```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
df = pd.read_csv(r"D:\Supervised Machine Learning lab (SMLL)\2\
Assignment 2 Advertising.csv")
df.head()
```

```
   Unnamed: 0     TV  Radio  Newspaper  Sales
0           1  230.1   37.8       69.2   22.1
1           2   44.5   39.3       45.1   10.4
2           3   17.2   45.9       69.3    9.3
3           4  151.5   41.3       58.5   18.5
4           5  180.8   10.8       58.4   12.9
```

```
dataset = df.iloc[: ,1:]
print(dataset)
```

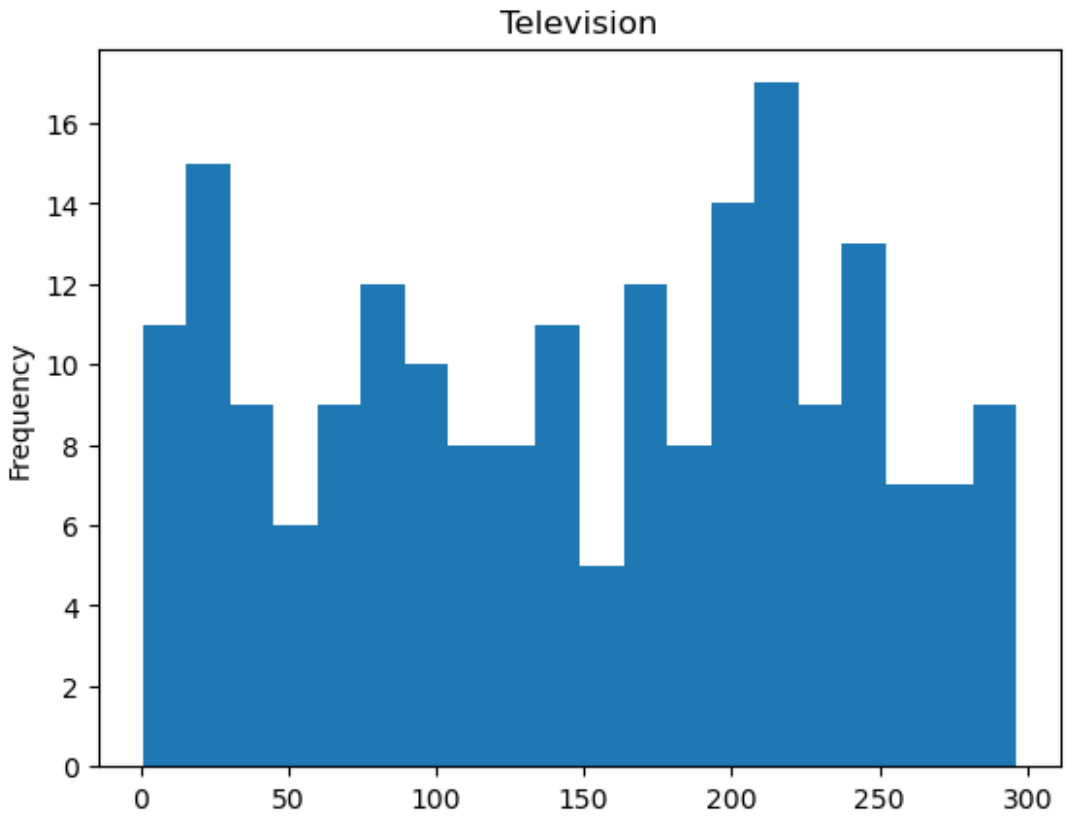
```
        TV  Radio  Newspaper  Sales
0    230.1   37.8       69.2   22.1
1     44.5   39.3       45.1   10.4
2     17.2   45.9       69.3    9.3
3    151.5   41.3       58.5   18.5
4    180.8   10.8       58.4   12.9
..     ...    ...        ...    ...
195   38.2    3.7       13.8    7.6
196   94.2    4.9        8.1    9.7
197  177.0    9.3        6.4   12.8
198  283.6   42.0       66.2   25.5
199  232.1    8.6        8.7   13.4
```

```
[200 rows x 4 columns]
```

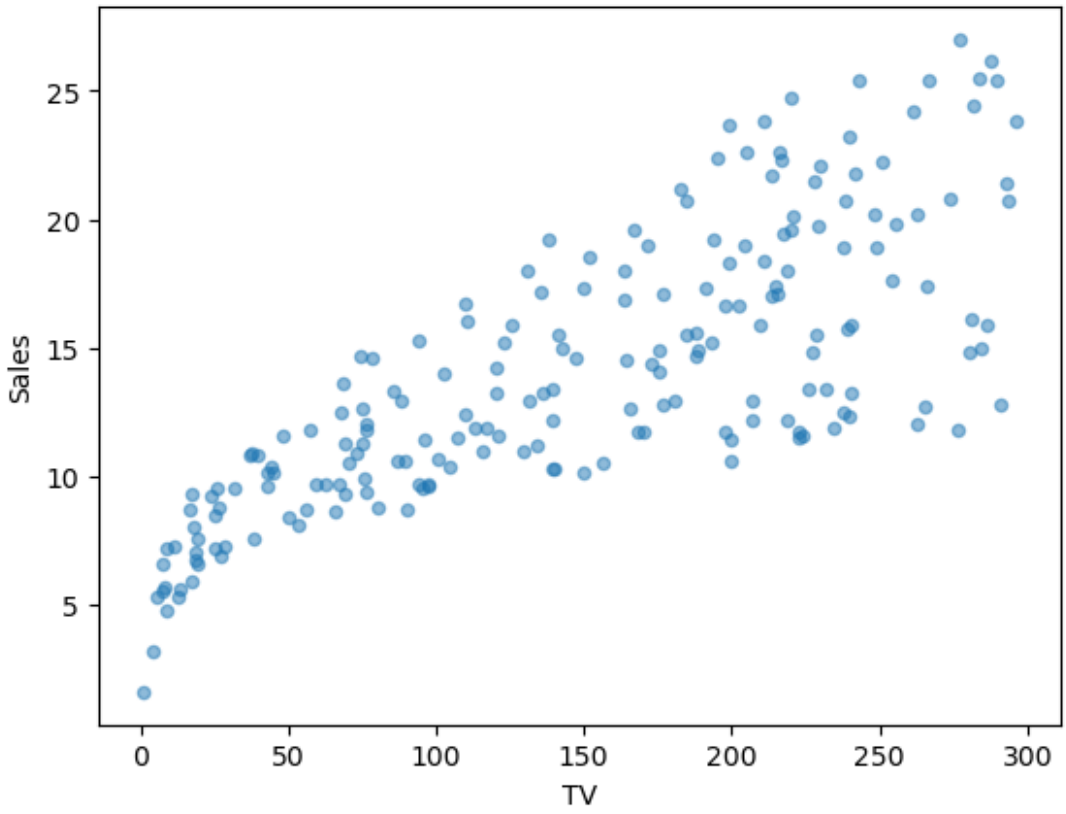
```
dataset.shape
```

```
(200, 4)
```

```
# fig, ax = plt.subplots(figsize=(10, 20))  # Corrected figure
creation
dataset['TV'].plot(kind='hist', bins=20, title='Television')
plt.show()
```

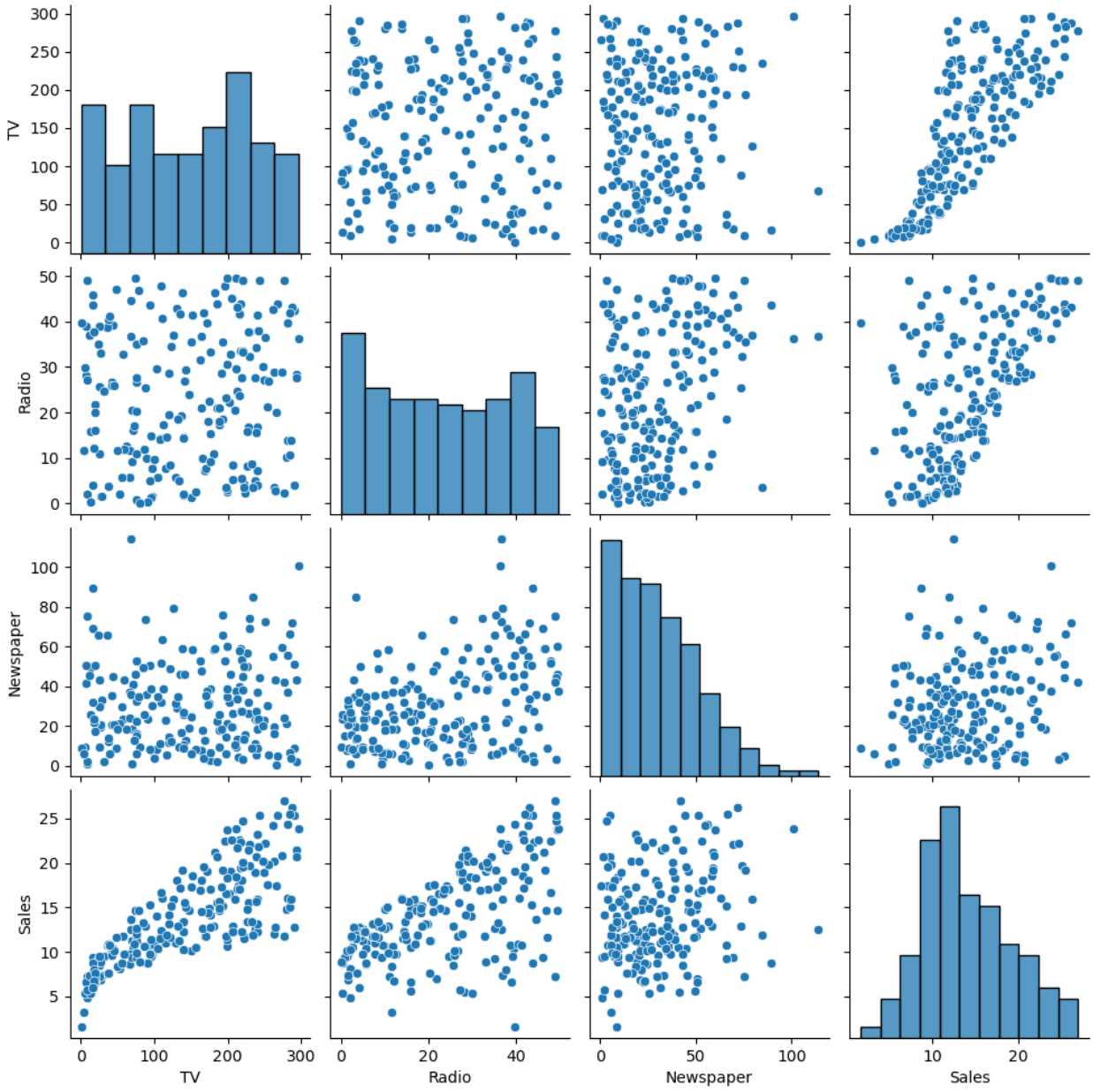



```
dataset.plot(kind='scatter',x='TV',y='Sales', alpha=0.5)
plt.show()
```




```
sns.pairplot(data=dataset)
```

```
<seaborn.axisgrid.PairGrid at 0x1fbed583830>
```




```
from statsmodels.stats.outliers_influence import
variance_inflation_factor
import pandas as pd

def calc_vif(X):
    """
    Calculate Variance Inflation Factor (VIF) for a given DataFrame of
features.

    Parameters:
    X: DataFrame
        A DataFrame containing the independent variables.
```

```
    Returns:
    DataFrame
        A DataFrame with features and their corresponding VIF values.
    """
    vif = pd.DataFrame()
    vif["features"] = X.columns  # Add column names
    vif["VIF"] = [variance_inflation_factor(X.values, i) for i in
range(X.shape[1])]  # Calculate VIF for all columns
    return vif

X_NEW = dataset.iloc[: ,:-1]
calc_vif(X_NEW)
```

```
    features       VIF
0         TV  2.486772
1      Radio  3.285462
2  Newspaper  3.055245
```

```
x = dataset[["TV", 'Radio', 'Newspaper']]
y = dataset['Sales']

x.head()
```

```
      TV  Radio  Newspaper
0  230.1   37.8       69.2
1   44.5   39.3       45.1
2   17.2   45.9       69.3
3  151.5   41.3       58.5
4  180.8   10.8       58.4
```

```
from sklearn.model_selection import train_test_split

# Assuming X and y are already defined (e.g., as NumPy arrays or
pandas DataFrames/Series)
X_train, X_test, y_train, y_test = train_test_split(x, y,
test_size=0.2, random_state=42)

from sklearn.linear_model import LinearRegression

mlr = LinearRegression()

mlr.fit(X_train,y_train)
```

```
LinearRegression()
```

```
y_pred = mlr.predict(X_test)
print(y_pred)
```

```
[16.4080242  20.88988209 21.55384318 10.60850256 22.11237326
13.10559172
 21.05719192  7.46101034 13.60634581 15.15506967  9.04831992
```

```
6.65328312
 14.34554487  8.90349333  9.68959028 12.16494386  8.73628397
16.26507258
 10.27759582 18.83109103 19.56036653 13.25103464 12.33620695
21.30695132
  7.82740305  5.80957448 20.75753231 11.98138077  9.18349576
8.5066991
 12.46646769 10.00337695 21.3876709  12.24966368 18.26661538
20.13766267
 14.05514005 20.85411186 11.0174441   4.56899622]
```

```
# Actual vs Predictied value
mlr_diff = pd.DataFrame({'Actual value': y_test, 'Predicted value' :
y_pred})
print(mlr_diff)
```

	Actual value	Predicted value
95	16.9	16.408024
15	22.4	20.889882
30	21.4	21.553843
158	7.3	10.608503
128	24.7	22.112373
115	12.6	13.105592
69	22.3	21.057192
170	8.4	7.461010
174	11.5	13.606346
45	14.9	15.155070
66	9.5	9.048320
182	8.7	6.653283
165	11.9	14.345545
78	5.3	8.903493
186	10.3	9.689590
177	11.7	12.164944
56	5.5	8.736284
152	16.6	16.265073
82	11.3	10.277596
68	18.9	18.831091
124	19.7	19.560367
16	12.5	13.251035
148	10.9	12.336207
93	22.2	21.306951
65	9.3	7.827403
60	8.1	5.809574
84	21.7	20.757532
67	13.4	11.981381
125	10.6	9.183496
132	5.7	8.506699
9	10.6	12.466468
18	11.3	10.003377
55	23.7	21.387671

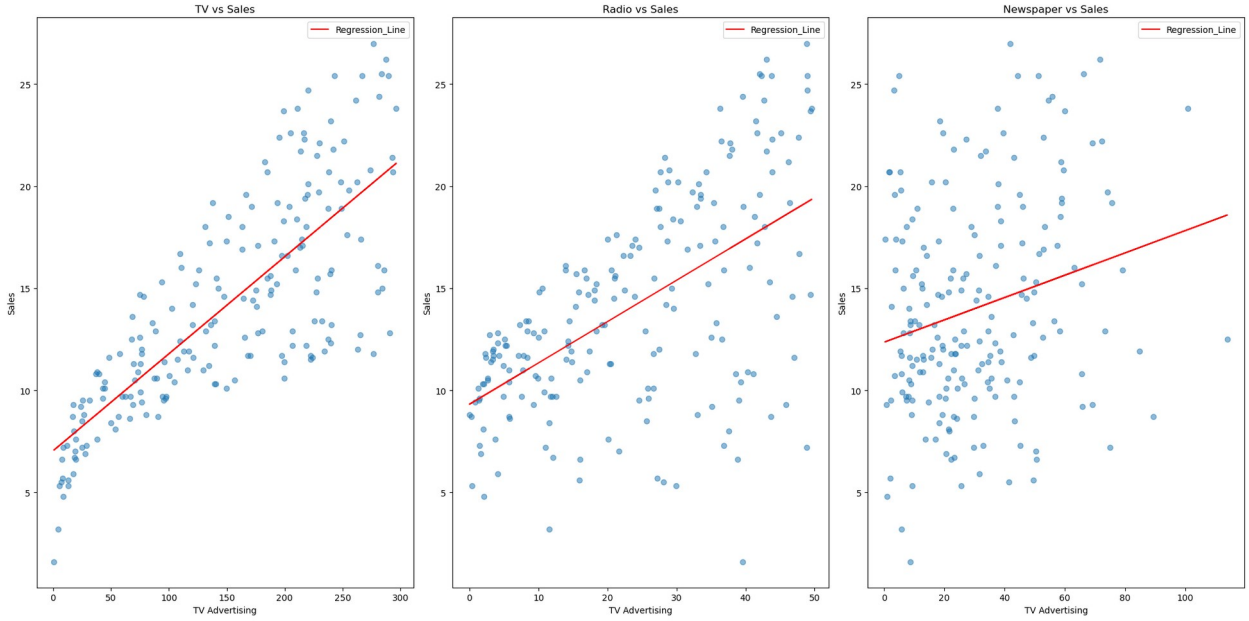
```
75            8.7        12.249664
150          16.1        18.266615
104          20.7        20.137663
135          11.6        14.055140
137          20.8        20.854112
164          11.9        11.017444
76            6.9         4.568996
```

```
# Errors
from sklearn.metrics import mean_squared_error, mean_absolute_error,
r2_score
# Mean Square Error
mean_square_error = mean_squared_error(y_test,y_pred)
print(f"Mean Square Error is : {mean_square_error}")
# Calculate Mean Absolute Error
mae = mean_absolute_error(y_test, y_pred)
print(f"Mean Absolute Error is : {mae}")
# Root Mean Square Error
root_mean_square_error = np.sqrt(mean_square_error)
print(f"Root Mean Square Error is : {root_mean_square_error}")
# Calculate R-squared
r2 = r2_score(y_test, y_pred)
print(f"R2 score is : {r2*100}")
#intecept
X_intercept = mlr.intercept_
print(f"X intercept is : {X_intercept}")
Y_intercept = mlr.coef_
print(f"Y intercept is : {Y_intercept}")
```

```
Mean Square Error is : 3.1740973539761015
Mean Absolute Error is : 1.4607567168117597
Root Mean Square Error is : 1.7815996615334495
R2 score is : 89.94380241009121
X intercept is : 2.979067338122631
Y intercept is : [0.04472952 0.18919505 0.00276111]
```

```
# Function to scatter plot with regression line
def
plot_scatter_with_regression(ax,x_data,y_data,x_label,y_label,title):
    ax.scatter(x_data,y_data,alpha=0.5)

    # Calculate regression line
    slope, intercept = np.polyfit(x_data,y_data,1)
    regression_line = slope*x_data + intercept

    ax.plot(x_data,regression_line, color='red',
label='Regression_Line')

    ax.set_title(title)
    ax.set_xlabel(x_label)
```

```
    ax.set_ylabel(y_label)
    ax.legend()


fig , ax = plt.subplots(1,3, figsize=(20,10))

# Scatter plot for TV vs Sales
plot_scatter_with_regression(ax[0],dataset['TV'],dataset['Sales'],'TV
Advertising','Sales','TV vs Sales')
plot_scatter_with_regression(ax[1],dataset['Radio'],dataset['Sales'],'
TV Advertising','Sales','Radio vs Sales')
plot_scatter_with_regression(ax[2],dataset['Newspaper'],dataset['Sales
'],'TV Advertising','Sales','Newspaper vs Sales')
plt.tight_layout()
plt.show()
```



Practice Datasets

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
df = pd.read_csv(r"C:\Users\Neil\Supervised Machine Learining Lab
(SMLL)\Practice dataset 1 Product performance.csv")
df.head()
```

	Ambience	Customer_service	Offers	Product_range	Performance
0	0.50	1.40	-0.68	0.48	2
1	-0.14	0.92	-0.14	0.11	7

```
2      0.65              0.06   -0.79           0.51            5
3      1.52             -0.65   -0.31           1.12            9
4     -0.23              0.70   -1.89           1.10            8
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 5 columns):
 #   Column            Non-Null Count  Dtype  
---  ------            --------------  -----  
 0   Ambience          1000 non-null   float64
 1   Customer_service  1000 non-null   float64
 2   Offers            1000 non-null   float64
 3   Product_range     1000 non-null   float64
 4   Performance       1000 non-null   int64  
dtypes: float64(4), int64(1)
memory usage: 39.2 KB
```

```
df.isnull()
```

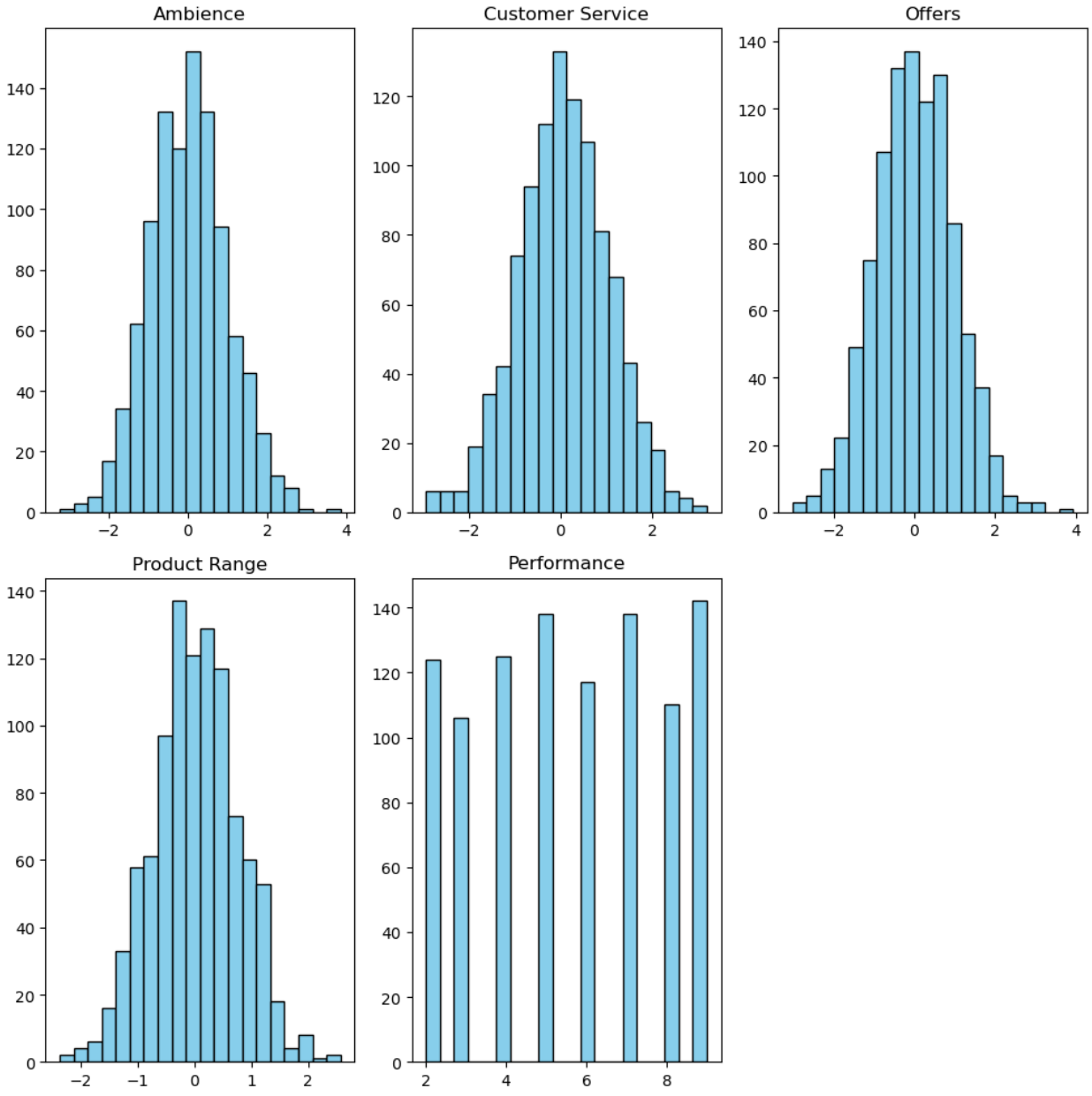
```
     Ambience  Customer_service  Offers  Product_range  Performance
0       False             False   False          False        False
1       False             False   False          False        False
2       False             False   False          False        False
3       False             False   False          False        False
4       False             False   False          False        False
..        ...               ...     ...            ...          ...
995     False             False   False          False        False
996     False             False   False          False        False
997     False             False   False          False        False
998     False             False   False          False        False
999     False             False   False          False        False

[1000 rows x 5 columns]
```

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

```
Ambience            0
Customer_service    0
Offers              0
Product_range       0
Performance         0
dtype: int64
```

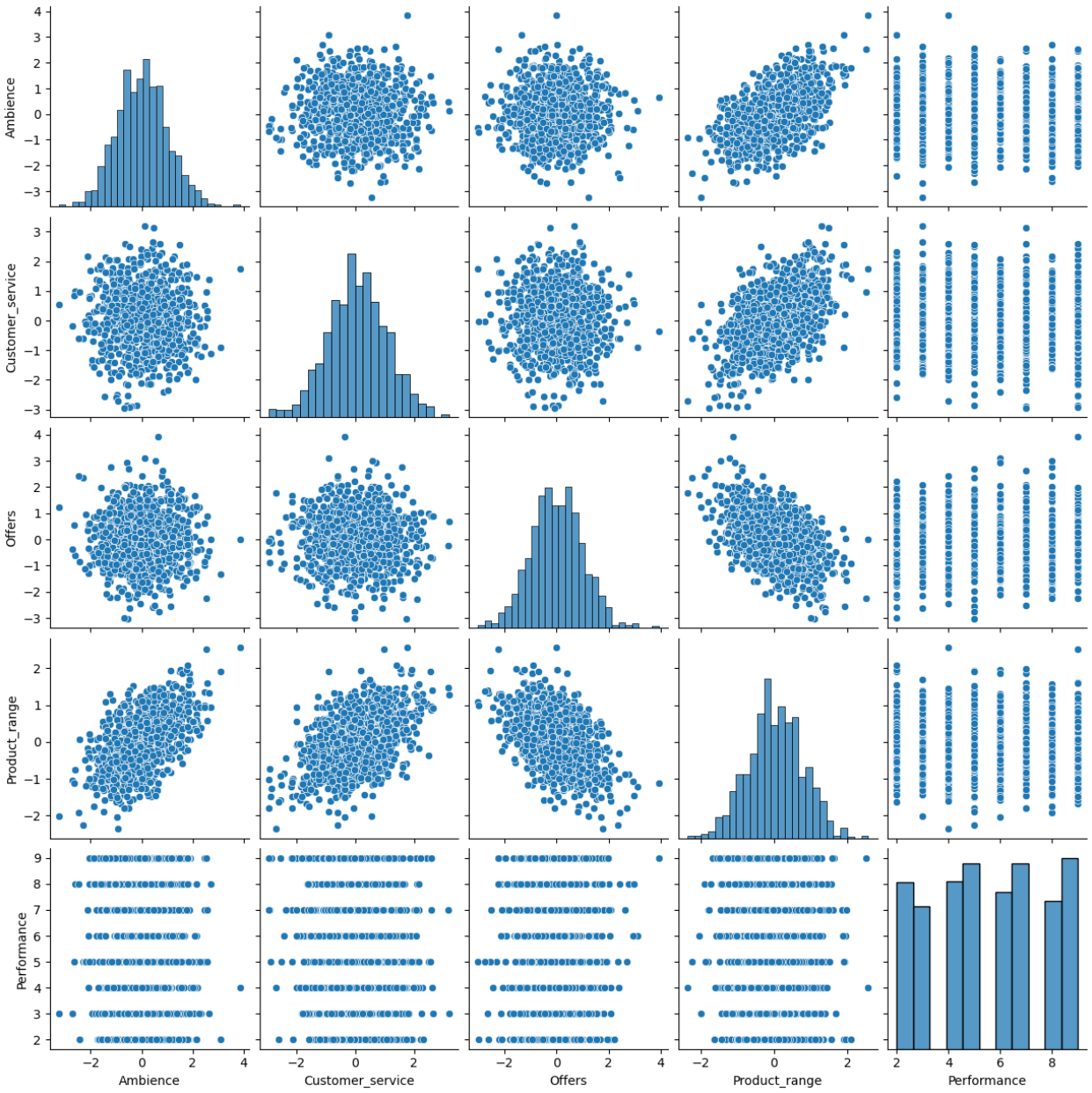
```
import matplotlib.pyplot as plt

# Assuming you have a DataFrame 'df' and columns like 'Ambience',
'Customer_service', etc.

# Create subplots
```

```
fig, ax = plt.subplots(2, 3, figsize=(10, 10))

# Plotting histograms for each column
ax[0, 0].hist(df['Ambience'], bins=20, color='skyblue',
edgecolor='black')
ax[0, 0].set_title('Ambience')

ax[0, 1].hist(df['Customer_service'], bins=20, color='skyblue',
edgecolor='black')
ax[0, 1].set_title('Customer Service')

ax[0, 2].hist(df['Offers'], bins=20, color='skyblue',
edgecolor='black')
ax[0, 2].set_title('Offers')

ax[1, 0].hist(df['Product_range'], bins=20, color='skyblue',
edgecolor='black')
ax[1, 0].set_title('Product Range')

ax[1, 1].hist(df['Performance'], bins=20, color='skyblue',
edgecolor='black')
ax[1, 1].set_title('Performance')

# If there are no more subplots to plot on the bottom row, we can hide
the last subplot
ax[1, 2].axis('off')

# Adjust layout to avoid overlapping
plt.tight_layout()

# Show the plot
plt.show()
```




```
import seaborn as sns
sns.pairplot(df[['Ambience', 'Customer_service', 'Offers',
'Product_range', 'Performance']])
```

```
<seaborn.axisgrid.PairGrid at 0x1fbef6941d0>
```




```
X = df[['Ambience', 'Customer_service', 'Offers', 'Product_range']]
y = df['Performance']

calc_vif(X)
```

	features	VIF
0	Ambience	3.007233
1	Customer_service	2.548359
2	Offers	2.581965
3	Product_range	5.950350

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

```
# Assuming X and y are already defined (e.g., as NumPy arrays or
pandas DataFrames/Series)
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=42)

from sklearn.linear_model import LinearRegression

mlr = LinearRegression()

mlr.fit(X_train,y_train)
```

```
LinearRegression()
```

```
y_pred = mlr.predict(X_test)
print(y_pred)
```

```
[5.73984783 5.75458812 5.605585   5.53832103 5.52401508 5.45839112
 5.65896229 5.90236869 5.63262708 5.3937337  5.56294797 5.67195242
 5.7574118  5.51846405 5.60036698 5.56781705 5.72319792 5.77840502
 5.57427673 5.44498475 5.44236346 5.80090699 5.60663555 5.28411913
 5.67052516 5.46374877 5.79367895 5.56657871 5.37917688 5.61997698
 5.81588281 5.56334874 5.70909175 5.53341567 5.64229652 5.64643802
 5.59402976 5.55285614 5.65006295 5.72098528 5.82681584 5.5132564
 5.33813977 5.54765323 5.54638695 5.57031719 5.50686688 5.50984052
 5.55899868 5.49390289 5.57348357 5.75555173 5.59285292 5.68730202
 5.2980137  5.81658959 5.73428942 5.52908078 5.46002957 5.64675657
 5.4124784  5.58176993 5.42070563 5.5785663  5.61662461 5.38961736
 5.7518863  5.52964192 5.72407893 5.81549666 5.64890459 5.58019588
 5.58756911 5.5212984  5.4759383  5.77303825 5.53528047 5.59264677
 5.60805699 5.56474256 5.71724722 5.62455131 5.5243427  5.55417345
 5.59420447 5.64099485 5.45253209 5.55978792 5.85928386 5.72080436
 5.31804402 5.63687529 5.68783196 5.68511149 5.80811888 5.65433361
 5.65672285 5.80178067 5.76630979 5.85179254 5.28551961 5.85006183
 5.45341757 5.5804542  5.53564594 5.79340631 5.83236157 5.6232368
 5.5671021  5.61437857 5.7852102  5.67499177 5.73235782 5.83807207
 5.58088998 5.4830693  5.81358195 5.55737961 5.45141841 5.75089222
 5.75054487 5.73681517 5.78000892 5.5402222  5.80424627 5.71900019
 5.78424282 5.79680304 5.4040674  5.6099711  5.72481397 5.69686874
 5.48743913 5.50667117 5.79687795 5.80686194 5.54036053 5.37230711
 5.61463519 5.58664701 5.52473401 5.7520825  5.4289274  5.66743372
 5.83859493 5.88604611 5.74180754 5.60262204 5.73402523 5.65674769
 5.53500898 5.33595863 5.32673656 5.47741641 5.58625135 5.57962981
 5.54736241 5.62371733 5.48112409 5.71181756 5.63113568 5.57510592
 5.43784961 5.62447658 5.81486067 5.43611127 5.7123201  5.65424993
 5.68414528 5.71985463 5.80653125 5.55929231 5.66962172 5.59425405
 5.58323269 5.81255455 5.44216837 5.51735242 5.78392208 5.60133826
 5.52536925 5.61252115 5.64857911 5.39505233 5.6748443  5.76515677
 5.80916389 5.4045961  5.65905162 5.60590992 5.54525905 5.56928042
 5.62539791 5.40027565 5.43748123 5.65153883 5.53147377 5.68431868
 5.54247254 5.47035188]
```

```
# Actual vs Predictied value
mlr_diff = pd.DataFrame({'Actual value': y_test, 'Predicted value' :
y_pred})
print(mlr_diff)
```

```
     Actual value  Predicted value
521             8         5.739848
737             2         5.754588
740             8         5.605585
660             5         5.538321
411             5         5.524015
..            ...              ...
408             7         5.651539
332             6         5.531474
208             4         5.684319
613             9         5.542473
78              5         5.470352

[200 rows x 2 columns]
```

```
# Errors
from sklearn.metrics import mean_squared_error, mean_absolute_error,
r2_score
# Mean Square Error
mean_square_error = mean_squared_error(y_test,y_pred)
print(f"Mean Square Error is : {mean_square_error}")
# Calculate Mean Absolute Error
mae = mean_absolute_error(y_test, y_pred)
print(f"Mean Absolute Error is : {mae}")
# Root Mean Square Error
root_mean_square_error = np.sqrt(mean_square_error)
print(f"Root Mean Square Error is : {root_mean_square_error}")
# Calculate R-squared
r2 = r2_score(y_test, y_pred)
print(f"R2 score is : {r2*100}")
#intecept
X_intercept = mlr.intercept_
print(f"X intercept is : {X_intercept}")
Y_intercept = mlr.coef_
print(f"Y intercept is : {Y_intercept}")
```

```
Mean Square Error is : 5.298737974453129
Mean Absolute Error is : 2.0080804261988128
Root Mean Square Error is : 2.301898775892009
R2 score is : -0.7599293457721368
X intercept is : 5.615687163039276
Y intercept is : [ 0.17437539  0.03220421 -0.14152898 -0.29759668]
```

```
fig , ax = plt.subplots(1,4, figsize=(20,10))
```

```
# Scatter plot for TV vs Sales
plot_scatter_with_regression(ax[0],df['Ambience'],df['Performance'],'Ambience','Performance','Ambience vs Performance')
plot_scatter_with_regression(ax[1],df['Customer_service'],df['Performance'],'Customer_service','Performance','Customer_service vs Performance')
plot_scatter_with_regression(ax[2],df['Offers'],df['Performance'],'Offers','Performance','Offers vs Performance')
plot_scatter_with_regression(ax[3],df['Product_range'],df['Performance'],'Product_range','Performance','Product_range vs Performance')
plt.tight_layout
plt.show()
```