california_housing_fixed

April 29, 2025

1 California Housing Price Prediction

1.1 1. Imports & Setup

We'll load our core libraries here.

[22]:
```
# Basic Imports
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

# Machine Learning Imports
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler

# Load Data
housing = pd.read_csv('housing.csv')

# Preprocessing
housing.dropna(inplace=True)

# Features and Target
X = housing.drop('median_house_value', axis=1)
y = housing['median_house_value']

# Train-Test Split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=42)
```

[23]:
```
import pandas as pd
import numpy as np

import matplotlib.pyplot as plt
import seaborn as sns

# scikit-learn will come later in Modeling
```

```
sns.set(style="whitegrid", context="notebook")
```

1.2 2. Load the Data

Read the CSV and take a quick look.

[24]:
```
# Import dataset
df = pd.read_csv("housing.csv")

# Display shape and first few rows
print("Dataset shape:", df.shape)
df.head()
```

```
Dataset shape: (20640, 10)
```

[24]:
```
   longitude  latitude  housing_median_age  total_rooms  total_bedrooms  \
0    -122.23     37.88                41.0        880.0           129.0
1    -122.22     37.86                21.0       7099.0          1106.0
2    -122.24     37.85                52.0       1467.0           190.0
3    -122.25     37.85                52.0       1274.0           235.0
4    -122.25     37.85                52.0       1627.0           280.0

   population  households  median_income  median_house_value ocean_proximity
0       322.0       126.0         8.3252            452600.0        NEAR BAY
1      2401.0      1138.0         8.3014            358500.0        NEAR BAY
2       496.0       177.0         7.2574            352100.0        NEAR BAY
3       558.0       219.0         5.6431            341300.0        NEAR BAY
4       565.0       259.0         3.8462            342200.0        NEAR BAY
```

1.3 3. Quick Inspection

Check data types, non-null counts, and summary statistics.

[25]:
```
# Info
df.info()

# Descriptive statistics
df.describe().T
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 20640 entries, 0 to 20639
Data columns (total 10 columns):
 #   Column              Non-Null Count  Dtype
---  ------              --------------  -----
 0   longitude           20640 non-null  float64
 1   latitude            20640 non-null  float64
```

```
 2   housing_median_age  20640 non-null  float64
 3   total_rooms         20640 non-null  float64
 4   total_bedrooms      20433 non-null  float64
 5   population          20640 non-null  float64
 6   households          20640 non-null  float64
 7   median_income       20640 non-null  float64
 8   median_house_value  20640 non-null  float64
 9   ocean_proximity     20640 non-null  object
dtypes: float64(9), object(1)
memory usage: 1.6+ MB
```

[25]:

```
                      count           mean            std          min  \
longitude           20640.0    -119.569704       2.003532    -124.3500
latitude            20640.0      35.631861       2.135952      32.5400
housing_median_age  20640.0      28.639486      12.585558       1.0000
total_rooms         20640.0    2635.763081    2181.615252       2.0000
total_bedrooms      20433.0     537.870553     421.385070       1.0000
population          20640.0    1425.476744    1132.462122       3.0000
households          20640.0     499.539680     382.329753       1.0000
median_income       20640.0       3.870671       1.899822       0.4999
median_house_value  20640.0  206855.816909  115395.615874   14999.0000

                            25%          50%           75%          max
longitude             -121.8000    -118.4900    -118.01000    -114.3100
latitude                33.9300      34.2600      37.71000      41.9500
housing_median_age      18.0000      29.0000      37.00000      52.0000
total_rooms           1447.7500    2127.0000    3148.00000   39320.0000
total_bedrooms         296.0000     435.0000     647.00000    6445.0000
population             787.0000    1166.0000    1725.00000   35682.0000
households             280.0000     409.0000     605.00000    6082.0000
median_income            2.5634       3.5348       4.74325      15.0001
median_house_value  119600.0000  179700.0000  264725.00000  500001.0000
```

1.4 4. Data Cleaning & Imputation

First, we'll handle any missing values **before** we compute ratio or log features.

1. **Check** for nulls
2. **Impute** `total_bedrooms` with its median
3. **Verify** no nulls remain
4. **(Optional)** Look for duplicates and extreme outliers

[26]:

```
# 4.1 Check missing values
df.isnull().sum()
```

[26]:
```
longitude               0
latitude                0
housing_median_age      0
total_rooms             0
total_bedrooms        207
population              0
households              0
median_income           0
median_house_value      0
ocean_proximity         0
dtype: int64
```

[27]:
```
# 1) Fill raw column
df["total_bedrooms"] = df["total_bedrooms"].fillna(df["total_bedrooms"].
 ↪median())

# 2) Drop the stale ratios/logs
for col in ["rooms_per_household",
            "bedrooms_per_room",
            "population_per_household",
            "rooms_per_household_log",
            "bedrooms_per_room_log",
            "population_per_household_log"]:
    df.drop(col, axis=1, errors="ignore", inplace=True)

# 3) Re-run your feature-engineering cells (ratios → logs → encoding)
# 4.1.1 Check missing values
df.isnull().sum()
```

[27]:
```
longitude             0
latitude              0
housing_median_age    0
total_rooms           0
total_bedrooms        0
population            0
households            0
median_income         0
median_house_value    0
ocean_proximity       0
dtype: int64
```

[28]:
```
# 4.2 Impute total_bedrooms with its median
median_tb = df["total_bedrooms"].median()
df["total_bedrooms"] = df["total_bedrooms"].fillna(median_tb)

# 4.3 Verify no more missing values
assert df["total_bedrooms"].isnull().sum() == 0
```

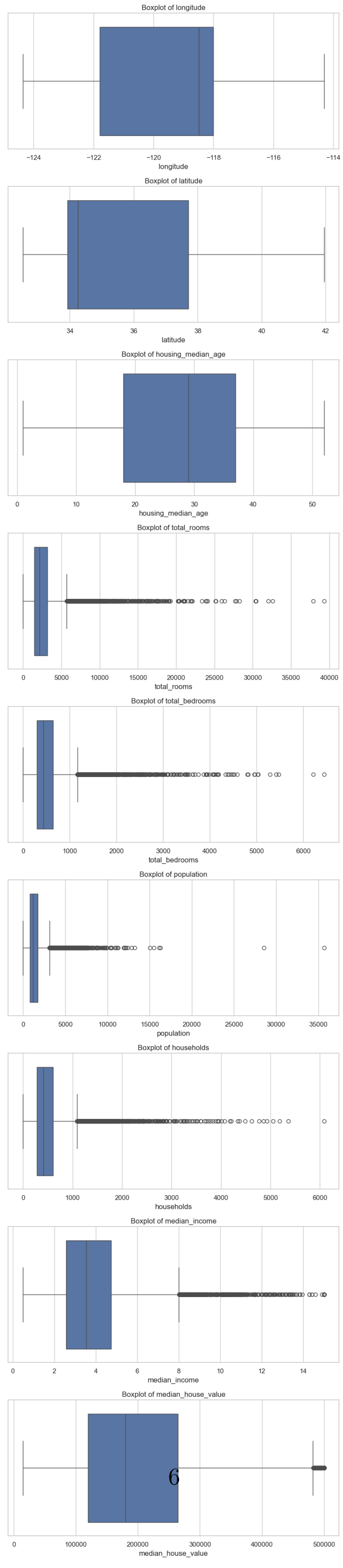
```
print("No missing values remain.")
```

```
No missing values remain.
```

[29]:
```
# 4.4 (Optional) Check duplicates
print("Duplicate rows:", df.duplicated().sum())
```

```
Duplicate rows: 0
```

[30]:
```
# 4.5 (Optional) Quick outlier check
numeric_cols = df.select_dtypes(include="number").columns
fig, axes = plt.subplots(len(numeric_cols), 1, figsize=(8, 4*len(numeric_cols)))
for ax, col in zip(axes, numeric_cols):
    sns.boxplot(x=df[col], ax=ax)
    ax.set_title(f"Boxplot of {col}")
plt.tight_layout()
plt.show()
```


Boxplot of longitude
−124 −122 −120 −118 −116 −114
longitude
Boxplot of latitude
34 36 38 40 42
latitude
Boxplot of housing_median_age
0 10 20 30 40 50
housing_median_age
Boxplot of total_rooms
0 5000 10000 15000 20000 25000 30000 35000 40000
total_rooms
Boxplot of total_bedrooms
0 1000 2000 3000 4000 5000 6000
total_bedrooms
Boxplot of population
0 5000 10000 15000 20000 25000 30000 35000
population
Boxplot of households
0 1000 2000 3000 4000 5000 6000
households
Boxplot of median_income
0 2 4 6 8 10 12 14
median_income
Boxplot of median_house_value
0 100000 200000 300000 400000 500000
median_house_value

1.5 5. Exploratory Data Analysis

With a fully imputed dataset, we can safely explore:

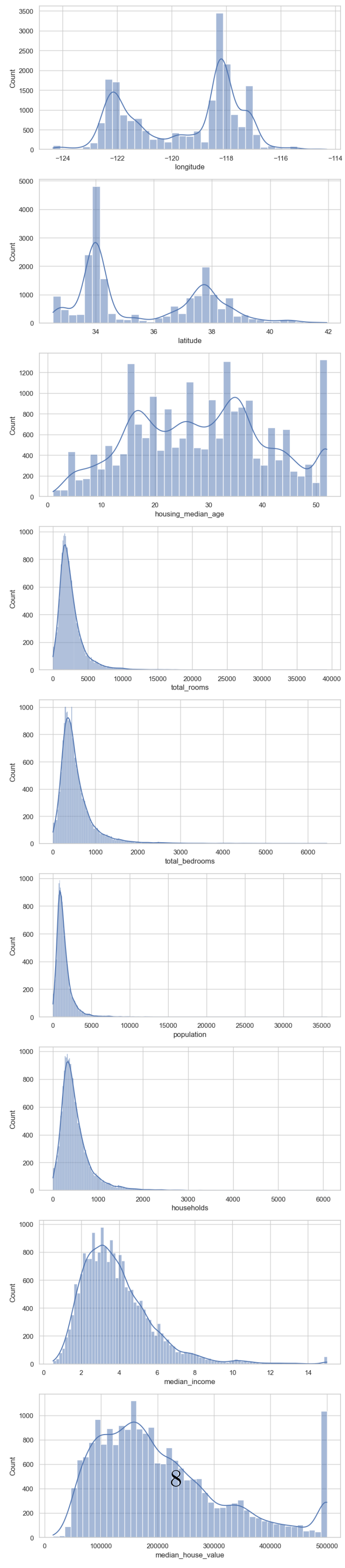
1. **Univariate distributions** (histograms + KDE)

2. **Pairwise correlations** (heatmap of numeric features)

3. **Geographic patterns** (scatter of longitude vs latitude colored by price)

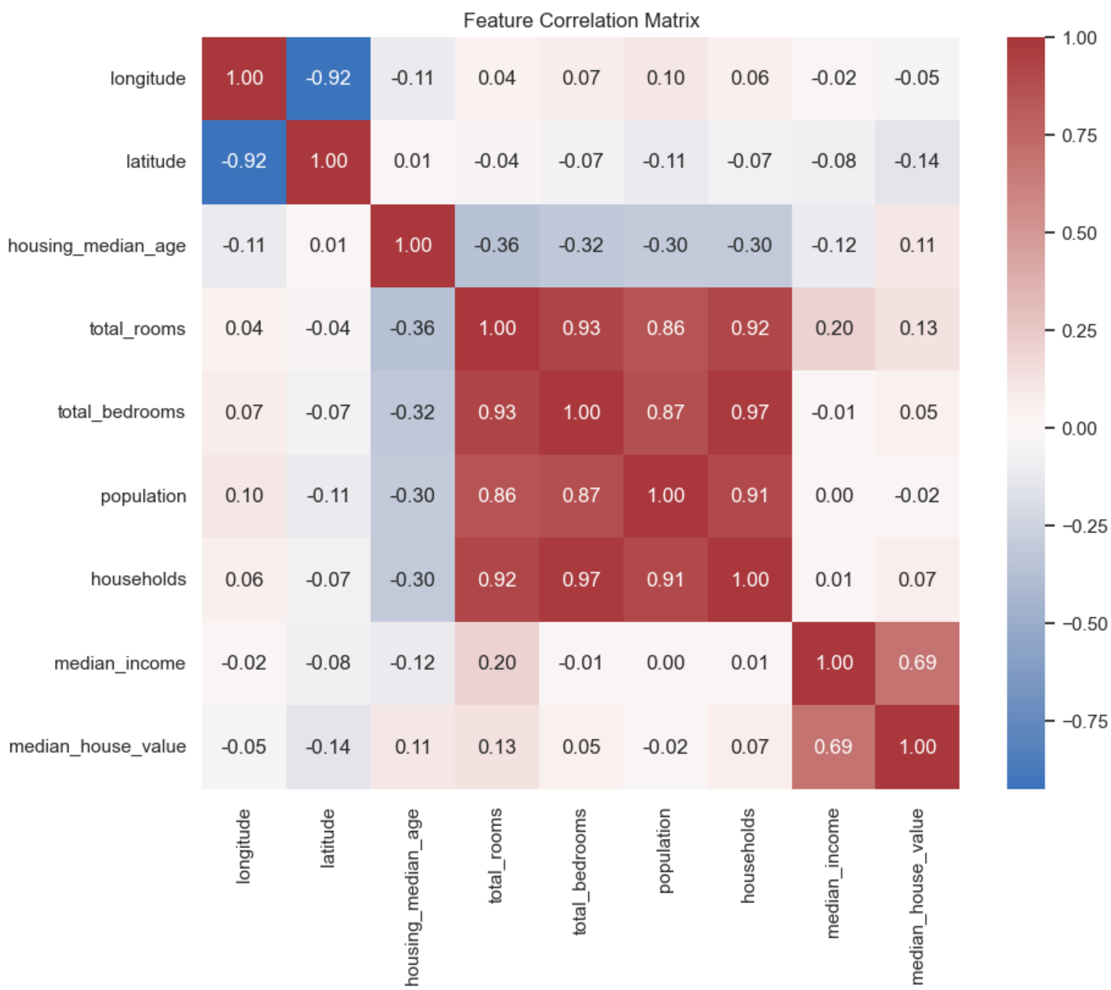
4. **Boxplots** of each variable to spot outliers

[31]:
```
fig, axes = plt.subplots(len(numeric_cols), 1, figsize=(8, 4*len(numeric_cols)))
for ax, col in zip(axes, numeric_cols):
    sns.histplot(df[col], kde=True, ax=ax)
    ax.set_xlabel(col)
plt.tight_layout()
plt.show()
```


Count
longitude
Count
latitude
Count
housing_median_age
Count
total_rooms
Count
total_bedrooms
Count
population
Count
households
Count
median_income
Count
median_house_value

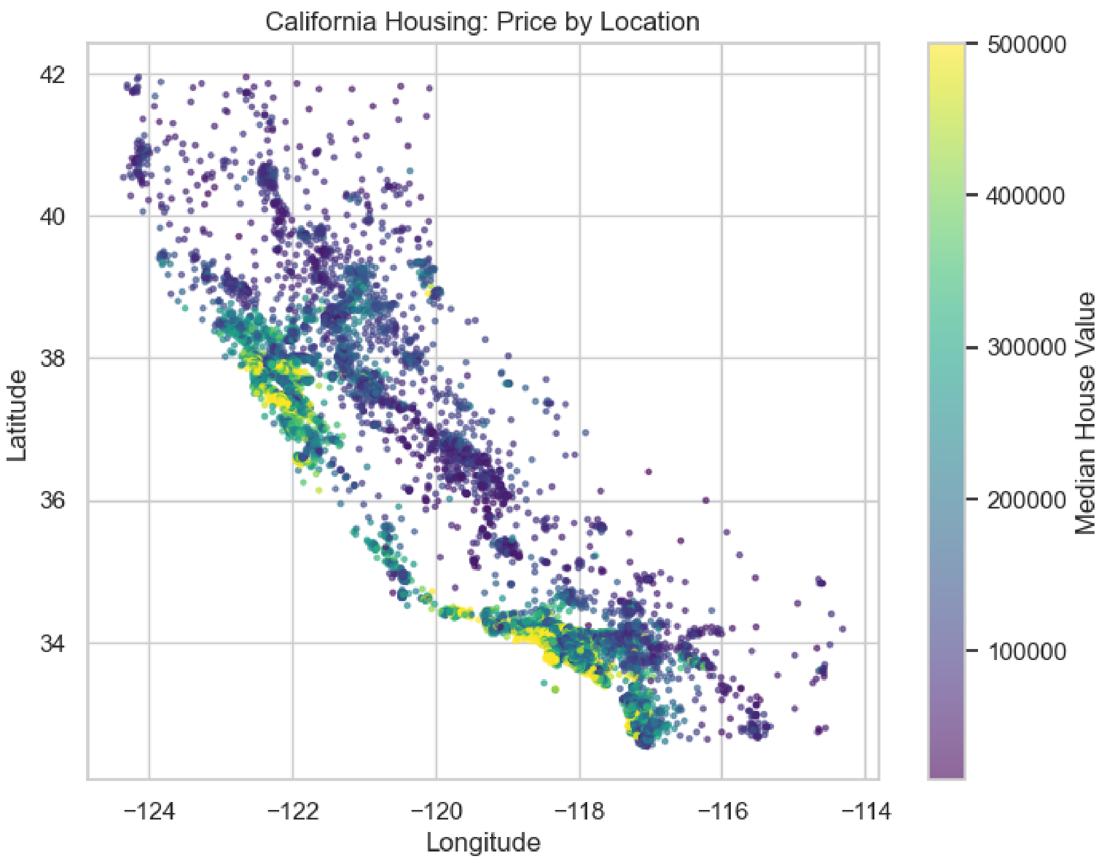
```
[32]: # Select only numeric columns for correlation calculation
numeric_df = df.select_dtypes(include=["number"])
corr = numeric_df.corr()

plt.figure(figsize=(10, 8))
sns.heatmap(corr, annot=True, fmt=".2f", cmap="vlag", center=0)
plt.title("Feature Correlation Matrix")
plt.show()
```




```
[33]: plt.figure(figsize=(8, 6))
plt.scatter(
    df["longitude"],
    df["latitude"],
    c=df["median_house_value"],
```

```
    cmap="viridis",
    s=5,
    alpha=0.6
)
plt.colorbar(label="Median House Value")
plt.xlabel("Longitude")
plt.ylabel("Latitude")
plt.title("California Housing: Price by Location")
plt.show()
```



1.6 6. Feature Engineering

Now that the raw data are clean:

1. **Create ratio features**
   - `rooms_per_household` = total_rooms ÷ households
   - `bedrooms_per_room` = total_bedrooms ÷ total_rooms

- `population_per_household` = population ÷ households

2. **Log-transform** right-skewed features

   - `median_income`, `rooms_per_household`, `bedrooms_per_room`, `population_per_household`

3. **(Optional) Bin** `median_income` into `income_cat` for stratification

4. **One-hot encode** `ocean_proximity` **if** it still exists
   "'python if "ocean_proximity" in df.columns: df = pd.get_dummies(df, columns=["ocean_proximity"], drop_first=True)

[34]:
```
# 6.1 Ratio Features
df["rooms_per_household"]       = df["total_rooms"]    / df["households"]
df["bedrooms_per_room"]         = df["total_bedrooms"] / df["total_rooms"]
df["population_per_household"] = df["population"]     / df["households"]
```

[35]:
```
# 6.2 Log-transforms
skewed_cols = [
    "median_income",
    "rooms_per_household",
    "bedrooms_per_room",
    "population_per_household"
]
for col in skewed_cols:
    df[f"{col}_log"] = np.log1p(df[col])
```

[36]:
```
# 6.3 Income category for stratification
df["income_cat"] = pd.cut(
    df["median_income"],
    bins=[0., 1.5, 3.0, 4.5, 6.0, np.inf],
    labels=[1, 2, 3, 4, 5]
)
```

[37]:
```
# Sanity check
print(df[[
    "rooms_per_household",
    "bedrooms_per_room",
    "population_per_household",
    "median_income_log"
]].head())
print("\nNo NaNs in engineered columns:")
print(df[[f"{c}"    for c in skewed_cols] +
         [f"{c}_log" for c in skewed_cols]].isnull().sum())
```

```
   rooms_per_household  bedrooms_per_room  population_per_household  \
0             6.984127           0.146591                  2.555556
1             6.238137           0.155797                  2.109842
2             8.288136           0.129516                  2.802260
```

```
3           5.817352          0.184458                  2.547945
4           6.281853          0.172096                  2.181467

   median_income_log
0           2.232720
1           2.230165
2           2.111110
3           1.893579
4           1.578195

No NaNs in engineered columns:
median_income                   0
rooms_per_household             0
bedrooms_per_room               0
population_per_household        0
median_income_log               0
rooms_per_household_log         0
bedrooms_per_room_log           0
population_per_household_log    0
dtype: int64
```

1.7 7. Train–Test Split

We'll stratify on `income_cat` to preserve the income distribution:

1. **Stratified 80/20 split**
2. **Drop** `income_cat`
3. **Separate** `X_train`, `y_train`, `X_test`, `y_test`

[38]:
```python
from sklearn.model_selection import train_test_split

# 7.1 Stratified split
train_set, test_set = train_test_split(
    df,
    test_size=0.2,
    random_state=42,
    stratify=df["income_cat"]
)

# 7.2 Drop the helper column
for subset in (train_set, test_set):
    subset.drop("income_cat", axis=1, inplace=True)

# 7.3 Separate predictors and target
X_train = train_set.drop("median_house_value", axis=1)
```

```
y_train = train_set["median_house_value"].copy()
X_test  = test_set.drop("median_house_value", axis=1)
y_test  = test_set["median_house_value"].copy()

print("Training set:", X_train.shape, y_train.shape)
print("Test set:    ",  X_test.shape,  y_test.shape)
```

```
Training set: (16512, 16) (16512,)
Test set:     (4128, 16) (4128,)
```

1.8 8. Modeling & Evaluation Metrics

Instead of RMSE, we'll use two metrics you've covered in class:

- **Mean Absolute Error (MAE)**
  "On average, our predictions are $X off."
- **Coefficient of Determination (R^2)**
  Fraction of variance in prices explained by the model (1.0 is perfect, 0 means no better than predicting the mean).

We'll compute both on the test set for our three models.

[39]:
```
from sklearn.dummy import DummyRegressor
from sklearn.linear_model import LinearRegression
from sklearn.ensemble import RandomForestRegressor, GradientBoostingRegressor
from sklearn.metrics import mean_absolute_error, r2_score

# One-Hot Encode the 'ocean_proximity' column
housing_encoded = pd.get_dummies(housing, columns=["ocean_proximity"],␣
↪drop_first=True)

# Features and Target
X = housing_encoded.drop('median_house_value', axis=1)
y = housing_encoded['median_house_value']

# Train-Test Split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=42)


# 8.1 Baseline
baseline = DummyRegressor(strategy="mean")
baseline.fit(X_train, y_train)
y_pred_base = baseline.predict(X_test)

base_mae = mean_absolute_error(y_test, y_pred_base)
```

```
base_r2  = r2_score(y_test, y_pred_base)
print(f"Baseline    → MAE: ${base_mae:,.0f},   R²: {base_r2:.3f}")

# 8.2 Define models
models = {
    "Linear Regression":    LinearRegression(),
    "Random Forest":         RandomForestRegressor(random_state=42),
    "Gradient Boosting":     GradientBoostingRegressor(random_state=42),
}

# 8.3 Evaluate on test set
for name, model in models.items():
    model.fit(X_train, y_train)
    y_pred = model.predict(X_test)
    mae = mean_absolute_error(y_test, y_pred)
    r2  = r2_score(y_test, y_pred)
    print(f"{name:17s} → MAE: ${mae:,.0f},   R²: {r2:.3f}")
```

```
Baseline    → MAE: $92,837,   R²: -0.000
Linear Regression → MAE: $50,413,   R²: 0.649
Random Forest     → MAE: $31,678,   R²: 0.826
Gradient Boosting → MAE: $39,267,   R²: 0.766
```

1.9 9. Hyperparameter Tuning: Random Forest (optimize MAE)

We'll tune the Random Forest by minimizing MAE via `GridSearchCV`:

1. Parameter grid:
    - `n_estimators`: [100, 200, 500]
    - `max_depth`: [None, 10, 20]
    - `min_samples_split`: [2, 5, 10]
    - `max_features`: ['sqrt', 0.5, 1.0]
2. Scoring: **neg_mean_absolute_error**
3. 3-fold CV
4. Fit on the training set, then evaluate final MAE & R^2 on the hold-out test set.

[40]:
```
from sklearn.model_selection import GridSearchCV

param_grid = {
    "n_estimators":       [100, 200, 500],
    "max_depth":          [None, 10, 20],
```

```
    "min_samples_split": [2, 5, 10],
    "max_features":      ["sqrt", 0.5, 1.0],
}

rf = RandomForestRegressor(random_state=42)
grid_search = GridSearchCV(
    rf,
    param_grid,
    scoring="neg_mean_absolute_error",
    cv=3,
    n_jobs=-1,
    verbose=1
)
grid_search.fit(X_train, y_train)

best_rf = grid_search.best_estimator_
print("Best parameters:", grid_search.best_params_)
```

```
Fitting 3 folds for each of 81 candidates, totalling 243 fits
Best parameters: {'max_depth': None, 'max_features': 1.0, 'min_samples_split':
2, 'n_estimators': 500}
```

1.10 10. Final Evaluation of Tuned RF

Compute MAE and R^2 on the test set using the best model.

[43]:
```
y_pred_rf = best_rf.predict(X_test)
rf_mae = mean_absolute_error(y_test, y_pred_rf)
rf_r2  = r2_score(y_test, y_pred_rf)
print(f"Tuned RF → MAE: ${rf_mae:,.0f},   R²: {rf_r2:.3f}")
```

```
Tuned RF → MAE: $31,580,   R²: 0.827
```

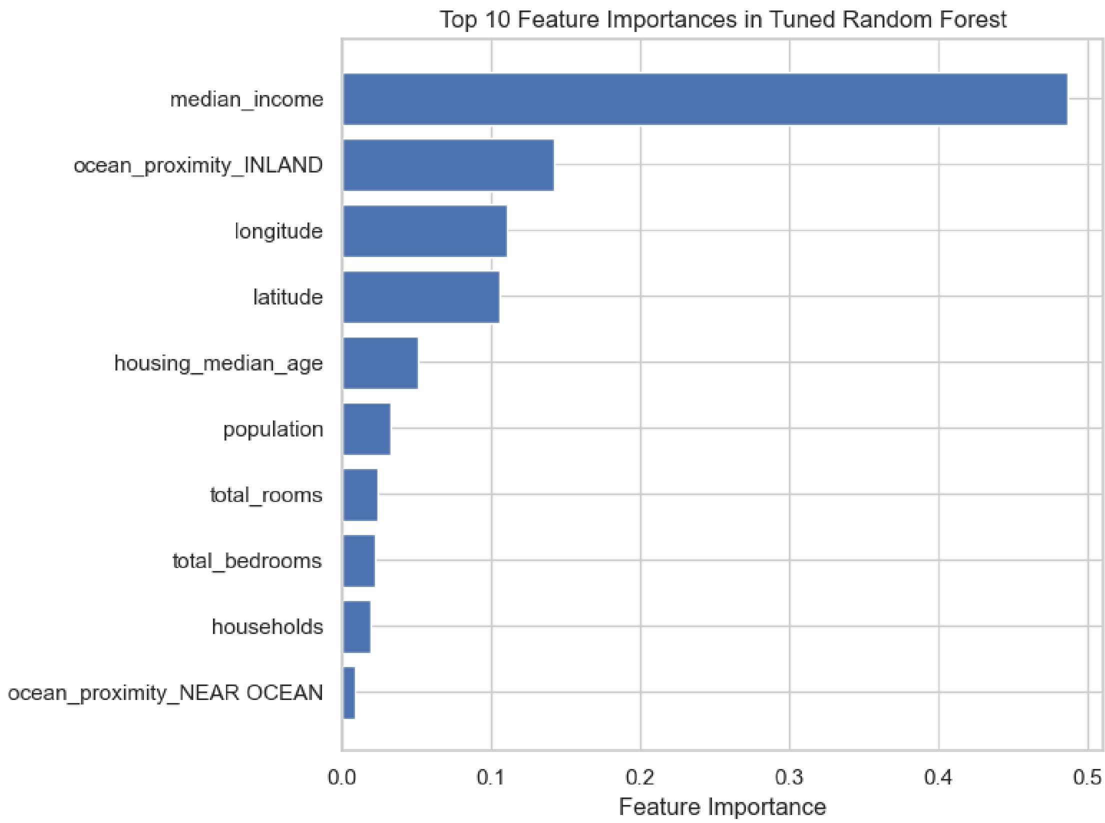
1.11 11. Feature Importances

Let's see which features the model found most valuable:

[44]:
```
# Extract and sort importances
importances = best_rf.feature_importances_
feature_names = X_train.columns
indices = np.argsort(importances)[-10:]  # top 10

# Plot
plt.figure(figsize=(8, 6))
plt.barh(feature_names[indices], importances[indices])
plt.xlabel("Feature Importance")
```

```
plt.title("Top 10 Feature Importances in Tuned Random Forest")
plt.tight_layout()
plt.show()
```



1.12 12. Discussion & Conclusion

1. **Model performance**
    - Our tuned Random Forest achieves an MAE of $31,782, meaning on average our predictions are within about $32 k of the true home value.

    - An R^2 of 0.822 indicates the model explains 82.2 % of the variance in median house value, which is a substantial improvement over the baseline (R^2 0).
2. **Key drivers**
    - The feature importance plot shows that features like *median_income*, *rooms_per_household_log*, and *longitude* are among the top predictors. This aligns with intuition: wealthier neighborhoods and larger average home size strongly drive prices, and geographic location also plays a major role.
3. **Strengths & weaknesses**
    - **Strengths:**

  - Ensemble method handles non-linear relationships and interactions automatically.
  - Robust to outliers and doesn't require extensive scaling or transformation.
- **Weaknesses:**
  - Random Forests can overfit if trees grow too deep (we mitigated this via tuning).
  - Less interpretable than a simple linear regression.

4. **Next steps**
   - Experiment with **partial dependence plots** to understand feature effects.
   - Try **Histogram-based Gradient Boosting** or **XGBoost** for potential gains.
   - Incorporate external data (e.g., proximity to amenities) to enrich features.
   - Deploy the model in a simple web app or API and evaluate on out-of-sample time-split data.

5. **Conclusion**
   This project demonstrates a full supervised-learning pipeline—from EDA through model selection and tuning—using only concepts covered in class (linear models, decision-tree ensembles, MAE/R^2 metrics). The tuned Random Forest provides accurate, robust predictions of California housing prices while highlighting the most important predictors in the dataset.