CPE 608: Applied Modeling and Optimization

Fall 2022 Project: Optimization of Advertisement Budget

Project Memebers

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Import required modules

In [ ]:
```
%matplotlib inline
import matplotlib.pyplot as plt
import pandas as pd
import numpy as np
import seaborn as sb
from sklearn.linear_model import LinearRegression
from sklearn.linear_model import SGDRegressor
from sklearn.linear_model import Lasso
from sklearn.linear_model import ElasticNet
from sklearn.linear_model import Ridge
from sklearn.metrics import mean_squared_error
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from pulp import *
```

Import advertising dataset for project and display its Information

In [ ]:
```
df = pd.read_csv("advertising.csv")
```

In [ ]:
```
df
```

Out[ ]:

	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
...	...	...	...	...
195	38.2	3.7	13.8	7.6
196	94.2	4.9	8.1	14.0
197	177.0	9.3	6.4	14.8
198	283.6	42.0	66.2	25.5
199	232.1	8.6	8.7	18.4

200 rows × 4 columns

In [ ]:
```
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 [ ]:
```
df.describe()
```

Out[ ]:

	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 [ ]:
```
df.mean()
```

Out[ ]:
```
TV           147.0425
Radio         23.2640
Newspaper     30.5540
Sales         15.1305
dtype: float64
```

- For imported dataset, it comprises 200 data points for each of the data variables, i.e., TV, Radio, Newspaper, and Sales. Columns "TV", "Radio", and "Newspaper" have recorded data for the budget in thousands of dollars. Column "Sales" has recorded data for the sales in thousands of units.
- The dataset gives one the opportunity to design an optimization problem of maximizing sales around a set of assumed constraints

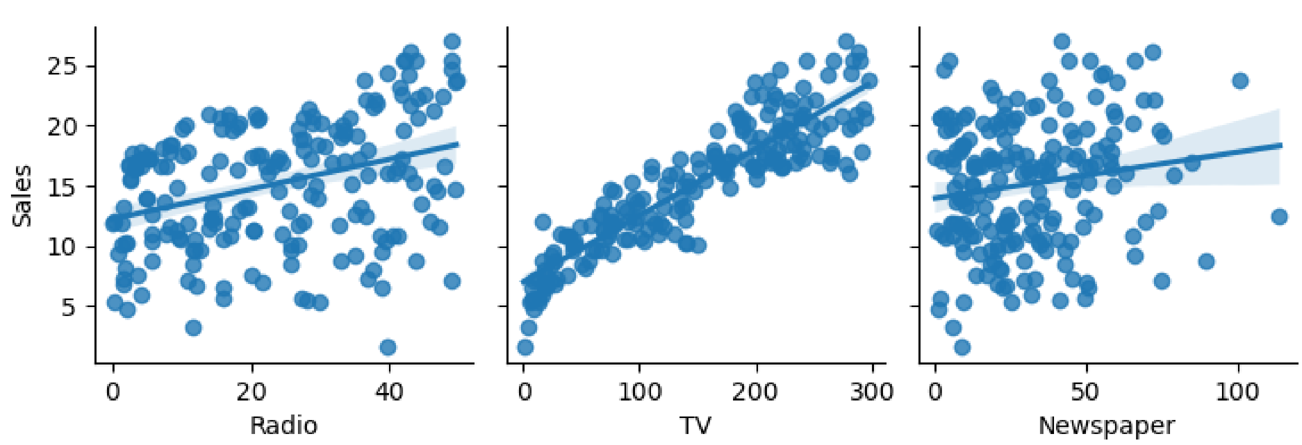
Visualizations for Dataset

Pair plots

Here we compare the sales of each data variable

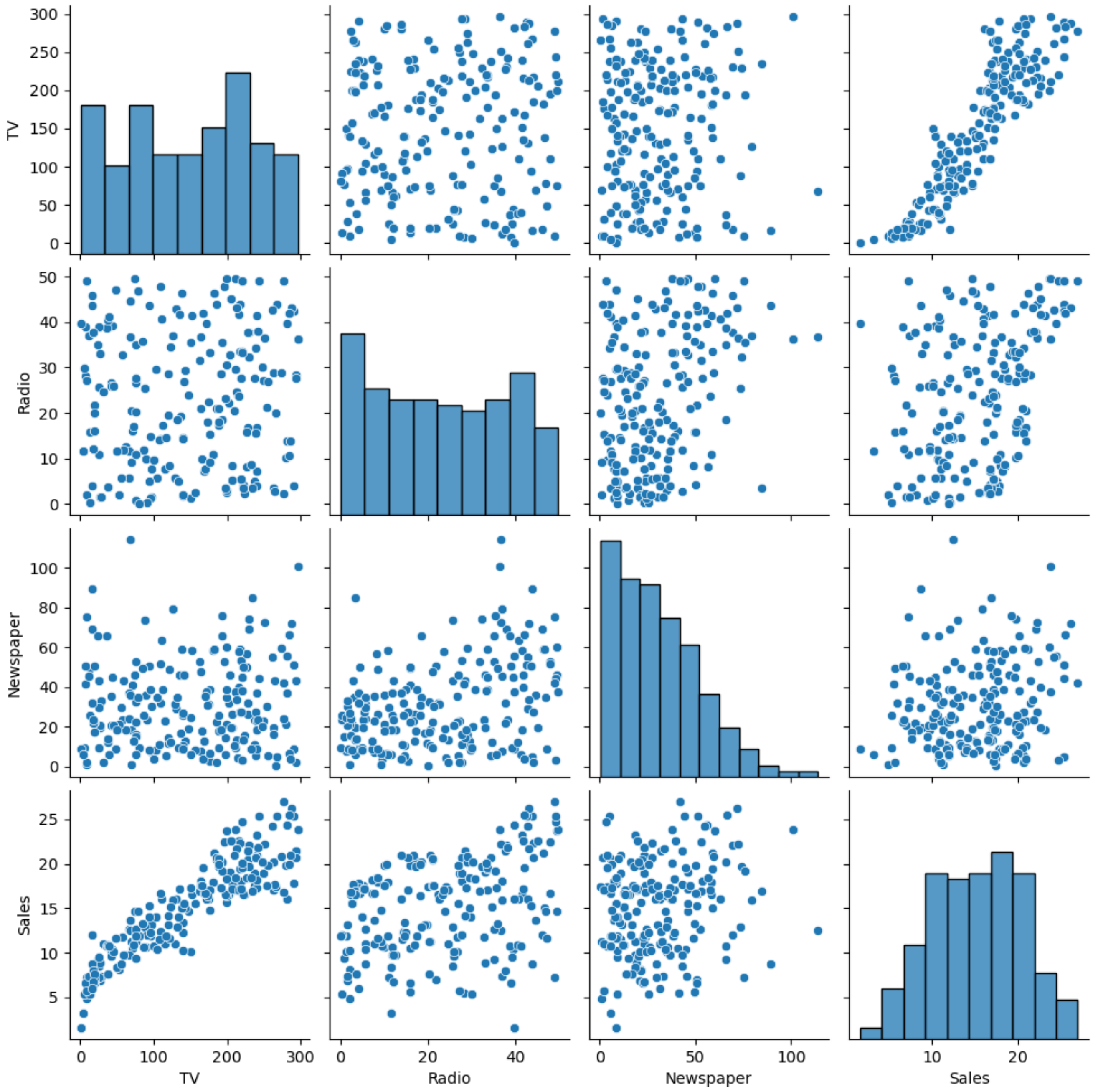
In [ ]:
```
sb.pairplot(df, x_vars=["Radio","TV","Newspaper"],y_vars= "Sales",kind="reg")
```

Out[ ]:
```
<seaborn.axisgrid.PairGrid at 0x1f851b31460>
```



Comparing data variables

In [ ]:
```
sb.pairplot(df);
```

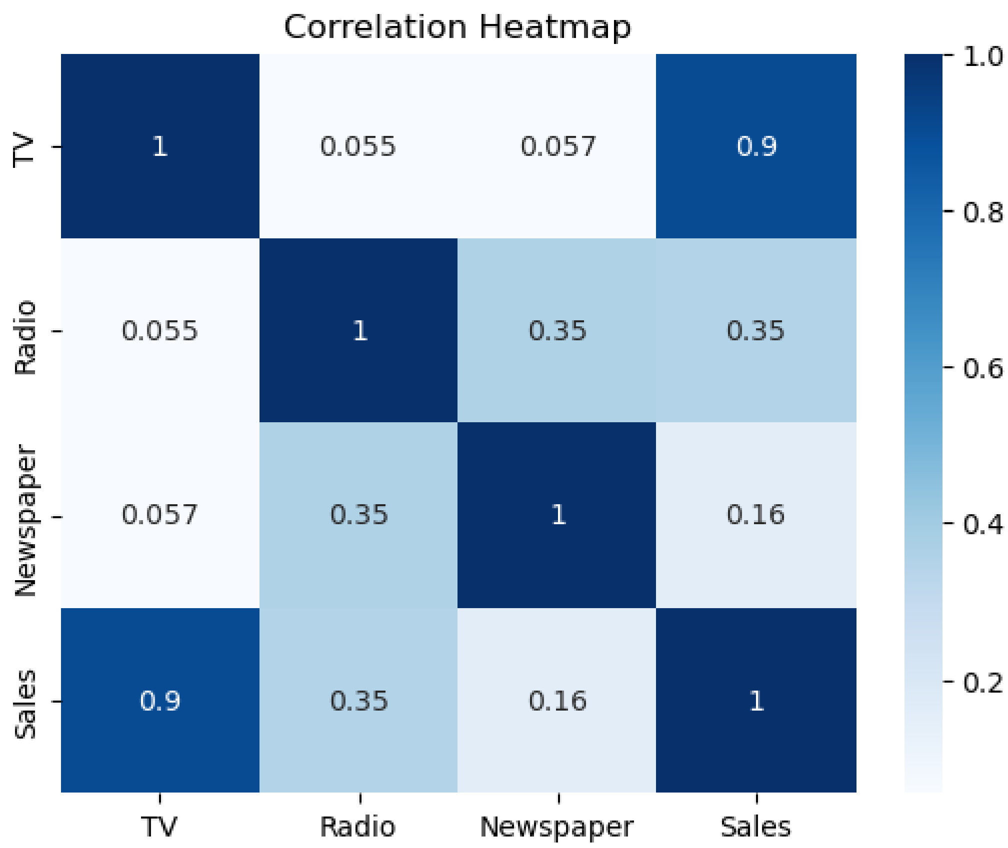


Correlation heatmap

Correlation between different variables

In [ ]:
```
corr = df.corr()
sb.heatmap(corr, cmap ='Blues', annot =True).set(title="Correlation Heatmap")
```

Out[ ]:
```
[Text(0.5, 1.0, 'Correlation Heatmap')]
```



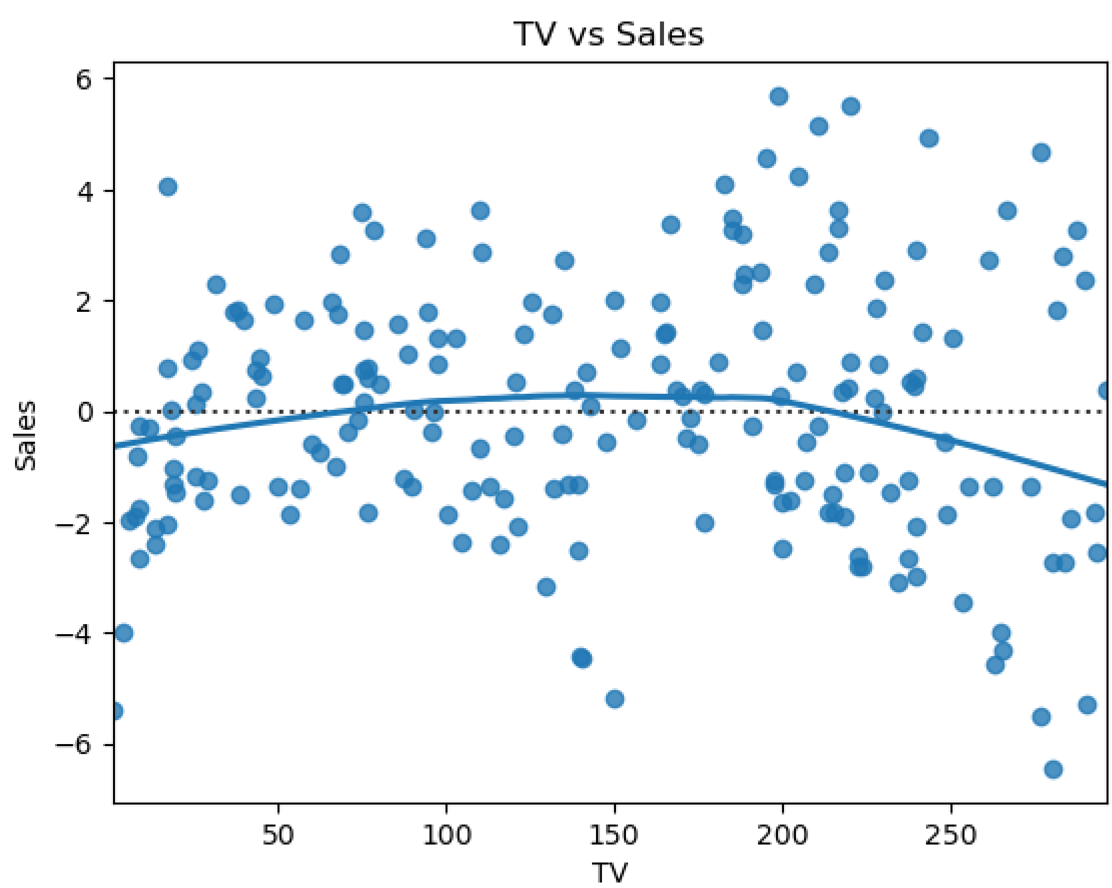
Residual plots

Here we compare the sales of data variables with each other

TV Vs Sales

In [ ]:
```
sb.residplot(x = df['TV'], y = df['Sales'], lowess = True).set(title="TV vs Sales")
```

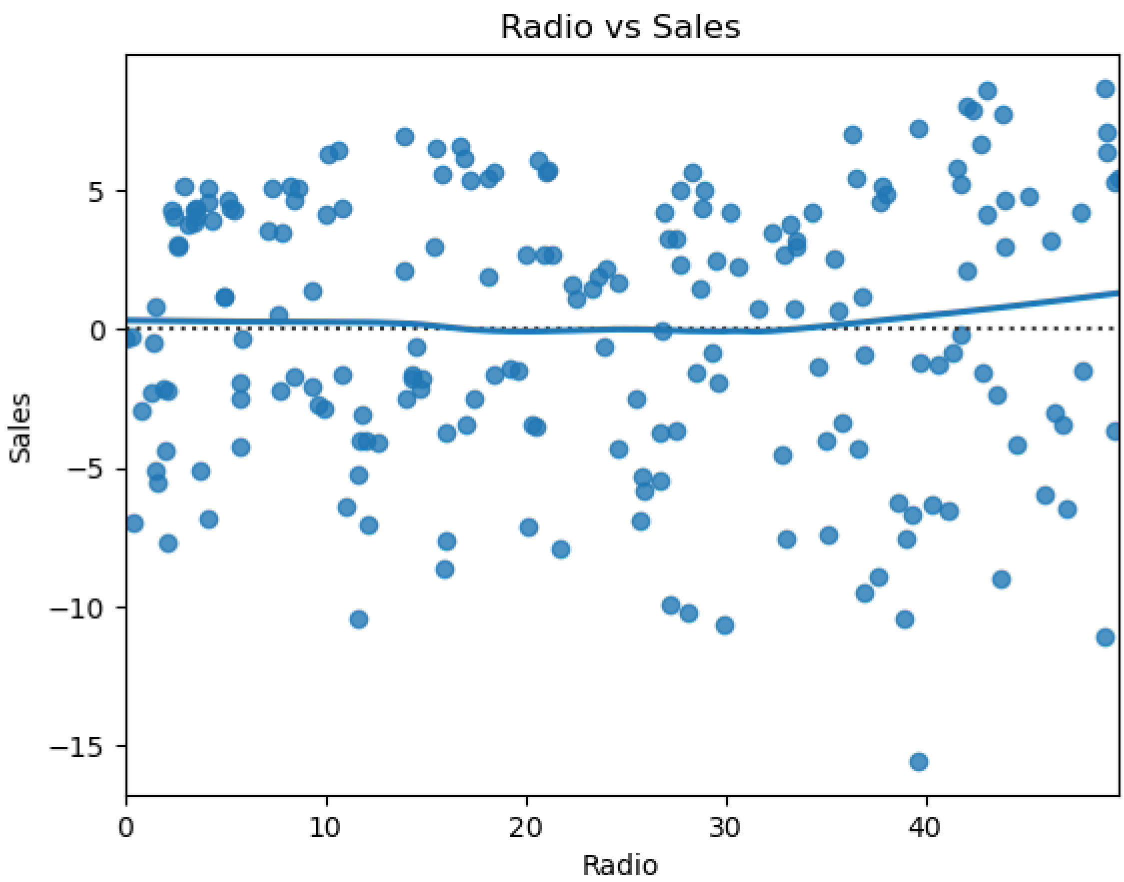
Out[ ]:
```
[Text(0.5, 1.0, 'TV vs Sales')]
```



Radio Vs Sales

In [ ]:
```
sb.residplot(x = df['Radio'], y = df['Sales'], lowess = True).set(title="Radio vs Sales")
```

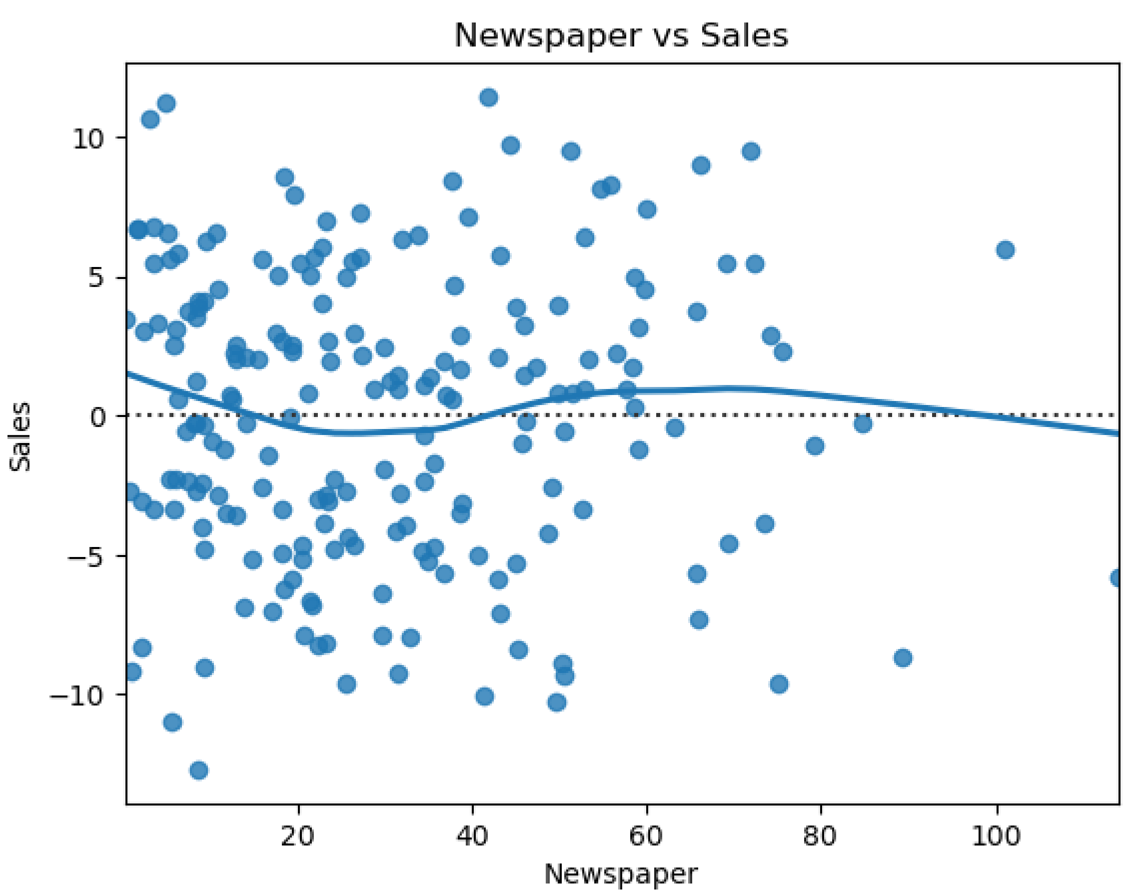
Out[ ]:
```
[Text(0.5, 1.0, 'Radio vs Sales')]
```



Newspaper Vs Sales

In [ ]:
```
sb.residplot(x = df['Newspaper'], y = df['Sales'], lowess = True).set(title="Newspaper vs Sa
```

Out[ ]:
```
[Text(0.5, 1.0, 'Newspaper vs Sales')]
```



Adding an additional column for average budget across different media

In [ ]:
```
df['Average Budget'] = df[['TV', 'Radio', 'Newspaper']].mean(numeric_only=True, axis=1)
df
```

Out[ ]:

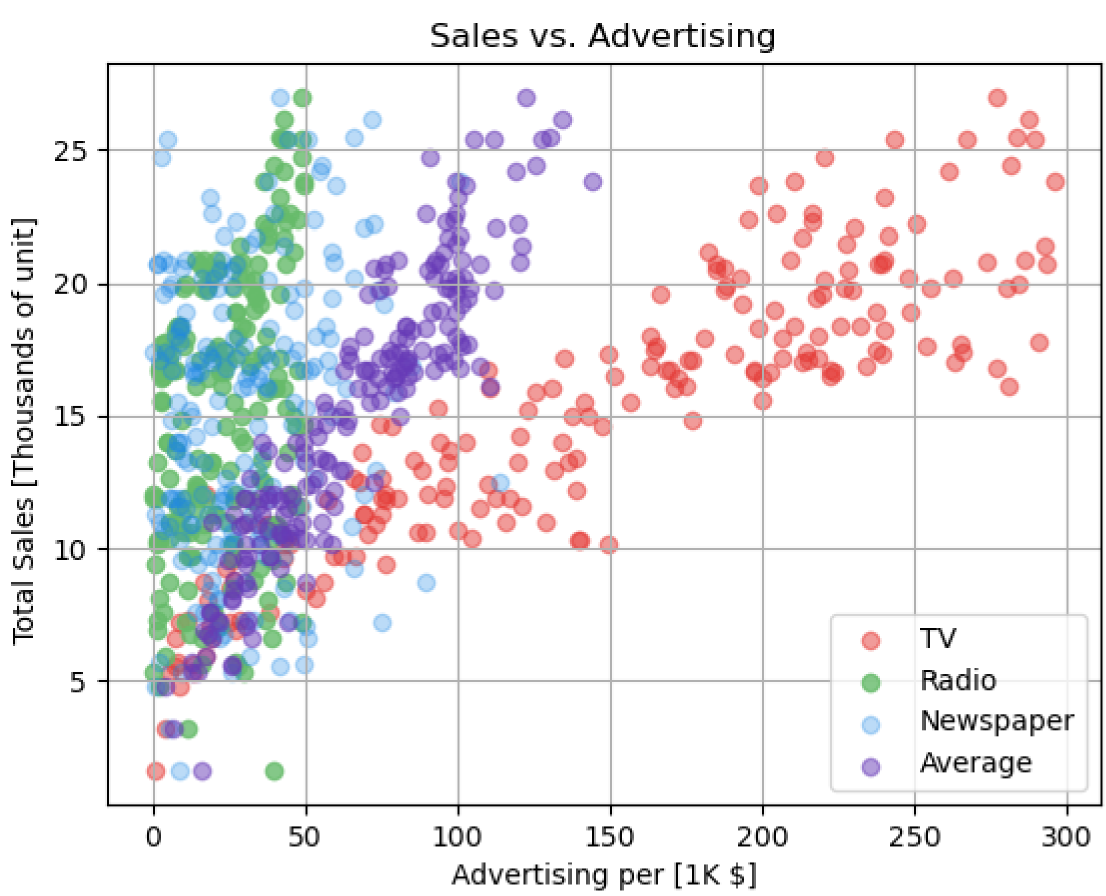
	TV	Radio	Newspaper	Sales	Average Budget
0	230.1	37.8	69.2	22.1	112.366667
1	44.5	39.3	45.1	10.4	42.966667
2	17.2	45.9	69.3	12.0	44.133333
3	151.5	41.3	58.5	16.5	83.766667
4	180.8	10.8	58.4	17.9	83.333333
...	...	...	...	...	...
195	38.2	3.7	13.8	7.6	18.566667
196	94.2	4.9	8.1	14.0	35.733333
197	177.0	9.3	6.4	14.8	64.233333
198	283.6	42.0	66.2	25.5	130.600000
199	232.1	8.6	8.7	18.4	83.133333

200 rows × 5 columns

Scatter plot

In [ ]:

```
plt.scatter(df['TV'],df['Sales'],c="#E53935",alpha=0.5, label='TV')
plt.scatter(df['Radio'],df['Sales'],c="#66BB6A",alpha=0.8, label='Radio')
plt.scatter(df['Newspaper'],df['Sales'],c="#1E88E5",alpha=0.3, label= 'Newspaper')
plt.scatter(df['Average Budget'],df['Sales'],c="#673AB7",alpha=0.5, label= 'Average')
plt.legend(loc="lower right")
plt.title("Sales vs. Advertising")
plt.xlabel("Advertising per [1K $]")
plt.ylabel(" Total Sales [Thousands of unit]")
plt.grid()
plt.show()
```



Optimization Problem

Problem Statement:

1. A budget constraint restricting the total amount of money to be allocated among three different channels (TV, Radio, Newspaper) takes the form x1 + x2 + x3 ≤ B, where B is the budget.

2. The total spend for each of these channels (TV, Radio, Newspaper) should be less than or equal to some constraints t, r, and n while total budget is capped at B.

3. Find out the objective function where we plan to maximize or minimize sales.

Approach:

1. Set constraint limits to variables B (total budget), t (TV), r (Radio), and Newspaper (n).
2. Build a linear regression model using the set constraints and data. Construct an objective function from the acquired results.
3. Maximize or Minimize for a desired output using linear programming (use Python's PuLP module).

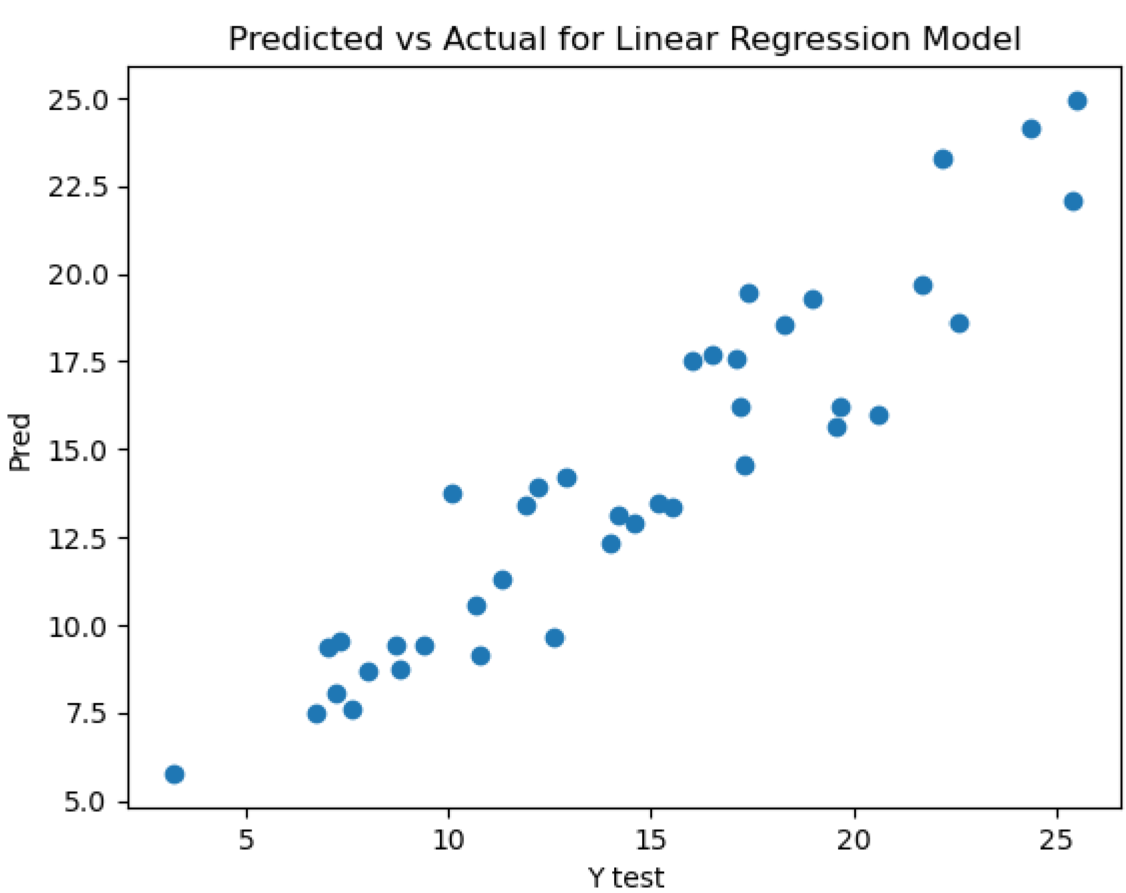
In [ ]:
```
y = df['Sales']
x = df[['Average Budget']]
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.20, random_state=57)
```

Using Linear Regression

In [ ]:
```
regression = LinearRegression()
regression.fit(x_train,y_train)
rgs_y_pred = regression.predict(x_test)
rgs_score = regression.score(x_test, y_test)
rgs_MSE = np.sqrt(mean_squared_error(y_test,rgs_y_pred))
rgs_coef = regression.coef_
rgs_intercept = regression.intercept_
print("Metrics for Linear Regression are as follows:")
print("-"*40)
print("Score:\t", rgs_score)
print("Error:\t", rgs_MSE)
print("Coef:\t",rgs_coef[0])
print("Intercept:\t",rgs_intercept)
```

```
Metrics for Linear Regression are as follows:
----------------------------------------
Score:	0.8723010124704045
Error:	2.026016654732277
Coef:	0.15518937421349988
Intercept:	4.671512412906933
```

In [ ]:
```
plt.scatter(y_test,rgs_y_pred)
plt.ylabel('Pred')
plt.xlabel('Y test')
plt.title("Predicted vs Actual for Linear Regression Model")
plt.show()
```

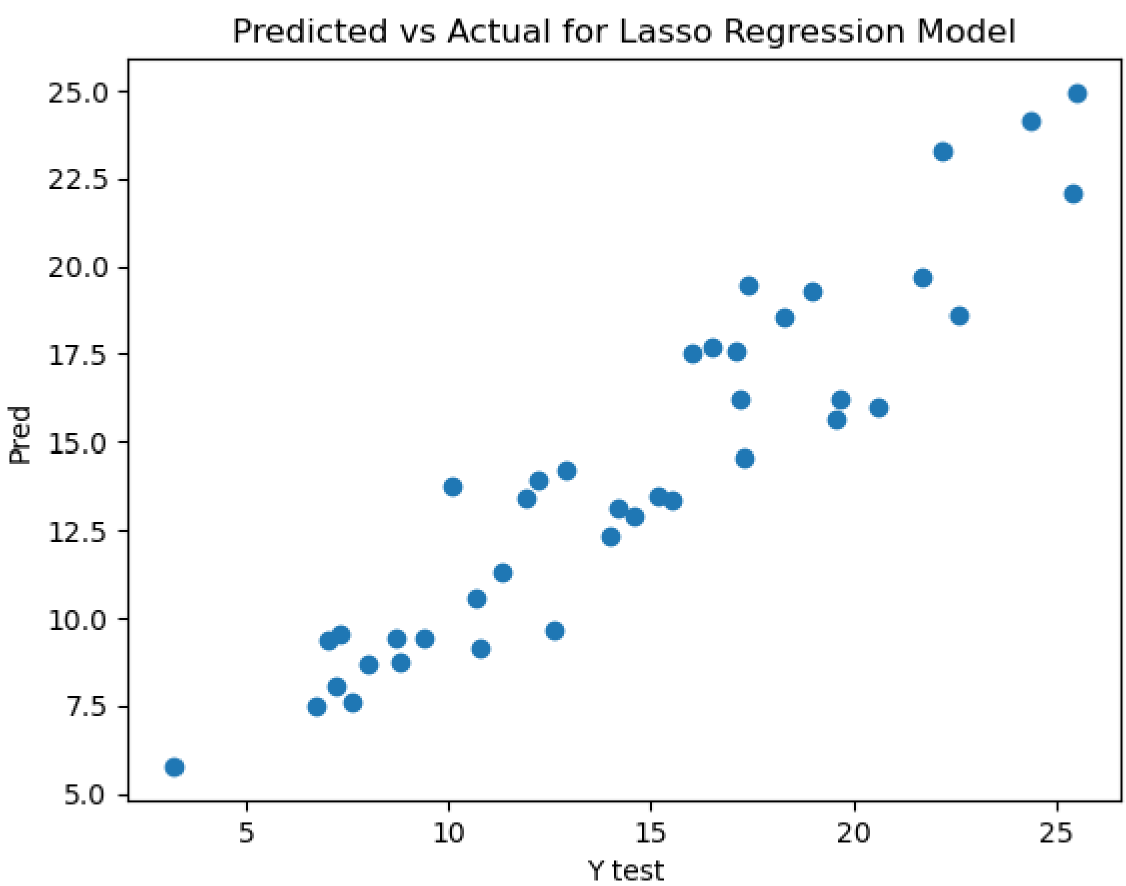


Using Lasso Model

In [ ]:
```
lasso = Lasso(alpha= 0.01)
lasso.fit(x_train,y_train)
lss_y_pred = lasso.predict(x_test)
lss_score = lasso.score(x_test, y_test)
lss_MSE = np.sqrt(mean_squared_error(y_test,lss_y_pred))
lss_coef = lasso.coef_
lss_intercept = lasso.intercept_
print("Metrics for Lasso Model are as follows:")
print("-"*40)
print("Score:\t", lss_score)
print("Error:\t", lss_MSE)
print("Coef:\t",lss_coef[0])
print("Intercept:\t",lss_intercept)
```

```
Metrics for Lasso Model are as follows:
----------------------------------------
Score:	0.8722934450614519
Error:	2.0260766844542673
Coef:	0.15517870012065144
Intercept:	4.672242463039764
```

In [ ]:
```
plt.scatter(y_test,lss_y_pred)
plt.ylabel('Pred')
plt.xlabel('Y test')
plt.title("Predicted vs Actual for Lasso Regression Model")
plt.show()
```

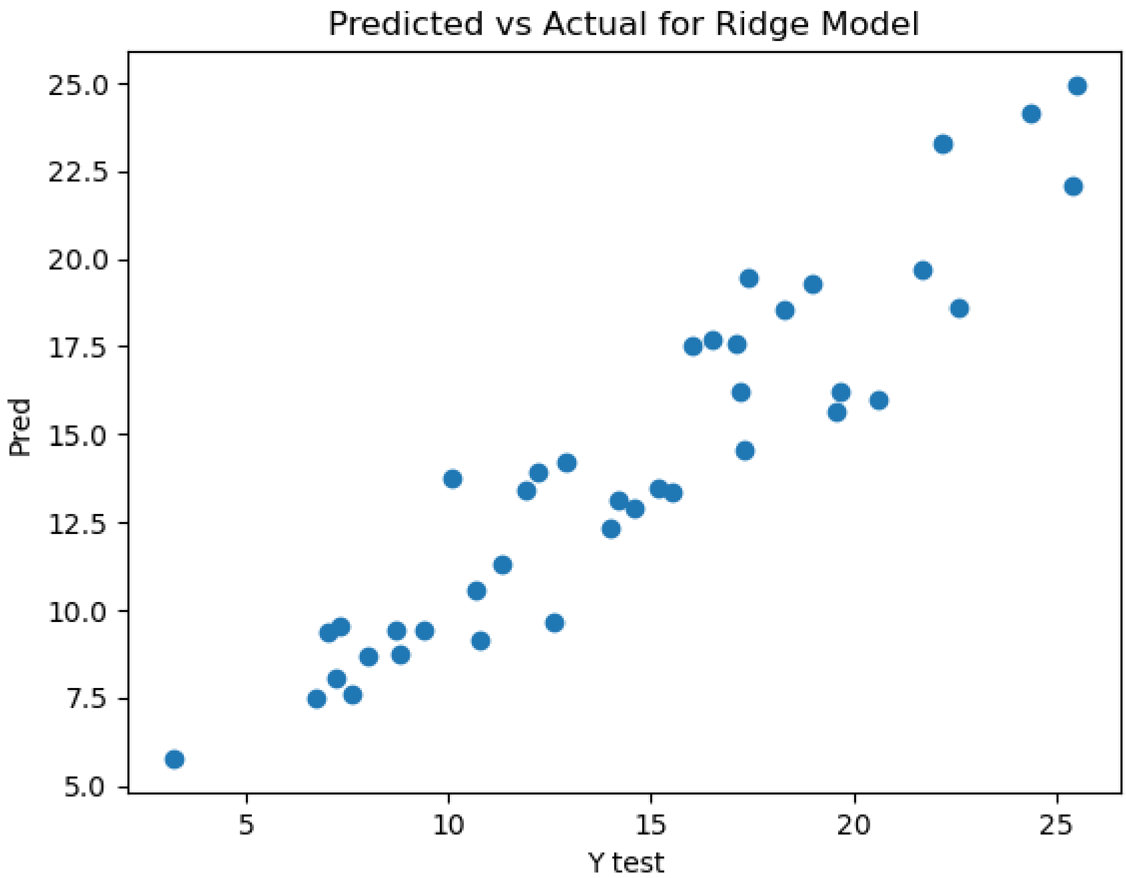


Using Ridge Model

In [ ]:
```
rm = Ridge(alpha=0.01)
rm.fit(x_train, y_train)
rm_y_pred= rm.predict(x_test)
rm_score = rm.score(x_test, y_test)
rm_MSE = np.sqrt(mean_squared_error(y_test,rm_y_pred))
rm_coef = rm.coef_
rm_intercept = rm.intercept_
print("Metrics for Ridge Model are as follows:")
print("-"*40)
print("Score:\t", rm_score)
print("Error:\t", rm_MSE)
print("Coef:\t",rm_coef[0])
print("Intercept:\t",rm_intercept)
```

```
Metrics for Ridge Model are as follows:
----------------------------------------
Score:	0.8723010051341012
Error:	2.0260167129295756
Coef:	0.1551893638603394
Intercept:	4.671513121007029
```

In [ ]:
```
plt.scatter(y_test,rm_y_pred)
plt.ylabel('Pred')
plt.xlabel('Y test')
plt.title("Predicted vs Actual for Ridge Model")
plt.show()
```

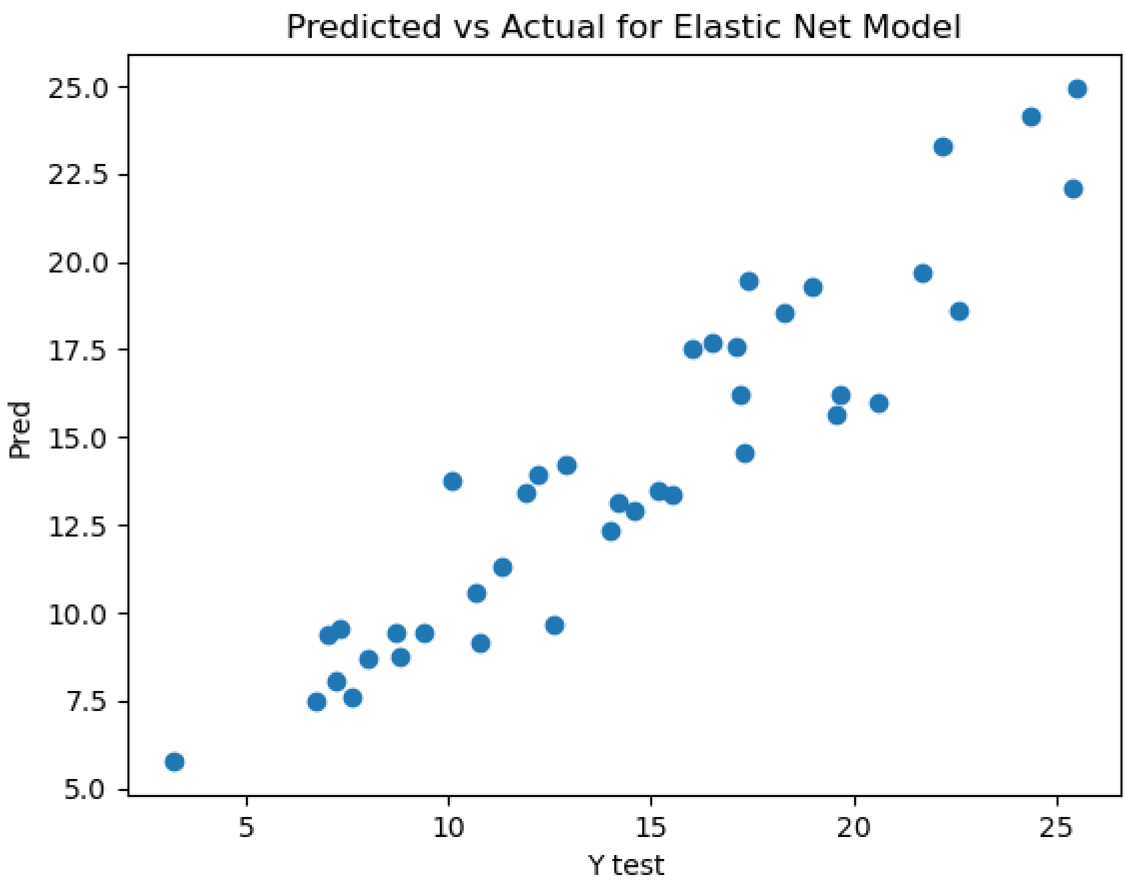


Using Elastic Net

In [ ]:
```
enet = ElasticNet(alpha = 0.01)
enet.fit(x_train, y_train)
enet_y_pred = enet.predict(x_test)
enet_score = enet.score(x_test, y_test)
enet_MSE = np.sqrt(mean_squared_error(y_test,enet_y_pred))
enet_coef = enet.coef_
enet_intercept = enet.intercept_
print("Metrics for Elastic Net are as follows:")
print("-"*40)
print("Score:\t", enet_score)
print("Error:\t", enet_MSE)
print("Coef:\t",enet_coef[0])
print("Intercept:\t",enet_intercept)
```

```
Metrics for Elastic Net are as follows:
----------------------------------------
Score:	 0.8722966425000338
Error:	 2.026051320461346
Coef:	 0.1551832089470853
Intercept:	 4.671934083734499
```

In [ ]:
```
plt.scatter(y_test,enet_y_pred)
plt.ylabel('Pred')
plt.xlabel('Y test')
plt.title("Predicted vs Actual for Elastic Net Model")
plt.show()
```



In [ ]:
```
avg_coef = (rgs_coef+lss_coef+rm_coef+enet_coef)/4
avg_intercept = (rgs_intercept+lss_intercept+rm_intercept+enet_intercept)/4
print("Average Metrics for all Models")
print("-"*40)
print("Average Coef: "+str(avg_coef[0]))
print("Average Intercept: "+str(avg_intercept))
```

```
Average Metrics for all Models
----------------------------------------
Average Coef: 0.155185161785394
Average Intercept: 4.671800520172056
```

Constraints:

Let the constraint on the total budget B be 1000, i.e., (T+R+N) <= 1000.

Let the constraint on each of the channels be as follows: T <= 200 R <= 500 N <= 500

Objective Function to Maximize Sales using PuLP

Maximize Sales, S = 0.05367932(T) + 0.11150177(R) - 0.0034977(N) + 4.773466912078015

In [ ]:
```
OpProb = LpProblem("AdvsSalesOpt", LpMaximize)
T = LpVariable("TV", 0, 200)
R = LpVariable("Radio", 0, 500)
N = LpVariable("Newspaper", 0, 500)
OpProb += T + R + N <= 1000
OpProb +=  0.05367932*T + 0.11150177*R - 0.0034977*N + 4.773466912078015
status = OpProb.solve()
LpStatus[status]
```

Out[ ]:
```
'Optimal'
```

In [ ]:
```
print(OpProb)
for v in OpProb.variables():
    print(v.name, "=", v.varValue)
```

```
AdvsSalesOpt:
MAXIMIZE
-0.0034977*Newspaper + 0.11150177*Radio + 0.05367932*TV + 4.773466912078015
SUBJECT TO
_C1: Newspaper + Radio + TV <= 1000

VARIABLES
Newspaper <= 500 Continuous
Radio <= 500 Continuous
TV <= 200 Continuous

Newspaper = 0.0
Radio = 500.0
TV = 200.0
```

In [ ]:

```
print("Objective Value = %f" % (OpProb.objective.value()))
# Optimized Value for Sales, Confirmation through calculation
OptVal = 0.05368006*200 + 0.11152624*500 - 0.00351166*0 + 4.773205203269837
print("Optimized Budget Sales: ",OptVal)
```

```
Objective Value = 71.260216
Optimized Budget Sales:  71.27233720326984
```