# PRODUCT DEMAND PREDICTION WITH MACHINE LEARNING


## NAME : GUNASEKARAN S
## REGISTER NUMBER: 723721205301
## NM ID: aut21leit01


**IMPORT LIBRARY:**

Import the required libraries such as PANDAS,NUMPY and Sklearn

NUMPY: It is used for mathematical and numerical functions

PANDAS: It is a analysis tool used for data manipulation

Sklearn: To implement Machine learning model and statistical Modelling

In [1]:
```
import pandas as pd
import numpy as np
```

**LOADING THE DATA SET:**

In [2]:
```
df = pd.read_csv('/kaggle/input/productdemand/PoductDemand.csv')
```

Loading the data set from the source of the data

In [3]:
```
df.head()
```

Out[3]:

| | ID | Store ID | Total Price | Base Price | Units Sold |
|---|---|---|---|---|---|
| 0 | 1 | 8091 | 99.0375 | 111.8625 | 20 |
| 1 | 2 | 8091 | 99.0375 | 99.0375 | 28 |
| 2 | 3 | 8091 | 133.9500 | 133.9500 | 19 |
| 3 | 4 | 8091 | 133.9500 | 133.9500 | 44 |
| 4 | 5 | 8091 | 141.0750 | 141.0750 | 52 |

The following program contains the Model Evaluation and training

In [4]:
```
df.isnull().sum()
```

Out[4]:
```
ID             0
Store ID       0
Total Price    1
Base Price     0
Units Sold     0
dtype: int64
```

In [5]:
```
df['Total Price'].fillna(df['Total Price'].mean(), inplace=True)
```

In [6]:
```
df.head(10)
```

Out[6]:

| | ID | Store ID | Total Price | Base Price | Units Sold |
|---|---|---|---|---|---|
| **0** | 1 | 8091 | 99.0375 | 111.8625 | 20 |
| **1** | 2 | 8091 | 99.0375 | 99.0375 | 28 |
| **2** | 3 | 8091 | 133.9500 | 133.9500 | 19 |
| **3** | 4 | 8091 | 133.9500 | 133.9500 | 44 |
| **4** | 5 | 8091 | 141.0750 | 141.0750 | 52 |
| **5** | 9 | 8091 | 227.2875 | 227.2875 | 18 |
| **6** | 10 | 8091 | 327.0375 | 327.0375 | 47 |
| **7** | 13 | 8091 | 210.9000 | 210.9000 | 50 |
| **8** | 14 | 8091 | 190.2375 | 234.4125 | 82 |
| **9** | 17 | 8095 | 99.0375 | 99.0375 | 99 |

In [7]:
```
df.set_index('ID', inplace=True)
```

In [8]:
```
df.describe()
```

Out[8]:

| | Store ID | Total Price | Base Price | Units Sold |
|---|---|---|---|---|
| **count** | 150150.000000 | 150150.000000 | 150150.000000 | 150150.000000 |
| **mean** | 9199.422511 | 206.626751 | 219.425927 | 51.674206 |
| **std** | 615.591445 | 103.308172 | 110.961712 | 60.207904 |
| **min** | 8023.000000 | 41.325000 | 61.275000 | 1.000000 |
| **25%** | 8562.000000 | 130.387500 | 133.237500 | 20.000000 |
| **50%** | 9371.000000 | 198.075000 | 205.912500 | 35.000000 |
| **75%** | 9731.000000 | 233.700000 | 234.412500 | 62.000000 |
| **max** | 9984.000000 | 562.162500 | 562.162500 | 2876.000000 |

In [9]:
```
import math
df['Total Price'] = df['Total Price'].apply(lambda x: math.floor(x*100)/100)
df['Base Price'] = df['Base Price'].apply(lambda x: math.floor(x*100)/100)
```

In [10]:
```
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
```

In [13]:
```
X = df[['Total Price', 'Base Price']]
y = df['Units Sold']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=200)
lr = LinearRegression()

lr.fit(X_train, y_train)
```

**LINEAR REGRESSION:**

Linear regression is used to predict the value of a variable of a variable based on the value of another variable.

In [14]:
```
print(lr.score(X_test, y_test)*100)
```
```
14.030587952437257
```

The instantiation ,Fitting the model, Predict the model are done with the value provided in the dataset

In [18]:
```
import numpy as np
import xgboost as xg
from sklearn.metrics import mean_squared_error as MSE
train_X, test_X, train_y, test_y = train_test_split(X, y,
                      test_size = 0.3, random_state = 123)

# Instantiation
xgb_r = xg.XGBRegressor(objective ='reg:linear',
                  n_estimators = 30, seed = 123)

# Fitting the model
xgb_r.fit(train_X, train_y)

# Predict the model
pred = xgb_r.predict(test_X)

# RMSE Computation
rmse = np.sqrt(MSE(test_y, pred))
print("RMSE : % f" %(rmse))
```
```
[09:26:26] WARNING: ../src/objective/regression_obj.cu:213: reg:linear is now deprecated in favor of reg:
squarederror.
RMSE :  46.590045
```

**MODEL EVALUATION:**

**For** Model Evaluation we use multiple models to check which one performs well and best in data. Because the linear regression did not perform well enough

Here we use methods like DecisionTree , RandomForest , LinearRegression , XGboost.

LinearRegression:It is used to predict the value of a variable of a variable based on the value of another variable.

RandomForest: It is a commonly used machine learning algorithm used for classification and regression.

DecisionTree: It is a tree-like decision support tool, displaying decisions and their outcomes.

XGboost: It is a machine learning algorithm that uses an ensemble of decision trees and gradient boosting to make predictions.

In [19]:

```
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor
import matplotlib.pyplot as plt
from sklearn.metrics import r2_score, mean_squared_error
from sklearn.metrics import mean_squared_error as MSE
```

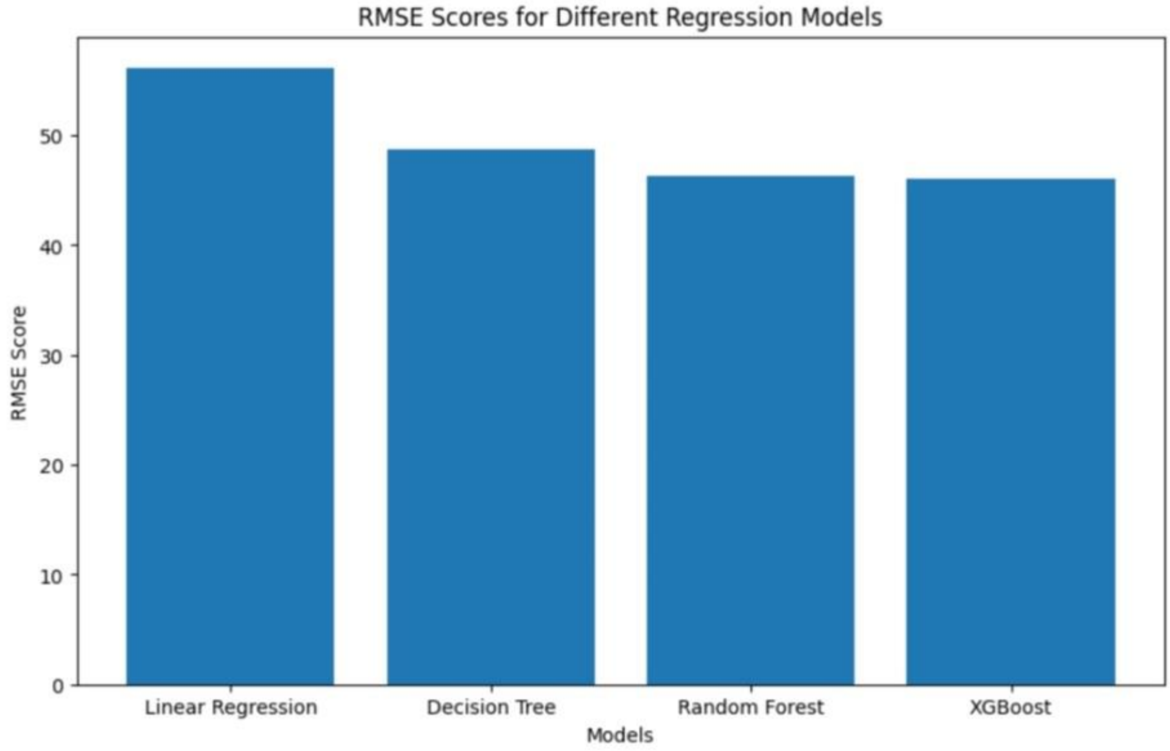
In [22]:

```
dt_regressor = DecisionTreeRegressor(random_state=123)
dt_regressor.fit(X_train, y_train)
dt_pred = dt_regressor.predict(X_test)

# Random Forest Regressor
rf_regressor = RandomForestRegressor(n_estimators=100, random_state=123)
rf_regressor.fit(X_train, y_train)
rf_pred = rf_regressor.predict(X_test)

# XGBoost Regressor
xgb_r = xg.XGBRegressor(objective='reg:linear', n_estimators=30, seed=123)
xgb_r.fit(X_train, y_train)
xgb_pred = xgb_r.predict(X_test)

# Calculate RMSE and R-squared for each model
models = [lr, dt_regressor, rf_regressor, xgb_r]
model_names = ["Linear Regression", "Decision Tree", "Random Forest", "XGBoost"]
rmse_scores = []
r2_scores = []

for model, name in zip(models, model_names):
    pred = model.predict(X_test)
    rmse = np.sqrt(MSE(y_test, pred))
    r2 = r2_score(y_test, pred)
    rmse_scores.append(rmse)
    r2_scores.append(r2)
    print(f"{name} - RMSE: {rmse:.2f}, R-squared: {r2:.2f}")

# Plot RMSE scores
plt.figure(figsize=(10, 6))
plt.bar(model_names, rmse_scores)
plt.xlabel("Models")
plt.ylabel("RMSE Score")
plt.title("RMSE Scores for Different Regression Models")
plt.show()
```

```
[09:30:41] WARNING: ../src/objective/regression_obj.cu:213: reg:linear is now deprecated in favor of reg:
squarederror.
Linear Regression - RMSE: 56.19, R-squared: 0.14
Decision Tree - RMSE: 48.74, R-squared: 0.35
Random Forest - RMSE: 46.27, R-squared: 0.42
XGBoost - RMSE: 46.07, R-squared: 0.42
```

BAR CHART:

The bar chart represents the difference between regression models and their RMSE

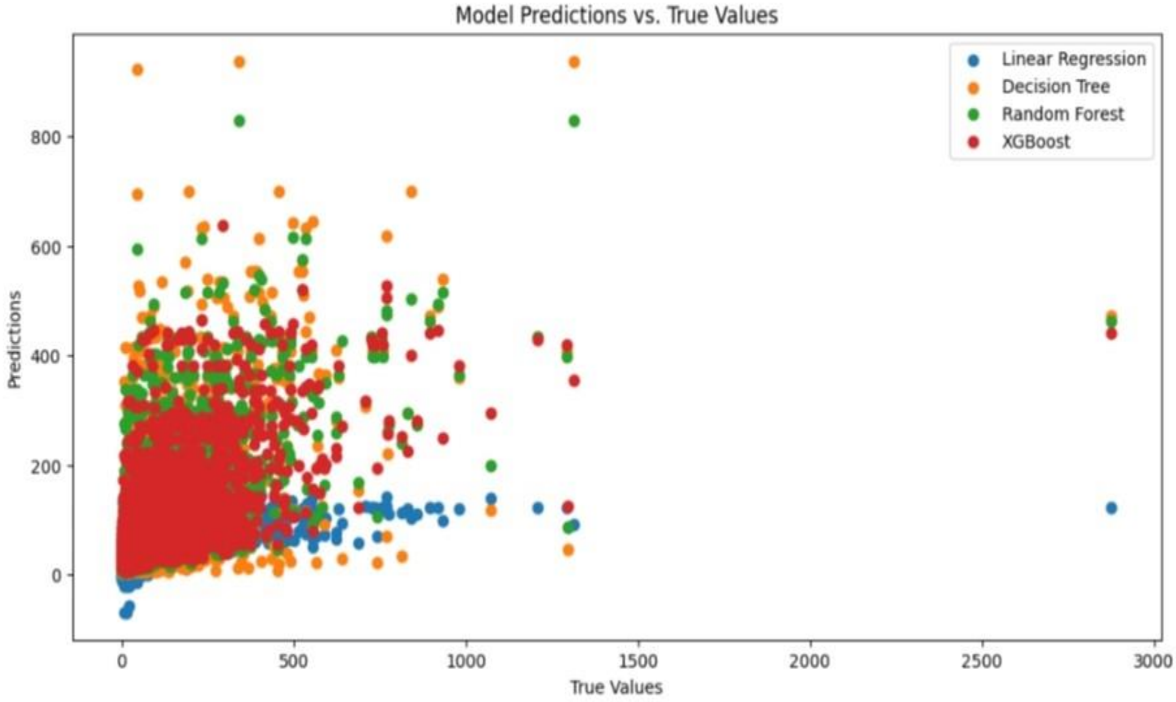



In [21]:

```
# Plot predictions
plt.figure(figsize=(12, 6))
plt.scatter(y_test, y_pred, label="Linear Regression")
plt.scatter(y_test, dt_pred, label="Decision Tree")
plt.scatter(y_test, rf_pred, label="Random Forest")
plt.scatter(y_test, xgb_pred, label="XGBoost")
plt.xlabel("True Values")
plt.ylabel("Predictions")
plt.legend()
plt.title("Model Predictions vs. True Values")
plt.show()
```

SCATTER PLOT:

The Scatter Plot represents the Actual predicts vs the Model Predictions and how their values differ




**CONCLUSION:**

Thus the Model Evaluation and training for the product demand prediction using regression is concluded **as we can see that, the Random Forest and The Decision Tree performs well in predicting.**