jupyter ML_3_Regression Last Checkpoint: 1 minute ago

File Edit View Run Kernel Settings Help

Trusted

Code

JupyterLab

Python 3 (ipykernel)

[1]:

```
#Qn no 1. Import necessary Libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LinearRegression
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor, GradientBoostingRegressor
from sklearn.svm import SVR
from sklearn.metrics import mean_squared_error, r2_score
```

[3]:

```
### Load dataset
file_path = "housing.csv"  # Change this path if necessary
df = pd.read_csv("C:\\Users\\amrut\\Downloads\\housing.csv")
df
```

[3]:

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	households	median_income	median_house_value	ocean_proximity
0	-122.23	37.88	41.0	880.0	129.0	322.0	126.0	8.3252	452600.0	NEAR BAY
1	-122.22	37.86	21.0	7099.0	1106.0	2401.0	1138.0	8.3014	358500.0	NEAR BAY
2	-122.24	37.85	52.0	1467.0	190.0	496.0	177.0	7.2574	352100.0	NEAR BAY
3	-122.25	37.85	52.0	1274.0	235.0	558.0	219.0	5.6431	341300.0	NEAR BAY
4	-122.25	37.85	52.0	1627.0	280.0	565.0	259.0	3.8462	342200.0	NEAR BAY
...	...	...	...	...	...	...	...	...	...	...
20635	-121.09	39.48	25.0	1665.0	374.0	845.0	330.0	1.5603	78100.0	INLAND
20636	-121.21	39.49	18.0	697.0	150.0	356.0	114.0	2.5568	77100.0	INLAND
20637	-121.22	39.43	17.0	2254.0	485.0	1007.0	433.0	1.7000	92300.0	INLAND
20638	-121.32	39.43	18.0	1860.0	409.0	741.0	349.0	1.8672	84700.0	INLAND
20639	-121.24	39.37	16.0	2785.0	616.0	1387.0	530.0	2.3886	89400.0	INLAND

20640 rows × 10 columns

jupyter ML_3_Regression Last Checkpoint: 1 minute ago

File Edit View Run Kernel Settings Help Trusted

Code JupyterLab Python 3 (ipykernel)

[4]:
```
### Handle missing values by filling with median
df.fillna(df.median(numeric_only=True), inplace=True)
```

[5]:
```
### Convert categorical column 'ocean_proximity' using one-hot encoding
df = pd.get_dummies(df, columns=['ocean_proximity'], drop_first=True)
```

[6]:
```
### Separate features and target variable
X = df.drop(columns=['median_house_value'])  # Features
y = df['median_house_value']  # Target variable
```

[7]:
```
### Split data into training and testing sets (80% train, 20% test)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
print(X_train.shape, X_test.shape, y_train.shape, y_test.shape)
```

```
(16512, 12) (4128, 12) (16512,) (4128,)
```

[8]:
```
X_train
```

[8]:

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	households	median_income	ocean_proximity_INLAND	ocean_proximity_ISLA
14196	-117.03	32.71	33.0	3126.0	627.0	2300.0	623.0	3.2596	False	F
8267	-118.16	33.77	49.0	3382.0	787.0	1314.0	756.0	3.8125	False	F
17445	-120.48	34.66	4.0	1897.0	331.0	915.0	336.0	4.1563	False	F
14265	-117.11	32.69	36.0	1421.0	367.0	1418.0	355.0	1.9425	False	F
2271	-119.80	36.78	43.0	2382.0	431.0	874.0	380.0	3.5542	True	F
...	...	...	...	...	...	...	...	...	...	
11284	-117.96	33.78	35.0	1330.0	201.0	658.0	217.0	6.3700	False	F
11964	-117.43	34.02	33.0	3084.0	570.0	1753.0	449.0	3.0500	True	F
5390	-118.38	34.03	36.0	2101.0	569.0	1756.0	527.0	2.9344	False	F

jupyter ML_3_Regression Last Checkpoint: 2 minutes ago

File Edit View Run Kernel Settings Help Trusted

Code JupyterLab Python 3 (ipykernel)

[9]:
```
X_test
```

[9]:

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	households	median_income	ocean_proximity_INLAND	ocean_proximity_ISLA
20046	-119.01	36.06	25.0	1505.0	435.0	1392.0	359.0	1.6812	True	F
3024	-119.46	35.14	30.0	2943.0	435.0	1565.0	584.0	2.5313	True	F
15663	-122.44	37.80	52.0	3830.0	435.0	1310.0	963.0	3.4801	False	F
20484	-118.72	34.28	17.0	3051.0	435.0	1705.0	495.0	5.7376	False	F
9814	-121.93	36.62	34.0	2351.0	435.0	1063.0	428.0	3.7250	False	F
...	...	...	...	...	...	...	...	...	...	
15362	-117.22	33.36	16.0	3165.0	482.0	1351.0	452.0	4.6050	False	F
16623	-120.83	35.36	28.0	4323.0	886.0	1650.0	705.0	2.7266	False	F
18086	-122.05	37.31	25.0	4111.0	538.0	1585.0	568.0	9.2298	False	F
2144	-119.76	36.77	36.0	2507.0	466.0	1227.0	474.0	2.7850	True	F
3665	-118.37	34.22	17.0	1787.0	463.0	1671.0	448.0	3.5521	False	F

4128 rows × 12 columns

[10]:
```
y_test
```

[10]:
```
20046     47700.0
3024      45800.0
15663    500001.0
20484    218600.0
9814     278000.0
           ...
15362    263300.0
16623    266800.0
18086    500001.0
2144      72300.0
3665     151500.0
Name: median_house_value, Length: 4128, dtype: float64
```

[11]:
```
y_train
```

[11]:
```
14196    103000.0
8267     382100.0
17445    172600.0
14265     93400.0
2271      96500.0
           ...
11284    229200.0
11964     97800.0
5390     222100.0
860      283500.0
15795    325000.0
Name: median_house_value, Length: 16512, dtype: float64
```

[29]:
```
### Standardize features (important for SVR and Gradient Boosting)
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

[30]:
```
####Qn no 2.Initialize regression models

models = {
    "Linear Regression": LinearRegression(),
    "Decision Tree": DecisionTreeRegressor(random_state=42),
    "Random Forest": RandomForestRegressor(random_state=42, n_estimators=100),
    "Gradient Boosting": GradientBoostingRegressor(random_state=42, n_estimators=100),
    "Support Vector Regressor": SVR()
}
```

[35]:
```
###Qn no 3. Train models and evaluate performance
results = {}
for name, model in models.items():
    # Use scaled data for SVR, otherwise use original
    if name == "Support Vector Regressor":
        model.fit(X_train_scaled, y_train)
        y_pred = model.predict(X_test_scaled)
    else:
        model.fit(X_train, y_train)
        y_pred = model.predict(X_test)
```

jupyter ML_3_Regression Last Checkpoint: 4 minutes ago

File Edit View Run Kernel Settings Help Trusted

Code JupyterLab Python 3 (ipykernel)

```
            y_pred = model.predict(X_test)
    # Calculate performance metrics
        mse = mean_squared_error(y_test, y_pred)
        r2 = r2_score(y_test, y_pred)
       # Store results
        results[name] = {"MSE": mse, "R² Score": r2}
```

[36]:
```
# Convert results to a DataFrame for better readability
results_df = pd.DataFrame(results).T
print(results_df)
```

```
                                    MSE  R² Score
Linear Regression          4.908477e+09  0.625424
Decision Tree              4.865869e+09  0.628676
Random Forest              2.404746e+09  0.816489
Gradient Boosting          3.123095e+09  0.761670
Support Vector Regressor  1.365597e+10 -0.042115
```

[ ]:
```
### Result analysis
1.Random Forest performed best with the lowest MSE and highest R² score (0.816).

2.Gradient Boosting also performed well, but slightly worse than Random Forest.

3.Linear Regression and Decision Tree had moderate performance.

4.Support Vector Regressor (SVR) performed poorly, likely due to improper hyperparameters.
```

[37]:
```
# Convert results to DataFrame for easier plotting
results_df = pd.DataFrame(results).T

# Set plot style
sns.set_style("whitegrid")

# Plot Mean Squared Error (MSE)
plt.figure(figsize=(10, 5))
sns.barplot(x=results_df.index, y=results_df["MSE"], palette="Blues_r")
plt.xlabel("Regression Models")
plt.ylabel("Mean Squared Error (MSE)")
plt.title("MSE of Different Regression Models")
plt.xticks(rotation=30)
plt.show()
```

jupyter ML_3_Regression Last Checkpoint: 4 minutes ago

File Edit View Run Kernel Settings Help Trusted

Code JupyterLab Python 3 (ipykernel)

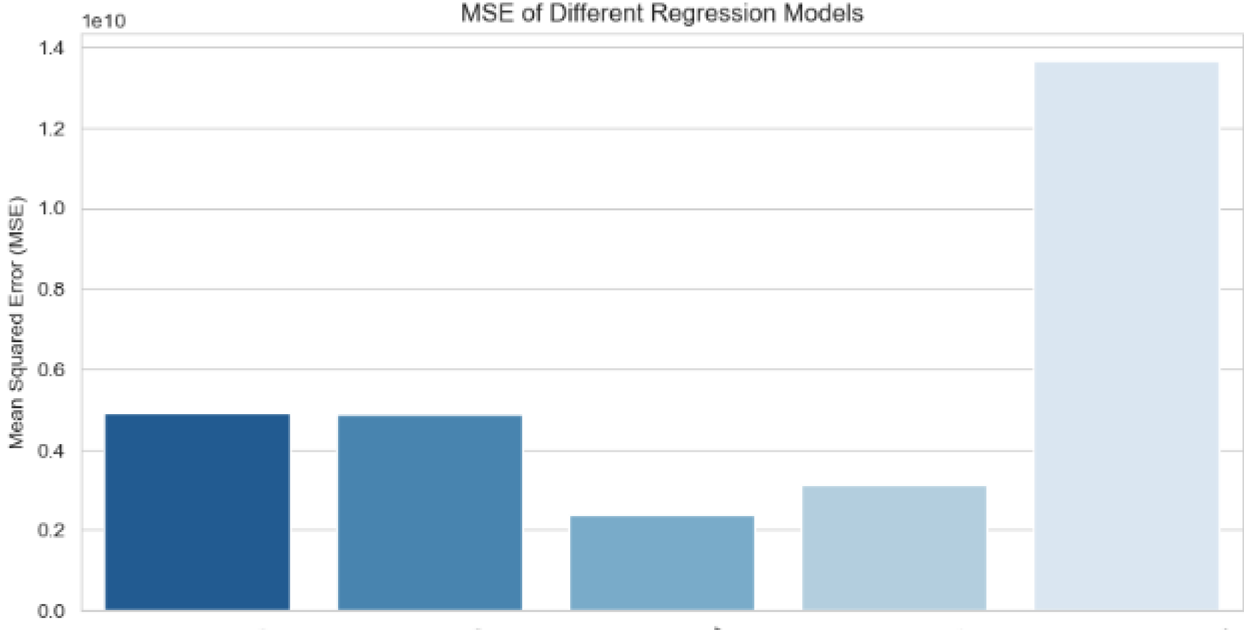
```
plt.show()

# Plot R² Score
plt.figure(figsize=(10, 5))
sns.barplot(x=results_df.index, y=results_df["R² Score"], palette="Greens_r")
plt.xlabel("Regression Models")
plt.ylabel("R² Score")
plt.title("R² Score of Different Regression Models")
plt.xticks(rotation=30)
plt.show()
```

```
C:\Users\amrut\AppData\Local\Temp\ipykernel_17904\2834807355.py:9: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same effect.

  sns.barplot(x=results_df.index, y=results_df["MSE"], palette="Blues_r")
```



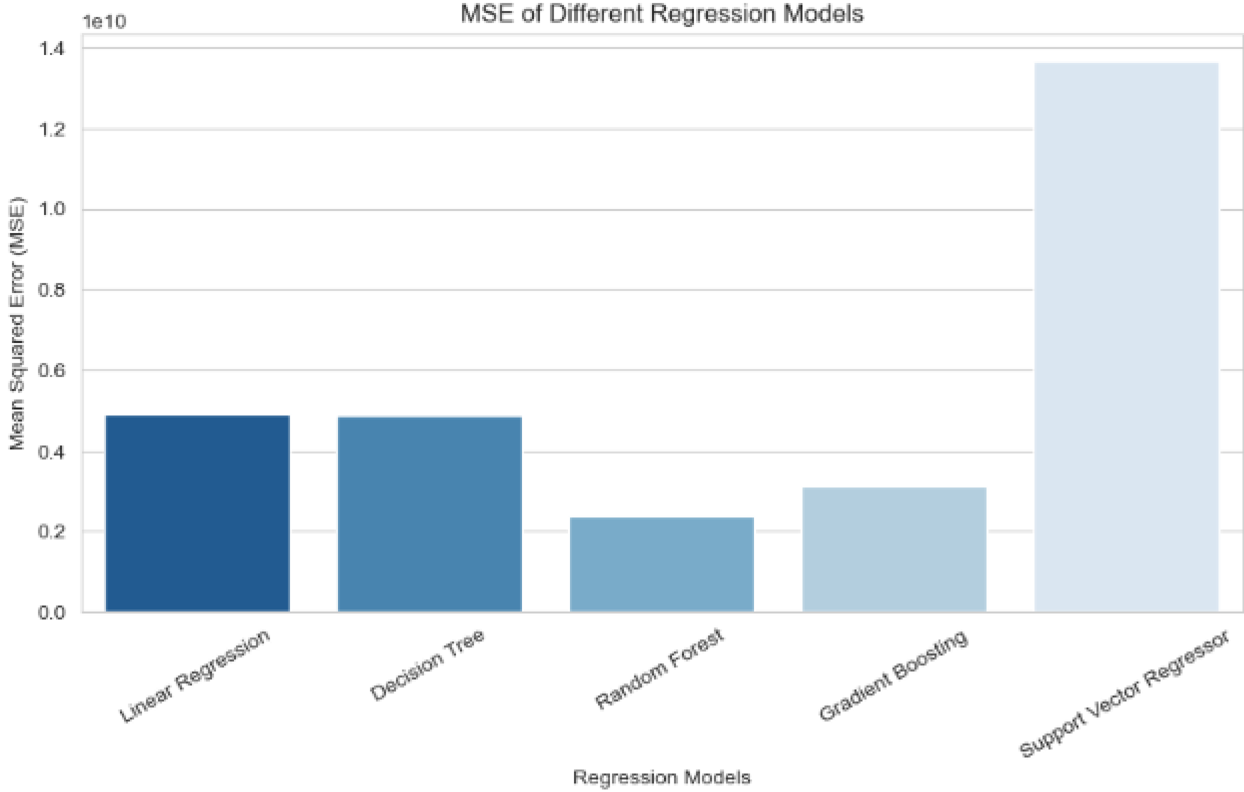
jupyter ML_3_Regression Last Checkpoint: 5 minutes ago

File Edit View Run Kernel Settings Help Trusted

Code JupyterLab Python 3 (ipykernel)

```
same effect.

  sns.barplot(x=results_df.index, y=results_df["MSE"], palette="Blues_r")
```



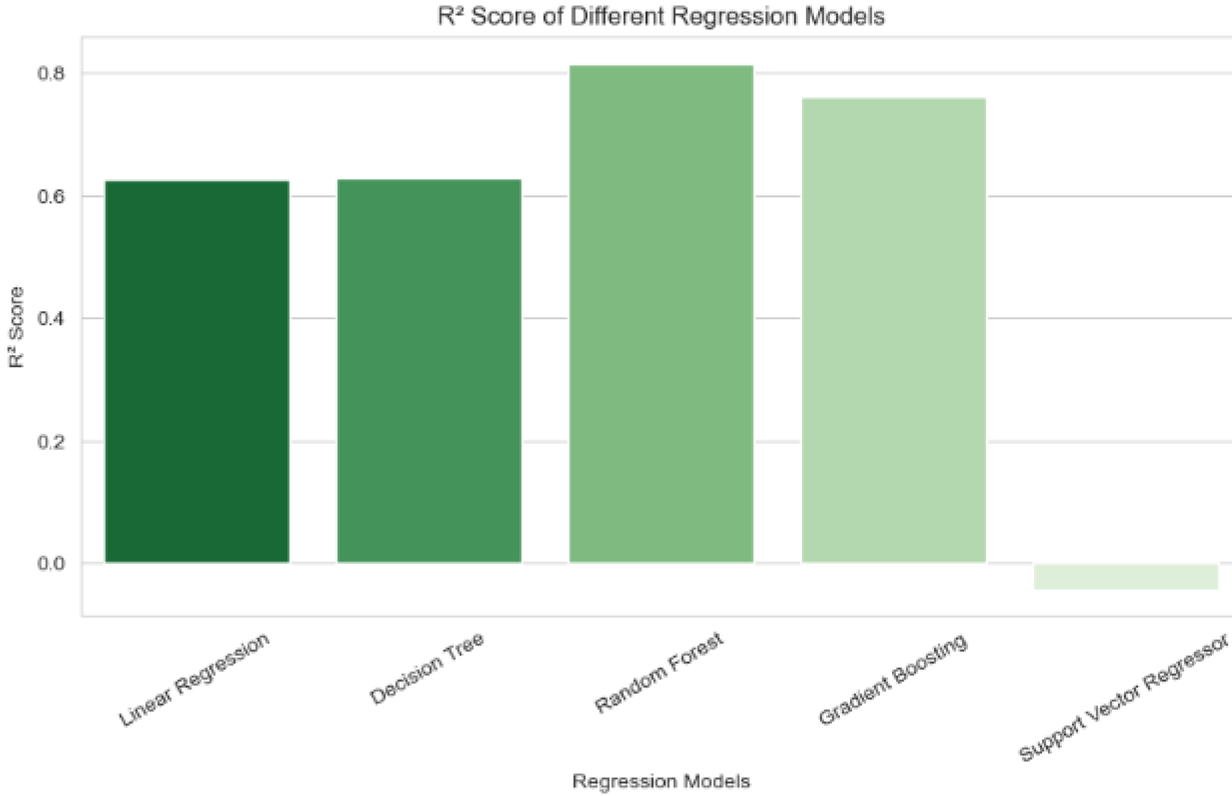

```
C:\Users\amrut\AppData\Local\Temp\ipykernel_17984\2834807355.py:18: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the
same effect.

  sns.barplot(x=results_df.index, y=results_df["R² Score"], palette="Greens_r")
```

R² Score of Different Regression Models

```
sns.barplot(x=results_df.index, y=results_df["R² Score"], palette="Greens_r")
```



[ ]:

[ ]: