house_price_predictor

September 25, 2024

[1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression, Ridge
from sklearn.metrics import mean_squared_error, mean_absolute_error
from sklearn.ensemble import RandomForestRegressor
import itertools
import shap
```

[2]:
```
def load_and_describe_data(data_file):
    df = pd.read_csv(data_file)
    df.rename(columns={'MEDV': 'median_price'}, inplace=True)
    print(f'Num rows : {df.shape[0]}')
    print(f'Num features : {df.shape[1] - 1}')

    print(f'Meaning of features')
    feature_names = '''
CRIM      per capita crime rate by town
ZN        proportion of residential land zoned for lots over ,000 sq.ft.
INDUS     proportion of non-retail business acres per town
CHAS      Charles River dummy variable (= 1 if tract bounds river; 0 otherwise)
NOX       nitric oxides concentration (parts per 10 million)
RM        average number of rooms per dwelling
AGE       proportion of owner-occupied units built prior to 1940
DIS       weighted distances to five Boston employment centres
RAD       index of accessibility to radial highways
TAX      full-value property-tax rate per $10,000
PTRATIO  pupil-teacher ratio by town
B        1000(Bk - 0.63)^2 where Bk is the proportion of blacks by town
LSTAT    % lower status of the population
'''
    print(feature_names)
    print(df.describe())

    print(f'\nCorrelation of features to median price')
    correlation = df.corr()['median_price'].sort_values(ascending=False)
    print(correlation)
```

```
    return df
```

[3]:
```
df = load_and_describe_data('housing.csv')
```

```
Num rows : 506
Num features : 13
Meaning of features

CRIM      per capita crime rate by town
ZN        proportion of residential land zoned for lots over ,000 sq.ft.
INDUS     proportion of non-retail business acres per town
CHAS      Charles River dummy variable (= 1 if tract bounds river; 0 otherwise)
NOX       nitric oxides concentration (parts per 10 million)
RM        average number of rooms per dwelling
AGE       proportion of owner-occupied units built prior to 1940
DIS       weighted distances to five Boston employment centres
RAD       index of accessibility to radial highways
TAX      full-value property-tax rate per $10,000
PTRATIO  pupil-teacher ratio by town
B        1000(Bk - 0.63)^2 where Bk is the proportion of blacks by town
LSTAT    % lower status of the population

              CRIM          ZN       INDUS        CHAS         NOX          RM  \
count  506.000000  506.000000  506.000000  506.000000  506.000000  506.000000
mean     3.613524   11.363636   11.136779    0.069170    0.554695    6.284634
std      8.601545   23.322453    6.860353    0.253994    0.115878    0.702617
min      0.006320    0.000000    0.460000    0.000000    0.385000    3.561000
25%      0.082045    0.000000    5.190000    0.000000    0.449000    5.885500
50%      0.256510    0.000000    9.690000    0.000000    0.538000    6.208500
75%      3.677083   12.500000   18.100000    0.000000    0.624000    6.623500
max     88.976200  100.000000   27.740000    1.000000    0.871000    8.780000

               AGE         DIS         RAD         TAX     PTRATIO           B  \
count  506.000000  506.000000  506.000000  506.000000  506.000000  506.000000
mean    68.574901    3.795043    9.549407  408.237154   18.455534  356.674032
std     28.148861    2.105710    8.707259  168.537116    2.164946   91.294864
min      2.900000    1.129600    1.000000  187.000000   12.600000    0.320000
25%     45.025000    2.100175    4.000000  279.000000   17.400000  375.377500
50%     77.500000    3.207450    5.000000  330.000000   19.050000  391.440000
75%     94.075000    5.188425   24.000000  666.000000   20.200000  396.225000
max    100.000000   12.126500   24.000000  711.000000   22.000000  396.900000

            LSTAT  median_price
count  506.000000    506.000000
mean    12.653063     22.532806
std      7.141062      9.197104
min      1.730000      5.000000
25%      6.950000     17.025000
```

```
50%     11.360000     21.200000
75%     16.955000     25.000000
max     37.970000     50.000000

Correlation of features to median price
median_price    1.000000
RM              0.695360
ZN              0.360445
B               0.333461
DIS             0.249929
CHAS            0.175260
AGE            -0.376955
RAD            -0.381626
CRIM           -0.388305
NOX            -0.427321
TAX            -0.468536
INDUS          -0.483725
PTRATIO        -0.507787
LSTAT          -0.737663
Name: median_price, dtype: float64
```

[4]:
```python
def get_training_test_data(df):
    result = {}
    X = df.drop('median_price', axis=1)
    y = df['median_price']

    X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2)
    result['X_train'] = X_train
    result['y_train'] = y_train
    result['X_test'] = X_test
    result['y_test'] = y_test



    return result
```

[5]:
```python
def plot_predictions(y_pred, y_test, model_name):
    '''
    Plots the difference between the predictions y_pred vs the actual values␣
 ↪y_test
    '''
    plt.figure(figsize=(10, 6))
    plt.scatter(y_test, y_pred, color='blue', label='Predicted Price vs Actual␣
 ↪Price')
    plt.plot([y_test.min(), y_test.max()], [y_test.min(), y_test.max()], 'r--',␣
 ↪label='Perfect Prediction')
    plt.xlabel('Actual Values')
    plt.ylabel('Predicted Values')
```

```
    plt.title('Predicted vs Actual Values')
    plt.legend()
    plt.grid()
    plt.savefig(f'{model_name}_predictions.png' )
    plt.show()
```

[6]:
```
def fit_linear_regression_model(X_train, y_train, X_test, y_test):

    model = LinearRegression()
    model.fit(X_train, y_train)
    coefficients = model.coef_
    intercept = model.intercept_

    y_pred = model.predict(X_test)

    mse = mean_squared_error(y_test, y_pred)
    mae = mean_absolute_error(y_test, y_pred)

    print(f'Plain linear regression model')
    print(f'Mean squared error : {mse:.3f}')
    rmse = np.sqrt(mse)
    print(f'Root mean squared error : {rmse:.3f}')
    print(f'Mean absolute error : {mae:.3f}')
    plot_predictions(y_pred, y_test, 'simple_linear_regression')

    coef_df = pd.DataFrame({
    'Feature': X_train.columns,
    'Coefficient': coefficients
    })
    print(f'{coef_df}')
    print(f'Model intercept : {intercept}')
```

[7]:
```
def holdout_grid_search(clf, Xtrain, ytrain, Xtest, ytest, hyperparams,␣
 ↪fixed_hyperparams={}):
    """
    Performs grid search on the validation dataset to find the best␣
 ↪hyperparameters.
    """
    best_estimator = None
    best_hyperparams = {}

    best_score = 0.0

    # get list of param values
    lists = hyperparams.values()
    # get all param combinations names to values in best_estimator
```

```
    param_combinations = list(itertools.product(*lists))
    total_param_combinations = len(param_combinations)

    # iterate through param combinations
    for i, params in enumerate(param_combinations, 1):
        # fill param dict with params
        param_dict = {}
        for param_index, param_name in enumerate(hyperparams):
            param_dict[param_name] = params[param_index]

        # create estimator with specified params
        estimator = clf(**param_dict, **fixed_hyperparams)

        # fit estimator
        estimator.fit(Xtrain, ytrain)
        # get predictions on the test
        y_preds = estimator.predict(Xtest)
        mse = mean_squared_error(ytest, y_preds)

#         print(f'[{i}/{total_param_combinations}] {param_dict}')
#         print(f'Val MSE: {mse}\n')

        if mse >= best_score:
            best_score = mse
            best_estimator = estimator
            best_hyperparams = param_dict

    best_hyperparams.update(fixed_hyperparams)

    return best_estimator, best_hyperparams
```

[8]:
```
def explain_model(classifier, X_importance):
    """
    Generates SHAP plots for the given classifier.
    """
    explainer = shap.TreeExplainer(classifier)
    shap_values = explainer.shap_values(X_importance)
    shap.summary_plot(shap_values, X_importance)
```

[9]:
```
def fit_random_forest_regression_model(X_train, y_train, X_test, y_test):
    X_dev, X_val, y_dev, y_val = train_test_split(X_train, y_train, test_size=0.
 ↪2, random_state=42)
    hyperparams = {
        'n_estimators': [25, 50, 75, 100, 125, 150],
        'max_depth': [3,4,5,6,7,8,9,10],
        'min_samples_leaf': [5,6,7,8,9,10]
    }
```

```
    fixed_hyperparams = {
        'random_state': 21
    }

    clf = RandomForestRegressor
#     clf.fit(X_dev, y_dev)
#     print(f'Criteria : {clf.criterion}')
#     best_clf = clf
    best_clf, best_hyperparams = holdout_grid_search(clf, X_dev, y_dev, X_val,␣
 ↪y_val, hyperparams, fixed_hyperparams)
    print(f"Best hyperparameters:\n{best_hyperparams}")

    y_pred = best_clf.predict(X_test)

    mse = mean_squared_error(y_test, y_pred)
    mae = mean_absolute_error(y_test, y_pred)

    print(f'Random Forest Regressor model')
    print(f'Mean squared error : {mse:.3f}')
    rmse = np.sqrt(mse)
    print(f'Root mean squared error : {rmse:.3f}')
    print(f'Mean absolute error : {mae:.3f}')
    plot_predictions(y_pred, y_test, 'random_forest_regression')
    explain_model(best_clf, X_test)
```

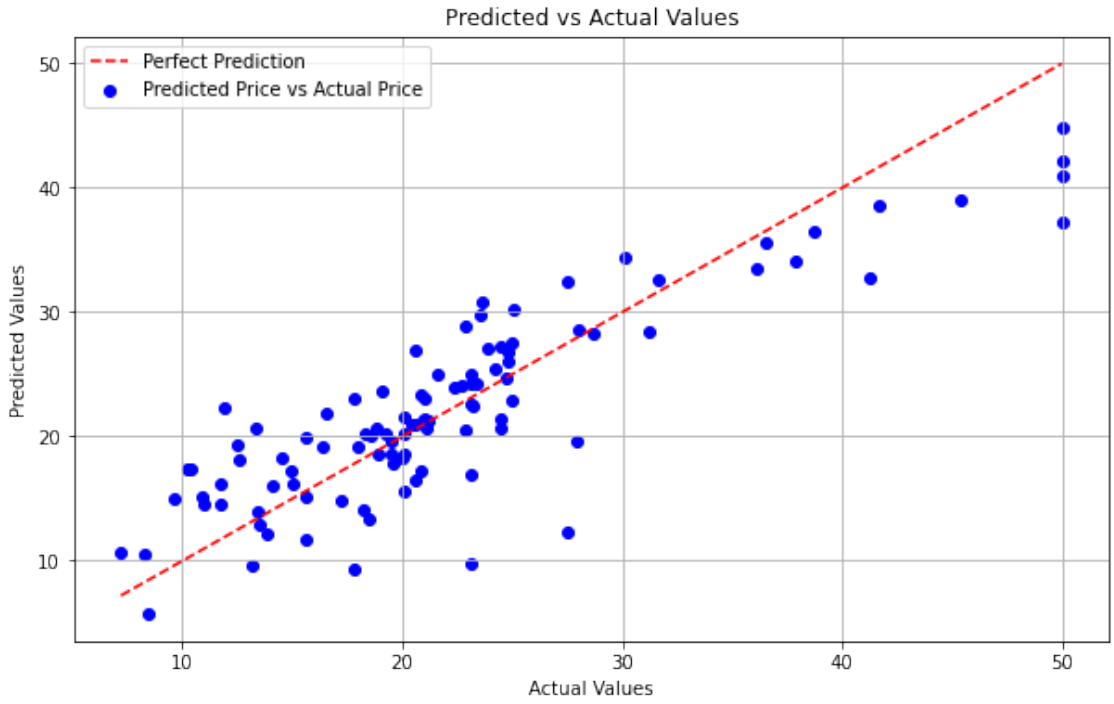
[10]:
```
def analyze_data(df):
    result = get_training_test_data(df)
    X_train = result['X_train']
    y_train = result['y_train']
    X_test = result['X_test']
    y_test = result['y_test']

    print(f'Shape of training set : {X_train.shape}')
    print(X_train.describe())
    print()
    print(f'Shape of test set : {X_test.shape}')
    print(X_test.describe())

    fit_linear_regression_model(X_train, y_train, X_test, y_test)
    fit_random_forest_regression_model(X_train, y_train, X_test, y_test)
```

[11]:
```
analyze_data(df)
```

```
Shape of training set : (404, 13)
             CRIM          ZN       INDUS        CHAS         NOX          RM  \
count  404.000000  404.000000  404.000000  404.000000  404.000000  404.000000
mean     3.378976   10.992574   11.000545    0.074257    0.550923    6.273290
std      7.791667   22.597046    6.824072    0.262514    0.113065    0.697196
```

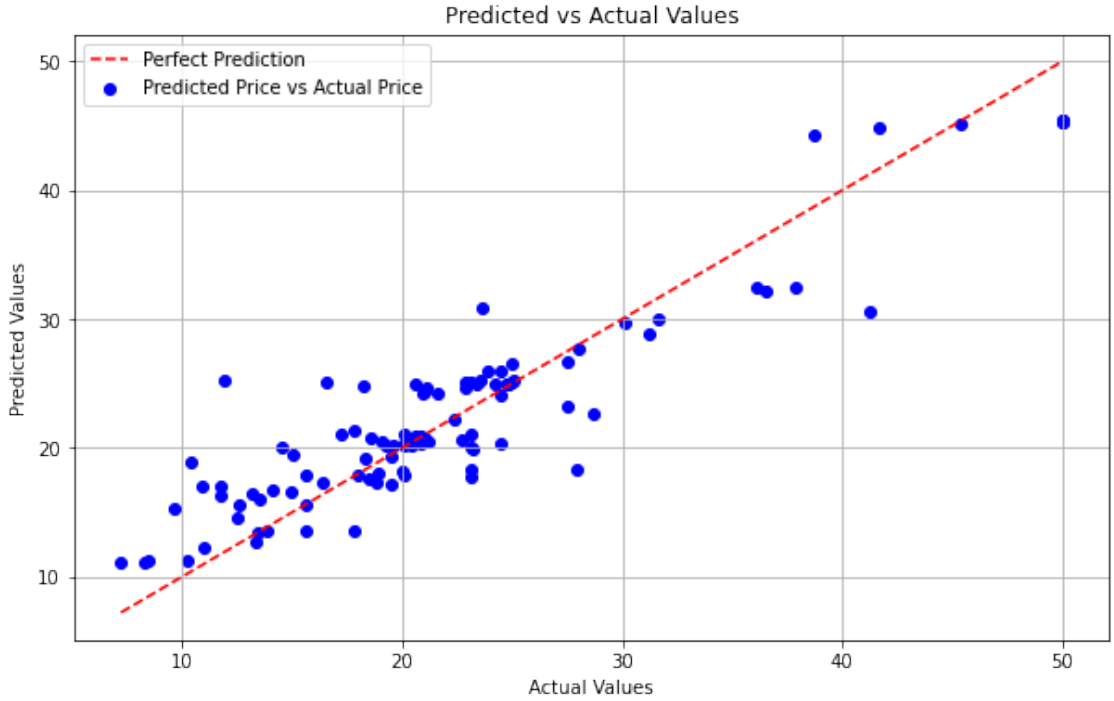
```
min      0.006320    0.000000    0.740000    0.000000    0.389000    4.138000
25%      0.082973    0.000000    5.190000    0.000000    0.449000    5.874750
50%      0.253715    0.000000    8.560000    0.000000    0.532000    6.179000
75%      3.202962   12.500000   18.100000    0.000000    0.624000    6.619750
max     73.534100   95.000000   27.740000    1.000000    0.871000    8.780000

              AGE         DIS         RAD         TAX     PTRATIO           B  \
count  404.000000  404.000000  404.000000  404.000000  404.000000  404.000000
mean    68.081931    3.795402    9.445545  404.695545   18.436634  363.378812
std     28.213249    2.040935    8.638279  168.574078    2.144528   80.218789
min      2.900000    1.129600    1.000000  187.000000   12.600000    0.320000
25%     44.675000    2.100525    4.000000  277.000000   17.375000  376.667500
50%     75.700000    3.317500    5.000000  329.000000   18.850000  391.705000
75%     94.100000    5.118000   24.000000  666.000000   20.200000  396.250000
max    100.000000   12.126500   24.000000  711.000000   21.200000  396.900000

            LSTAT
count  404.000000
mean    12.720421
std      7.296091
min      1.730000
25%      6.840000
50%     11.300000
75%     17.210000
max     37.970000

Shape of test set : (102, 13)
             CRIM          ZN       INDUS        CHAS         NOX          RM  \
count  102.000000  102.000000  102.000000  102.000000  102.000000  102.000000
mean     4.542514   12.833333   11.676373    0.049020    0.569636    6.329569
std     11.251758   26.067252    7.010220    0.216975    0.125888    0.725454
min      0.013810    0.000000    0.460000    0.000000    0.385000    3.561000
25%      0.062240    0.000000    5.145000    0.000000    0.455750    5.935250
50%      0.302500    0.000000   10.410000    0.000000    0.548500    6.250000
75%      4.703245   18.125000   18.100000    0.000000    0.671000    6.626500
max     88.976200  100.000000   27.740000    1.000000    0.871000    8.375000

              AGE         DIS         RAD         TAX     PTRATIO           B  \
count  102.000000  102.000000  102.000000  102.000000  102.000000  102.000000
mean    70.527451    3.793619    9.960784  422.264706   18.530392  330.117843
std     27.944606    2.355769    9.007062  168.485562    2.253305  122.903329
min      6.200000    1.285200    1.000000  188.000000   13.000000    2.600000
25%     46.625000    2.073525    4.000000  281.750000   17.400000  358.600000
50%     81.400000    2.756800    5.000000  384.000000   19.200000  389.545000
75%     93.875000    5.287300   24.000000  666.000000   20.200000  395.617500
max    100.000000   10.585700   24.000000  711.000000   22.000000  396.900000

            LSTAT
```

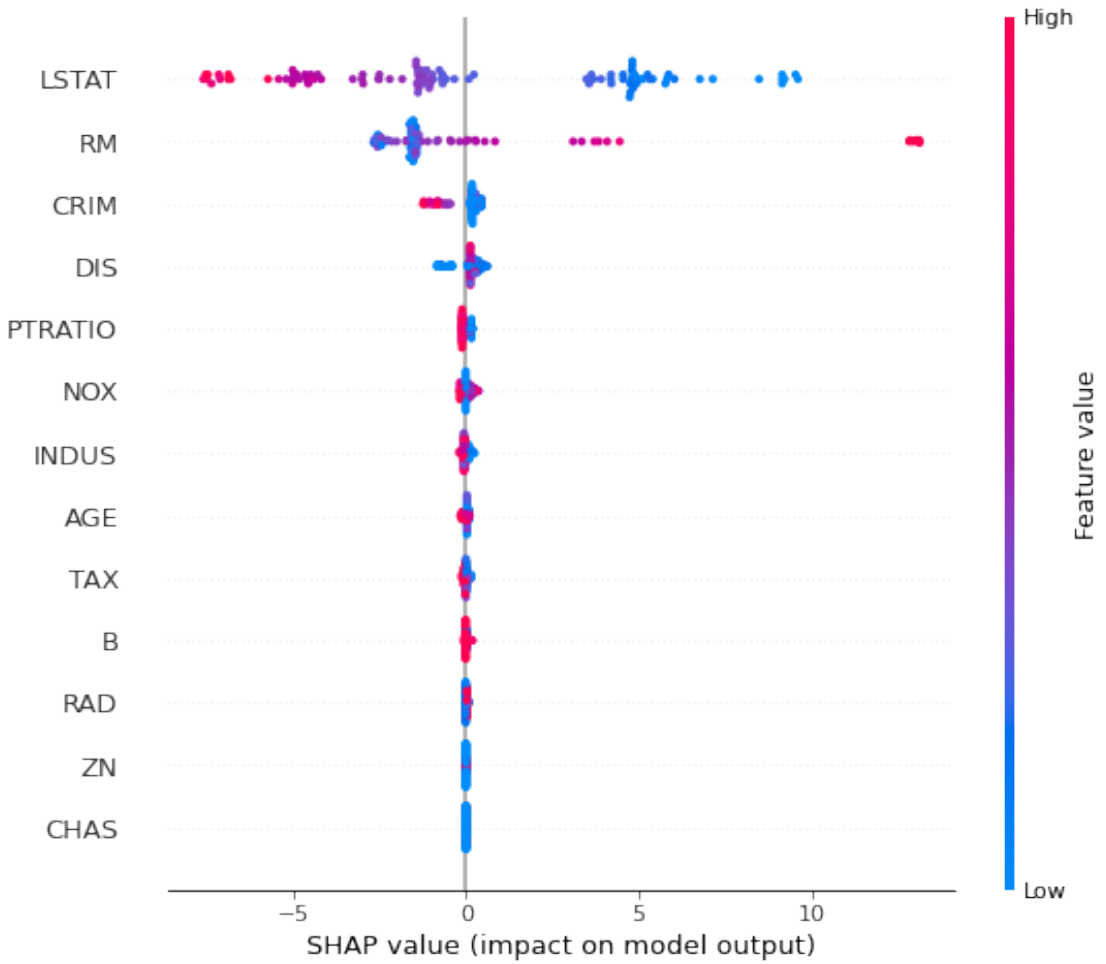
```
count  102.000000
mean    12.386275
std      6.517594
min      2.470000
25%      7.465000
50%     11.835000
75%     16.372500
max     34.020000
Plain linear regression model
Mean squared error : 21.066
Root mean squared error : 4.590
Mean absolute error : 3.488
```



	Feature	Coefficient
0	CRIM	-0.075957
1	ZN	0.042377
2	INDUS	0.016432
3	CHAS	2.838339
4	NOX	-18.276177
5	RM	4.332665
6	AGE	-0.002793
7	DIS	-1.474854
8	RAD	0.294135
9	TAX	-0.012942
10	PTRATIO	-0.861111

```
11         B     0.008856
12     LSTAT    -0.482091
Model intercept : 31.970665539362567
Best hyperparameters:
{'n_estimators': 75, 'max_depth': 3, 'min_samples_leaf': 7, 'random_state': 21}
Random Forest Regressor model
Mean squared error : 13.678
Root mean squared error : 3.698
Mean absolute error : 2.704
```





The SHAP plot for the Random Forest classifier shows that house prices increase as the number of rooms increase. Moreover, house price decrease as LSTAT (% of the lower status of the population) and CRIM (per capita crime rate) increase. Moreover, the house price is inversely proportional to DIS (the distance from emoloyment).

Intuitively, these make sense.