

Housing Price Prediction model



Machine Learning with Random Forest

By: Yug Sharma



Introduction

Objective: To predict Housing prices from a synthetic dataset unique to this project

Target: Achieve a regression model with an R^2 score of at least 80.

Methodology: Machine Learning using Random Forest



Data Overview

Source of Data: Synthetic Dataset

Key Features: Area, Bedrooms, Bathrooms etc.

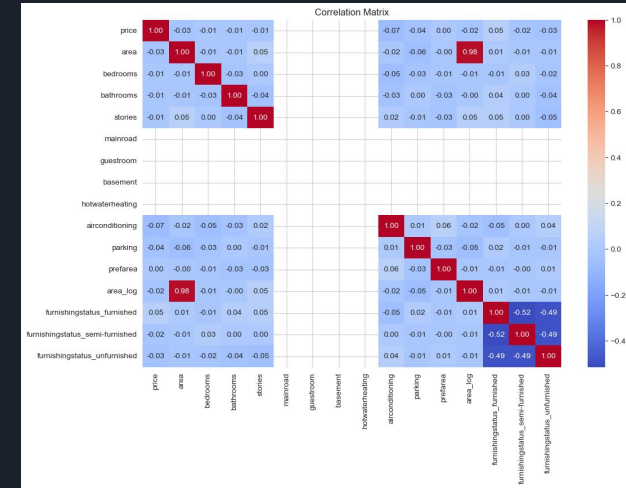
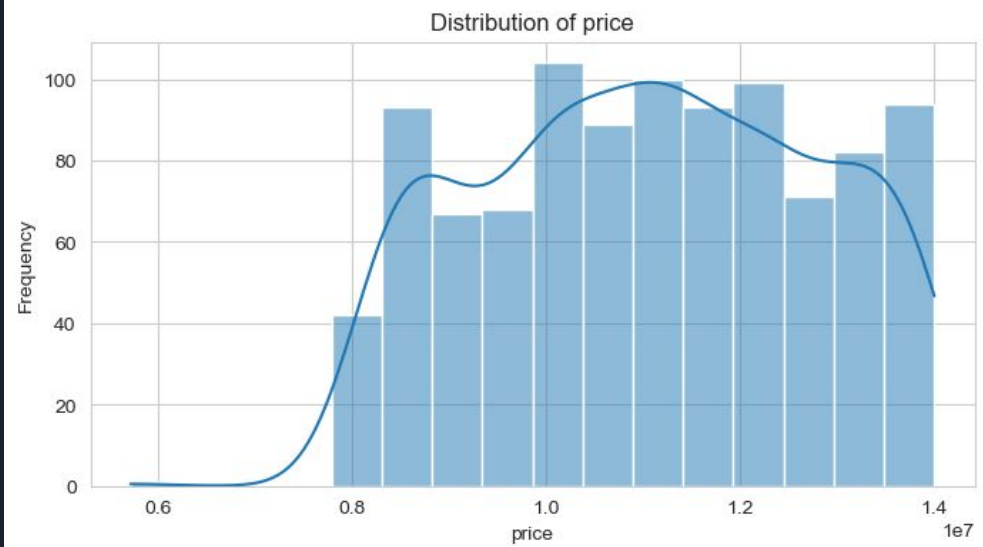
Out [3]:

	price	area	bedrooms	bathrooms	stories	parking
count	9.910000e+02	988.000000	990.000000	985.000000	983.000000	1003.000000
mean	1.105174e+07	8957.272267	3.978788	2.608122	2.423194	1.448654
std	1.742147e+06	32301.033484	0.816014	4.030213	1.114591	1.214560
min	-1.120000e+02	-998877.000000	3.000000	1.000000	1.000000	-12.000000
25%	9.709294e+06	6776.250000	3.000000	2.000000	1.000000	0.000000
50%	1.106197e+07	10077.500000	4.000000	2.000000	2.000000	1.000000
75%	1.243362e+07	13006.250000	5.000000	4.000000	3.000000	2.000000
max	1.399908e+07	16196.000000	5.000000	124.000000	4.000000	3.000000

A1	price	area	bedrooms	bathrooms	stories	mainroad	guestroom	basement	hotwaterhea	airconditioni	parking	prefarea	furnishingstatus
1	11991472	14139	3	1	4	FALSE	TRUE	FALSE	FALSE	FALSE	1	TRUE	unfurnished
2	11991472	14139	3	1	4	FALSE	TRUE	FALSE	FALSE	FALSE	1	TRUE	unfurnished
3	8632694	4182	3	3	1	TRUE	FALSE	FALSE	TRUE	TRUE	3	FALSE	unfurnished
4	8481911	10645	4	4	4	FALSE	TRUE	TRUE	FALSE	FALSE	0	FALSE	semi-furnished
5	13556045	6415	4	2	1	FALSE	TRUE	FALSE	TRUE	FALSE	0	TRUE	furnished
6	9925983	9504	3	2	2	FALSE	TRUE	FALSE	FALSE	TRUE	1	FALSE	furnished
7	9101598	5752	3	1	1	FALSE	FALSE	TRUE	FALSE	TRUE	1	TRUE	semi-furnished
8	9979630	7420	3	3	1	FALSE	FALSE	TRUE	TRUE	FALSE	0	TRUE	furnished
9	9979630	7420	3	3	1	FALSE	FALSE	TRUE	TRUE	FALSE	0	TRUE	furnished
10	10179634	7400	4	1	1	TRUE	FALSE	FALSE	TRUE	FALSE	0	TRUE	furnished
11	10161840	8918	4	2	4	FALSE	TRUE	TRUE	FALSE	TRUE	0	FALSE	unfurnished
12	12045879	15243	4	4	1	FALSE	TRUE	FALSE	FALSE	TRUE	3	FALSE	unfurnished
13	-112	8687	3	4	1	TRUE	TRUE	FALSE	TRUE	TRUE	3	FALSE	semi-furnished
14	11420591	12697	3	3	3	TRUE	TRUE	TRUE	TRUE	TRUE	1	FALSE	unfurnished
15	12047335	5109	3	3	3	FALSE	FALSE	FALSE	TRUE	TRUE	2	FALSE	unfurnished
16	8277674	13807	3	2	4	FALSE	FALSE	TRUE	TRUE	TRUE	3	FALSE	furnished
17	8666997	9556	3	1	4	TRUE	FALSE	TRUE	FALSE	FALSE	3	TRUE	unfurnished
18	12352573	6792	5	4	4	TRUE	FALSE	FALSE	TRUE	FALSE	0	FALSE	furnished
19	10357357	5033	4	3	3	FALSE	TRUE	TRUE	FALSE	FALSE	0	FALSE	unfurnished
20	12284409	5175	4	1	2	FALSE	TRUE	TRUE	TRUE	TRUE	3	FALSE	unfurnished
21	13023367	6476	5	1	2	TRUE	FALSE	TRUE	FALSE	FALSE	1	TRUE	semi-furnished
22	10013209	5745	4	2	1	TRUE	TRUE	TRUE	FALSE	FALSE	1	FALSE	unfurnished
23	10741460	9204	5	4	2	TRUE	TRUE	TRUE	TRUE	FALSE	0	TRUE	furnished
24		13148	4	3	2	FALSE	TRUE	FALSE	FALSE	FALSE	1	FALSE	unfurnished
25	11443414	10566	5	2	2	FALSE	FALSE	TRUE	TRUE	TRUE	3	TRUE	semi-furnished
26	10251397	12243	3	2		TRUE	TRUE	FALSE	FALSE	TRUE	1	TRUE	semi-furnished
27	8257015	16112	3	4	3	FALSE	TRUE	TRUE	FALSE	TRUE	1	TRUE	semi-furnished
28	8646789	5370	3	4	3	TRUE	FALSE	TRUE	TRUE	TRUE	1	FALSE	furnished
29	8905447	8206	3	3	2	FALSE	FALSE	FALSE	TRUE	FALSE	0	TRUE	semi-furnished
30	10552257	7270	5	4	3	FALSE	TRUE	FALSE	TRUE	FALSE	1	FALSE	furnished
31	12507071	14748	4	1	3	FALSE	TRUE	TRUE	FALSE	TRUE	1	TRUE	furnished
32	10056972	5399	4	4	2	TRUE	FALSE	TRUE	TRUE	TRUE	1	TRUE	unfurnished
33	12904621	-998877	4	2	3	FALSE	TRUE	TRUE	TRUE	TRUE	0	FALSE	furnished
34	13353346	4146	5	1	3	TRUE	FALSE	FALSE	TRUE	FALSE	1	FALSE	semi-furnished
35	13501570	5429	3	3	3	FALSE	TRUE	TRUE	TRUE	FALSE	1	FALSE	semi-furnished
36	13986836	7732		3	1	FALSE	FALSE	FALSE	TRUE	TRUE	3	FALSE	semi-furnished

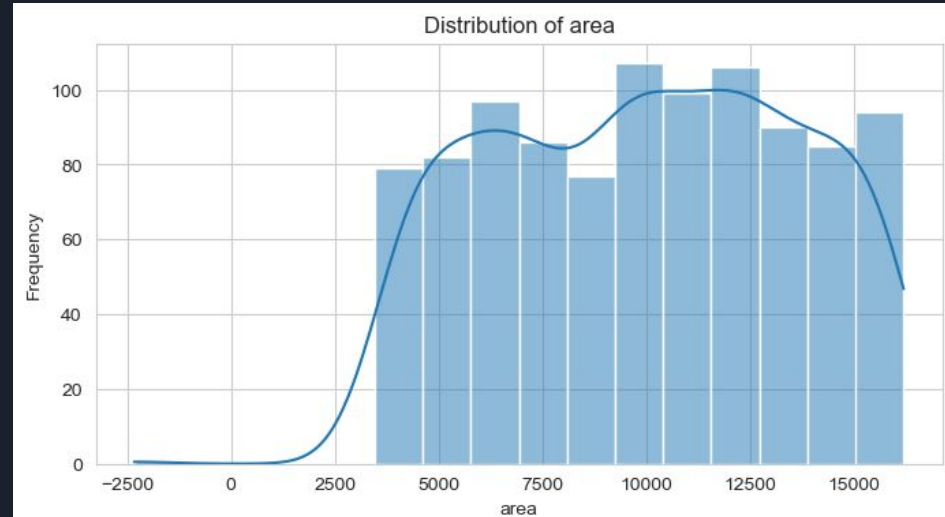
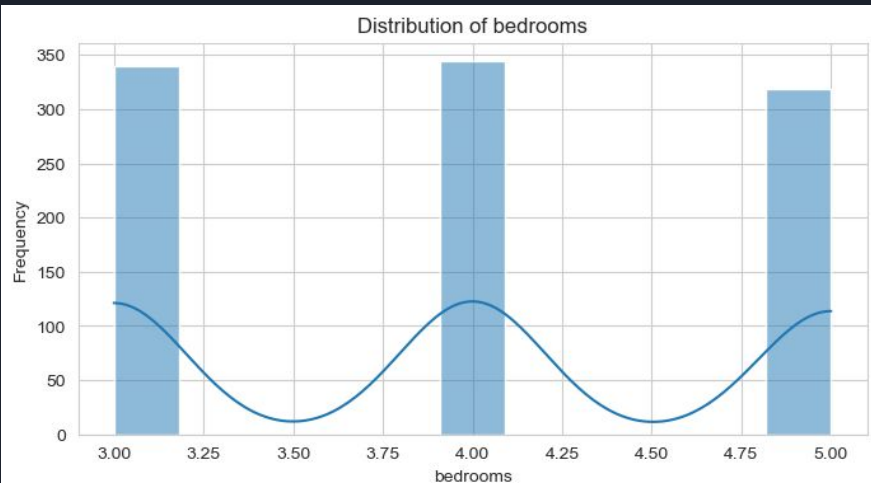
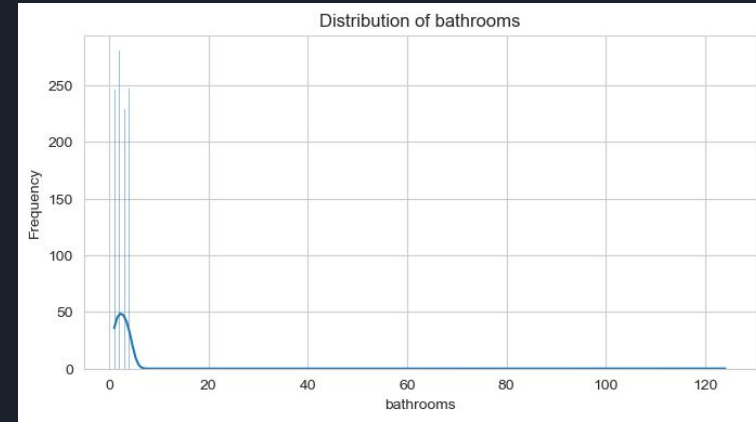
Exploratory Data Analysis (EDA)

Libraries used: Pandas, Matplotlib



Data Cleaning and Preprocessing

- Cleaned through Pandas in python





Model Building and Selection

```
#Perform cross-validated feature importance evaluation
best_rf_model = RandomForestRegressor(**best_params)
cv_feature_importances = []
for train_idx, test_idx in KFold(n_splits=5).split(X_train):
    fold_X_train, fold_X_test = X_train.iloc[train_idx], X_train.iloc[te
    fold_y_train, fold_y_test = y_train.iloc[train_idx], y_train.iloc[te
    best_rf_model.fit(fold_X_train, fold_y_train)
    cv_feature_importances.append(best_rf_model.feature_importances_)

# Average feature importances across folds
avg_feature_importances = np.mean(cv_feature_importances, axis=0)
```

Hyperparameter Tuning

```
#Define a hyperparameter distribution and initialize RandomizedSearchCV
param_dist = {
    'n_estimators': range(100, 601, 100),
    'max_depth': [None] + list(range(10, 31, 10)),
    'min_samples_split': range(2, 11, 2),
    'min_samples_leaf': range(1, 11, 2),
    'max_features': ['sqrt', 'log2'] # Correct options
}

random_search = RandomizedSearchCV(
    estimator=RandomForestRegressor(random_state=42),
    param_distributions=param_dist,
    n_iter=10,
    cv=3,
    scoring='r2',
    random_state=42,
    n_jobs=-1
)

# fit random search to data
random_search.fit(X_train, y_train)
best_params = random_search.best_params_
print("Best Hyperparameters:", best_params)
```

Best Hyperparameters: {'n_estimators': 500, 'min_samples_split': 6, 'min_samples_leaf': 1, 'max_features': 'log2', 'max_depth': 10}

Model Evaluation

Final Results: R^2 of ~90%

```
In [10]: # Instead of selecting the top features, use all features for training a
X_train_all_features = X_train
X_test_all_features = X_test
```

```
# Retrain the model on all features with cross-validation
cv_scores_all_features = cross_val_score(best_rf_model, X_train_all_features, y_train, cv=5)
print("Cross-Validation R2 Scores on All Features:", cv_scores_all_features)
print("Mean CV R2 Score on All Features:", cv_scores_all_features.mean())
```

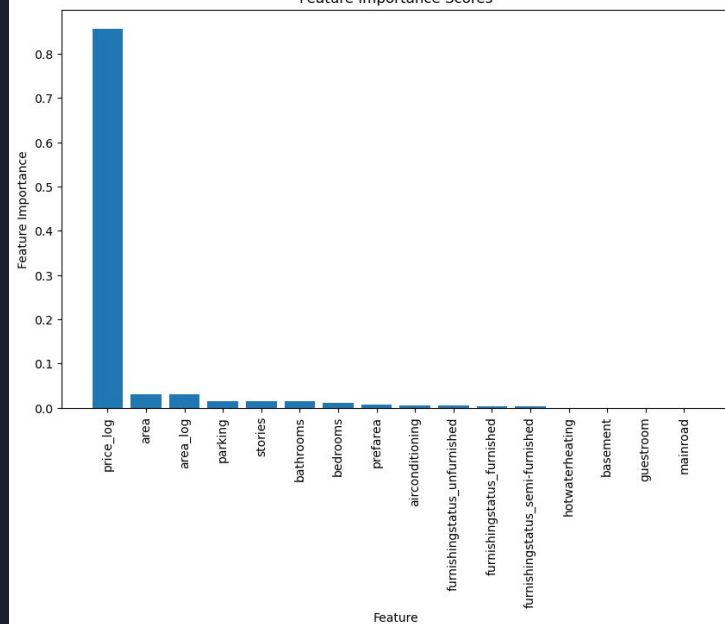
```
# Refit the model on the entire training set with all features
best_rf_model.fit(X_train_all_features, y_train)
```

```
# Make predictions and evaluate on the test set with all features
y_pred_test_all_features = best_rf_model.predict(X_test_all_features)
test_r2_all_features = r2_score(y_test, y_pred_test_all_features)
print("Test R2 Score on All Features:", test_r2_all_features)
```

Cross-Validation R^2 Scores on All Features: [0.9431587 0.95546198 0.95083541 0.93929218 0.93964358]

Mean CV R^2 Score on All Features: 0.9456783700068371

Test R^2 Score on All Features: 0.9352216263387702



```
# Make predictions and evaluate on the test set
y_pred_test = best_rf_model.predict(X_test)
test_r2 = r2_score(y_test, y_pred_test)
print("Test R2 Score on Selected Features:", test_r2)
```

```
# Evaluate with additional metrics
test_mae = mean_absolute_error(y_test, y_pred_test)
test_mse = mean_squared_error(y_test, y_pred_test)
print("Test MAE:", test_mae)
print("Test MSE:", test_mse)
```

Test R^2 Score on Selected Features: 0.9259274500968896

Test MAE: 0.11033008092490257

Test MSE: 0.022965514293246492



Conclusions

Takeaways:

- Random Forest is a robust algorithm suitable for complex regression tasks.
- Feature importance analysis is crucial for understanding model behavior.
- Hyperparameter tuning significantly improves model performance.
- Cross-validation is essential for assessing model generalizability

Conclusions:

- The model exceeded the target R^2 score, demonstrating high predictive accuracy.
- The synthetic dataset provided a controlled environment for model training and evaluation.
- The project showcases the effectiveness of machine learning in real estate price prediction.

Limitations:

- The synthetic nature of the data may not capture all real-world complexities.
- The model's performance on actual market data is yet to be tested.
- There's a trade-off between model complexity and interpretability with Random Forest.
- The current model may not account for time-series trends in the housing market.



Thanks for watching

Any Questions?