myNotebook

August 18, 2024

1 Notebook: Housing Prices Prediction

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2 1. Inspecting data

[1]:
```python
import numpy as np
import pandas as pd
```

[2]:
```python
mycsv = 'data/housing.csv'
df = pd.read_csv(mycsv)
df.head()
```

[2]:
```
   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
```

[3]:
```python
df.shape
```

[3]:
```
(20640, 10)
```

[4]:
```python
df.info()
```

```
<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
```

3 1.1 Inspecting Data: Define X,Y columns

- X: feature columns = {numeric columns, categorical columns}
- y: target column

[5]:
```python
columns = list(df.columns)
print(columns)
```

```
['longitude', 'latitude', 'housing_median_age', 'total_rooms', 'total_bedrooms',
'population', 'households', 'median_income', 'median_house_value',
'ocean_proximity']
```

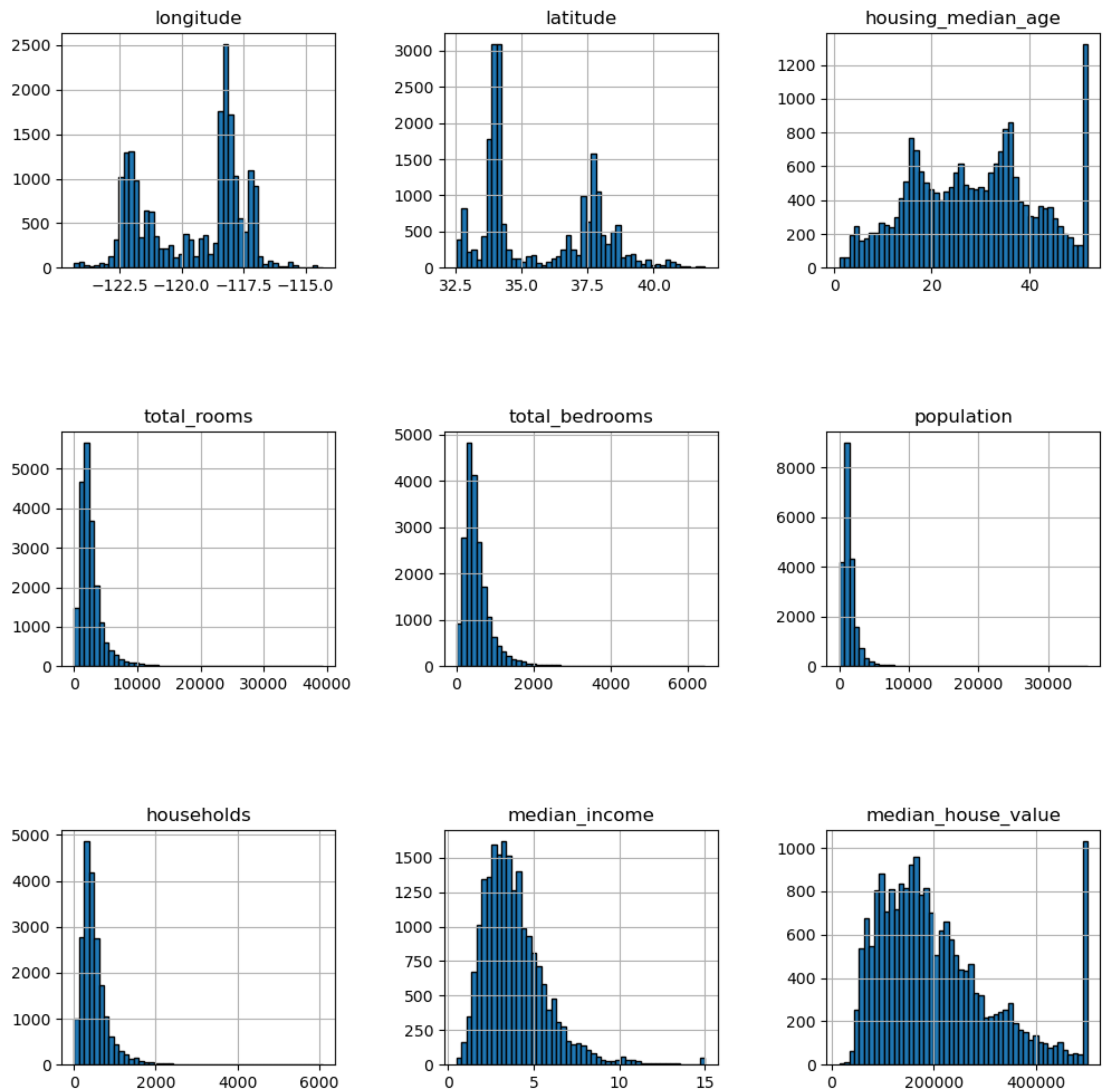
[6]:
```python
numeric_columns = columns[:-2]
cat_columns = [columns[-1]]
y_column = "median_house_value"
print("Features/num columns:\n", numeric_columns)
print("Feature/cat columns:\n", cat_columns)
print("Target column:\n", y_column)
```

```
Features/num columns:
 ['longitude', 'latitude', 'housing_median_age', 'total_rooms',
'total_bedrooms', 'population', 'households', 'median_income']
Feature/cat columns:
 ['ocean_proximity']
Target column:
 median_house_value
```

4 1.2 Inspecting Data: Basic Exploration

[7]:
```python
import seaborn as sns
import matplotlib.pyplot as plt
```

[8]:
```
df[numeric_columns + [y_column]].hist(figsize=(12, 12), bins=50,␣
↪edgecolor="black")
plt.subplots_adjust(hspace=0.7, wspace=0.4)
```



5 1.2.1. Basic Exploration: Linear Correlations between Num Columns and Target Column

[9]:
```
correlation_matrix = df[numeric_columns + [y_column]].corr()
correlation_matrix[y_column].sort_values(ascending=False)
```

[9]:
```
median_house_value    1.000000
median_income         0.688075
total_rooms           0.134153
housing_median_age    0.105623
households            0.065843
total_bedrooms        0.049686
population           -0.024650
longitude            -0.045967
latitude             -0.144160
Name: median_house_value, dtype: float64
```

6 1.2.2. Basic Exploration: Cat Columns

[11]:
```
df[cat_columns].value_counts()
```

[11]:
```
ocean_proximity
<1H OCEAN        9136
INLAND           6551
NEAR OCEAN       2658
NEAR BAY         2290
ISLAND              5
Name: count, dtype: int64
```

7 1.2.3. Basic Exploration: Missing Data. Is it serious?

[12]:
```
df.isnull().sum()
```

[12]:
```
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
```

8 The Heart: from Data to Models to Predictions

Here, we will train models using two different algorithms: * Linear regression with regularization, Lasso * Random forest regression

Then, * Comparing cross-validation (CV) performance of models from the two algorithms * Settling down with the winning algorithm and building model artifacts based on that

9 2. Training/Test data split

[13]:
```
from sklearn.model_selection import train_test_split
```

[14]:
```
RANDOM_STATE = 123
TEST_SIZE = 0.2
```

[16]:
```
def get_train_test_x_y(df:pd.DataFrame, test_size=TEST_SIZE,␣
↪random_state=RANDOM_STATE):
    train_df, test_df = train_test_split(df, test_size=test_size,␣
↪random_state=random_state)
    x_train = train_df[numeric_columns + cat_columns]
    y_train = train_df[y_column]
    x_test = test_df[numeric_columns + cat_columns]
    y_test = test_df[y_column]
    return x_train, y_train, x_test, y_test
```

[17]:
```
x_train, y_train, x_test, y_test = get_train_test_x_y(df)
print("x_train:", x_train.shape)
print("y_train:", x_train.shape)
print("x_test:", x_test.shape)
print("y_test:", y_test.shape)
```

```
x_train: (16512, 9)
y_train: (16512, 9)
x_test: (4128, 9)
y_test: (4128,)
```

10 3. Feature Engineering

Objective: create a feature-transformer object that transforms raw X_train, X_test

[18]:
```
# For num features
from sklearn.impute import SimpleImputer
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import StandardScaler
# For cat features
from sklearn.preprocessing import OneHotEncoder
from sklearn.compose import ColumnTransformer
```

[24]:
```
def get_feature_transformer(x_train:pd.DataFrame):
    num_pipeline = Pipeline([
        ("imputer", SimpleImputer(strategy="median")),
        ("std_scaler", StandardScaler())
    ])

    full_pipeline=ColumnTransformer([
```

```
        ('num', num_pipeline, numeric_columns),
        ('cat', OneHotEncoder(), cat_columns)
    ])

    full_pipeline.fit_transform(x_train)

    return full_pipeline
```

[38]:
```
feature_transformer = get_feature_transformer(x_train)
features = feature_transformer.get_feature_names_out()
print(f"After transform, there are {len(features)} features:\n", features)
```

```
After transform, there are 13 features:
 ['num__longitude' 'num__latitude' 'num__housing_median_age'
 'num__total_rooms' 'num__total_bedrooms' 'num__population'
 'num__households' 'num__median_income' 'cat__ocean_proximity_<1H OCEAN'
 'cat__ocean_proximity_INLAND' 'cat__ocean_proximity_ISLAND'
 'cat__ocean_proximity_NEAR BAY' 'cat__ocean_proximity_NEAR OCEAN']
```

[39]:
```
transformed_x_train = feature_transformer.transform(x_train)
print(transformed_x_train.shape)
```

```
(16512, 13)
```

11 4. Modeling

[41]:
```
from sklearn.metrics import mean_squared_error, mean_absolute_error
from sklearn.model_selection import cross_val_score
```

12 4.1. Pre-Modeling experiments: which of the two regression algorithms works better, Lasso (regularized Linear Regression) or Random Forest?

12.1 Will do 5-fold cross-validation

[42]:
```
CV = 5
```

[56]:
```
import warnings
warnings.filterwarnings('ignore')
```

12.2 Experiment set-up: get cross-validation (CV) metrics from Lasso and Random Forest

[48]:
```
from sklearn.linear_model import Lasso
from sklearn.ensemble import RandomForestRegressor
```

[73]:
```
# CV-fold cross-validation
CV = 5
```

[52]:
```
N_EXPERIMENTS = 5
```

[53]:
```
RANDOM_STATES = np.random.randint(0, 100, N_EXPERIMENTS)
RANDOM_STATES
```

[53]:
```
array([26, 59, 78, 16, 93])
```

[58]:
```
def get_cv_train_rmse_mae(
    model_class:str,
    cv:int=CV,
    n_experiments:int=N_EXPERIMENTS,
    random_states:"List[int] of length n_experiments"=RANDOM_STATES
) -> "List[int]":
    if model_class.lower() == "lasso":
        reg_model = Lasso()
    if model_class.lower() == "randomforest":
        reg_model = RandomForestRegressor()

    train_rmse = [0.0] * n_experiments
    train_mae = [0.0] * n_experiments
    test_rmse = [0.0] * n_experiments
    test_mae = [0.0] * n_experiments

    for i in range(n_experiments):
        x_train, y_train, x_test, y_test = get_train_test_x_y(df,␣
 ↪random_state=random_states[i])

        feature_transformer = get_feature_transformer(x_train)

        transformed_x_train = feature_transformer.transform(x_train)

        reg_scores = cross_val_score(reg_model, transformed_x_train, y_train,␣
 ↪scoring='neg_mean_squared_error', cv=cv)
        train_rmse[i] = np.sqrt(-reg_scores.mean())

        reg_scores=cross_val_score(reg_model, transformed_x_train, y_train,␣
 ↪scoring='neg_mean_absolute_error', cv=cv)
        train_mae[i] = -reg_scores.mean()

    return {"train_rmse": train_rmse, "train_mae": train_mae}
```

[59]:
```
lasso_cv_metrics = get_cv_train_rmse_mae("lasso")
```

[60]:
```
forest_cv_metrics = get_cv_train_rmse_mae("randomforest")
```

[64]:
```python
print("Lasso regression:")
print(lasso_cv_metrics)
print("Random Forest regression:")
print(forest_cv_metrics)
```

```
Lasso regression:
{'train_rmse': [69335.29106522657, 69244.47427886889, 69085.33095234899,
68609.77538339482, 69068.04777219422], 'train_mae': [50070.4827298464,
50030.33825303199, 49944.77441737708, 49964.73999277492, 50022.066994883615]}
Random Forest regression:
{'train_rmse': [49377.12748252578, 49380.265901945524, 49586.65237063296,
49778.0672840542, 49819.31350553705], 'train_mae': [32118.778635725128,
32337.593139164826, 32223.577921248838, 32552.66007190974, 32436.120594123728]}
```

12.3 Experiment conclusion: from the results, it seems Random Forest regression outperforms/wins over Lasso

[70]:
```python
print("Lasso regression:")
print("RMSE = root mean squared error, MAE = mean absolute error")
mu, sigma = np.mean(lasso_cv_metrics["train_rmse"]), np.
 ↪std(lasso_cv_metrics["train_rmse"])
print(f"Train RMSE: {mu:.4f} +/- {sigma:.4f}")
mu, sigma = np.mean(lasso_cv_metrics["train_mae"]), np.
 ↪std(lasso_cv_metrics["train_mae"])
print(f"Train MAE: {mu:.4f} +/- {sigma:.4f}")
```

```
Lasso regression:
RMSE = root mean squared error, MAE = mean absolute error
Train RMSE: 69068.5839 +/- 250.1424
Train MAE: 50006.4805 +/- 45.7347
```

[71]:
```python
print("Random Forest regression:")
print("RMSE = root mean squared error, MAE = mean absolute error")
mu, sigma = np.mean(forest_cv_metrics["train_rmse"]), np.
 ↪std(forest_cv_metrics["train_rmse"])
print(f"Train RMSE: {mu:.4f} +/- {sigma:.4f}")
mu, sigma = np.mean(forest_cv_metrics["train_mae"]), np.
 ↪std(forest_cv_metrics["train_mae"])
print(f"Train MAE: {mu:.4f} +/- {sigma:.4f}")
```

```
Random Forest regression:
RMSE = root mean squared error, MAE = mean absolute error
Train RMSE: 49588.2853 +/- 188.2836
Train MAE: 32333.7461 +/- 152.8180
```

13 4.2. Build Random Forest Regressor with Grid Search Cross-Validation

(since we found Random Forest at least beats Lasso)

with an added training element: use Grid Search Cross Validation to find the optimal model hyperparams

[72]:
```
from sklearn.model_selection import GridSearchCV
```

[74]:
```
forest_reg = RandomForestRegressor()

param_grid=[
    {'n_estimators': [10, 30, 100], 'max_features':[4, 6, 8, 10]},
    {'bootstrap':[False], 'n_estimators':[3, 10], 'max_features':[2, 3, 4]}
]

grid_search = GridSearchCV(
    forest_reg, param_grid, cv=CV, scoring='neg_mean_absolute_error',␣
 ↪return_train_score=True
)

grid_search.fit(transformed_x_train, y_train)
```

[74]:
```
GridSearchCV(cv=5, estimator=RandomForestRegressor(),
             param_grid=[{'max_features': [4, 6, 8, 10],
                          'n_estimators': [10, 30, 100]},
                         {'bootstrap': [False], 'max_features': [2, 3, 4],
                          'n_estimators': [3, 10]}],
             return_train_score=True, scoring='neg_mean_absolute_error')
```

13.0.1 Just curious: what turned out to be the best hyperparams for Random Forest regressor

[75]:
```
grid_search.best_params_
```

[75]:
```
{'max_features': 10, 'n_estimators': 100}
```

13.1 4.3. Get the model's test performance

[102]:
```
final_model=grid_search.best_estimator_
```

[103]:
```
transformed_x_test = feature_transformer.transform(x_test)
y_test_pred = final_model.predict(transformed_x_test)
```

[104]:
```
test_rmse = np.sqrt(mean_squared_error(y_true=y_test, y_pred=y_test_pred))
test_mae = mean_absolute_error(y_true=y_test, y_pred=y_test_pred)
```

[105]:
```python
print("RMSE = root mean squared error, MAE = mean absolute error")
print(f"Test RMSE: {test_rmse:.4f}")
print(f"Test MAE: {test_mae:.4f}")
```

```
RMSE = root mean squared error, MAE = mean absolute error
Test RMSE: 46857.9324
Test MAE: 30764.8299
```

13.1.1 Interpretation of Test Performance test_mae = 30765:

On average, the absolute error between predicted and actual house price is $30765

14 4.4. What can the Random Forest regression model tell us about feature importance?

It is interesting to see: 1. Both linear correlation and Random Forest regressor (a non-linear model) identify `median_income` as the most important feature 2. Linear correlation gives geo-location (longitude, latitude) weak importance, but Random Forest gives them higher importance.

[113]:
```python
feature_importances = grid_search.best_estimator_.feature_importances_

cat_encoder = feature_transformer.named_transformers_["cat"]
cat_one_hot_features = list(cat_encoder.categories_[0])
features = numeric_columns + cat_one_hot_features

df_feature_importance = pd.DataFrame(sorted(zip(feature_importances, features), reverse=True))
df_feature_importance.columns = ['Feature', 'Importance']
df_feature_importance
```

[113]:

	Feature	Importance
0	0.462840	median_income
1	0.155850	INLAND
2	0.109420	longitude
3	0.103742	latitude
4	0.048905	housing_median_age
5	0.033307	population
6	0.026229	total_rooms
7	0.023891	total_bedrooms
8	0.021437	households
9	0.006482	NEAR OCEAN
10	0.005980	<1H OCEAN
11	0.001503	NEAR BAY
12	0.000415	ISLAND

15 5. Conclusions

15.1 Conclusion 0:

For this dataset, Random Forest regression seems outperforms Linear Regression

15.2 Conclusion 1:

The test performance is consistent with, or within the boundary of, previously estimated RMSE/MAE via cross-validation. Recall: we estimated that RMSE: 49588.2853 +/- 188.2836, MAE: 32333.7461 +/- 152.8180

Also, if you compare with the fluctuaion of the actual housing prices, the test performance is well within the actual fluctuation. See below, the `std` value

[112]:
```
df.describe()[y_column]
```

[112]:
```
count     20640.000000
mean     206855.816909
std      115395.615874
min       14999.000000
25%      119600.000000
50%      179700.000000
75%      264725.000000
max      500001.000000
Name: median_house_value, dtype: float64
```

15.3 Conclusion 2:

In this machine learning experiment, we have done the following: * Basic data exploration: identify what numeric columns, categorical columns, target column are; if there is severe missing data problem (fortunately, no). * Defined raw data transformation (i.e. feature engineering): scaling numerical features, one-hot encoding categorical features * Conducted experiments to compare which regression algorithms seem to work better: Lasso (regularized linear regression) vs. Random Forest, and settled with Random Forest based on experiment results. * Trained a Random Forest regressor, using cross-validation to choose the optimal hyperparameters. * Found that the test performance (rmse, mae) is within the estimated range.

16 6. Next steps:

- Write model building script to create two main artifacts: (1) feature transformer, (2) ML model - Random Forest regressor
- Write inference script
- Wrap the inference with FastAPI
- Containerize the FastAPI inference app with Docker

[ ]:
```

```