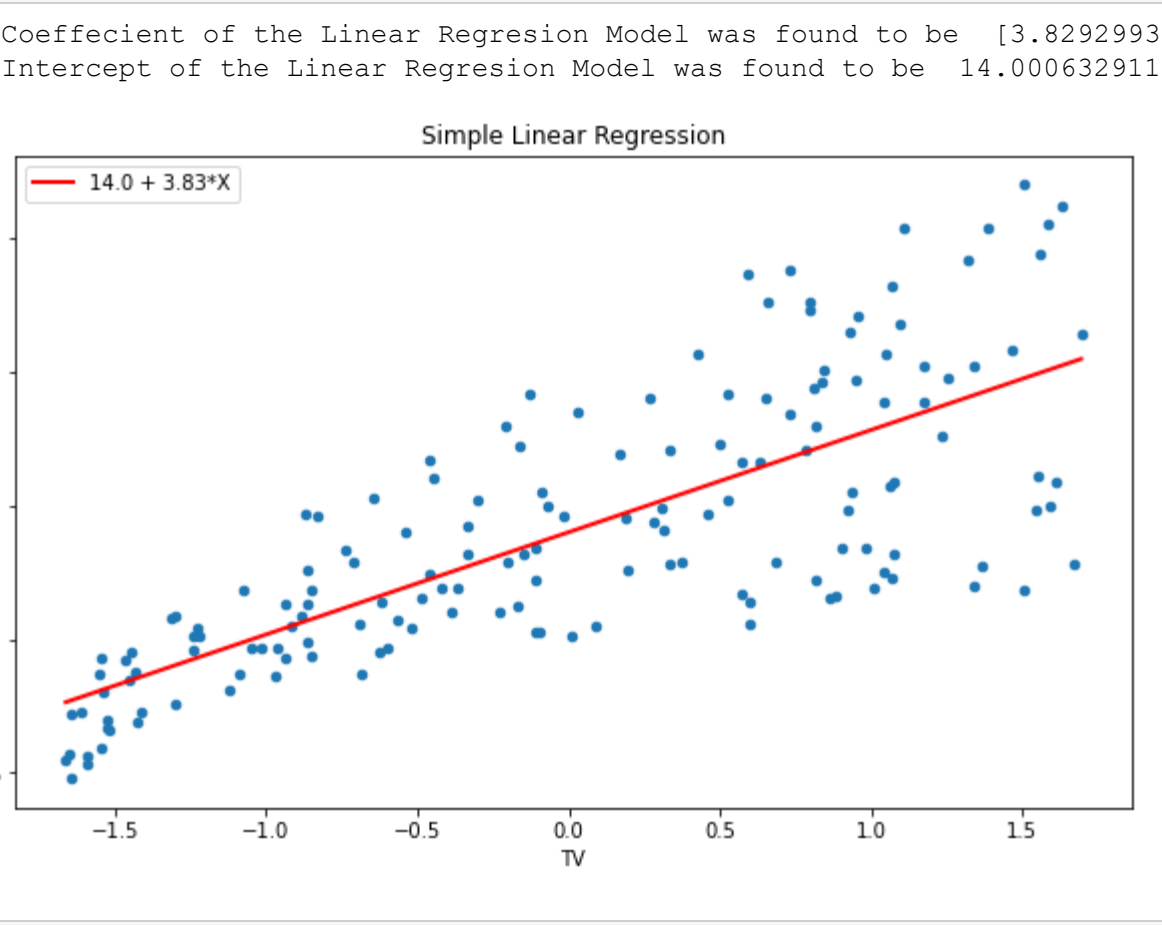
	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	7.0306	0.462	15.219	0.000	6.120	7.942
TV	0.0474	0.003	17.400	0.000	0.042	0.053

Omnibus:	0.404	Durbin-Watson:	1.872
Prob(Omnibus):	0.817	Jarque-Bera (JB):	0.551
Skew:	-0.062	Prob(JB):	0.759
Kurtosis:	2.774	Cond. No.	338.

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

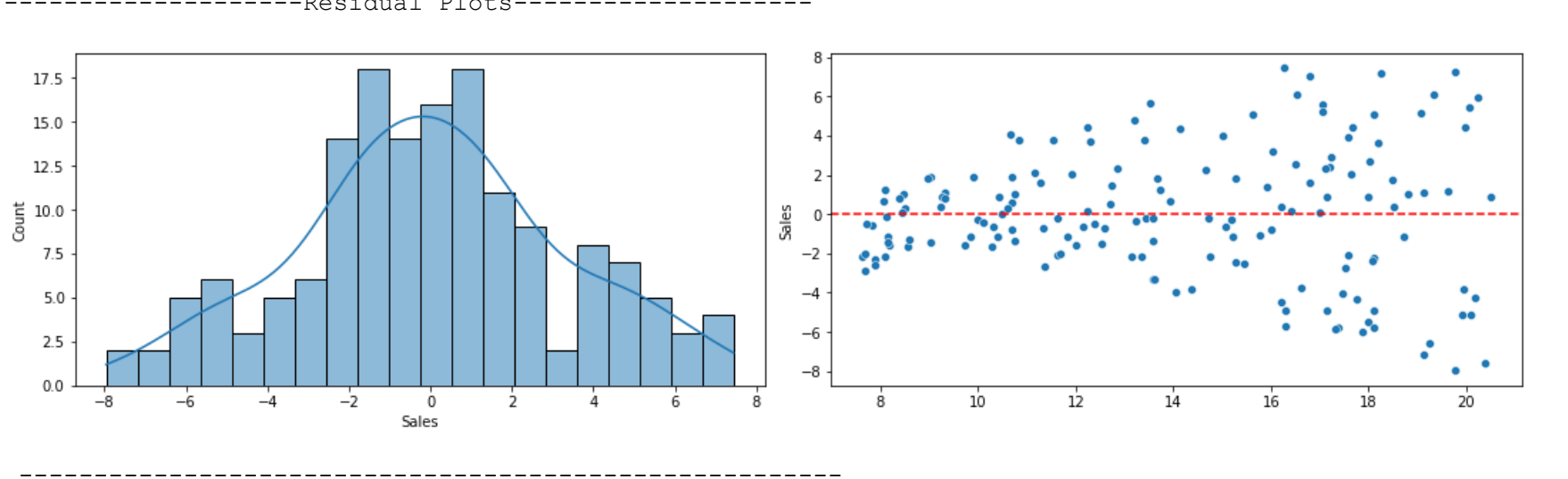
In [229]:
```
#Creating a Simple Linear Regression model with Sklearn

from sklearn.linear_model import LinearRegression
from sklearn.metrics import r2_score, mean_absolute_error, mean_squared_error

SLR = LinearRegression().fit(Train_X_std[[c[0]]],Train_Y)

print('The Coeffecient of the Linear Regresion Model was found to be ',SLR.coef_)
print('The Intercept of the Linear Regresion Model was found to be ',SLR.intercept_)

#Plotting predicted regression Line

Xmm = pd.DataFrame({'TV':[Train_X_std[[c[0]]].min().values[0],Train_X_std[[c[0]]].max().values[0]]})
RLine = SLR.predict(Xmm)

pd.concat([Train_X_std, pd.DataFrame(Train_Y.values, columns=['Sales'])], axis=1).plot(kind='scatter',x=c[0],y=c[3])
plt.plot(Xmm,RLine, c='r',linewidth=2, label=f'{round(SLR.intercept_,2)} + {round(SLR.coef_[0],2)}*X')
plt.title('Simple Linear Regression')
plt.legend()
plt.show()
```

```
The Coeffecient of the Linear Regresion Model was found to be  [3.82929935]
The Intercept of the Linear Regresion Model was found to be  14.000632911392405
```



In [230]:
```
#Evaluating the Simple Linear Regression Model

print('{}{}\033[1mEvaluating Simple Linear Regression Model\033[0m{}{}\n'.format('<'*3,'-'*35, '-'*35, '>'*3))

print('\n\n{}Training Set Metrics{}'.format('-'*20, '-'*20))
pred1 = SLR.predict(Train_X_std[[c[0]]])#Test_X_sm)
print('\nR2-Score on Training set --->',round(r2_score(Train_Y, pred1),2))
print('Residual Sum of Squares (RSS) on Training set  --->',round(np.sum(np.square(Train_Y-pred1)),2))
print('Mean Squared Error (MSE) on Training set       --->',round(mean_squared_error(Train_Y, pred1),2))
print('Root Mean Squared Error (RMSE) on Training set --->',round(np.sqrt(mean_squared_error(Train_Y, pred1)),2))

print('\n{}Test Set Metrics{}'.format('-'*20, '-'*20))
pred2 = SLR.predict(Test_X_std[[c[0]]])#Test_X_sm)
print('\nR2-Score on Testing set --->',round(r2_score(Test_Y, pred2),2))
print('Residual Sum of Squares (RSS) on Training set  --->',round(np.sum(np.square(Test_Y-pred2)),2))
print('Mean Squared Error (MSE) on Training set       --->',round(mean_squared_error(Test_Y, pred2),2))
print('Root Mean Squared Error (RMSE) on Training set --->',round(np.sqrt(mean_squared_error(Test_Y, pred2)),2))
print('\n{}Residual Plots{}'.format('-'*20, '-'*20))

plt.figure(figsize=[15,4])

plt.subplot(1,2,1)
residuals=(Train_Y-pred1)
sns.histplot(residuals, bins=20, kde=True)

plt.subplot(1,2,2)
sns.scatterplot(pred1, residuals)
plt.axhline(y=0, color='r', linestyle='--')
plt.tight_layout()
plt.show()

print('\n','-'*55)

print('\033[1m\nInference: \033[0m\nAs we can observe from the summary of the Simple Linear Regression Model, we can note \
that the regression line fits well on the data & the error terms are normally distributed. Let us futher check if we get \
Resiudal scores for multiple regression model')
```

```
<<<-----------------------------------Evaluating Simple Linear Regression Model----------------------------------->>>



--------------------Training Set Metrics--------------------

R2-Score on Training set ---> 0.58
Residual Sum of Squares (RSS) on Training set  ---> 1681.01
Mean Squared Error (MSE) on Training set       ---> 10.64
Root Mean Squared Error (RMSE) on Training set ---> 3.26

--------------------Test Set Metrics--------------------

R2-Score on Testing set ---> 0.68
Residual Sum of Squares (RSS) on Training set  ---> 418.4
Mean Squared Error (MSE) on Training set       ---> 10.46
Root Mean Squared Error (RMSE) on Training set ---> 3.23

--------------------Residual Plots--------------------
```




```
 -------------------------------------------------------
```

Inference:
As we can observe from the summary of the Simple Linear Regression Model, we can note that the regression line fits well on the data & the error terms are normally distributed. Let us futher check if we get Resiudal scores for multiple regression model

In [231]:
```
#Let create a function to store the results of all the regression models

Model_Evaluation_Comparison_Matrix = pd.DataFrame(np.zeros([7,7]), columns=['R2-Score','Train_RSS', 'Train_MSE','Train_RMSE','Test_RSS', 'Test_MSE','Test_RMSE'])
Model_Evaluation_Comparison_Matrix.index=['SLR', 'MLR', 'RLR', 'LLR', 'ENR', 'PR3', 'PR6']
Model_Evaluation_Comparison_Matrix

def ME(p1,p2,a):
    Model_Evaluation_Comparison_Matrix.loc[a,'R2-Score']=round(r2_score(Train_Y, pred1),2)
    Model_Evaluation_Comparison_Matrix.loc[a,'Train_RSS']=round(np.sum(np.square(Train_Y-pred1)),2)
    Model_Evaluation_Comparison_Matrix.loc[a,'Train_MSE']=round(mean_squared_error(Train_Y, pred1),2)
    Model_Evaluation_Comparison_Matrix.loc[a,'Train_RMSE']=round(np.sqrt(mean_squared_error(Train_Y, pred1)),2)
    Model_Evaluation_Comparison_Matrix.loc[a,'Test_RSS']=round(np.sum(np.square(Test_Y-pred2)),2)
    Model_Evaluation_Comparison_Matrix.loc[a,'Test_MSE']=round(mean_squared_error(Test_Y, pred2),2)
    Model_Evaluation_Comparison_Matrix.loc[a,'Test_RMSE']=round(np.sqrt(mean_squared_error(Test_Y, pred2)),2)

ME(pred1, pred2,'SLR')

Model_Evaluation_Comparison_Matrix
```

Out[231]:

	R2-Score	Train_RSS	Train_MSE	Train_RMSE	Test_RSS	Test_MSE	Test_RMSE
SLR	0.58	1681.01	10.64	3.26	418.4	10.46	3.23
MLR	0.00	0.00	0.00	0.00	0.0	0.00	0.00
RLR	0.00	0.00	0.00	0.00	0.0	0.00	0.00
LLR	0.00	0.00	0.00	0.00	0.0	0.00	0.00
ENR	0.00	0.00	0.00	0.00	0.0	0.00	0.00
PR3	0.00	0.00	0.00	0.00	0.0	0.00	0.00
PR6	0.00	0.00	0.00	0.00	0.0	0.00	0.00

7. Multiple Regression Model

In [232]:
```
#Creating a Linear Regression model with statsmodels

from statsmodels.formula import api
API = api.ols(formula=f'{c[3]} ~ {c[0]} + {c[1]} + {c[2]}', data=df).fit()
#print(API.conf_int())
#print(API.pvalues)
API.summary()
```

Out[232]:

OLS Regression Results

Dep. Variable:	Sales	R-squared:	0.895
Model:	OLS	Adj. R-squared:	0.894
Method:	Least Squares	F-statistic:	553.5
Date:	Mon, 08 Nov 2021	Prob (F-statistic):	8.35e-95
Time:	19:35:16	Log-Likelihood:	-383.24
No. Observations:	198	AIC:	774.5
Df Residuals:	194	BIC:	787.6
Df Model:	3		
Covariance Type:	nonrobust		

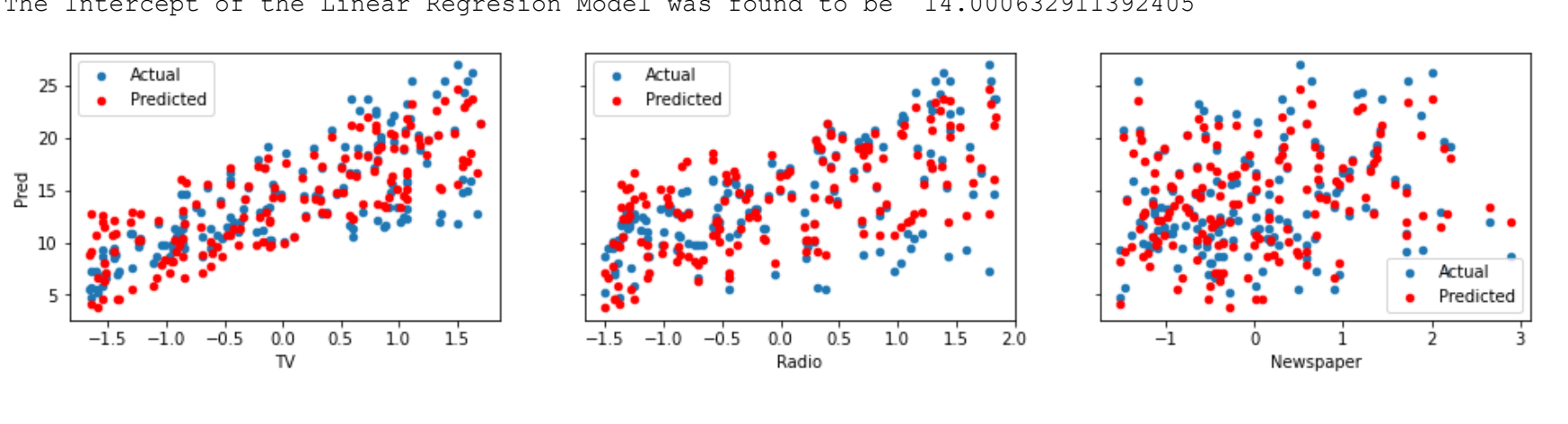
	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	2.9523	0.318	9.280	0.000	2.325	3.580
TV	0.0457	0.001	32.293	0.000	0.043	0.048
Radio	0.1886	0.009	21.772	0.000	0.171	0.206
Newspaper	-0.0012	0.006	-0.187	0.852	-0.014	0.011

Omnibus:	59.593	Durbin-Watson:	2.041
Prob(Omnibus):	0.000	Jarque-Bera (JB):	147.654
Skew:	-1.324	Prob(JB):	8.66e-33
Kurtosis:	6.299	Cond. No.	457.

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

In [233]:
```
#Creating a Multiple Linear Regression model with Sklearn

from sklearn.linear_model import LinearRegression
from sklearn.metrics import r2_score, mean_absolute_error, mean_squared_error

MLR = LinearRegression().fit(Train_X_std,Train_Y)

print('The Coeffecient of the Linear Regresion Model was found to be ',MLR.coef_)
print('The Intercept of the Linear Regresion Model was found to be ',MLR.intercept_)

#Plotting predicted predicteds alongside the actual datapoints

pred = MLR.predict(Train_X_std)

fig,axs = plt.subplots(1,3, sharey=True)
Tr=pd.concat([Train_X_std, pd.DataFrame(Train_Y.values, columns=['Sales'])], axis=1)
Ts=pd.concat([Test_X_std, pd.DataFrame(Test_Y.values, columns=['Sales'])], axis=1)

Pr = Tr.copy()
Pr['Pred'] = pred

Tr.plot(kind='scatter',x='TV',y='Sales', ax=axs[0], figsize=(16,3), label='Actual')
Pr.plot(kind='scatter',x='TV',y='Pred',ax=axs[0], color='r', label='Predicted')

Tr.plot(kind='scatter',x='Radio',y='Sales',ax=axs[1], label='Actual')
Pr.plot(kind='scatter',x='Radio',y='Pred',ax=axs[1], color='r', label='Predicted')

Tr.plot(kind='scatter',x='Newspaper',y='Sales',ax=axs[2], label='Actual')
Pr.plot(kind='scatter',x='Newspaper',y='Pred',ax=axs[2], color='r', label='Predicted')

plt.show()
```

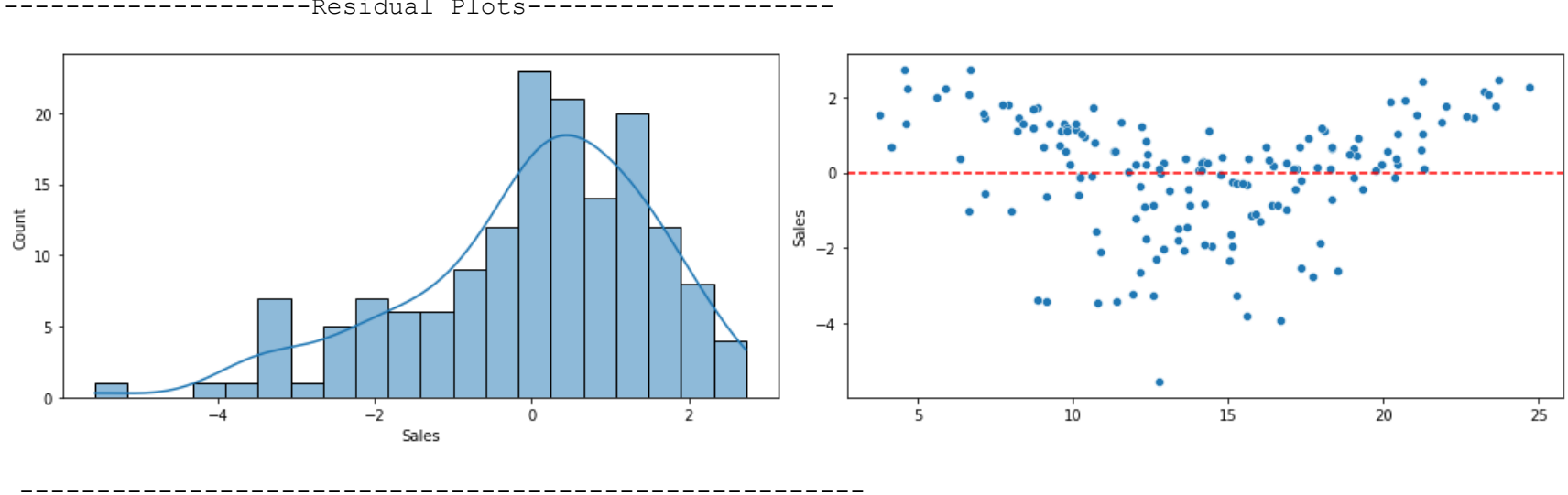
```
The Coeffecient of the Linear Regresion Model was found to be  [ 3.69637815  2.94662484 -0.19283051]
The Intercept of the Linear Regresion Model was found to be  14.000632911392405
```



In [234]:

```
#Evaluating the Multiple Linear Regression Model

print('{}{}\033[1mEvaluating Simple Linear Regression Model\033[0m{}{}\n'.format('<'*3,'-'*35, '-'*35,
'>'*3))

print('\n\n{}Training Set Metrics{}'.format('-'*20, '-'*20))
pred1 = MLR.predict(Train_X_std) #Test_X_sm)
print('\nR2-Score on Training set --->',round(r2_score(Train_Y, pred1),2))
print('Residual Sum of Squares (RSS) on Training set  --->',round(np.sum(np.square(Train_Y-pred1)),2))
print('Mean Squared Error (MSE) on Training set       --->',round(mean_squared_error(Train_Y, pred1),2
))
print('Root Mean Squared Error (RMSE) on Training set --->',round(np.sqrt(mean_squared_error(Train_Y, p
red1)),2))

print('\n{}Test Set Metrics{}'.format('-'*20, '-'*20))
pred2 = MLR.predict(Test_X_std) #Test_X_sm)
print('\nR2-Score on Testing set --->',round(r2_score(Test_Y, pred2),2))
print('Residual Sum of Squares (RSS) on Training set  --->',round(np.sum(np.square(Test_Y-pred2)),2))
print('Mean Squared Error (MSE) on Training set       --->',round(mean_squared_error(Test_Y, pred2),2))
print('Root Mean Squared Error (RMSE) on Training set --->',round(np.sqrt(mean_squared_error(Test_Y, pr
ed2)),2))
print('\n{}Residual Plots{}'.format('-'*20, '-'*20))

ME(pred1, pred2,'MLR')
plt.figure(figsize=[15,4])

plt.subplot(1,2,1)
residuals=(Train_Y-pred1)
sns.histplot(residuals, bins=20, kde=True)

plt.subplot(1,2,2)
sns.scatterplot(pred1, residuals)
plt.axhline(y=0, color='r', linestyle='--')
plt.tight_layout()
plt.show()

print('\n','-'*55)

print('\033[1m\nInference: \033[0m\nAs we can observe from the summary of the Multiple Regression Mode
l, we can note \
that it performs better compared to the SLR, but the error terms are slightly not normally distributed
 around 0. \
Let us futher check for the Resiudal scores for other regression models')
```

```
<<<-----------------------------------Evaluating Simple Linear Regression Model-----------------------------------
>>>



--------------------Training Set Metrics--------------------

R2-Score on Training set ---> 0.9
Residual Sum of Squares (RSS) on Training set  ---> 381.14
Mean Squared Error (MSE) on Training set       ---> 2.41
Root Mean Squared Error (RMSE) on Training set ---> 1.55

--------------------Test Set Metrics--------------------

R2-Score on Testing set ---> 0.86
Residual Sum of Squares (RSS) on Training set  ---> 190.69
Mean Squared Error (MSE) on Training set       ---> 4.77
Root Mean Squared Error (RMSE) on Training set ---> 2.18

--------------------Residual Plots--------------------
```




```
 -------------------------------------------------------
```

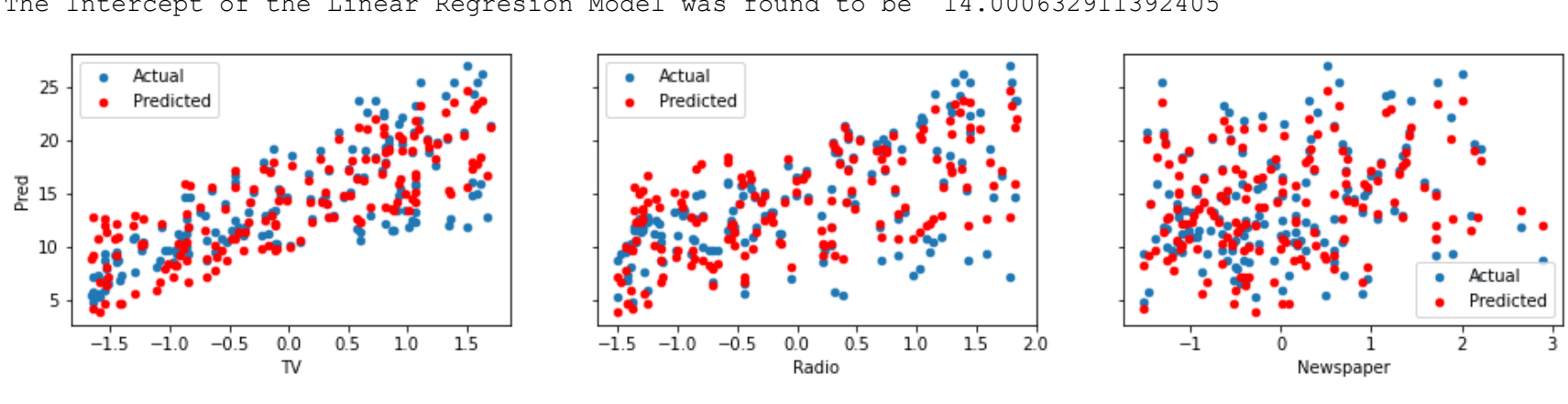
Inference:
As we can observe from the summary of the Multiple Regression Model, we can note that it performs better compared to the SLR, but the error terms are slightly not normally distributed around 0. Let us further check for the Resiudal scores for other regression models

8. Ridge, Lasso & ElasticNet Regression Models

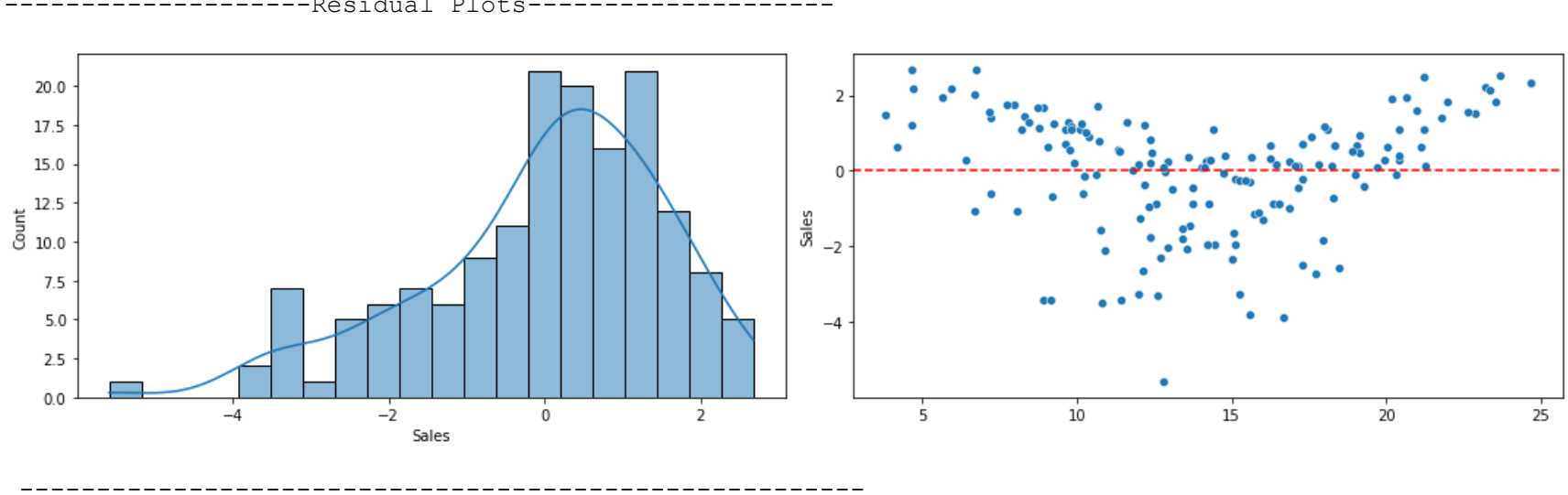
In [235]:

```
#Creating a Ridge Regression model

from sklearn.linear_model import Ridge

print('{}{}\033[1mTraining Ridge Regression Model\033[0m{}{}\n'.format('<'*3,'-'*35, '-'*35,'>'*3))

RLR = Ridge().fit(Train_X_std,Train_Y)

print('The Coeffecient of the Linear Regresion Model was found to be ',RLR.coef_)
print('The Intercept of the Linear Regresion Model was found to be ',RLR.intercept_)

#Plotting predicted predicteds alongside the actual datapoints

pred = RLR.predict(Train_X_std)

fig,axs = plt.subplots(1,3, sharey=True)
Tr=pd.concat([Train_X_std, pd.DataFrame(Train_Y.values, columns=['Sales'])], axis=1)
Ts=pd.concat([Test_X_std, pd.DataFrame(Test_Y.values, columns=['Sales'])], axis=1)

Pr = Tr.copy()
Pr['Pred'] = pred

Tr.plot(kind='scatter',x='TV',y='Sales', ax=axs[0], figsize=(16,3), label='Actual')
Pr.plot(kind='scatter',x='TV',y='Pred',ax=axs[0], color='r', label='Predicted')

Tr.plot(kind='scatter',x='Radio',y='Sales',ax=axs[1], label='Actual')
Pr.plot(kind='scatter',x='Radio',y='Pred',ax=axs[1], color='r', label='Predicted')

Tr.plot(kind='scatter',x='Newspaper',y='Sales',ax=axs[2], label='Actual')
Pr.plot(kind='scatter',x='Newspaper',y='Pred',ax=axs[2], color='r', label='Predicted')

plt.show()

#Evaluating the Simple Linear Regression Model

print('{}{}\033[1mEvaluating Ridge Regression Model\033[0m{}{}\n'.format('<'*3,'-'*35, '-'*35,'>'*3))

print('\n\n{}Training Set Metrics{}'.format('-'*20, '-'*20))
pred1 = RLR.predict(Train_X_std) #Test_X_sm)
print('\nR2-Score on Training set --->',round(r2_score(Train_Y, pred1),2))
print('Residual Sum of Squares (RSS) on Training set  --->',round(np.sum(np.square(Train_Y-pred1)),2))
print('Mean Squared Error (MSE) on Training set       --->',round(mean_squared_error(Train_Y, pred1),2
))
print('Root Mean Squared Error (RMSE) on Training set --->',round(np.sqrt(mean_squared_error(Train_Y, p
red1)),2))

print('\n{}Test Set Metrics{}'.format('-'*20, '-'*20))
pred2 = RLR.predict(Test_X_std) #Test_X_sm)
print('\nR2-Score on Testing set --->',round(r2_score(Test_Y, pred2),2))
print('Residual Sum of Squares (RSS) on Training set  --->',round(np.sum(np.square(Test_Y-pred2)),2))
print('Mean Squared Error (MSE) on Training set       --->',round(mean_squared_error(Test_Y, pred2),2))
print('Root Mean Squared Error (RMSE) on Training set --->',round(np.sqrt(mean_squared_error(Test_Y, pr
ed2)),2))
print('\n{}Residual Plots{}'.format('-'*20, '-'*20))

ME(pred1, pred2,'RLR')
plt.figure(figsize=[15,4])

plt.subplot(1,2,1)
residuals=(Train_Y-pred1)
sns.histplot(residuals, bins=20, kde=True)

plt.subplot(1,2,2)
sns.scatterplot(pred1, residuals)
plt.axhline(y=0, color='r', linestyle='--')
plt.tight_layout()
plt.show()

print('\n','-'*55)

print('\033[1m\nInference: \033[0m\nAs we can observe from the summary of the Multiple Regression Mode
l, we can note \
that it performs better compared to the SLR, but the error terms are slightly not normally distributed
 around 0. \
Let us futher check for the Resiudal scores for other regression models')
```

```
<<<-----------------------------------Training Ridge Regression Model-----------------------------------
--->>>

The Coeffecient of the Linear Regresion Model was found to be  [ 3.67402151  2.92473564 -0.18230258]
The Intercept of the Linear Regresion Model was found to be  14.000632911392405
```




```
<<<-----------------------------------Evaluating Ridge Regression Model-----------------------------------
----->>>



--------------------Training Set Metrics--------------------

R2-Score on Training set ---> 0.9
Residual Sum of Squares (RSS) on Training set  ---> 381.29
Mean Squared Error (MSE) on Training set       ---> 2.41
Root Mean Squared Error (RMSE) on Training set ---> 1.55

--------------------Test Set Metrics--------------------

R2-Score on Testing set ---> 0.86
Residual Sum of Squares (RSS) on Training set  ---> 191.07
Mean Squared Error (MSE) on Training set       ---> 4.78
Root Mean Squared Error (RMSE) on Training set ---> 2.19

--------------------Residual Plots--------------------
```



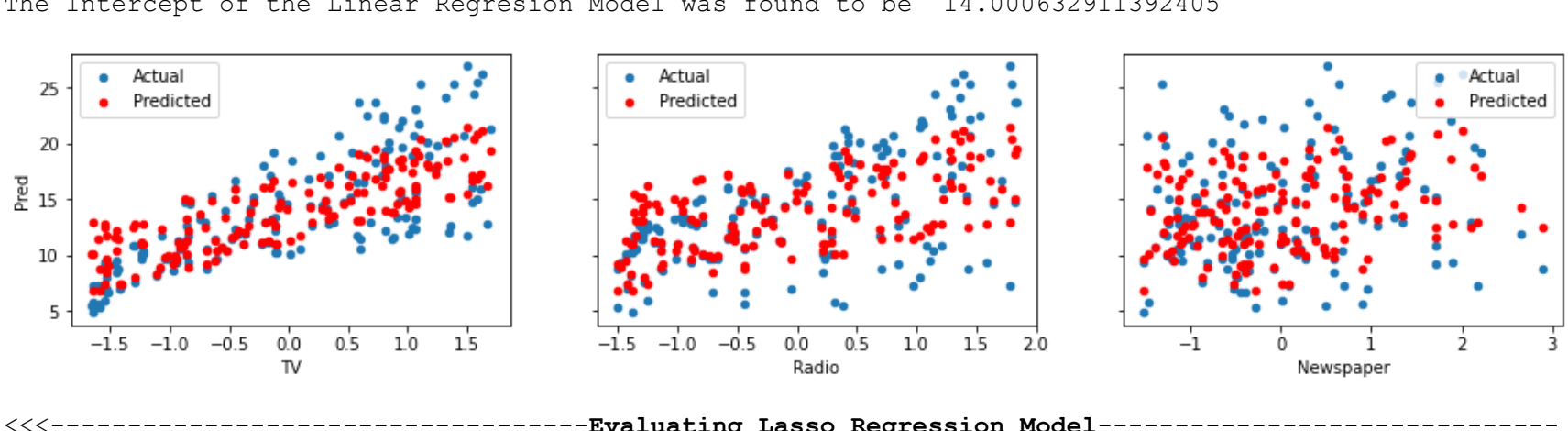

```
 -------------------------------------------------------
```

Inference:
As we can observe from the summary of the Multiple Regression Model, we can note that it performs better compared to the SLR, but the error terms are slightly not normally distributed around 0. Let us further check for the Resiudal scores for other regression models

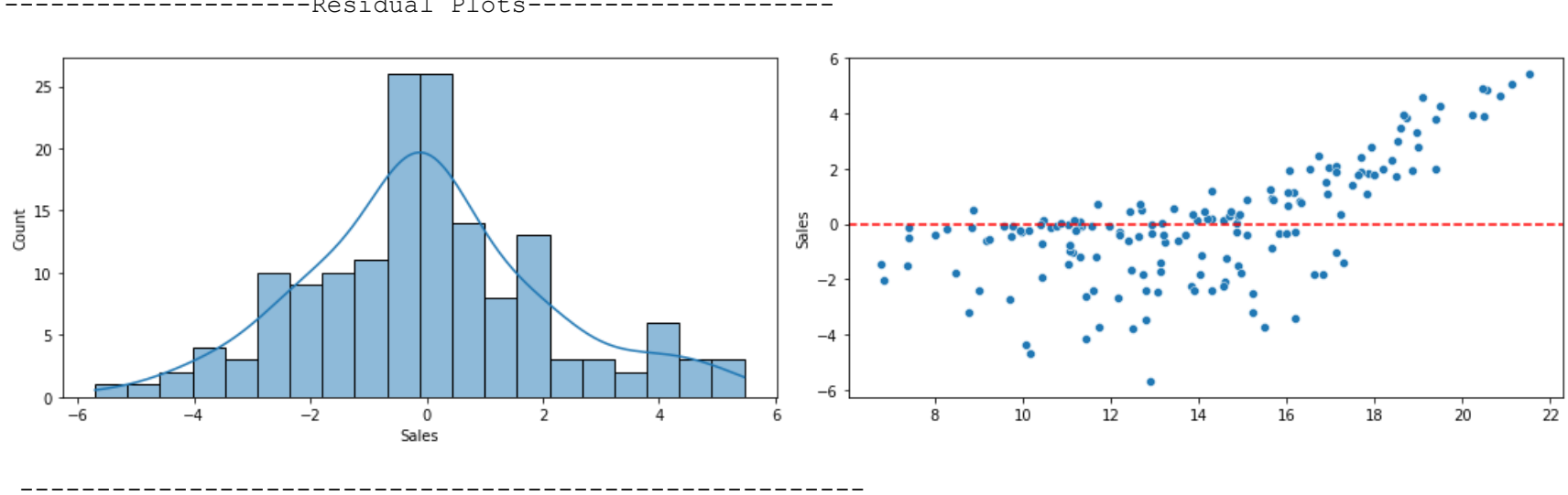
In [236]:

```
#Creating a Ridge Regression model

from sklearn.linear_model import Lasso

print('{}{}\033[1mTraining Lasso Regression Model\033[0m{}{}\n'.format('<'*3,'-'*35, '-'*35,'>'*3))

LLR = Lasso().fit(Train_X_std,Train_Y)

print('The Coeffecient of the Linear Regresion Model was found to be ',LLR.coef_)
print('The Intercept of the Linear Regresion Model was found to be ',LLR.intercept_)

#Plotting predicted predicteds alongside the actual datapoints

pred = LLR.predict(Train_X_std)

fig,axs = plt.subplots(1,3, sharey=True)
Tr=pd.concat([Train_X_std, pd.DataFrame(Train_Y.values, columns=['Sales'])], axis=1)
Ts=pd.concat([Test_X_std, pd.DataFrame(Test_Y.values, columns=['Sales'])], axis=1)

Pr = Tr.copy()
Pr['Pred'] = pred

Tr.plot(kind='scatter',x='TV',y='Sales', ax=axs[0], figsize=(16,3), label='Actual')
Pr.plot(kind='scatter',x='TV',y='Pred',ax=axs[0], color='r', label='Predicted')

Tr.plot(kind='scatter',x='Radio',y='Sales',ax=axs[1], label='Actual')
Pr.plot(kind='scatter',x='Radio',y='Pred',ax=axs[1], color='r', label='Predicted')

Tr.plot(kind='scatter',x='Newspaper',y='Sales',ax=axs[2], label='Actual')
Pr.plot(kind='scatter',x='Newspaper',y='Pred',ax=axs[2], color='r', label='Predicted')

plt.show()

#Evaluating the Simple Linear Regression Model

print('{}{}\033[1mEvaluating Lasso Regression Model\033[0m{}{}\n'.format('<'*3,'-'*35, '-'*35,'>'*3))

print('\n\n{}Training Set Metrics{}'.format('-'*20, '-'*20))
pred1 = LLR.predict(Train_X_std) #Test_X_sm)
print('\nR2-Score on Training set --->',round(r2_score(Train_Y, pred1),2))
print('Residual Sum of Squares (RSS) on Training set  --->',round(np.sum(np.square(Train_Y-pred1)),2))
print('Mean Squared Error (MSE) on Training set       --->',round(mean_squared_error(Train_Y, pred1),2
))
print('Root Mean Squared Error (RMSE) on Training set --->',round(np.sqrt(mean_squared_error(Train_Y, p
red1)),2))

print('\n{}Test Set Metrics{}'.format('-'*20, '-'*20))
pred2 = LLR.predict(Test_X_std) #Test_X_sm)
print('\nR2-Score on Testing set --->',round(r2_score(Test_Y, pred2),2))
print('Residual Sum of Squares (RSS) on Training set  --->',round(np.sum(np.square(Test_Y-pred2)),2))
print('Mean Squared Error (MSE) on Training set       --->',round(mean_squared_error(Test_Y, pred2),2))
print('Root Mean Squared Error (RMSE) on Training set --->',round(np.sqrt(mean_squared_error(Test_Y, pr
ed2)),2))
print('\n{}Residual Plots{}'.format('-'*20, '-'*20))

ME(pred1, pred2,'LLR')
plt.figure(figsize=[15,4])

plt.subplot(1,2,1)
residuals=(Train_Y-pred1)
sns.histplot(residuals, bins=20, kde=True)

plt.subplot(1,2,2)
sns.scatterplot(pred1, residuals)
plt.axhline(y=0, color='r', linestyle='--')
plt.tight_layout()
plt.show()

print('\n','-'*55)

print('\033[1m\nInference: \033[0m\nAs we can observe from the summary of the Multiple Regression Mode
l, we can note \
that it performs better compared to the SLR, but the error terms are slightly not normally distributed
 around 0. \
Let us futher check for the Resiudal scores for other regression models')
```

```
<<<-----------------------------------Training Lasso Regression Model-----------------------------------
--->>>

The Coeffecient of the Linear Regresion Model was found to be  [2.74190729 1.909689   0.        ]
The Intercept of the Linear Regresion Model was found to be  14.000632911392405
```




```
<<<-----------------------------------Evaluating Lasso Regression Model-----------------------------------
----->>>



--------------------Training Set Metrics--------------------

R2-Score on Training set ---> 0.83
Residual Sum of Squares (RSS) on Training set  ---> 688.16
Mean Squared Error (MSE) on Training set       ---> 4.36
Root Mean Squared Error (RMSE) on Training set ---> 2.09

--------------------Test Set Metrics--------------------

R2-Score on Testing set ---> 0.77
Residual Sum of Squares (RSS) on Training set  ---> 299.78
Mean Squared Error (MSE) on Training set       ---> 7.49
Root Mean Squared Error (RMSE) on Training set ---> 2.74

--------------------Residual Plots--------------------
```



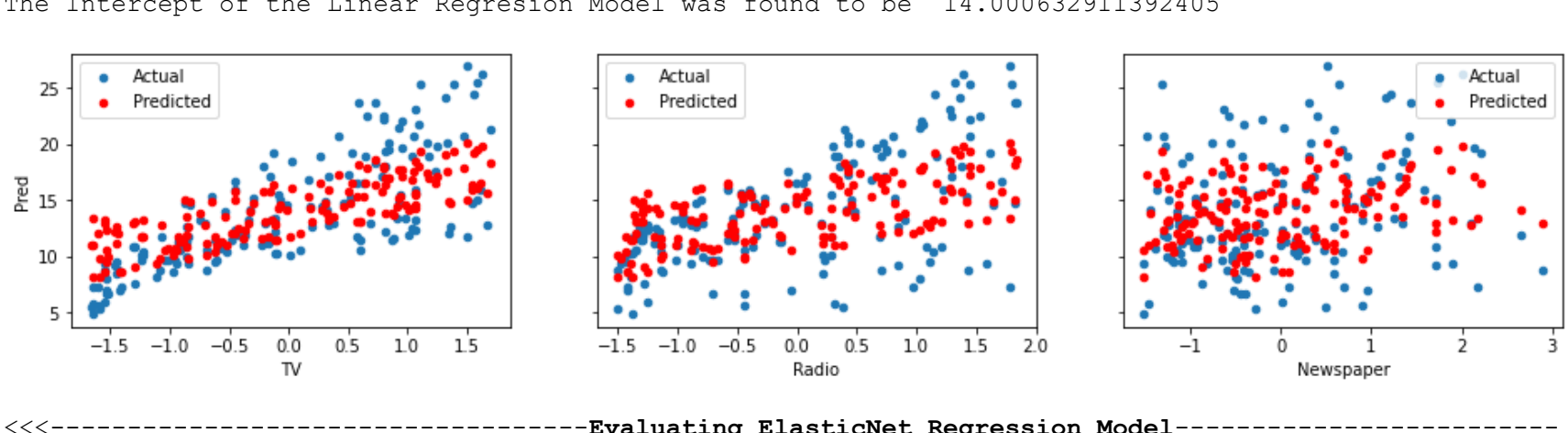

```
 -------------------------------------------------------
```

Inference:
As we can observe from the summary of the Multiple Regression Model, we can note that it performs better compared to the SLR, but the error terms are slightly not normally distributed around 0. Let us further check for the Resiudal scores for other regression models

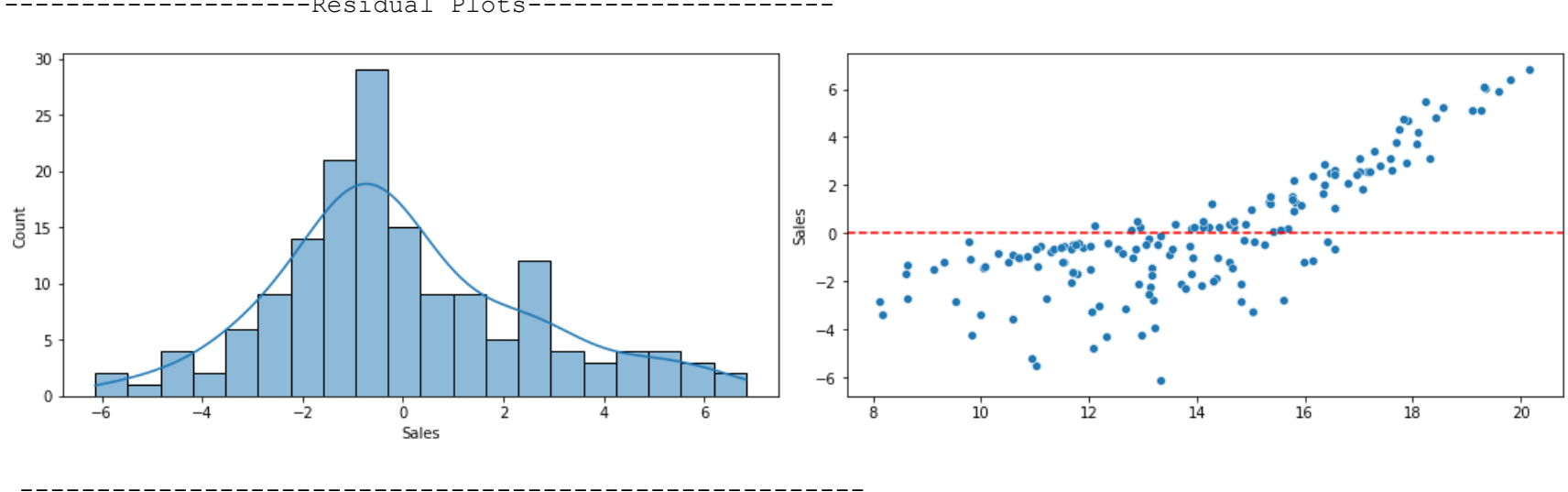
In [237]:

```
#Creating a ElasticNet Regression model

from sklearn.linear_model import ElasticNet

print('{}{}\033[1mTraining ElasticNet Regression Model\033[0m{}{}\n'.format('<'*3,'-'*35, '-'*35,'>'*3
))

ENR = ElasticNet().fit(Train_X_std,Train_Y)

print('The Coeffecient of the Linear Regresion Model was found to be ',ENR.coef_)
print('The Intercept of the Linear Regresion Model was found to be ',ENR.intercept_)

#Plotting predicted predicteds alongside the actual datapoints

pred = ENR.predict(Train_X_std)

fig,axs = plt.subplots(1,3, sharey=True)
Tr=pd.concat([Train_X_std, pd.DataFrame(Train_Y.values, columns=['Sales'])], axis=1)
Ts=pd.concat([Test_X_std, pd.DataFrame(Test_Y.values, columns=['Sales'])], axis=1)

Pr = Tr.copy()
Pr['Pred'] = pred

Tr.plot(kind='scatter',x='TV',y='Sales', ax=axs[0], figsize=(16,3), label='Actual')
Pr.plot(kind='scatter',x='TV',y='Pred',ax=axs[0], color='r', label='Predicted')

Tr.plot(kind='scatter',x='Radio',y='Sales',ax=axs[1], label='Actual')
Pr.plot(kind='scatter',x='Radio',y='Pred',ax=axs[1], color='r', label='Predicted')

Tr.plot(kind='scatter',x='Newspaper',y='Sales',ax=axs[2], label='Actual')
Pr.plot(kind='scatter',x='Newspaper',y='Pred',ax=axs[2], color='r', label='Predicted')

plt.show()

#Evaluating the Simple Linear Regression Model

print('{}{}\033[1mEvaluating ElasticNet Regression Model\033[0m{}{}\n'.format('<'*3,'-'*35, '-'*35,'>'*
3))

print('\n\n{}Training Set Metrics{}'.format('-'*20, '-'*20))
pred1 = ENR.predict(Train_X_std) #Test_X_sm)
print('\nR2-Score on Training set --->',round(r2_score(Train_Y, pred1),2))
print('Residual Sum of Squares (RSS) on Training set  --->',round(np.sum(np.square(Train_Y-pred1)),2))
print('Mean Squared Error (MSE) on Training set       --->',round(mean_squared_error(Train_Y, pred1),2
))
print('Root Mean Squared Error (RMSE) on Training set --->',round(np.sqrt(mean_squared_error(Train_Y, p
red1)),2))

print('\n{}Test Set Metrics{}'.format('-'*20, '-'*20))
pred2 = ENR.predict(Test_X_std) #Test_X_sm)
print('\nR2-Score on Testing set --->',round(r2_score(Test_Y, pred2),2))
print('Residual Sum of Squares (RSS) on Training set  --->',round(np.sum(np.square(Test_Y-pred2)),2))
print('Mean Squared Error (MSE) on Training set       --->',round(mean_squared_error(Test_Y, pred2),2))
print('Root Mean Squared Error (RMSE) on Training set --->',round(np.sqrt(mean_squared_error(Test_Y, pr
ed2)),2))
print('\n{}Residual Plots{}'.format('-'*20, '-'*20))

ME(pred1, pred2,'ENR')
plt.figure(figsize=[15,4])

plt.subplot(1,2,1)
residuals=(Train_Y-pred1)
sns.histplot(residuals, bins=20, kde=True)

plt.subplot(1,2,2)
sns.scatterplot(pred1, residuals)
plt.axhline(y=0, color='r', linestyle='--')
plt.tight_layout()
plt.show()

print('\n','-'*55)

print('\033[1m\nInference: \033[0m\nAs we can observe from the summary of the Multiple Regression Mode
l, we can note \
that it performs better compared to the SLR, but the error terms are slightly not normally distributed
 around 0. \
Let us futher check for the Resiudal scores for other regression models')
```

```
<<<-----------------------------------Training ElasticNet Regression Model-----------------------------------
--------->>>

The Coeffecient of the Linear Regresion Model was found to be  [2.16999006 1.62390763 0.        ]
The Intercept of the Linear Regresion Model was found to be  14.000632911392405
```




```
<<<-----------------------------------Evaluating ElasticNet Regression Model-----------------------------------
---------->>>



--------------------Training Set Metrics--------------------

R2-Score on Training set ---> 0.74
Residual Sum of Squares (RSS) on Training set  ---> 1026.14
Mean Squared Error (MSE) on Training set       ---> 6.49
Root Mean Squared Error (RMSE) on Training set ---> 2.55

--------------------Test Set Metrics--------------------

R2-Score on Testing set ---> 0.68
Residual Sum of Squares (RSS) on Training set  ---> 422.57
Mean Squared Error (MSE) on Training set       ---> 10.56
Root Mean Squared Error (RMSE) on Training set ---> 3.25

--------------------Residual Plots--------------------
```




```
 -------------------------------------------------------
```

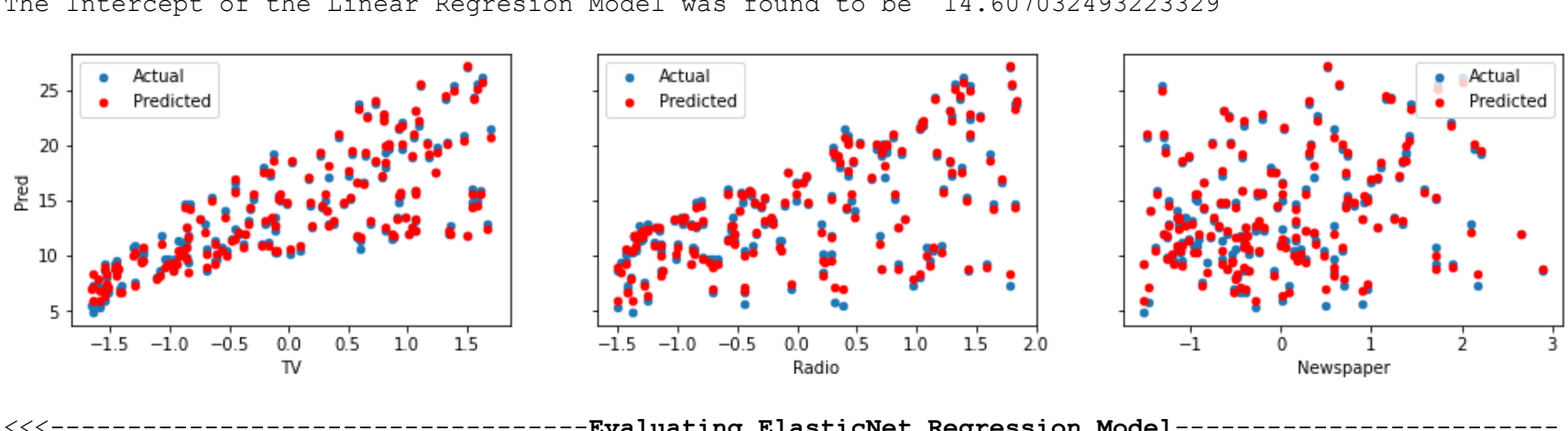
Inference:
As we can observe from the summary of the Multiple Regression Model, we can note that it performs better compared to the SLR, but the error terms are slightly not normally distributed around 0. Let us further check for the Resiudal scores for other regression models

9. Polynomial Regression Model

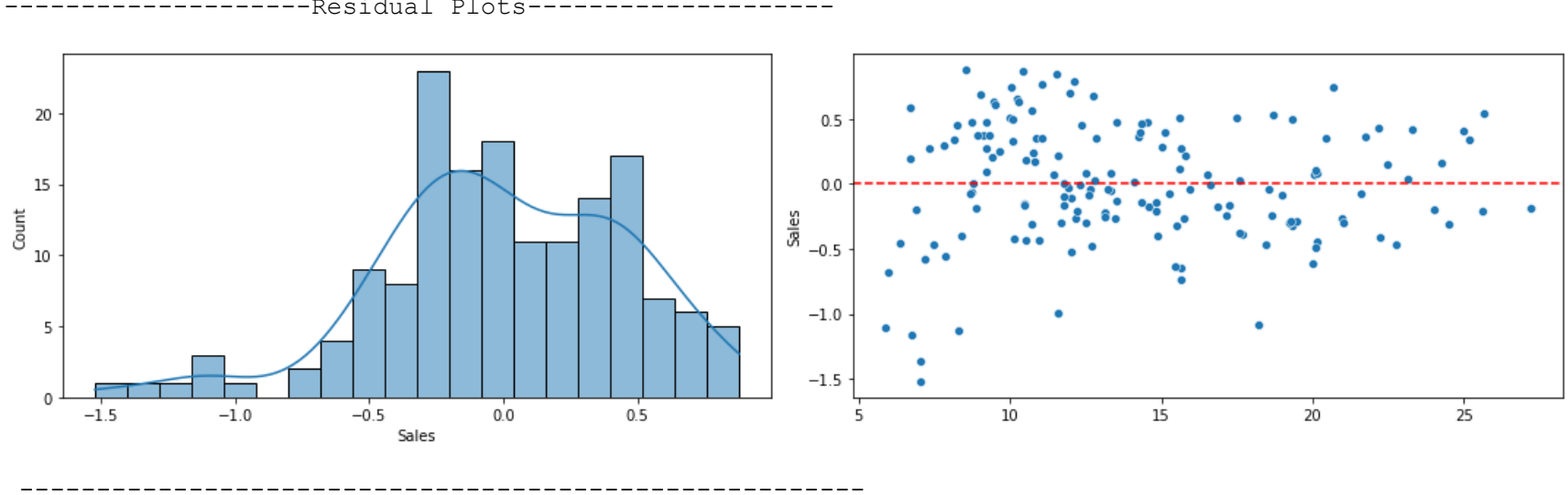
In [238]:

```
#Creating a Polynomial Regression model (degree=2)

from sklearn.preprocessing import PolynomialFeatures
poly_reg = PolynomialFeatures(degree=2)
X_poly = poly_reg.fit_transform(Train_X_std)
X_poly1 = poly_reg.fit_transform(Test_X_std)
PR2 = LinearRegression()
PR2.fit(X_poly, Train_Y)

print('The Coeffecient of the Linear Regresion Model was found to be ',PR2.coef_)
print('The Intercept of the Linear Regresion Model was found to be ',PR2.intercept_)

#Plotting predicted predicteds alongside the actual datapoints

pred = PR2.predict(X_poly)

fig,axs = plt.subplots(1,3, sharey=True)
Tr=pd.concat([Train_X_std, pd.DataFrame(Train_Y.values, columns=['Sales'])], axis=1)
Ts=pd.concat([Test_X_std, pd.DataFrame(Test_Y.values, columns=['Sales'])], axis=1)

Pr = Tr.copy()
Pr['Pred'] = pred

Tr.plot(kind='scatter',x='TV',y='Sales', ax=axs[0], figsize=(16,3), label='Actual')
Pr.plot(kind='scatter',x='TV',y='Pred',ax=axs[0], color='r', label='Predicted')

Tr.plot(kind='scatter',x='Radio',y='Sales',ax=axs[1], label='Actual')
Pr.plot(kind='scatter',x='Radio',y='Pred',ax=axs[1], color='r', label='Predicted')

Tr.plot(kind='scatter',x='Newspaper',y='Sales',ax=axs[2], label='Actual')
Pr.plot(kind='scatter',x='Newspaper',y='Pred',ax=axs[2], color='r', label='Predicted')

plt.show()

#Evaluating the Simple Linear Regression Model

print('{}{}\033[1mEvaluating ElasticNet Regression Model\033[0m{}{}\n'.format('<'*3,'-'*35, '-'*35,'>'*
3))

print('\n\n{}Training Set Metrics{}'.format('-'*20, '-'*20))
pred1 = PR2.predict(X_poly) #Test_X_sm)
print('\nR2-Score on Training set --->',round(r2_score(Train_Y, pred1),2))
print('Residual Sum of Squares (RSS) on Training set  --->',round(np.sum(np.square(Train_Y-pred1)),2))
print('Mean Squared Error (MSE) on Training set       --->',round(mean_squared_error(Train_Y, pred1),2
))
print('Root Mean Squared Error (RMSE) on Training set --->',round(np.sqrt(mean_squared_error(Train_Y, p
red1)),2))

print('\n{}Test Set Metrics{}'.format('-'*20, '-'*20))
pred2 = PR2.predict(X_poly1) #Test_X_sm)
print('\nR2-Score on Testing set --->',round(r2_score(Test_Y, pred2),2))
print('Residual Sum of Squares (RSS) on Training set  --->',round(np.sum(np.square(Test_Y-pred2)),2))
print('Mean Squared Error (MSE) on Training set       --->',round(mean_squared_error(Test_Y, pred2),2))
print('Root Mean Squared Error (RMSE) on Training set --->',round(np.sqrt(mean_squared_error(Test_Y, pr
ed2)),2))
print('\n{}Residual Plots{}'.format('-'*20, '-'*20))

plt.figure(figsize=[15,4])

plt.subplot(1,2,1)
residuals=(Train_Y-pred1)
sns.histplot(residuals, bins=20, kde=True)

plt.subplot(1,2,2)
sns.scatterplot(pred1, residuals)
plt.axhline(y=0, color='r', linestyle='--')
plt.tight_layout()
plt.show()

print('\n','-'*55)

print('\033[1m\nInference: \033[0m\nAs we can observe from the summary of the 2nd order Polynomial Regr
ession Model, \
we can note that it performs better compared to the MLR, Let us check with higher degree Models.')
```

```
The Coeffecient of the Linear Regresion Model was found to be  [ 0.00000000e+00  3.56696251e+00  2.89
992429e+00 -6.09129639e-04
 -7.00059706e-01  1.30270164e+00  6.99507531e-03  2.68286612e-02
  2.17237704e-02 -1.93528832e-03]
The Intercept of the Linear Regresion Model was found to be  14.607032493223329
```




```
<<<-----------------------------------Evaluating ElasticNet Regression Model-----------------------------------
---------->>>



--------------------Training Set Metrics--------------------

R2-Score on Training set ---> 0.99
Residual Sum of Squares (RSS) on Training set  ---> 33.11
Mean Squared Error (MSE) on Training set       ---> 0.21
Root Mean Squared Error (RMSE) on Training set ---> 0.46

--------------------Test Set Metrics--------------------

R2-Score on Testing set ---> 0.97
Residual Sum of Squares (RSS) on Training set  ---> 45.89
Mean Squared Error (MSE) on Training set       ---> 1.15
Root Mean Squared Error (RMSE) on Training set ---> 1.07

--------------------Residual Plots--------------------
```



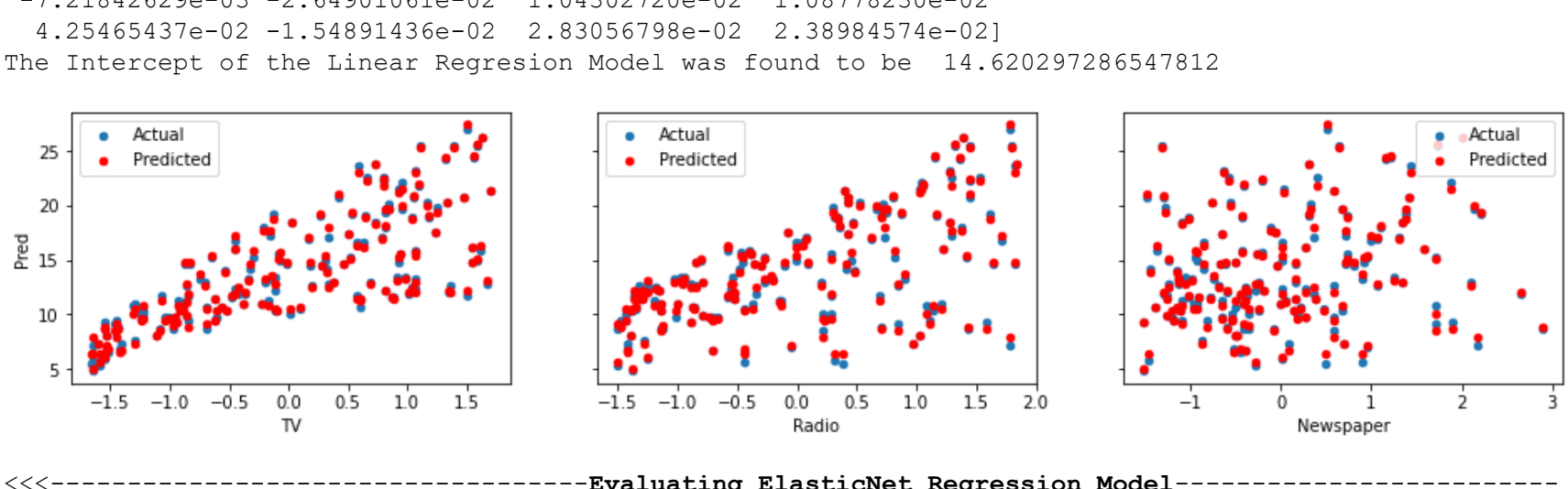

```
 -------------------------------------------------------
```

Inference:
As we can observe from the summary of the 2nd order Polynomial Regression Model, we can note that it performs better compared to the MLR, Let us check with higher degree Models.

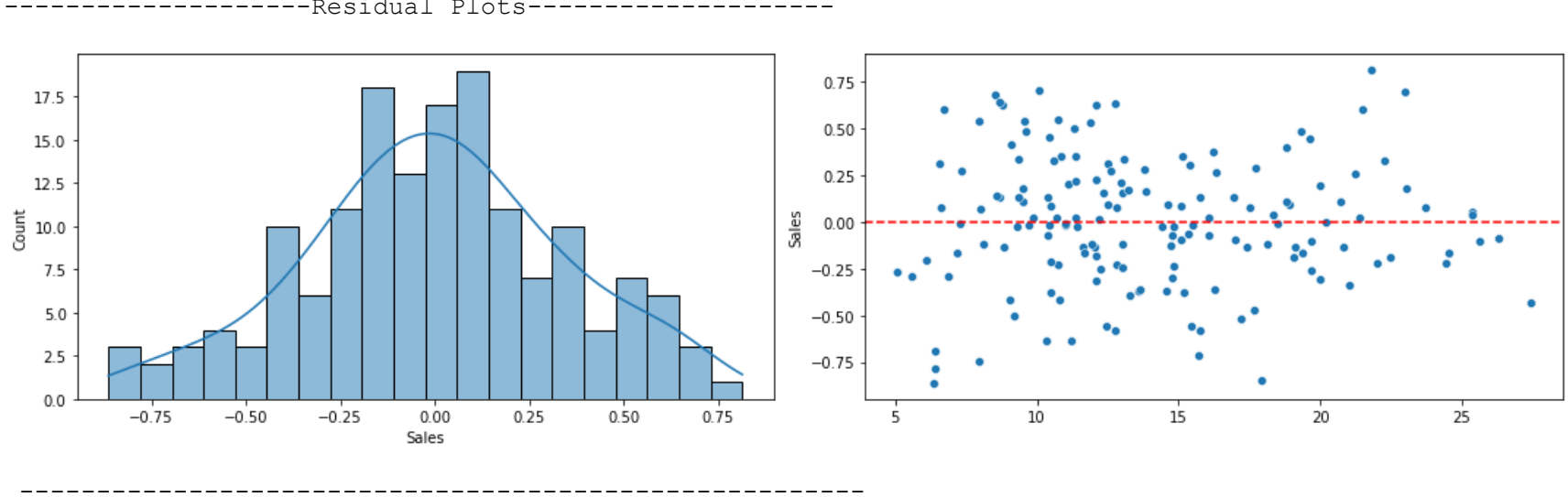
In [239]:

```
#Creating a Polynomial Regression model (degree=3)

from sklearn.preprocessing import PolynomialFeatures
poly_reg = PolynomialFeatures(degree=3)
X_poly = poly_reg.fit_transform(Train_X_std)
X_poly1 = poly_reg.fit_transform(Test_X_std)
PR3 = LinearRegression()
PR3.fit(X_poly, Train_Y)

print('The Coeffecient of the Linear Regresion Model was found to be ',PR3.coef_)
print('The Intercept of the Linear Regresion Model was found to be ',PR3.intercept_)

#Plotting predicted predicteds alongside the actual datapoints

pred = PR3.predict(X_poly)

fig,axs = plt.subplots(1,3, sharey=True)
Tr=pd.concat([Train_X_std, pd.DataFrame(Train_Y.values, columns=['Sales'])], axis=1)
Ts=pd.concat([Test_X_std, pd.DataFrame(Test_Y.values, columns=['Sales'])], axis=1)

Pr = Tr.copy()
Pr['Pred'] = pred

Tr.plot(kind='scatter',x='TV',y='Sales', ax=axs[0], figsize=(16,3), label='Actual')
Pr.plot(kind='scatter',x='TV',y='Pred',ax=axs[0], color='r', label='Predicted')

Tr.plot(kind='scatter',x='Radio',y='Sales',ax=axs[1], label='Actual')
Pr.plot(kind='scatter',x='Radio',y='Pred',ax=axs[1], color='r', label='Predicted')

Tr.plot(kind='scatter',x='Newspaper',y='Sales',ax=axs[2], label='Actual')
Pr.plot(kind='scatter',x='Newspaper',y='Pred',ax=axs[2], color='r', label='Predicted')

plt.show()

#Evaluating the Simple Linear Regression Model

print('{}{}\033[1mEvaluating ElasticNet Regression Model\033[0m{}{}\n'.format('<'*3,'-'*35, '-'*35,'>'*
3))

print('\n\n{}Training Set Metrics{}'.format('-'*20, '-'*20))
pred1 = PR3.predict(X_poly) #Test_X_sm)
print('\nR2-Score on Training set --->',round(r2_score(Train_Y, pred1),2))
print('Residual Sum of Squares (RSS) on Training set  --->',round(np.sum(np.square(Train_Y-pred1)),2))
print('Mean Squared Error (MSE) on Training set       --->',round(mean_squared_error(Train_Y, pred1),2
))
print('Root Mean Squared Error (RMSE) on Training set --->',round(np.sqrt(mean_squared_error(Train_Y, p
red1)),2))

print('\n{}Test Set Metrics{}'.format('-'*20, '-'*20))
pred2 = PR3.predict(X_poly1) #Test_X_sm)
print('\nR2-Score on Testing set --->',round(r2_score(Test_Y, pred2),2))
print('Residual Sum of Squares (RSS) on Training set  --->',round(np.sum(np.square(Test_Y-pred2)),2))
print('Mean Squared Error (MSE) on Training set       --->',round(mean_squared_error(Test_Y, pred2),2))
print('Root Mean Squared Error (RMSE) on Training set --->',round(np.sqrt(mean_squared_error(Test_Y, pr
ed2)),2))
print('\n{}Residual Plots{}'.format('-'*20, '-'*20))

ME(pred1, pred2,'PR3')
plt.figure(figsize=[15,4])

plt.subplot(1,2,1)
residuals=(Train_Y-pred1)
sns.histplot(residuals, bins=20, kde=True)

plt.subplot(1,2,2)
sns.scatterplot(pred1, residuals)
plt.axhline(y=0, color='r', linestyle='--')
plt.tight_layout()
plt.show()

print('\n','-'*55)

print('\033[1m\nInference: \033[0m\nAs we can observe from the summary of the 3rd order Polynomial Regr
ession Model, \
we can note that it performs better compared to the 2nd Order, Let us check with higher degree Models.'
)
```

```
The Coeffecient of the Linear Regresion Model was found to be  [ 0.00000000e+00  2.90175333e+00  2.84
261280e+00 -1.15552561e-02
 -6.85716786e-01  1.29981682e+00 -1.62145354e-02  3.34488549e-02
 -4.92721858e-02 -2.26498202e-03  3.87192287e-01 -1.44715194e-02
 -7.21842629e-03 -2.64901061e-02  1.04302720e-02  1.08778230e-02
  4.25465437e-02 -1.54891436e-02  2.83056798e-02  2.38984574e-02]
The Intercept of the Linear Regresion Model was found to be  14.620297286547812
```




```
<<<-----------------------------------Evaluating ElasticNet Regression Model-----------------------------------
---------->>>



--------------------Training Set Metrics--------------------

R2-Score on Training set ---> 1.0
Residual Sum of Squares (RSS) on Training set  ---> 18.92
Mean Squared Error (MSE) on Training set       ---> 0.12
Root Mean Squared Error (RMSE) on Training set ---> 0.35

--------------------Test Set Metrics--------------------

R2-Score on Testing set ---> 0.98
Residual Sum of Squares (RSS) on Training set  ---> 31.96
Mean Squared Error (MSE) on Training set       ---> 0.8
Root Mean Squared Error (RMSE) on Training set ---> 0.89

--------------------Residual Plots--------------------
```

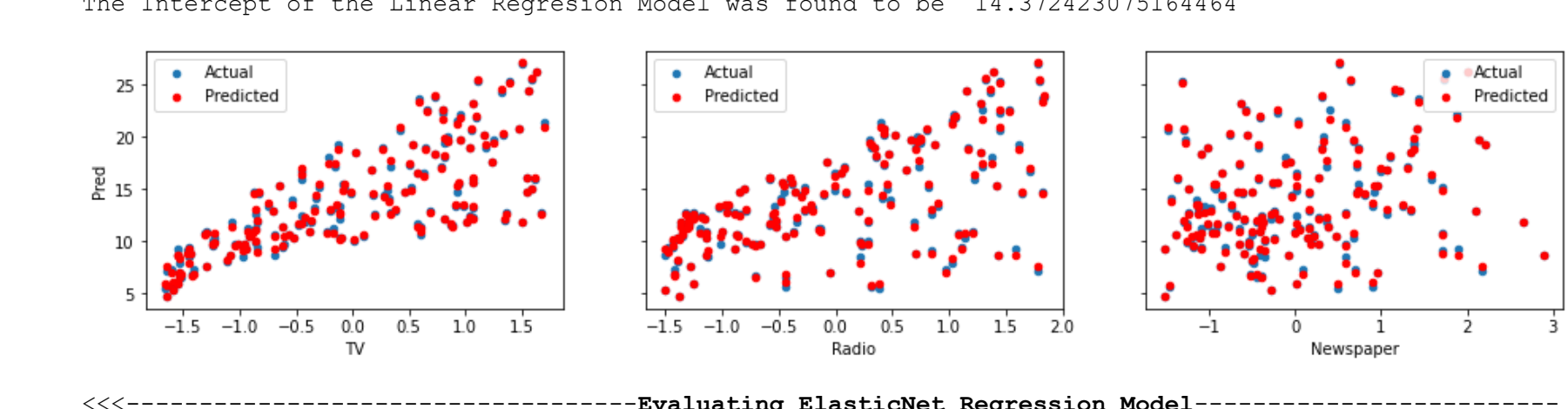



```
 -------------------------------------------------------
```

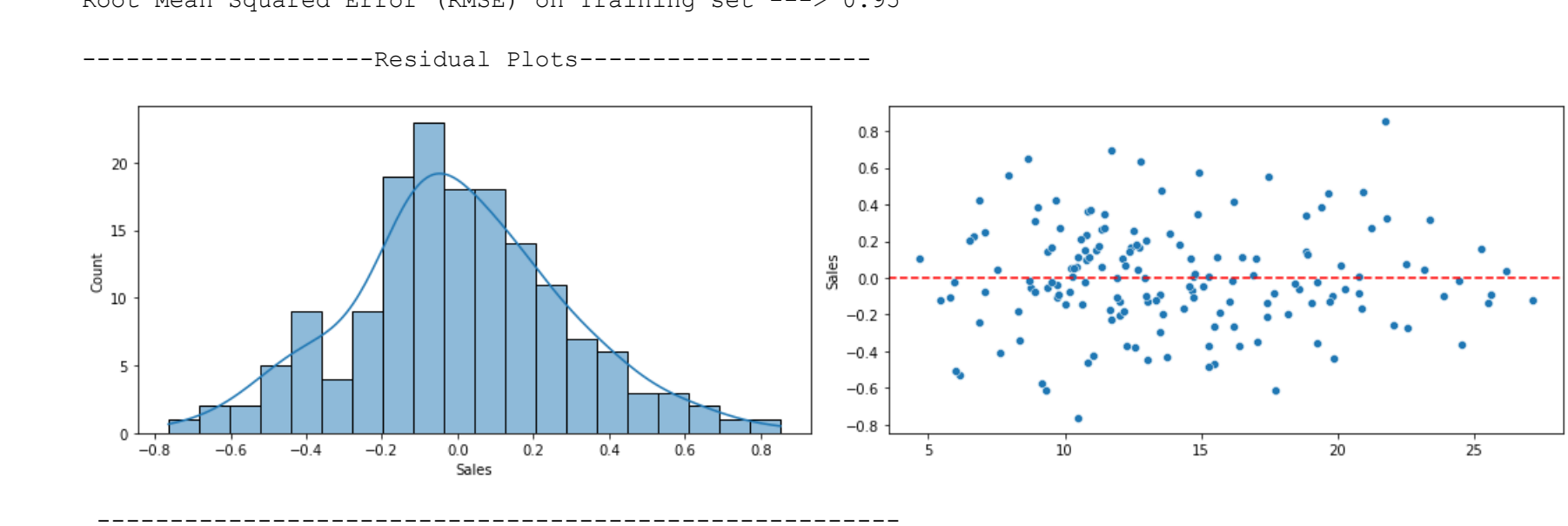
Inference:
As we can observe from the summary of the 3rd order Polynomial Regression Model, we can note that it performs better compared to the 2nd Order, Let us check with higher degree Models.

In [240]:
```
#Creating a Polynomial Regression model (degree=4)

from sklearn.preprocessing import PolynomialFeatures
poly_reg = PolynomialFeatures(degree=4)
X_poly = poly_reg.fit_transform(Train_X_std)
X_poly1 = poly_reg.fit_transform(Test_X_std)
PR4 = LinearRegression()
PR4.fit(X_poly, Train_Y)

print('The Coeffecient of the Linear Regresion Model was found to be ',PR4.coef_)
print('The Intercept of the Linear Regresion Model was found to be ',PR4.intercept_)

#Plotting predicted predicteds alongside the actual datapoints

pred = PR4.predict(X_poly)

fig,axs = plt.subplots(1,3, sharey=True)
Tr=pd.concat([Train_X_std, pd.DataFrame(Train_Y.values, columns=['Sales'])], axis=1)
Ts=pd.concat([Test_X_std, pd.DataFrame(Test_Y.values, columns=['Sales'])], axis=1)

Pr = Tr.copy()
Pr['Pred'] = pred

Tr.plot(kind='scatter',x='TV',y='Sales', ax=axs[0], figsize=(16,3), label='Actual')
Pr.plot(kind='scatter',x='TV',y='Pred',ax=axs[0], color='r', label='Predicted')

Tr.plot(kind='scatter',x='Radio',y='Sales',ax=axs[1], label='Actual')
Pr.plot(kind='scatter',x='Radio',y='Pred',ax=axs[1], color='r', label='Predicted')

Tr.plot(kind='scatter',x='Newspaper',y='Sales',ax=axs[2], label='Actual')
Pr.plot(kind='scatter',x='Newspaper',y='Pred',ax=axs[2], color='r', label='Predicted')

plt.show()

#Evaluating the Simple Linear Regression Model

print('{}{}\033[1mEvaluating ElasticNet Regression Model\033[0m{}{}\n'.format('<'*3,'-'*35, '-'*35,'>'*
3))

print('\n\n{}Training Set Metrics{}'.format('-'*20, '-'*20))
pred1 = PR4.predict(X_poly) #Test_X_sm)
print('\nR2-Score on Training set --->',round(r2_score(Train_Y, pred1),2))
print('Residual Sum of Squares (RSS) on Training set  --->',round(np.sum(np.square(Train_Y-pred1)),2))
print('Mean Squared Error (MSE) on Training set       --->',round(mean_squared_error(Train_Y, pred1),2
))
print('Root Mean Squared Error (RMSE) on Training set --->',round(np.sqrt(mean_squared_error(Train_Y, p
red1)),2))

print('\n{}Test Set Metrics{}'.format('-'*20, '-'*20))
pred2 = PR4.predict(X_poly1) #Test_X_sm)
print('\nR2-Score on Testing set --->',round(r2_score(Test_Y, pred2),2))
print('Residual Sum of Squares (RSS) on Training set  --->',round(np.sum(np.square(Test_Y-pred2)),2))
print('Mean Squared Error (MSE) on Training set       --->',round(mean_squared_error(Test_Y, pred2),2))
print('Root Mean Squared Error (RMSE) on Training set --->',round(np.sqrt(mean_squared_error(Test_Y, pr
ed2)),2))
print('\n{}Residual Plots{}'.format('-'*20, '-'*20))

plt.figure(figsize=[15,4])

plt.subplot(1,2,1)
residuals=(Train_Y-pred1)
sns.histplot(residuals, bins=20, kde=True)

plt.subplot(1,2,2)
sns.scatterplot(pred1, residuals)
plt.axhline(y=0, color='r', linestyle='--')
plt.tight_layout()
plt.show()

print('\n','-'*55)

print('\033[1m\nInference: \033[0m\nAs we can observe from the summary of the 4th order Polynomial Regr
ession Model, \
we can note that it performs doesn\'t better compared to the 3rd Order, Let us check with higher degree
 Models.')
```

```
The Coeffecient of the Linear Regresion Model was found to be  [ 1.16132742e-13  2.92518821e+00  2.85
016895e+00 -8.86514173e-01
 -9.03107043e-02  1.35427725e+00 -1.50802960e-01 -1.04597766e-01
  1.16746875e-01  1.84098540e-01  3.77169855e-01 -4.07546927e-02
  2.00067102e-02 -7.35498873e-02  2.33714674e-02  2.95366657e-02
  3.37454755e-02  9.12190348e-02 -7.97242202e-02  1.45896267e-01
 -2.27385896e-01 -9.38839495e-02  9.61013713e-02 -2.66409345e-03
 -6.71540054e-02  4.61227443e-03  4.57760220e-02  5.85710034e-02
  1.11998215e-02 -5.33597929e-02  6.40355027e-02 -1.77085075e-01
  1.11800589e-01  5.32423929e-02 -3.95913581e-02]
The Intercept of the Linear Regresion Model was found to be  14.372423075164464
```



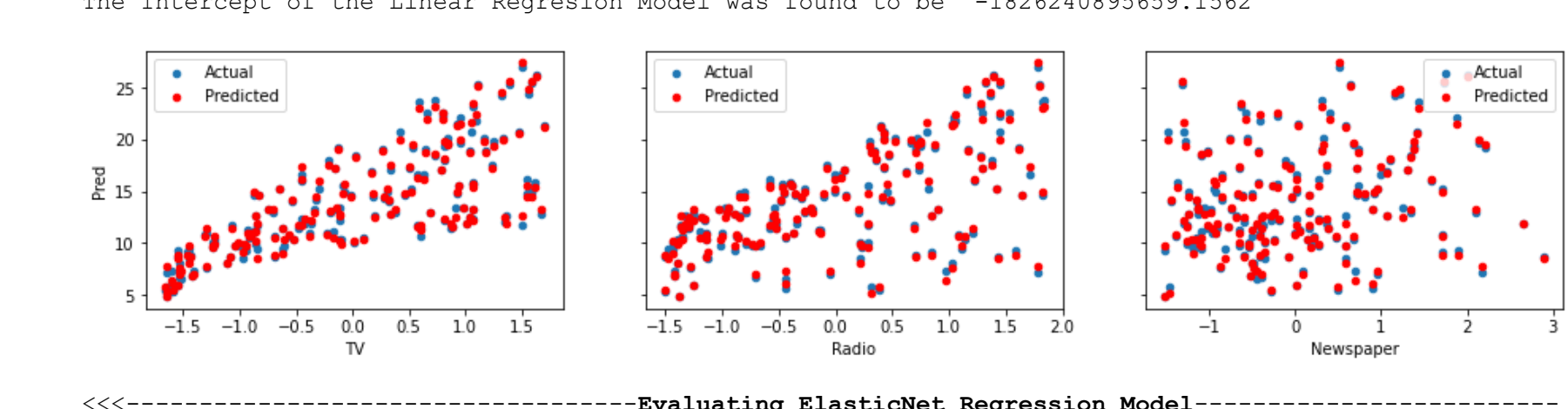
```
<<<-----------------------------------Evaluating ElasticNet Regression Model-----------------------------------
>>>


--------------------Training Set Metrics--------------------

R2-Score on Training set ---> 1.0
Residual Sum of Squares (RSS) on Training set  ---> 12.64
Mean Squared Error (MSE) on Training set       ---> 0.08
Root Mean Squared Error (RMSE) on Training set ---> 0.28

--------------------Test Set Metrics--------------------

R2-Score on Testing set ---> 0.97
Residual Sum of Squares (RSS) on Training set  ---> 36.02
Mean Squared Error (MSE) on Training set       ---> 0.9
Root Mean Squared Error (RMSE) on Training set ---> 0.95

--------------------Residual Plots--------------------
```



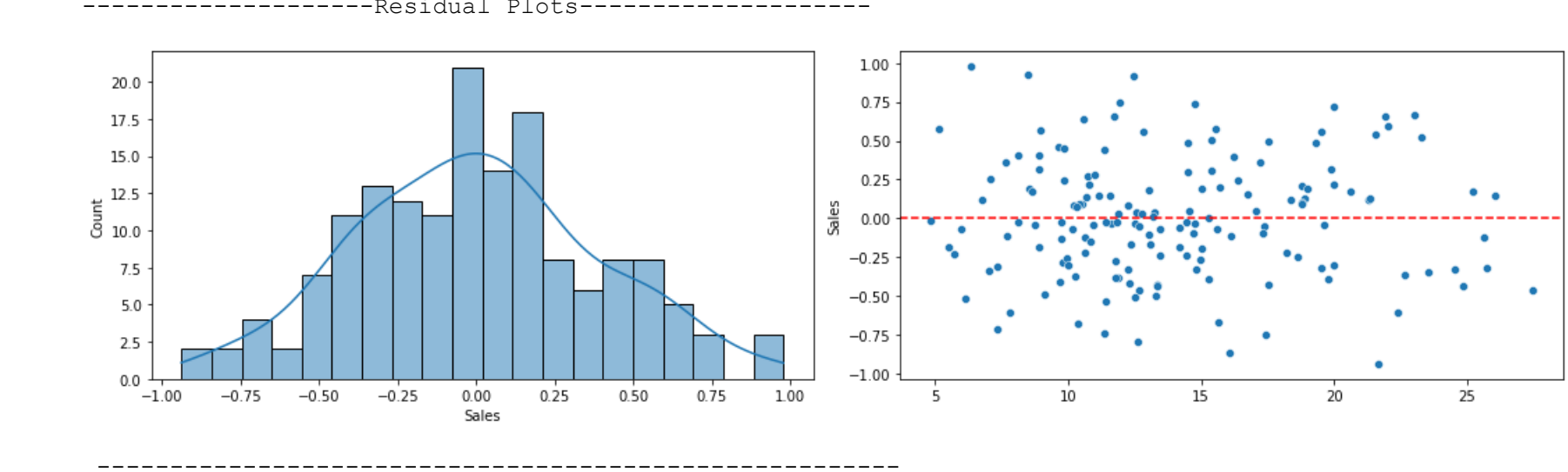
Inference:
As we can observe from the summary of the 4th order Polynomial Regression Model, we can note that it performs doesn't better compared to the 3rd Order, Let us check with higher degree Models.

In [241]:
```
#Creating a Polynomial Regression model (degree=5)

from sklearn.preprocessing import PolynomialFeatures
poly_reg = PolynomialFeatures(degree=5)
X_poly = poly_reg.fit_transform(Train_X_std)
X_poly1 = poly_reg.fit_transform(Test_X_std)
PR5 = LinearRegression()
PR5.fit(X_poly, Train_Y)

print('The Coeffecient of the Linear Regresion Model was found to be ',PR5.coef_)
print('The Intercept of the Linear Regresion Model was found to be ',PR5.intercept_)

#Plotting predicted predicteds alongside the actual datapoints

pred = PR5.predict(X_poly)

fig,axs = plt.subplots(1,3, sharey=True)
Tr=pd.concat([Train_X_std, pd.DataFrame(Train_Y.values, columns=['Sales'])], axis=1)
Ts=pd.concat([Test_X_std, pd.DataFrame(Test_Y.values, columns=['Sales'])], axis=1)

Pr = Tr.copy()
Pr['Pred'] = pred

Tr.plot(kind='scatter',x='TV',y='Sales', ax=axs[0], figsize=(16,3), label='Actual')
Pr.plot(kind='scatter',x='TV',y='Pred',ax=axs[0], color='r', label='Predicted')

Tr.plot(kind='scatter',x='Radio',y='Sales',ax=axs[1], label='Actual')
Pr.plot(kind='scatter',x='Radio',y='Pred',ax=axs[1], color='r', label='Predicted')

Tr.plot(kind='scatter',x='Newspaper',y='Sales',ax=axs[2], label='Actual')
Pr.plot(kind='scatter',x='Newspaper',y='Pred',ax=axs[2], color='r', label='Predicted')

plt.show()

#Evaluating the Simple Linear Regression Model

print('{}{}\033[1mEvaluating ElasticNet Regression Model\033[0m{}{}\n'.format('<'*3,'-'*35, '-'*35,'>'*
3))

print('\n\n{}Training Set Metrics{}'.format('-'*20, '-'*20))
pred1 = PR5.predict(X_poly) #Test_X_sm)
print('\nR2-Score on Training set --->',round(r2_score(Train_Y, pred1),2))
print('Residual Sum of Squares (RSS) on Training set  --->',round(np.sum(np.square(Train_Y-pred1)),2))
print('Mean Squared Error (MSE) on Training set       --->',round(mean_squared_error(Train_Y, pred1),2
))
print('Root Mean Squared Error (RMSE) on Training set --->',round(np.sqrt(mean_squared_error(Train_Y, p
red1)),2))

print('\n{}Test Set Metrics{}'.format('-'*20, '-'*20))
pred2 = PR5.predict(X_poly1) #Test_X_sm)
print('\nR2-Score on Testing set --->',round(r2_score(Test_Y, pred2),2))
print('Residual Sum of Squares (RSS) on Training set  --->',round(np.sum(np.square(Test_Y-pred2)),2))
print('Mean Squared Error (MSE) on Training set       --->',round(mean_squared_error(Test_Y, pred2),2))
print('Root Mean Squared Error (RMSE) on Training set --->',round(np.sqrt(mean_squared_error(Test_Y, pr
ed2)),2))
print('\n{}Residual Plots{}'.format('-'*20, '-'*20))

plt.figure(figsize=[15,4])

plt.subplot(1,2,1)
residuals=(Train_Y-pred1)
sns.histplot(residuals, bins=20, kde=True)

plt.subplot(1,2,2)
sns.scatterplot(pred1, residuals)
plt.axhline(y=0, color='r', linestyle='--')
plt.tight_layout()
plt.show()

print('\n','-'*55)

print('\033[1m\nInference: \033[0m\nAs we can observe from the summary of the 5th order Polynomial Regr
ession Model, \
we can note that it performs better compared to the 4th Order, Let us check with higher degree Models.'
)
```

```
The Coeffecient of the Linear Regresion Model was found to be  [ 1.82624090e+12  3.38616779e+00  2.13
166273e+00  3.27060204e-02
 -1.16328005e-01  1.38506675e+00  1.14847352e-01 -2.67039628e-02
 -2.28114035e-01  3.47675652e-01 -4.27429849e-01  1.82315564e-01
 -2.91972044e-02  4.34584861e-02  2.51429840e-01 -2.07268546e-01
  8.37114083e-01 -5.86445837e-01  3.94426835e-01 -2.05060127e-03
 -2.18948741e-01  1.02340573e-01 -1.17155205e-02  3.81521246e-03
  2.05100640e-01 -1.69738333e-01 -8.87210932e-02 -1.16959785e-01
  8.15785490e-02 -9.50284783e-02  1.03903280e-01 -2.23334683e-01
  1.54101567e-01 -7.93528009e-03 -3.84859185e-02  2.21262700e-01
 -3.21321064e-02  4.03857334e-02  1.40703503e-01 -1.43853446e-01
  9.12824932e-02 -6.52963404e-02 -2.45863760e-01  1.71100481e-01
 -1.89616108e-02 -5.15915376e-02  8.28042291e-02 -1.81891389e-01
  6.02510047e-02  1.90948893e-02 -2.47708701e-01  4.58147426e-01
 -3.62020579e-01  8.82912594e-02 -2.29407197e-02  1.67796521e-03]
The Intercept of the Linear Regresion Model was found to be  -1826240895659.1562
```



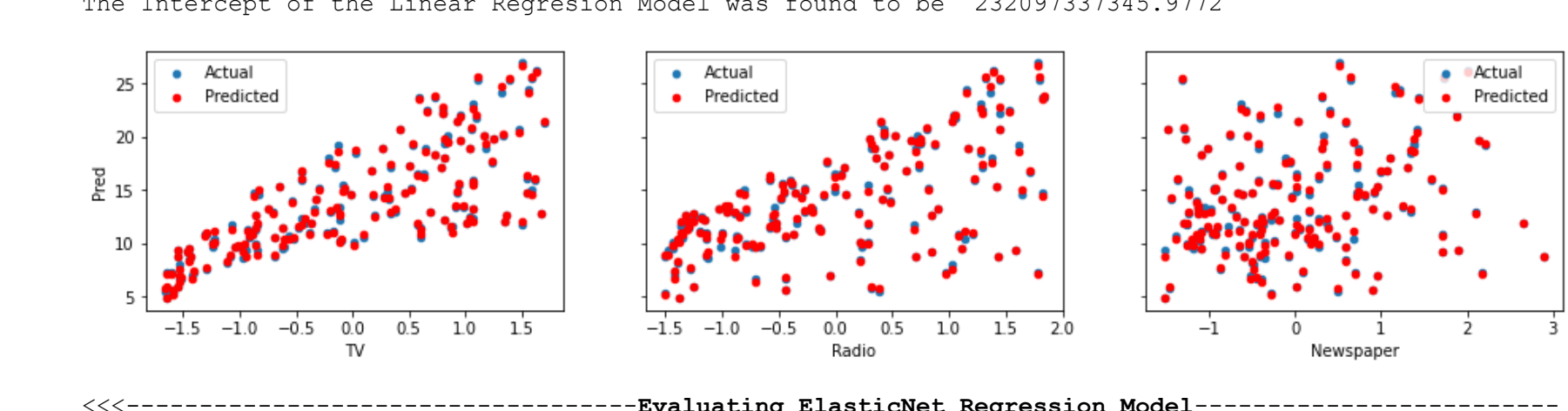
```
<<<-----------------------------------Evaluating ElasticNet Regression Model-----------------------------------
>>>


--------------------Training Set Metrics--------------------

R2-Score on Training set ---> 0.99
Residual Sum of Squares (RSS) on Training set  ---> 23.45
Mean Squared Error (MSE) on Training set       ---> 0.15
Root Mean Squared Error (RMSE) on Training set ---> 0.39

--------------------Test Set Metrics--------------------

R2-Score on Testing set ---> 0.96
Residual Sum of Squares (RSS) on Training set  ---> 57.61
Mean Squared Error (MSE) on Training set       ---> 1.44
Root Mean Squared Error (RMSE) on Training set ---> 1.2

--------------------Residual Plots--------------------
```



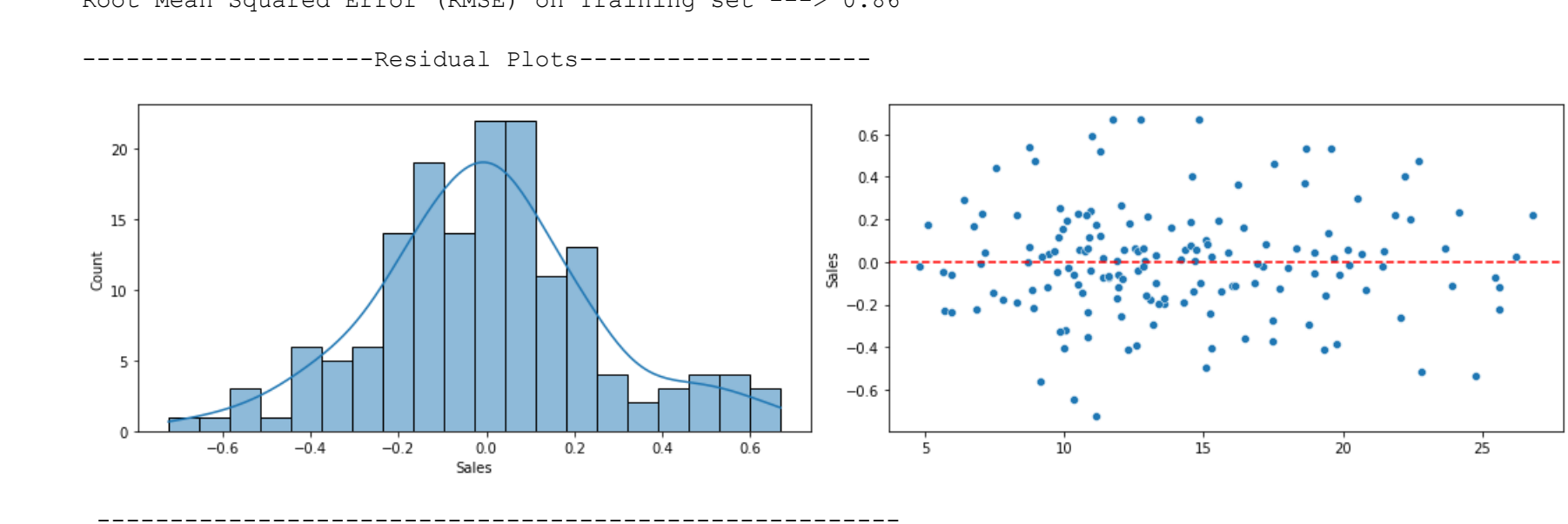
Inference:
As we can observe from the summary of the 5th order Polynomial Regression Model, we can note that it performs better compared to the 4th Order, Let us check with higher degree Models.

In [242]:
```
#Creating a Polynomial Regression model (degree=6)

from sklearn.preprocessing import PolynomialFeatures
poly_reg = PolynomialFeatures(degree=6)
X_poly = poly_reg.fit_transform(Train_X_std)
X_poly1 = poly_reg.fit_transform(Test_X_std)
PR6 = LinearRegression()
PR6.fit(X_poly, Train_Y)

print('The Coeffecient of the Linear Regresion Model was found to be ',PR6.coef_)
print('The Intercept of the Linear Regresion Model was found to be ',PR6.intercept_)

#Plotting predicted predicteds alongside the actual datapoints

pred = PR6.predict(X_poly)

fig,axs = plt.subplots(1,3, sharey=True)
Tr=pd.concat([Train_X_std, pd.DataFrame(Train_Y.values, columns=['Sales'])], axis=1)
Ts=pd.concat([Test_X_std, pd.DataFrame(Test_Y.values, columns=['Sales'])], axis=1)

Pr = Tr.copy()
Pr['Pred'] = pred

Tr.plot(kind='scatter',x='TV',y='Sales', ax=axs[0], figsize=(16,3), label='Actual')
Pr.plot(kind='scatter',x='TV',y='Pred',ax=axs[0], color='r', label='Predicted')

Tr.plot(kind='scatter',x='Radio',y='Sales',ax=axs[1], label='Actual')
Pr.plot(kind='scatter',x='Radio',y='Pred',ax=axs[1], color='r', label='Predicted')

Tr.plot(kind='scatter',x='Newspaper',y='Sales',ax=axs[2], label='Actual')
Pr.plot(kind='scatter',x='Newspaper',y='Pred',ax=axs[2], color='r', label='Predicted')

plt.show()

#Evaluating the Simple Linear Regression Model

print('{}{}\033[1mEvaluating ElasticNet Regression Model\033[0m{}{}\n'.format('<'*3,'-'*35, '-'*35,'>'*
3))

print('\n\n{}Training Set Metrics{}'.format('-'*20, '-'*20))
pred1 = PR6.predict(X_poly) #Test_X_sm)
print('\nR2-Score on Training set --->',round(r2_score(Train_Y, pred1),2))
print('Residual Sum of Squares (RSS) on Training set  --->',round(np.sum(np.square(Train_Y-pred1)),2))
print('Mean Squared Error (MSE) on Training set       --->',round(mean_squared_error(Train_Y, pred1),2
))
print('Root Mean Squared Error (RMSE) on Training set --->',round(np.sqrt(mean_squared_error(Train_Y, p
red1)),2))

print('\n{}Test Set Metrics{}'.format('-'*20, '-'*20))
pred2 = PR6.predict(X_poly1) #Test_X_sm)
print('\nR2-Score on Testing set --->',round(r2_score(Test_Y, pred2),2))
print('Residual Sum of Squares (RSS) on Training set  --->',round(np.sum(np.square(Test_Y-pred2)),2))
print('Mean Squared Error (MSE) on Training set       --->',round(mean_squared_error(Test_Y, pred2),2))
print('Root Mean Squared Error (RMSE) on Training set --->',round(np.sqrt(mean_squared_error(Test_Y, pr
ed2)),2))
print('\n{}Residual Plots{}'.format('-'*20, '-'*20))

ME(pred1, pred2,'PR6')
plt.figure(figsize=[15,4])

plt.subplot(1,2,1)
residuals=(Train_Y-pred1)
sns.histplot(residuals, bins=20, kde=True)

plt.subplot(1,2,2)
sns.scatterplot(pred1, residuals)
plt.axhline(y=0, color='r', linestyle='--')
plt.tight_layout()
plt.show()

print('\n','-'*55)

print('\033[1m\nInference: \033[0m\nAs we can observe from the summary of the 6th order Polynomial Regr
ession Model, \
we can note that it performs doesn\'t better compared to the 5th Order, Let us check with higher degree
 Models.')
```

```
The Coeffecient of the Linear Regresion Model was found to be  [-2.32097337e+11  3.24341327e+00  2.25
145354e+00  4.45590086e-02
 -4.78814152e-02  1.69730670e+00 -3.44185997e-01 -6.31439001e-01
  1.20514810e-01  9.79500934e-02 -3.10025786e-01  3.58344133e-01
 -3.33478402e-01  3.54446290e-01  2.41132014e-01 -3.07954850e-01
  3.75152541e-01 -3.24417993e-01  6.10369212e-01 -9.78805801e-02
  1.81176190e-02  2.80072705e-02  1.34664161e-01 -6.63890136e-02
 -3.31929224e-01 -4.04456024e-01 -2.87474445e-01  2.18257255e-01
 -7.12587622e-01  4.15223038e-01  7.37747958e-01  6.27307114e-02
 -3.07912395e-01  1.65298450e-01  2.07138375e-01  2.38738977e-01
 -8.60851463e-02  1.94524187e-01  4.38694437e-02 -1.99764274e-01
  3.16293275e-02 -1.14630024e-01  2.96053560e-02  4.97236581e-02
 -9.85719331e-02 -2.50359296e-01  1.76010147e-01 -2.35544178e-01
  4.25486610e-02  2.04842172e-01 -3.86455629e-03  4.07117711e-01
 -7.22498302e-01  2.08124411e-01 -7.54820775e-02  6.66746595e-02
 -8.14824941e-02 -2.08345083e-02 -1.73797394e-02  4.29190518e-02
  1.92123195e-02  8.00845007e-03 -7.22273006e-02  1.17060860e-02
 -5.79725072e-02 -1.45196030e-02 -6.42448599e-02  2.87062596e-01
  8.29655877e-02 -1.40772478e-01  1.31741919e-01  1.36158100e-01
 -1.37778816e-01  4.66443160e-01 -1.70584112e-01  1.28877381e-01
 -1.51279530e-01 -1.71198203e-01 -2.28147639e-01  3.70981908e-01
 -1.96078715e-01  3.04816430e-02  1.82060465e-02 -7.38664744e-02]
The Intercept of the Linear Regresion Model was found to be  232097337345.9772
```



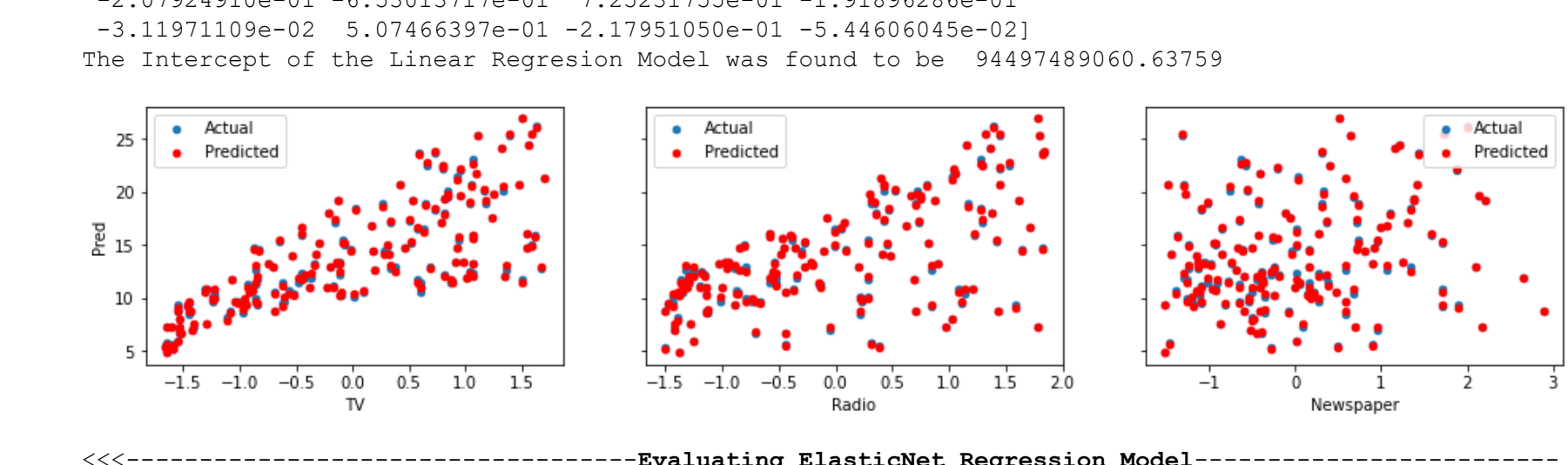
```
<<<-----------------------------------Evaluating ElasticNet Regression Model-----------------------------------
>>>


--------------------Training Set Metrics--------------------

R2-Score on Training set ---> 1.0
Residual Sum of Squares (RSS) on Training set  ---> 10.54
Mean Squared Error (MSE) on Training set       ---> 0.07
Root Mean Squared Error (RMSE) on Training set ---> 0.26

--------------------Test Set Metrics--------------------

R2-Score on Testing set ---> 0.98
Residual Sum of Squares (RSS) on Training set  ---> 29.3
Mean Squared Error (MSE) on Training set       ---> 0.73
Root Mean Squared Error (RMSE) on Training set ---> 0.86

--------------------Residual Plots--------------------
```



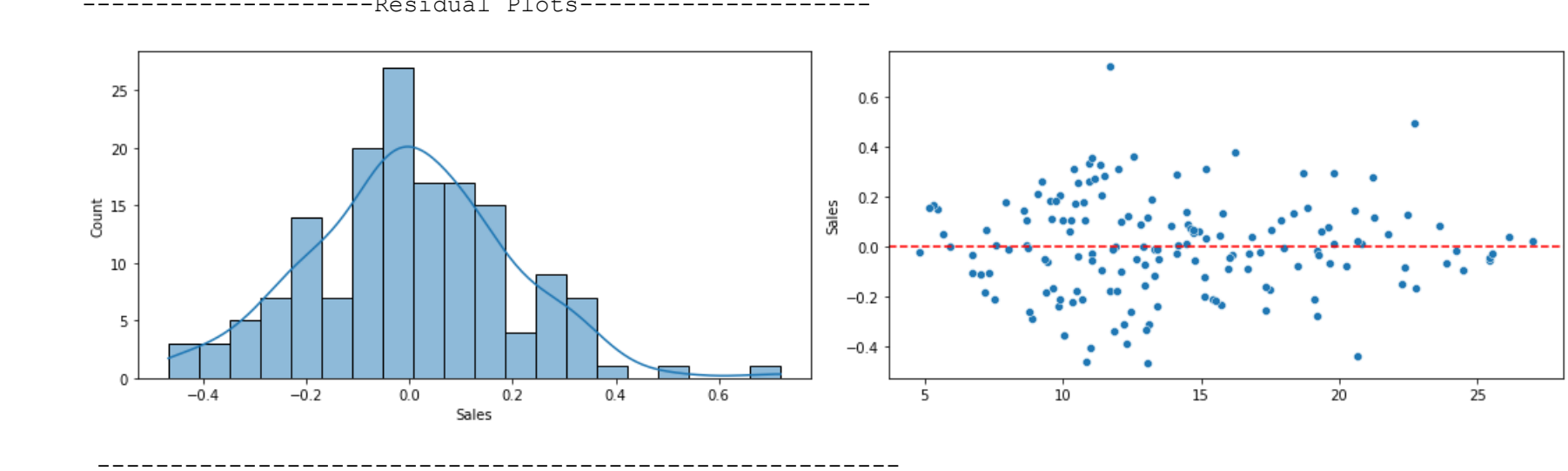
Inference:
As we can observe from the summary of the 6th order Polynomial Regression Model, we can note that it performs doesn't better compared to the 5th Order, Let us check with higher degree Models.

In [243]:
```
#Creating a Polynomial Regression model (degree=7)

from sklearn.preprocessing import PolynomialFeatures
poly_reg = PolynomialFeatures(degree=7)
X_poly = poly_reg.fit_transform(Train_X_std)
X_poly1 = poly_reg.fit_transform(Test_X_std)
PR7 = LinearRegression()
PR7.fit(X_poly, Train_Y)

print('The Coeffecient of the Linear Regresion Model was found to be ',PR7.coef_)
print('The Intercept of the Linear Regresion Model was found to be ',PR7.intercept_)

#Plotting predicted predicteds alongside the actual datapoints

pred = PR7.predict(X_poly)

fig,axs = plt.subplots(1,3, sharey=True)
Tr=pd.concat([Train_X_std, pd.DataFrame(Train_Y.values, columns=['Sales'])], axis=1)
Ts=pd.concat([Test_X_std, pd.DataFrame(Test_Y.values, columns=['Sales'])], axis=1)

Pr = Tr.copy()
Pr['Pred'] = pred

Tr.plot(kind='scatter',x='TV',y='Sales', ax=axs[0], figsize=(16,3), label='Actual')
Pr.plot(kind='scatter',x='TV',y='Pred',ax=axs[0], color='r', label='Predicted')

Tr.plot(kind='scatter',x='Radio',y='Sales',ax=axs[1], label='Actual')
Pr.plot(kind='scatter',x='Radio',y='Pred',ax=axs[1], color='r', label='Predicted')

Tr.plot(kind='scatter',x='Newspaper',y='Sales',ax=axs[2], label='Actual')
Pr.plot(kind='scatter',x='Newspaper',y='Pred',ax=axs[2], color='r', label='Predicted')

plt.show()

#Evaluating the Simple Linear Regression Model

print('{}{}\033[1mEvaluating ElasticNet Regression Model\033[0m{}{}\n'.format('<'*3,'-'*35, '-'*35,'>'*
3))

print('\n\n{}Training Set Metrics{}'.format('-'*20, '-'*20))
pred1 = PR7.predict(X_poly) #Test_X_sm)
print('\nR2-Score on Training set --->',round(r2_score(Train_Y, pred1),2))
print('Residual Sum of Squares (RSS) on Training set  --->',round(np.sum(np.square(Train_Y-pred1)),2))
print('Mean Squared Error (MSE) on Training set       --->',round(mean_squared_error(Train_Y, pred1),2
))
print('Root Mean Squared Error (RMSE) on Training set --->',round(np.sqrt(mean_squared_error(Train_Y, p
red1)),2))

print('\n{}Test Set Metrics{}'.format('-'*20, '-'*20))
pred2 = PR7.predict(X_poly1) #Test_X_sm)
print('\nR2-Score on Testing set --->',round(r2_score(Test_Y, pred2),2))
print('Residual Sum of Squares (RSS) on Training set  --->',round(np.sum(np.square(Test_Y-pred2)),2))
print('Mean Squared Error (MSE) on Training set       --->',round(mean_squared_error(Test_Y, pred2),2))
print('Root Mean Squared Error (RMSE) on Training set --->',round(np.sqrt(mean_squared_error(Test_Y, pr
ed2)),2))
print('\n{}Residual Plots{}'.format('-'*20, '-'*20))

plt.figure(figsize=[15,4])

plt.subplot(1,2,1)
residuals=(Train_Y-pred1)
sns.histplot(residuals, bins=20, kde=True)

plt.subplot(1,2,2)
sns.scatterplot(pred1, residuals)
plt.axhline(y=0, color='r', linestyle='--')
plt.tight_layout()
plt.show()

print('\n','-'*55)

print('\033[1m\nInference: \033[0m\nAs we can observe from the summary of the 7th order Polynomial Regr
ession Model, \
we can note that it performs doesn\'t better compared to the 6th Order, Let us check with higher degree
 Models.')
```

```
The Coeffecient of the Linear Regresion Model was found to be  [-9.44974890e+10  3.25569666e+00  2.27
302715e+00  7.89892924e-01
  6.73934113e-01  1.86796792e+00 -7.12110461e-01 -3.04843776e-01
 -1.12593125e-01  1.71858465e+00  5.13136390e-02  1.26696659e+00
 -6.69746278e-01  3.79432306e-01 -6.74705525e-01 -1.08378358e-01
 -8.81769130e-01 -1.47483346e+00  2.26098815e+00 -1.78461614e+00
 -4.61577216e-01  4.15349037e-01 -4.89211571e-01 -1.06851496e+00
  1.80063420e-01 -1.38608179e+00 -9.94796812e-01  4.08081855e+00
 -4.09442472e+00  1.32553873e+00  8.08658116e-01 -8.12043852e-01
 -2.42687239e+00  3.32380735e+00 -1.97694637e+00 -1.75951217e-01
 -1.24140556e+00  4.34028541e-02  7.19935711e-01  2.68666187e+00
 -2.68141955e+00  3.65870348e-01 -1.40536785e+00  9.68294300e-01
  1.33748636e+00 -1.20992149e+00  1.07585177e+00  2.62894262e+00
 -4.04269988e+00  1.78368400e+00  1.11651435e+00  1.57280363e+00
 -2.18335096e+00  3.90833796e+00 -7.02684449e-02  5.00344756e-01
 -8.21630552e-03 -1.93419010e-01  2.68281139e-01  4.22525868e-01
  2.21852325e-02 -1.27271081e-01 -6.82969367e-02 -8.61464340e-01
  1.32855571e+00 -6.03989965e-01  2.24997604e-01 -2.60937322e-01
  2.06049732e+00 -2.31294842e+00  1.36348849e+00  2.58923772e+00
 -1.66202537e+00  1.31108702e+00 -2.54899861e+00  6.21730131e-01
  7.74090264e-02 -2.75352823e-01  6.59392685e-01  4.82367014e-01
 -1.71743006e+00  1.57349545e+00 -8.08866631e-01  3.13744817e-01
  6.78818341e-02  2.08544719e-01  1.42519822e-01 -1.13304142e-01
 -9.60029101e-01  1.24403595e+00  4.00317252e-01 -2.43073852e-01
  1.50879382e-01 -2.97742122e-01 -2.11147404e-01 -6.56397970e-01
  1.91415419e-01  4.24391080e-01 -3.81410289e-01 -4.59910045e-01
  1.70454401e+00 -2.01873291e+00  7.46358323e-01 -5.90043609e-01
 -9.93482498e-02  4.59453392e-01 -3.54526154e-01 -1.61241823e+00
  2.94462692e+00 -2.27218770e+00  1.42554550e+00 -4.54951227e-01
 -2.07924910e-01 -6.53013717e-01  7.25231755e-01 -1.91896286e-01
 -3.11971109e-02  5.07466397e-01 -2.17951050e-01 -5.44606045e-02]
The Intercept of the Linear Regresion Model was found to be  94497489060.63759
```



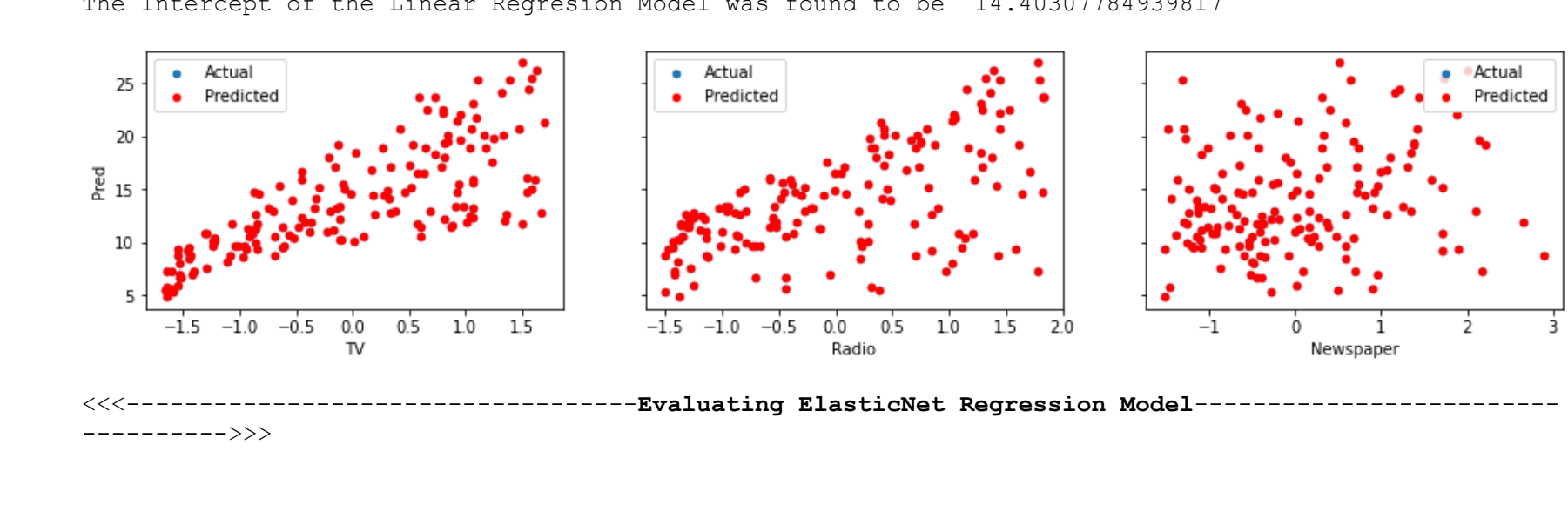
```
<<<-----------------------------------Evaluating ElasticNet Regression Model-----------------------------------
>>>


--------------------Training Set Metrics--------------------

R2-Score on Training set ---> 1.0
Residual Sum of Squares (RSS) on Training set  ---> 5.95
Mean Squared Error (MSE) on Training set       ---> 0.04
Root Mean Squared Error (RMSE) on Training set ---> 0.19

--------------------Test Set Metrics--------------------

R2-Score on Testing set ---> 0.5
Residual Sum of Squares (RSS) on Training set  ---> 655.72
Mean Squared Error (MSE) on Training set       ---> 16.39
Root Mean Squared Error (RMSE) on Training set ---> 4.05

--------------------Residual Plots--------------------
```



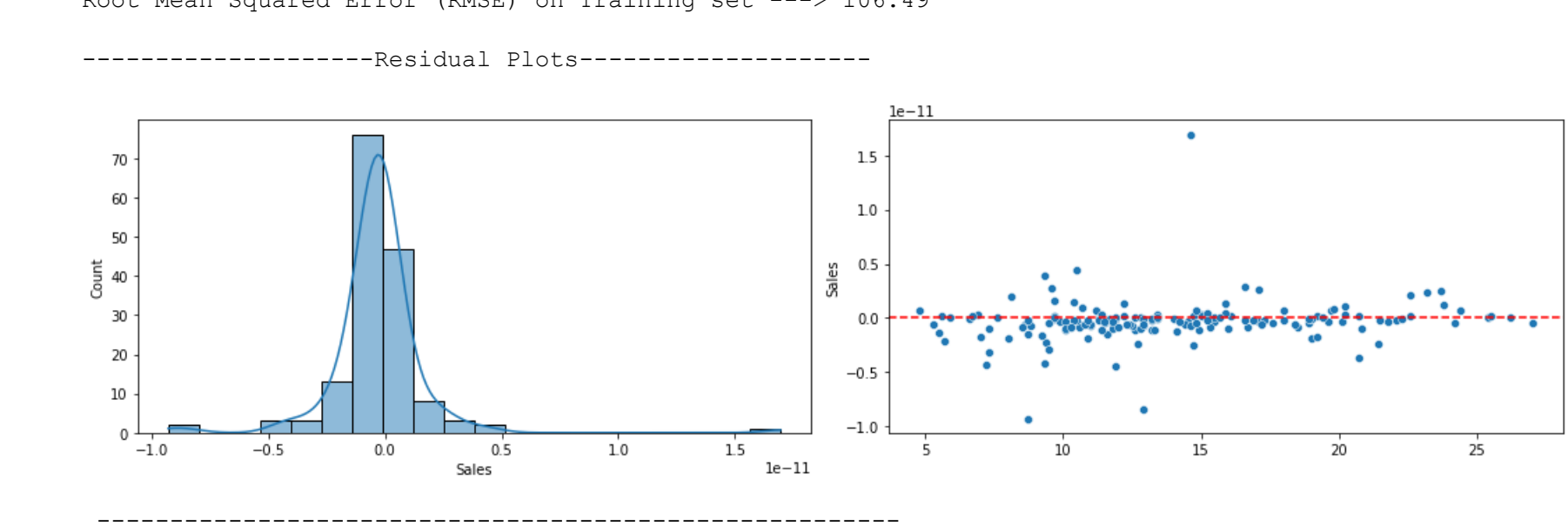
Inference:
As we can observe from the summary of the 7th order Polynomial Regression Model, we can note that it performs doesn't better compared to the 6th Order, Let us check with higher degree Models.

In [244]:
```
#Creating a Polynomial Regression model (degree=8)

from sklearn.preprocessing import PolynomialFeatures
poly_reg = PolynomialFeatures(degree=8)
X_poly = poly_reg.fit_transform(Train_X_std)
X_poly1 = poly_reg.fit_transform(Test_X_std)
PR9 = LinearRegression()
PR9.fit(X_poly, Train_Y)

print('The Coeffecient of the Linear Regresion Model was found to be ',PR9.coef_)
print('The Intercept of the Linear Regresion Model was found to be ',PR9.intercept_)

#Plotting predicted predicteds alongside the actual datapoints

pred = PR9.predict(X_poly)

fig,axs = plt.subplots(1,3, sharey=True)
Tr=pd.concat([Train_X_std, pd.DataFrame(Train_Y.values, columns=['Sales'])], axis=1)
Ts=pd.concat([Test_X_std, pd.DataFrame(Test_Y.values, columns=['Sales'])], axis=1)

Pr = Tr.copy()
Pr['Pred'] = pred

Tr.plot(kind='scatter',x='TV',y='Sales', ax=axs[0], figsize=(16,3), label='Actual')
Pr.plot(kind='scatter',x='TV',y='Pred',ax=axs[0], color='r', label='Predicted')

Tr.plot(kind='scatter',x='Radio',y='Sales',ax=axs[1], label='Actual')
Pr.plot(kind='scatter',x='Radio',y='Pred',ax=axs[1], color='r', label='Predicted')

Tr.plot(kind='scatter',x='Newspaper',y='Sales',ax=axs[2], label='Actual')
Pr.plot(kind='scatter',x='Newspaper',y='Pred',ax=axs[2], color='r', label='Predicted')

plt.show()

#Evaluating the Simple Linear Regression Model

print('{}{}\033[1mEvaluating ElasticNet Regression Model\033[0m{}{}\n'.format('<'*3,'-'*35, '-'*35,'>'*
3))

print('\n\n{}Training Set Metrics{}'.format('-'*20, '-'*20))
pred1 = PR9.predict(X_poly) #Test_X_sm)
print('\nR2-Score on Training set --->',round(r2_score(Train_Y, pred1),2))
print('Residual Sum of Squares (RSS) on Training set  --->',round(np.sum(np.square(Train_Y-pred1)),2))
print('Mean Squared Error (MSE) on Training set       --->',round(mean_squared_error(Train_Y, pred1),2
))
print('Root Mean Squared Error (RMSE) on Training set --->',round(np.sqrt(mean_squared_error(Train_Y, p
red1)),2))

print('\n{}Test Set Metrics{}'.format('-'*20, '-'*20))
pred2 = PR9.predict(X_poly1) #Test_X_sm)
print('\nR2-Score on Testing set --->',round(r2_score(Test_Y, pred2),2))
print('Residual Sum of Squares (RSS) on Training set  --->',round(np.sum(np.square(Test_Y-pred2)),2))
print('Mean Squared Error (MSE) on Training set       --->',round(mean_squared_error(Test_Y, pred2),2))
print('Root Mean Squared Error (RMSE) on Training set --->',round(np.sqrt(mean_squared_error(Test_Y, pr
ed2)),2))
print('\n{}Residual Plots{}'.format('-'*20, '-'*20))

plt.figure(figsize=[15,4])

plt.subplot(1,2,1)
residuals=(Train_Y-pred1)
sns.histplot(residuals, bins=20, kde=True)

plt.subplot(1,2,2)
sns.scatterplot(pred1, residuals)
plt.axhline(y=0, color='r', linestyle='--')
plt.tight_layout()
plt.show()

print('\n','-'*55)

print('\033[1m\nInference: \033[0m\nAs we can observe from the summary of the 8th order Polynomial Regr
ession Model, \
we can note that it does fully overfit on the data hence it\'s better to stop at this stage.')
```

```
The Coeffecient of the Linear Regresion Model was found to be  [ 8.87965425e-09  5.95392631e-01  6.98
580640e+00  8.94559432e-01
 -2.71110394e-01 -1.08558880e+01 -4.37634488e+00  1.31902994e+01
 -9.72802455e+00 -8.17537490e+00  1.25416438e+01  2.03304899e+00
  1.91284483e+01 -7.35910839e+00 -1.13452396e+01  1.32610846e+01
 -6.87504854e+00  4.72362705e+00  2.00303816e+00 -1.42196312e+01
  7.11425609e+00  2.42969968e+01  1.34685301e+01  5.48561191e+00
 -2.55056678e+00  2.60878851e+01  4.37036370e+00 -4.97735056e+00
  7.82795229e+01  5.29038237e+00 -1.12104311e+01 -7.12240439e+00
 -3.95253178e+01  1.01304908e+01  1.80185940e+01 -1.41395861e+01
  4.74055113e+01 -3.33621328e+01  5.95448848e+00 -1.71421547e+01
 -1.45928506e+01 -2.58417213e+00  9.58966367e+00  8.95713198e+00
  5.64830719e+00  4.34836205e+00 -3.85643524e+00 -8.81466758e+00
 -3.93055862e+00 -3.31745679e+00  1.07348634e+01  4.86161974e+00
  9.02729404e+00 -3.38328646e+00 -1.73925221e+00  1.28581483e+01
  1.20824593e+01 -3.29631432e+00 -2.84581069e+01  2.68463929e+01
  1.01534546e+00 -1.07668920e+01 -1.05156009e+01 -7.30119838e+00
  2.09581572e+00 -8.08501959e+00 -2.57644046e+00 -1.50579612e+01
  1.63166817e+01 -2.24812960e+00 -8.00584413e+00  1.24588346e+01
 -1.48011671e+01 -2.41836876e+01 -6.07752579e+00  5.03015229e+01
 -2.69195669e+01 -2.22582827e+00  3.58145789e+00  2.32136469e+00
 -2.48489073e+01  3.64390731e+00 -1.46752671e+01 -5.22770135e+00
  3.74488224e+00 -2.95963956e+00  1.14150839e+01 -8.37216107e+00
  2.35617034e+00  8.28082431e+00  7.84039191e+00 -6.73535655e+00
  1.06889623e+01 -1.82588589e+01  2.99938827e+00 -7.33808799e+00
  1.76931782e+01 -2.97903768e+00  1.19046859e+01 -3.06445357e+00
 -2.69573541e+00  8.90714846e+00 -4.07892365e+00 -2.14746396e+01
  2.39681313e+00 -7.70526311e+00  6.91561941e+00 -2.30380943e+01
  1.18365276e+01  1.04070878e+01 -8.82948400e+00  4.97382492e+00
 -1.59312362e+00  8.99437100e+00 -1.47114376e+01  1.68212135e+01
 -2.35552006e+00 -5.19013990e+00  1.41553392e+01 -8.33426669e+00
 -3.25247797e+01  1.32654854e+00  4.11316894e+01 -3.18385584e+00
 -2.57638654e+00  1.07205779e+01  1.84413446e+00  4.05059134e+00
 -5.02241137e+00  1.07275472e+01  6.75767513e+00 -2.60313203e+00
  1.94814077e+01 -1.02037132e+01 -4.11884124e+00  2.94867385e+00
 -7.36091551e+00  1.55669056e+01  7.41209852e+00 -1.89556289e+00
  1.04558724e+00  3.02133723e+01  6.82246754e+00 -2.46229898e+01
  2.79634482e+01 -1.07001551e+01 -3.16334238e+00  7.48321627e+00
 -5.31655130e+00  1.08049911e+00  3.34637184e+00 -1.23234427e+01
  1.15831283e+00  1.16919729e+01 -1.82554050e+01  7.07491142e+00
  2.34431287e+00 -1.69503785e+00  2.01756853e+01 -1.50026644e+01
 -7.45706577e+00  1.62106414e+00 -9.96751903e+00  2.25087464e+00
  8.02682567e+01]
The Intercept of the Linear Regresion Model was found to be  14.40307784939817
```

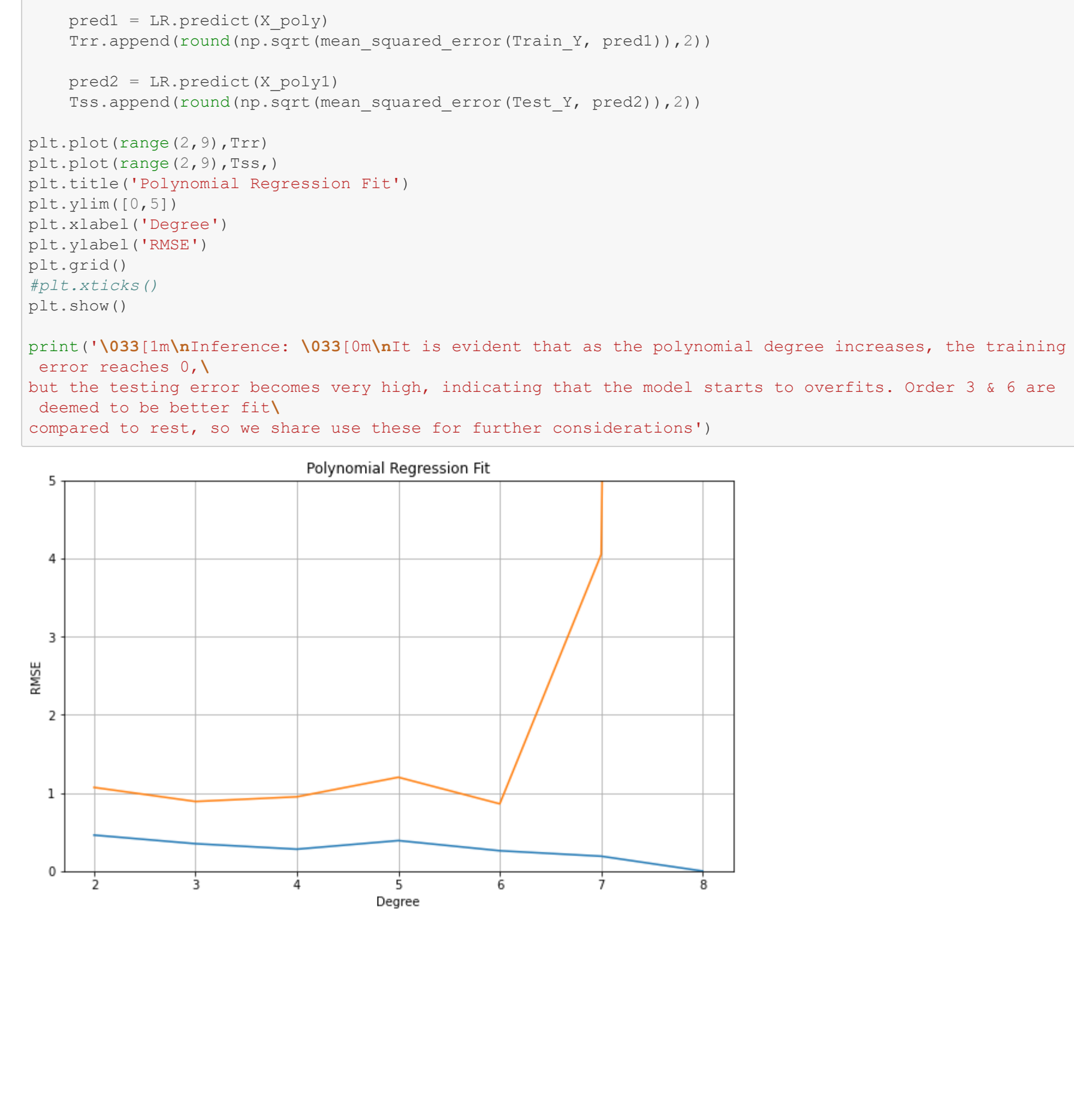


```
<<<-----------------------------------Evaluating ElasticNet Regression Model-----------------------------------
>>>


--------------------Training Set Metrics--------------------

R2-Score on Training set ---> 1.0
Residual Sum of Squares (RSS) on Training set  ---> 0.0
Mean Squared Error (MSE) on Training set       ---> 0.0
Root Mean Squared Error (RMSE) on Training set ---> 0.0

--------------------Test Set Metrics--------------------

R2-Score on Testing set ---> -342.45
Residual Sum of Squares (RSS) on Training set  ---> 453601.81
Mean Squared Error (MSE) on Training set       ---> 11340.05
Root Mean Squared Error (RMSE) on Training set ---> 106.49

--------------------Residual Plots--------------------
```



Inference:
As we can observe from the summary of the 8th order Polynomial Regression Model, we can note that it does fully overfit on the data hence it's better to stop at this stage.

In [245]:
```
#Plotting polynomial regression results

Trr=[]; Tss=[]

for i in range(2,9):
    #print(f'{i} Degree')
    poly_reg = PolynomialFeatures(degree=i)
    X_poly = poly_reg.fit_transform(Train_X_std)
    X_poly1 = poly_reg.fit_transform(Test_X_std)
    LR = LinearRegression()
    LR.fit(X_poly, Train_Y)

    pred1 = LR.predict(X_poly)
    Trr.append(round(np.sqrt(mean_squared_error(Train_Y, pred1)),2))

    pred2 = LR.predict(X_poly1)
    Tss.append(round(np.sqrt(mean_squared_error(Test_Y, pred2)),2))

plt.plot(range(2,9),Trr)
plt.plot(range(2,9),Tss,)
plt.title('Polynomial Regression Fit')
plt.ylim([0,5])
plt.xlabel('Degree')
plt.ylabel('RMSE')
plt.grid()
#plt.xticks()
plt.show()

print('\033[1m\nInference: \033[0m\nIt is evident that as the polynomial degree increases, the training
 error reduces 0,\
but the testing error becomes very high, indicating that the model starts to overfits. Order 3 & 6 are
 deemed to be better fit\
compared to rest, so we shae use these for further considerations')
```

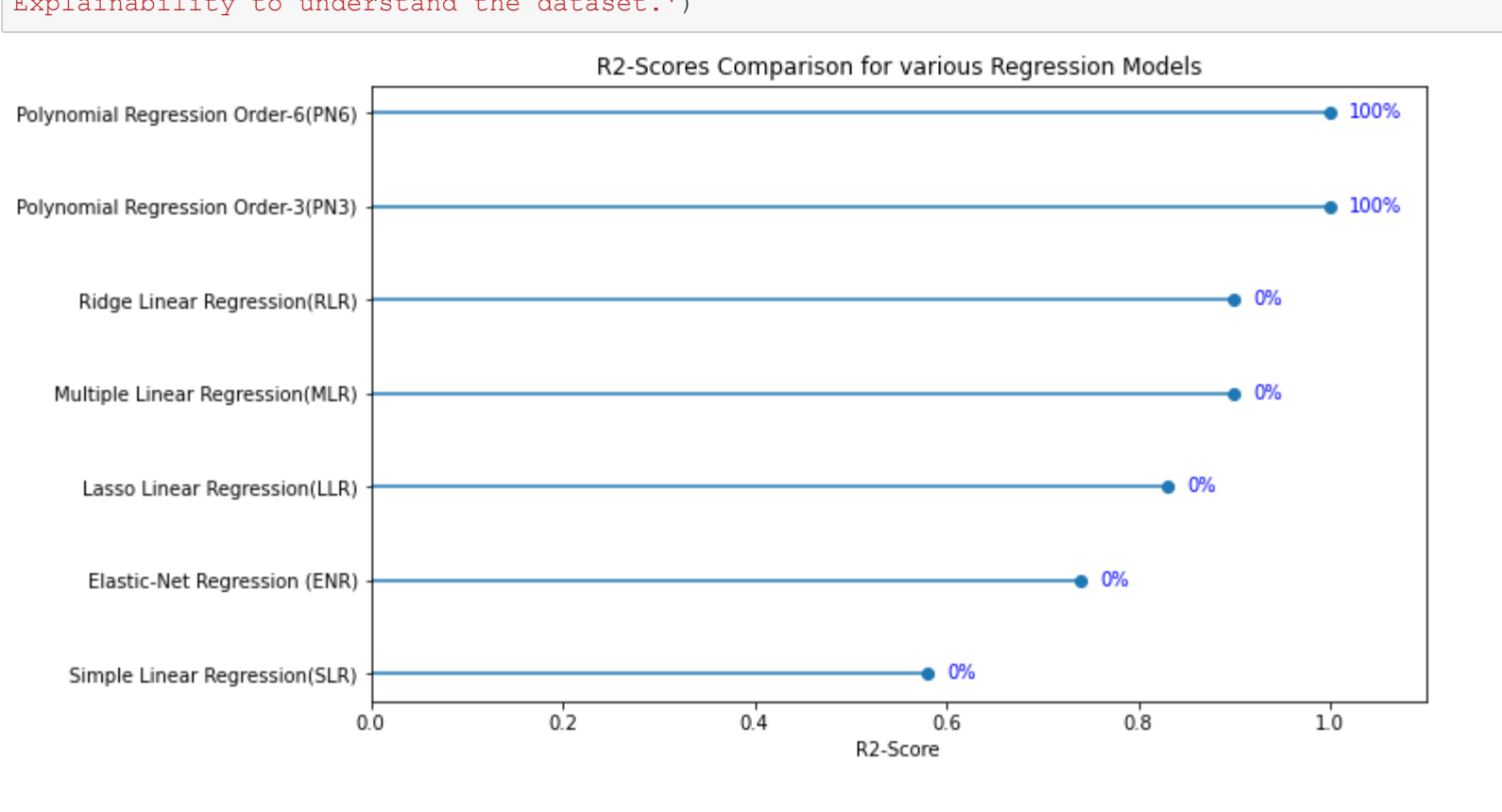


In [311]:
```
# Regression Models Results Evaluation

Model_Evaluation_Comparison_Matrix
EMC = Model_Evaluation_Comparison_Matrix.copy()
EMC.index=['Simple Linear Regression(SLR)', 'Multiple Linear Regression(MLR)','Ridge Linear Regression
(RLR)','Lasso Linear Regression(LLR)','Elastic-Net Regression (ENR)','Polynomial Regression Order-3(PN
3)','Polynomial Regression Order-6(PN6)']
EMC
```

Out[311]:

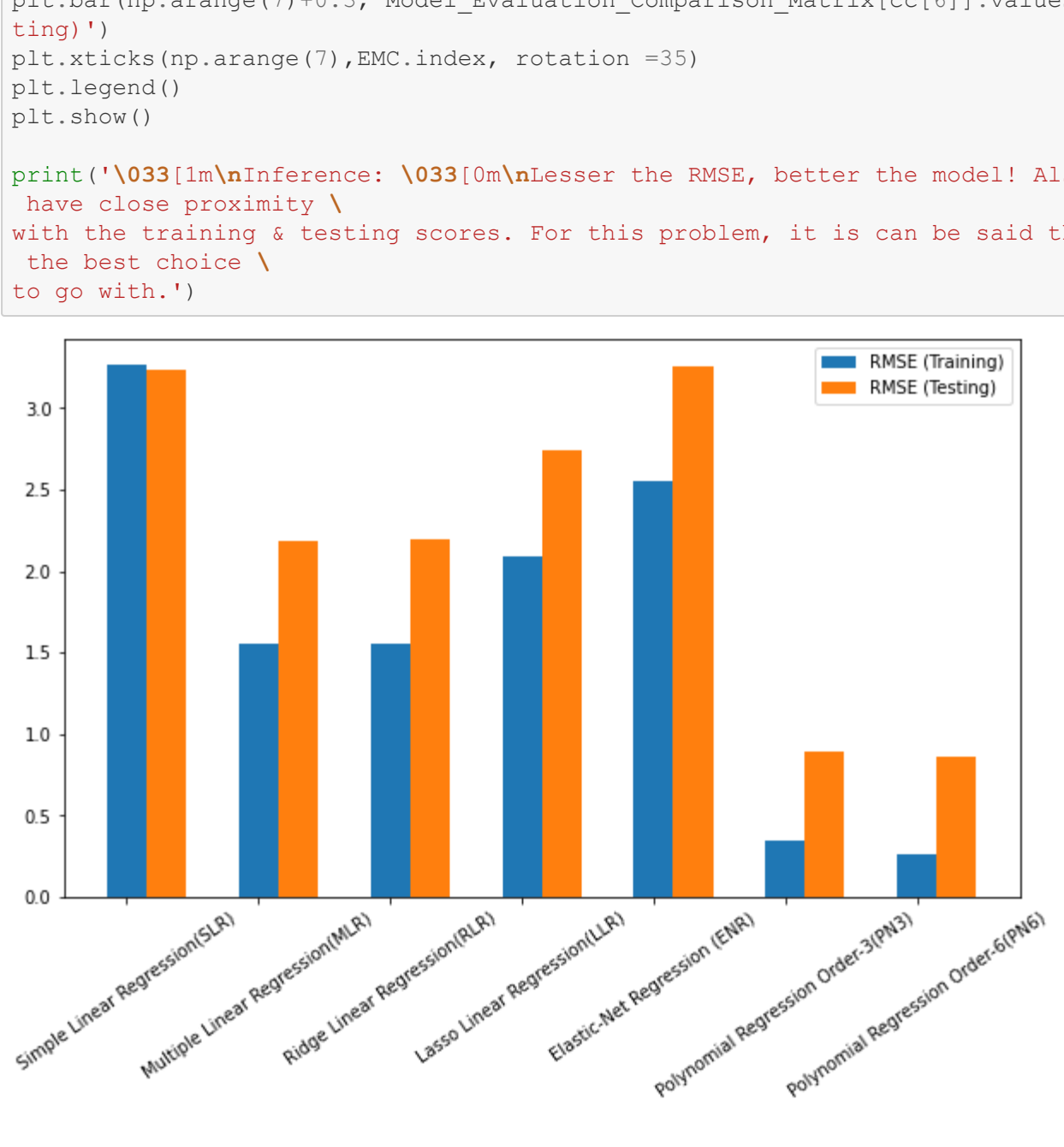
	R2-Score	Train_RSS	Train_MSE	Train_RMSE	Test_RSS	Test_MSE	Test_RMSE
Simple Linear Regression(SLR)	0.58	1681.01	10.64	3.26	418.40	10.46	3.23
Multiple Linear Regression(MLR)	0.90	381.14	2.41	1.55	190.69	4.77	2.18
Ridge Linear Regression(RLR)	0.90	381.29	2.41	1.55	191.07	4.78	2.19
Lasso Linear Regression(LLR)	0.83	688.16	4.36	2.09	299.78	7.49	2.74
Elastic-Net Regression (ENR)	0.74	1026.14	6.49	2.55	422.57	10.56	3.25
Polynomial Regression Order-3(PN3)	1.00	18.92	0.12	0.35	31.96	0.80	0.89
Polynomial Regression Order-6(PN6)	1.00	10.54	0.07	0.26	29.30	0.73	0.86

In [345]:
```
# R2-Scores Comparison for different Regression Models

R2 = EMC['R2-Score'].sort_values(ascending=True)
plt.hlines(y=R2.index, xmin=0, xmax=R2.values)
plt.plot(R2.values, R2.index,'o')
plt.title('R2-Scores Comparison for various Regression Models')
plt.xlabel('R2-Score')
#plt.ylabel('Regression Models')
for i, v in enumerate(R2):
    plt.text(v+0.02, i-0.05, str(int(v)*100)+'%', color='blue')
plt.xlim([0,1.1])
plt.show()

print('\033[1m\nInference: \033[0m\nFrom the above plot, it is clear that the polynomial regresion mode
ls have the highest \
Explainability to understand the dataset.')
```




```
Inference:
From the above plot, it is clear that the polynomial regresion models have the highest Explainability
 to understand the dataset.
```

In [359]:
```
# Root Mean SquaredError Comparison for different Regression Models

plt.bar(np.arange(7), Model_Evaluation_Comparison_Matrix[cc[3]].values, width=0.3, label='RMSE (Trainin
g)')
plt.bar(np.arange(7)+0.3, Model_Evaluation_Comparison_Matrix[cc[6]].values, width=0.3, label='RMSE (Tes
ting)')
plt.xticks(np.arange(7),EMC.index, rotation =35)
plt.legend()
plt.show()

print('\033[1m\nInference: \033[0m\nLesser the RMSE, better the model! Also, provided the model should
 have close proximity \
with the training & testing scores. For this problem, it is can be said that polynomial regressions are
 the best choice \
to go with.')
```




```
Inference:
Lesser the RMSE, better the model! Also, provided the model should have close proximity with the trai
ning & testing scores. For this problem, it is can be said that polynomial regressions are the best c
hoice to go with.
```

---

10. Project Outcomes & Conclusions

Here are some of the key outcomes of the project:

- The Dataset was quiet small totally just 200 samples & after preprocessing 1% of the datasamples were dropped.
- Visualising the distribution of data & their relationships, helped us to get some insights on the target-feature.
- Feature selection or feature extracting as there were only 3 features, which all contributed towards the right prediction.
- Testing multiple algorithms with default hyperparamters gave us some understanding for various models performance on this specific dataset.
- While, Polynomial Regression (Order-6) gave the best overall scores for the current dataset, yet it wise to also consider simpler models like MLR & ENR as they are more generalisable.

In [ ]:
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