Project Name: Regression-Based Approach for Accurate House Price Forecasting

Group No: 15

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1. Imports and Data Loading

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.datasets import fetch_california_housing
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LinearRegression
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score

# Load dataset
california = fetch_california_housing()
X = pd.DataFrame(california.data, columns=california.feature_names)
y = pd.Series(california.target, name='MedHouseVal')
```

2. Data Exploration

```
df = X.copy()
df['MedHouseVal'] = y

print(df.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 20640 entries, 0 to 20639
Data columns (total 9 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   MedInc       20640 non-null  float64
 1   HouseAge     20640 non-null  float64
 2   AveRooms     20640 non-null  float64
 3   AveBedrms    20640 non-null  float64
 4   Population   20640 non-null  float64
 5   AveOccup     20640 non-null  float64
 6   Latitude     20640 non-null  float64
 7   Longitude    20640 non-null  float64
 8   MedHouseVal  20640 non-null  float64
dtypes: float64(9)
memory usage: 1.4 MB
None
```

```
df.head()
```

	MedInc	HouseAge	AveRooms	AveBedrms	Population	AveOccup	Latitude	Longit
0	8.3252	41.0	6.984127	1.023810	322.0	2.555556	37.88	-12
1	8.3014	21.0	6.238137	0.971880	2401.0	2.109842	37.86	-12
2	7.2574	52.0	8.288136	1.073446	496.0	2.802260	37.85	-12
3	5.6431	52.0	5.817352	1.073059	558.0	2.547945	37.85	-12
4	3.8462	52.0	6.281853	1.081081	565.0	2.181467	37.85	-12

```
print(df.describe())
```

```
             MedInc      HouseAge      AveRooms     AveBedrms    Population  \
count  20640.000000  20640.000000  20640.000000  20640.000000  20640.000000
mean       3.870671     28.639486      5.429000      1.096675   1425.476744
std        1.899822     12.585558      2.474173      0.473911   1132.462122
min        0.499900      1.000000      0.846154      0.333333      3.000000
25%        2.563400     18.000000      4.440716      1.006079    787.000000
50%        3.534800     29.000000      5.229129      1.048780   1166.000000
75%        4.743250     37.000000      6.052381      1.099526   1725.000000
max       15.000100     52.000000    141.909091     34.066667  35682.000000

           AveOccup      Latitude     Longitude   MedHouseVal
count  20640.000000  20640.000000  20640.000000  20640.000000
mean       3.070655     35.631861   -119.569704      2.068558
std       10.386050      2.135952      2.003532      1.153956
min        0.692308     32.540000   -124.350000      0.149990
25%        2.429741     33.930000   -121.800000      1.196000
50%        2.818116     34.260000   -118.490000      1.797000
75%        3.282261     37.710000   -118.010000      2.647250
max     1243.333333     41.950000   -114.310000      5.000010
```

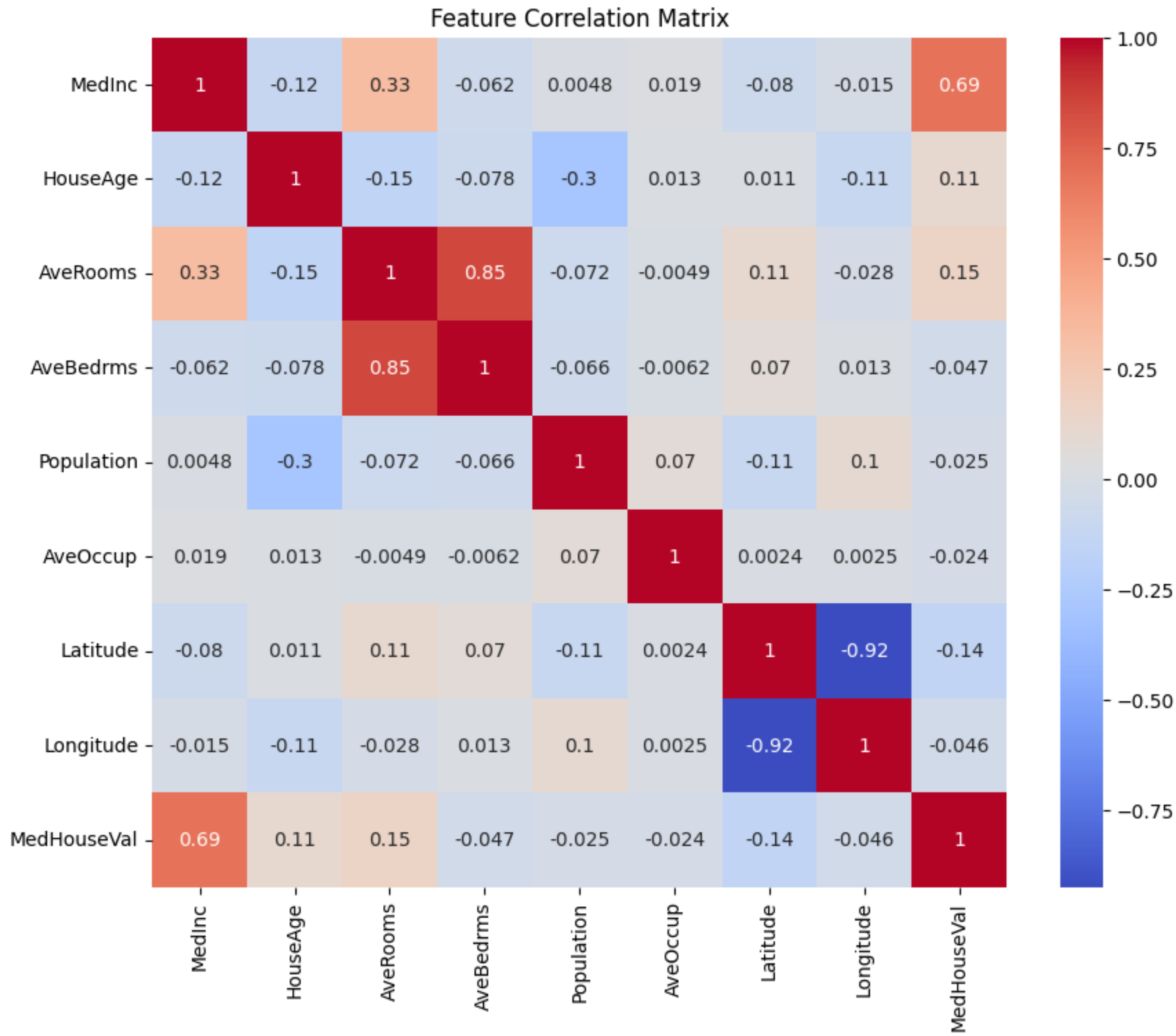
3. Data Preprocessing

```
# Null check
print("\nMissing values:\n", df.isnull().sum())
```

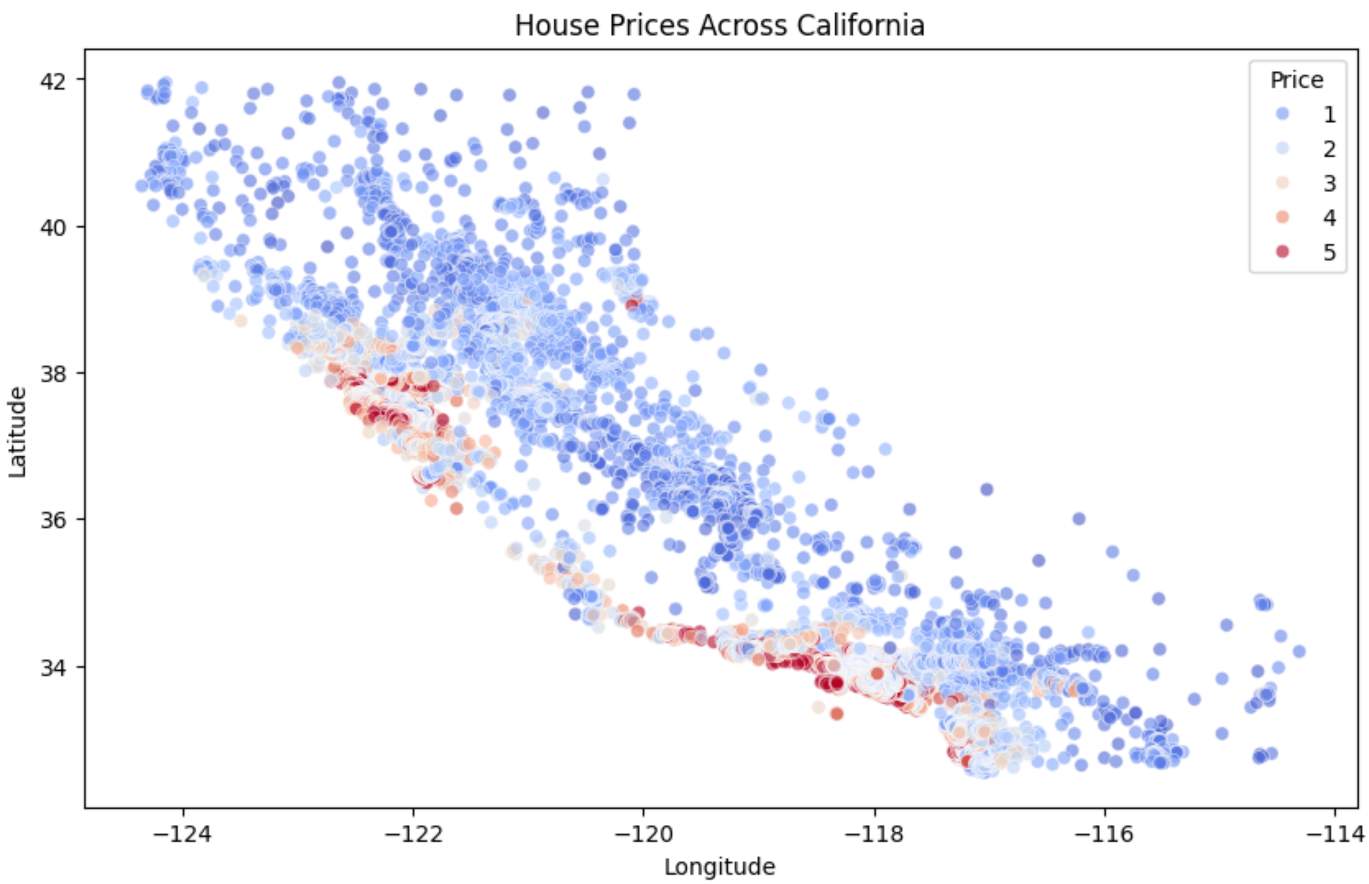
```
Missing values:
 MedInc        0
HouseAge      0
AveRooms      0
AveBedrms     0
Population    0
AveOccup      0
Latitude      0
Longitude     0
MedHouseVal   0
dtype: int64
```

```
# Correlation Heatmap
plt.figure(figsize=(10,8))
sns.heatmap(df.corr(), annot=True, cmap='coolwarm')
plt.title("Feature Correlation Matrix")
```

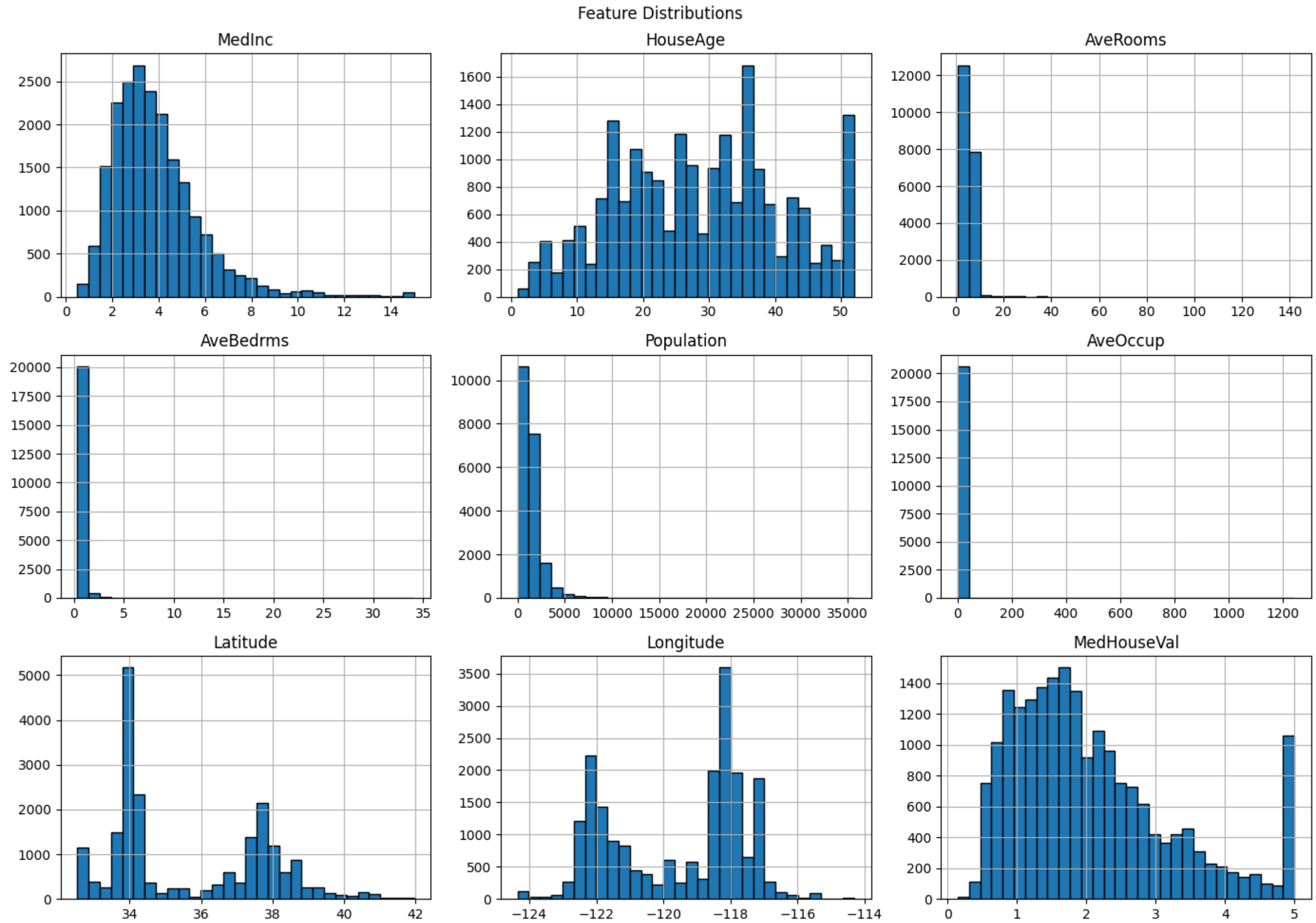
```
plt.show()
```


Feature Correlation Matrix
MedInc
HouseAge
AveRooms
AveBedrms
Population
AveOccup
Latitude
Longitude
MedHouseVal
1 -0.12 0.33 -0.062 0.0048 0.019 -0.08 -0.015 0.69
-0.12 1 -0.15 -0.078 -0.3 0.013 0.011 -0.11 0.11
0.33 -0.15 1 0.85 -0.072 -0.0049 0.11 -0.028 0.15
-0.062 -0.078 0.85 1 -0.066 -0.0062 0.07 0.013 -0.047
0.0048 -0.3 -0.072 -0.066 1 0.07 -0.11 0.1 -0.025
0.019 0.013 -0.0049 -0.0062 0.07 1 0.0024 0.0025 -0.024
-0.08 0.011 0.11 0.07 -0.11 0.0024 1 -0.92 -0.14
-0.015 -0.11 -0.028 0.013 0.1 0.0025 -0.92 1 -0.046
0.69 0.11 0.15 -0.047 -0.025 -0.024 -0.14 -0.046 1
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75

```
# Color-coded scatterplot showing geographic pattern
plt.figure(figsize=(10, 6))
sns.scatterplot(data=df, x='Longitude', y='Latitude', hue='MedHouseVal', palette=
plt.title('House Prices Across California')
plt.legend(title='Price')
plt.show()
```




```
# Histograms
df.hist(bins=30, figsize=(14, 10), edgecolor='black')
plt.suptitle("Feature Distributions")
plt.tight_layout()
plt.show()
```


Feature Distributions
MedInc
HouseAge
AveRooms
AveBedrms
Population
AveOccup
Latitude
Longitude
MedHouseVal

4. Feature Engineering

```
# Add Engineered Features
X["RoomsPerHousehold"] = X["AveRooms"] / X["AveOccup"]
X["BedroomsPerRoom"] = X["AveBedrms"] / X["AveRooms"]
X["PopulationPerHousehold"] = X["Population"] / X["AveOccup"]

# Train-Test Split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_s

# Standard Scaling
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

5. Model Training

```
# Train Models
lr = LinearRegression()
rf = RandomForestRegressor(random_state=42)

lr.fit(X_train_scaled, y_train)
rf.fit(X_train_scaled, y_train)

# Predictions
lr_preds = lr.predict(X_test_scaled)
rf_preds = rf.predict(X_test_scaled)
```

```
# Evaluation Function
def evaluate_model(y_true, y_pred, name):
    mse = mean_squared_error(y_true, y_pred)
    mae = mean_absolute_error(y_true, y_pred)
    r2 = r2_score(y_true, y_pred)
    print(f" {name}")
    print(f"  MSE: {mse:.4f}")
    print(f"  MAE: {mae:.4f}")
    print(f"  R²:  {r2:.4f}\n")

# Evaluate
evaluate_model(y_test, lr_preds, "Linear Regression")
evaluate_model(y_test, rf_preds, "Random Forest Regressor")
```

```
 Linear Regression
  MSE: 0.4540
  MAE: 0.4874
  R²:  0.6535

 Random Forest Regressor
  MSE: 0.2561
  MAE: 0.3299
  R²:  0.8046
```

6. Model Tuning

```
from sklearn.model_selection import GridSearchCV

# Define parameter grid for Random Forest
param_grid = {
    'n_estimators': [50, 100, 200],
    'max_depth': [None, 10, 20],
    'min_samples_split': [2, 5],
    'min_samples_leaf': [1, 2]
}

# Set up GridSearchCV
grid_search = GridSearchCV(
    estimator=RandomForestRegressor(random_state=42),
    param_grid=param_grid,
    cv=3,
    scoring='r2',
    verbose=1,
    n_jobs=-1
)

# Fit the grid search to the data
grid_search.fit(X_train_scaled, y_train)

# Best model
best_rf = grid_search.best_estimator_
print("Best Parameters Found:\n", grid_search.best_params_)
```

```
Fitting 3 folds for each of 36 candidates, totalling 108 fits
Best Parameters Found:
 {'max_depth': 20, 'min_samples_leaf': 2, 'min_samples_split': 2, 'n_estimato
```

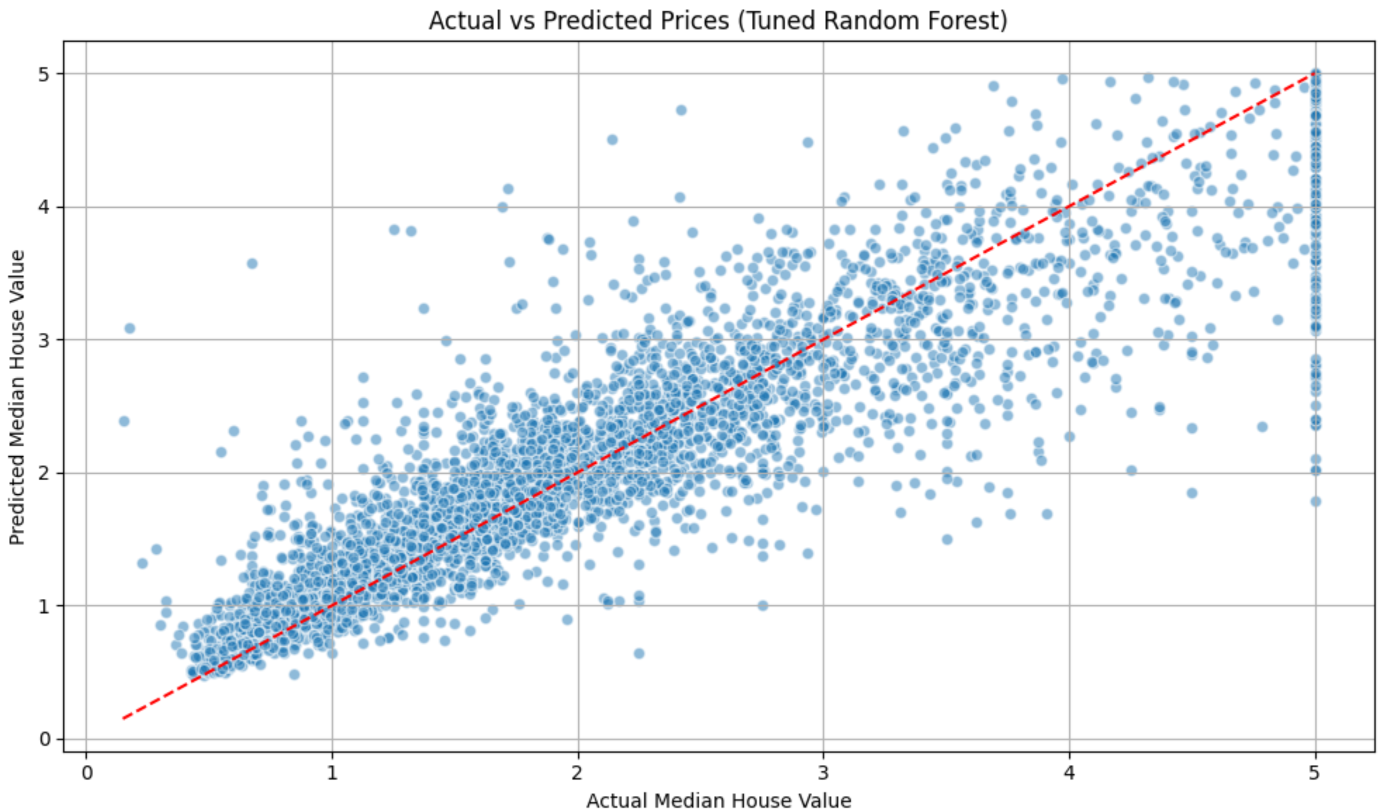
```
# Use the best estimator found by GridSearchCV
best_rf = grid_search.best_estimator_

# Predict on the test set
best_rf_preds = best_rf.predict(X_test_scaled)
```

7. Final Prediction & Interpretation

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

# Evaluation Function
def evaluate_model(y_true, y_pred, name="Model"):
    print(f"\n🔍 {name} Evaluation:")
    print(f"  ➤ Mean Squared Error (MSE):      {mean_squared_error(y_true, y_pred
    print(f"  ➤ Mean Absolute Error (MAE):     {mean_absolute_error(y_true, y_pre
    print(f"  ➤ R-squared (R² Score):          {r2_score(y_true, y_pred):.4f}")

# Evaluate
evaluate_model(y_test, best_rf_preds, "Tuned Random Forest")
```

```
🔍 Tuned Random Forest Evaluation:
  ➤ Mean Squared Error (MSE):      0.2549
  ➤ Mean Absolute Error (MAE):     0.3284
  ➤ R-squared (R² Score):          0.8054
```

```
import matplotlib.pyplot as plt

plt.figure(figsize=(10, 6))
plt.scatter(y_test, best_rf_preds, alpha=0.5, edgecolors='w')
plt.plot([y_test.min(), y_test.max()], [y_test.min(), y_test.max()], 'r--')
plt.xlabel("Actual Median House Value")
plt.ylabel("Predicted Median House Value")
plt.title("Actual vs Predicted Prices (Tuned Random Forest)")
plt.grid(True)
plt.tight_layout()
plt.show()
```




```
import seaborn as sns
import pandas as pd

# Get feature importances
feature_importance = pd.Series(best_rf.feature_importances_, index=X.columns)
feature_importance = feature_importance.sort_values(ascending=True)

# Plot
plt.figure(figsize=(10, 6))
sns.barplot(x=feature_importance.values, y=feature_importance.index, palette="vir
plt.title("Feature Importances from Tuned Random Forest")
plt.xlabel("Importance Score")
```

```
plt.ylabel("Feature")
plt.tight_layout()
plt.show()
```

```
<ipython-input-35-95bf0b323307>:10: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed ir

  sns.barplot(x=feature_importance.values, y=feature_importance.index, palette
```