Statistical Methods in Engineering Project - Task 1

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Task 1 - Regression

Dataset - https://www.kaggle.com/datasets/harrimansaragih/dummy-advertising-and-sales-data/data

```
# importing the necessary libraries to carry out analysis
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import scipy.stats as stats
from scipy.stats import pointbiserialr

from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_squared_error
```

Exploring the dataset

```
# reading the dataset and storing it in the variable called df1
df1 = pd.read_csv('Marketing_Sales.csv')
df1.head()
```

	TV	Radio	Social Media	Influencer	Sales
0	16.0	6.566231	2.907983	Mega	54.732757
1	13.0	9.237765	2.409567	Mega	46.677897
2	41.0	15.886446	2.913410	Mega	150.177829
3	83.0	30.020028	6.922304	Mega	298.246340
4	15.0	8.437408	1.405998	Micro	56.594181

```
# displaying the shape of the dataframe
df1.shape
```

```
(4572, 5)
```

```
# displaying the type of information containd in the dataframe
df1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4572 entries, 0 to 4571
Data columns (total 5 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   TV            4562 non-null   float64
 1   Radio         4568 non-null   float64
 2   Social Media  4566 non-null   float64
 3   Influencer    4572 non-null   object
 4   Sales         4566 non-null   float64
dtypes: float64(4), object(1)
memory usage: 178.7+ KB
```

```
# getting a description of the numerical values of the dataframe
df1.describe()
```

	TV	Radio	Social Media	Sales
count	4562.000000	4568.000000	4566.000000	4566.000000
mean	54.066857	18.160356	3.323956	192.466602
std	26.125054	9.676958	2.212670	93.133092
min	10.000000	0.000684	0.000031	31.199409
25%	32.000000	10.525957	1.527849	112.322882
50%	53.000000	17.859513	3.055565	189.231172
75%	77.000000	25.649730	4.807558	272.507922
max	100.000000	48.871161	13.981662	364.079751

```
# describing the nature of the categorical column
df1['Influencer'].describe()
```

```
count     4572
unique       4
top       Mega
freq      1158
Name: Influencer, dtype: object
```

Handling missing values

```
# finding the sum of missing values in every column
df1.isna().sum()
```

```
TV              10
Radio            4
Social Media     6
```

```
Influencer       0
Sales            6
dtype: int64
```

```
# creating a copy of the dataframe to handle missing values
df1_null = df1[df1.isnull().any(axis = 1)]
df1_null.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 26 entries, 13 to 236
Data columns (total 5 columns):
 #   Column        Non-Null Count  Dtype  
---  ------        --------------  -----  
 0   TV            16 non-null     float64
 1   Radio         22 non-null     float64
 2   Social Media  20 non-null     float64
 3   Influencer    26 non-null     object 
 4   Sales         20 non-null     float64
dtypes: float64(4), object(1)
memory usage: 1.2+ KB
```

```
# taking a look at all the null values
df1_null.head(26)
```

	TV	Radio	Social Media	Influencer	Sales
13	NaN	22.351667	3.031815	Mega	276.165351
26	NaN	34.111674	4.624148	Nano	342.913372
46	NaN	34.859637	7.781417	Mega	318.969784
75	NaN	6.482293	0.866845	Macro	91.177216
99	NaN	7.635819	1.554146	Macro	56.186730
119	NaN	30.470485	6.806919	Micro	336.818690
141	NaN	9.164464	1.096681	Macro	65.259189
163	NaN	38.118424	6.676611	Micro	328.555184
182	81.0	26.425422	NaN	Macro	288.649441

```
# creating an updated dataframe after dropping missing values
df1_cleaned = df1.dropna()
```

184 25.0 0.413849 NaN Macro 92.357092

```
# verifying the columns of the cleaned dataframe
df1_cleaned.columns
```

```
Index(['TV', 'Radio', 'Social Media', 'Influencer', 'Sales'], dtype='object')
```

```
# taking a look at the new, cleaned dataset
df1_cleaned.head()
```

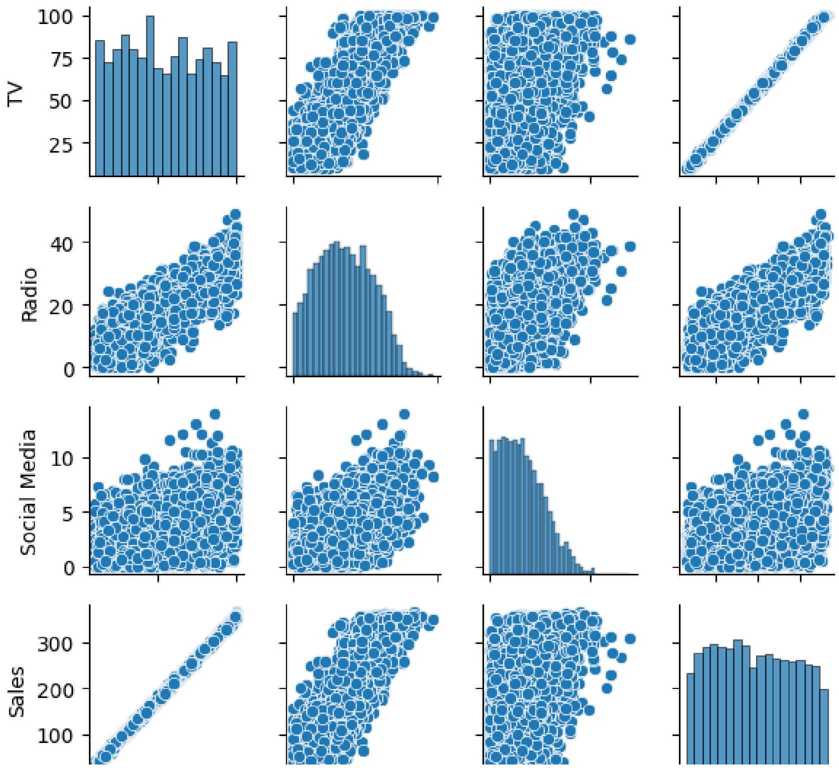
	TV	Radio	Social Media	Influencer	Sales
0	16.0	6.566231	2.907983	Mega	54.732757
1	13.0	9.237765	2.409567	Mega	46.677897
2	41.0	15.886446	2.913410	Mega	150.177829
3	83.0	30.020028	6.922304	Mega	298.246340
4	15.0	8.437408	1.405998	Micro	56.594181

Since we are making use of Linear Regression, it is important that the 'Sales' column is linearly dependent on other features of the dataset. Hence, making use of PairGrid

236 27.0 1.384415 2.398129 Nano NaN

```
# making use of Seaborn to plot the PairGrid
g = sns.PairGrid(df1_cleaned, height = 1.5)
g.map_diag(sns.histplot)
g.map_offdiag(sns.scatterplot)
```

```
<seaborn.axisgrid.PairGrid at 0x7ff644003c70>
```



From the above plot, we can observe that:

- 'Sales' shows a strong positive linear dependency from 'TV'
- 'Sales' shows a kind of positive linear depdendency from 'Social Media'
- 'Sales' shows a positive linear depdendency from 'Radio'
- 'Radio' and 'Social Media' features show a positive linear relationship

Correlation Matrix

```
# extracting the numerical columns and creating the correlation matrix
numerical_cols = ['TV', 'Radio', 'Social Media', 'Sales']
correlation = df1_cleaned[numerical_cols].corr()
correlation.round(3)
```

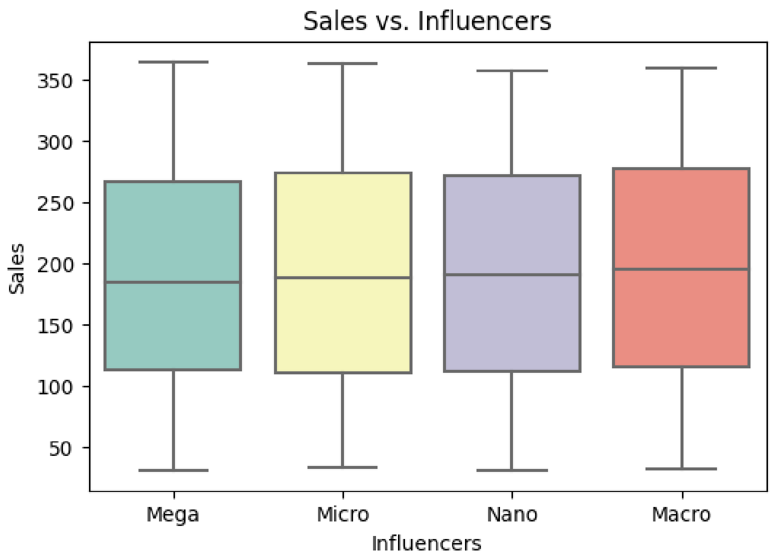
	TV	Radio	Social Media	Sales

We can confirm the results of our visualization through the correlation matrix obtained above

Radio	0.869	1.000	0.606	0.869

```
# creating a box-plot for the categorical feature
plt.figure(figsize = (6, 4))
sns.boxplot(x = 'Influencer', y = 'Sales', data = df1_cleaned, palette = 'Set3')
plt.title('Sales vs. Influencers')
plt.xlabel('Influencers')
plt.ylabel('Sales')
```

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



We can observe that there are no outliers and the plots are almost similar for the different values present in the 'Influencers' column

Encoding

```
# performing one-hot encoding to convert categorical into numerical data
df1_modified = pd.get_dummies(df1_cleaned, columns = ["Influencer"]).astype(int)
df1_modified.head()
```

	TV	Radio	Social Media	Sales	Influencer_Macro	Influencer_Mega	Influencer_Micro	Influencer_Nano
0	16	6	2	54	0	1	0	0

```
# taking a look at the columns of the new dataframe
df1_modified.columns
```

```
Index(['TV', 'Radio', 'Social Media', 'Sales', 'Influencer_Macro',
       'Influencer_Mega', 'Influencer_Micro', 'Influencer_Nano'],
      dtype='object')
```

P-Values

```
# finding the Point-Biseral correlation between different values in the 'Influencers' column
influencer_columns = ['Influencer_Macro', 'Influencer_Mega', 'Influencer_Micro', 'Influencer_Nano']
for col in influencer_columns:
    correlation, p_value = pointbiserialr(df1_modified[col], df1_modified['Sales'])
    print(f'{correlation:.4f}: Point-Biserial Correlation for {col} with p-value {p_value:.4f}')
```

```
0.0224: Point-Biserial Correlation for Influencer_Macro with p-value 0.1313
-0.0125: Point-Biserial Correlation for Influencer_Mega with p-value 0.4006
-0.0052: Point-Biserial Correlation for Influencer_Micro with p-value 0.7242
-0.0044: Point-Biserial Correlation for Influencer_Nano with p-value 0.7646
```

Since none of the p-values are above 0.05, we can conclude that 'Influencer' has no strong correlation with 'Sales'

```
# adding an additional feature called 'TV-Radio' to the dataframe
df1_modified['TV_Radio'] = df1_modified['TV'] + df1_modified['Radio']
df1_modified.head()
```

	TV	Radio	Social Media	Sales	Influencer_Macro	Influencer_Mega	Influencer_Micro	Influencer_Nano	TV_Radio
0	16	6	2	54	0	1	0	0	22
1	13	9	2	46	0	1	0	0	22
2	41	15	2	150	0	1	0	0	56
3	83	30	6	298	0	1	0	0	113

```
# splitting the dataset into testing and training sets
X = df1_modified[['TV', 'Radio', 'Social Media', \
                  'Influencer_Macro', 'Influencer_Mega', 'Influencer_Micro', 'Influencer_Nano',\
                  'TV_Radio']]
y = df1_modified ['Sales']
X_train, X_test, y_train, y_test = train_test_split(X, y, random_state = 7)
```

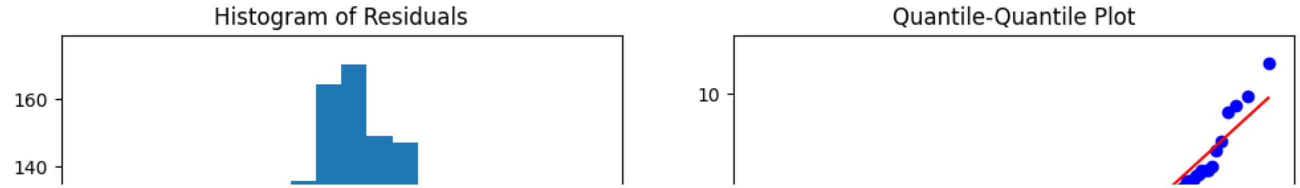
```
# creating a dictionary to store accuracy metrics of our models
rmse = {}
```

Linear Regression

```
# creating a Linear Regression model using the 'TV' feature
model_lr = LinearRegression()
model_lr.fit(X_train[['TV']], y_train)
predictions_lr = model_lr.predict(X_test[['TV']])
print('Linear Regression RMSE: ' + str(mean_squared_error(predictions_lr, y_test) ** 0.5))
rmse['Linear Regression with the TV feature'] = mean_squared_error(predictions_lr, y_test) ** 0.5
print(rmse)
```

```
Linear Regression RMSE: 2.9679611281793905
{'Linear Regression with the TV feature': 2.9679611281793905}
```

```
# creating residuals to obtain information regarding distribution
residuals_lr = y_test - predictions_lr
plt.figure(figsize = (12, 6))
plt.subplot(1, 2, 1)
plt.hist(residuals_lr, bins = 20)
plt.xlabel("Residuals")
plt.ylabel("Frequency")
plt.title("Histogram of Residuals")
plt.subplot(1, 2, 2)
stats.probplot(residuals_lr, dist = "norm", plot = plt)
plt.title("Quantile-Quantile Plot")
plt.show()
```



From the above plot and histogram, we can confirm that the residuals are normally distributed

```
# displying the intercept and co-efficient of the model
print("Intercept:", model_lr.intercept_)
print("Co-efficients:", model_lr.coef_)
```

```
Intercept: -0.5997179531463246
Co-efficients: [3.56001866]
```

```
# creating a Linear Regression model using 'TV' and 'Social Media'
model_lr = LinearRegression()
model_lr.fit(X_train[['TV', 'Social Media']], y_train)
predictions_lr = model_lr.predict(X_test[['TV', 'Social Media']])
print('Linear Regression RMSE: ' + str(mean_squared_error(predictions_lr, y_test) ** 0.5))
rmse['Linear regression with the TV and Social Media features'] = mean_squared_error(predictions_lr, y_test) ** 0.5
print(rmse)
```

```
Linear Regression RMSE: 2.968040381008341
{'Linear Regression with the TV feature': 2.9679611281793905, 'Linear regression with the TV and Social Media features': 2.968040381008341}
```

We can omit this step as we can observe that adding an additional feature 'Social Media' is not improving the RMSE value

```
# creating a Linear Regression model using combined 'TV' and 'Radio' spend
model_lr = LinearRegression()
model_lr.fit(X_train[['TV_Radio']], y_train)
predictions_lr = model_lr.predict(X_test[['TV_Radio']])
print('Linear Regression RMSE: ' + str(mean_squared_error(predictions_lr, y_test) ** 0.5))
rmse['Linear regression with the combined TV and Radio feature'] = mean_squared_error(predictions_lr, y_test) ** 0.5
```

```
Linear Regression RMSE: 13.229503050574062
```

Decision Tree

```
# building a decision tree with depth = 2
model_dt = DecisionTreeRegressor(max_depth = 2)
model_dt.fit(X_train, y_train)
predictions_dt  = model_dt.predict(X_test)
print('Decision Tree RMSE (max_depth = 2): ' + str(mean_squared_error(predictions_dt, y_test) ** 0.5))
rmse['Decision Tree with max_depth = 2'] = mean_squared_error(predictions_dt, y_test) ** 0.5
```

```
Decision Tree RMSE (max_depth = 2): 23.305238142648893
```

```
# building a decision tree with depth = 3
model_dt = DecisionTreeRegressor(max_depth = 3)
model_dt.fit(X_train, y_train)
predictions_dt  = model_dt.predict(X_test)
print('Decision Tree RMSE (max_depth = 3): ' + str(mean_squared_error(predictions_dt, y_test) ** 0.5))
rmse['Decision Tree with max_depth = 3'] = mean_squared_error(predictions_dt, y_test) ** 0.5
```

```
    Decision Tree RMSE (max_depth = 3): 11.973162281275224
```

```
# building a decision tree with depth = 4
model_dt = DecisionTreeRegressor(max_depth = 4)
model_dt.fit(X_train, y_train)
predictions_dt  = model_dt.predict(X_test)
print('Decision Tree RMSE (max_depth = 4): ' + str(mean_squared_error(predictions_dt, y_test) ** 0.5))
rmse['Decision Tree with max_depth = 4']= mean_squared_error(predictions_dt, y_test) ** 0.5
```

```
    Decision Tree RMSE (max_depth = 4): 6.505668607737348
```

```
# building a decision tree with depth = 5
model_dt = DecisionTreeRegressor(max_depth = 5)
model_dt.fit(X_train, y_train)
predictions_dt  = model_dt.predict(X_test)
print('Decision Tree RMSE (max_depth = 5): ' + str(mean_squared_error(predictions_dt, y_test) ** 0.5))
rmse['Decision Tree with max_depth = 5'] = mean_squared_error(predictions_dt, y_test) ** 0.5
```

```
    Decision Tree RMSE (max_depth = 5): 4.1736633257165625
```

Random Forest

```
# using random forest with depth = 2
model_rf = RandomForestRegressor(max_depth = 2, random_state = 7)
model_rf.fit(X_train, y_train)
predictions_random_forest  = model_rf.predict(X_test)
print('Random Forest RMSE (max_depth = 2): ' + str(mean_squared_error(predictions_random_forest, y_test) ** 0.5))
rmse['Random Forest with max_depth = 2'] = mean_squared_error(predictions_random_forest, y_test) ** 0.5
```

```
    Random Forest RMSE (max_depth = 2): 22.220051660684128
```

```
# using random forest with depth = 3
model_rf = RandomForestRegressor(max_depth = 3, random_state = 7)
model_rf.fit(X_train, y_train)
predictions_random_forest  = model_rf.predict(X_test)
print('Random Forest RMSE (max_depth = 3): ' + str(mean_squared_error(predictions_random_forest, y_test) ** 0.5))
rmse['Random Forest with max_depth = 3'] = mean_squared_error(predictions_random_forest, y_test) ** 0.5
```

```
    Random Forest RMSE (max_depth = 3): 10.46736100820533
```

```
# using random forest with depth = 4
model_rf = RandomForestRegressor(max_depth = 4,  random_state = 7)
model_rf.fit(X_train, y_train)
predictions_random_forest  = model_rf.predict(X_test)
print('Random Forest RMSE (max_depth = 4): ' + str(mean_squared_error(predictions_random_forest, y_test) ** 0.5))
rmse['Random Forest with max_depth = 4'] = mean_squared_error(predictions_random_forest, y_test) ** 0.5
```

```
Random Forest RMSE (max_depth = 4): 5.201931407991952
```

```
# using random forest with depth = 5
model_rf = RandomForestRegressor(max_depth = 5,  random_state = 7)
model_rf.fit(X_train, y_train)
predictions_random_forest  = model_rf.predict(X_test)
print('Random Forest RMSE (max_depth = 5): ' + str(mean_squared_error(predictions_random_forest, y_test) ** 0.5))
rmse['Random Forest with max_depth = 5'] = mean_squared_error(predictions_random_forest,y_test) ** 0.5
```

```
Random Forest RMSE (max_depth = 5): 3.3847229030932087
```

Results

```
# plotting the bar plot for the result dictionary created earlier 'rmse'
plt.figure(figsize=(8, 6))
plt.barh(*zip(*rmse.items()))
plt.gca().invert_yaxis()
plt.show()
```

Conclusion

- TV advertisement spend has the highest impact on Sales when compared to other media
- Linear Regression model with 'TV' gave the least RMSE
- Sales can be calculated by:

  Sales = -0.6 + 3.56 * (TV)
- The above point indicates that is potentially a 3.56 increase in sales when 1 million USD is spent on TV adverstisin