```python
import pandas as pd
import numpy as np
```

In [2]:

```python
df = pd.read_csv('/kaggle/input/productdemand/PoductDemand.csv')
```

In [3]:

```python
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

In [4]:

```python
df.isnull().sum()
```

Out[4]:

```
ID             0
Store ID       0
Total Price    1
Base Price     0
Units Sold     0
dtype: int64
```

In [5]:

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

In [6]:

```python
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

	ID	Store ID	Total Price	Base Price	Units Sold
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)
```

Out[13]:

```
LinearRegression()
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [14]:

```
print(lr.score(X_test, y_test)*100)
```

```
14.030587952437257
```

In [15]:

```
import matplotlib.pyplot as plt
y_pred = lr.predict(X_test)
```

In [16]:

```
from sklearn.metrics import r2_score
from sklearn.metrics import mean_squared_error

r2_score(y_test, y_pred)
```

Out[16]:

```
0.14030587952437257
```

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 n
ow deprecated in favor of reg:squarederror.
RMSE :  46.590045
```

We can use multiple models to check which one performs best in the data! Because, XGBoost and LinearRegression did not perform well enough!

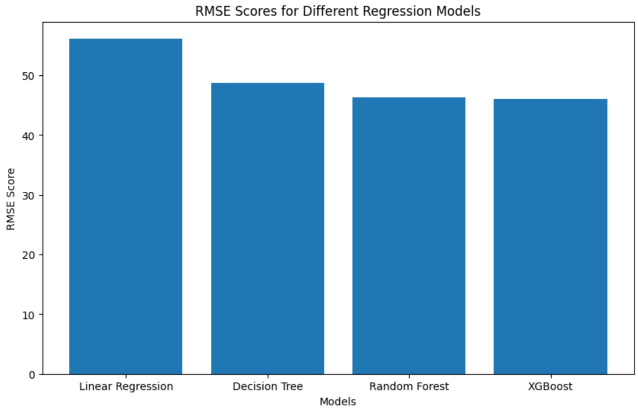
In [19]:

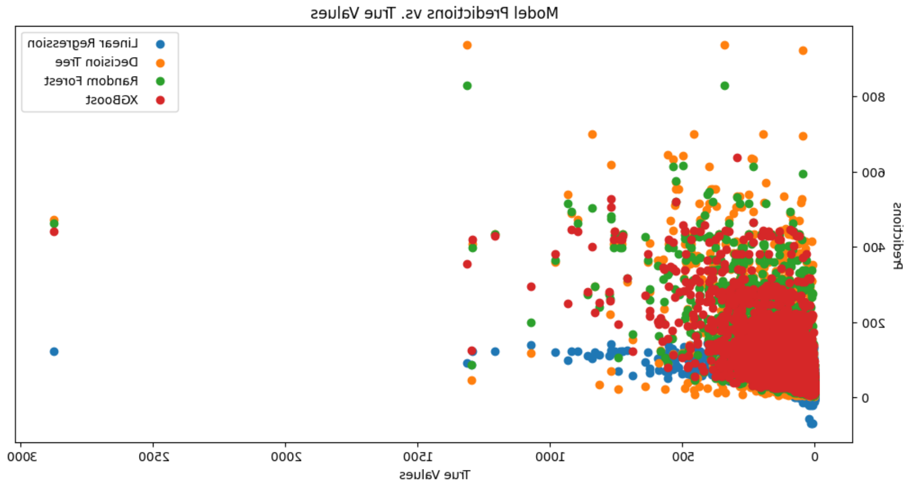
```
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor
import matplotlib.pyplot as plt
from sklearn.metrics import r2_score, mean_squared_error
from sklearn.metrics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





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()
```

From the above plots we can see that, the Random Forest and the decision tree performs well in predicting