housing-price-prediction

May 11, 2023

IMPORT LIBRARY

[1]:
```
from pathlib import Path
import re

import pandas as pd
from scipy import stats
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings("ignore")
```

LOADING THE DATASET

[2]:
```
df = pd.read_csv("housing_price.csv")
```

EXPLORATORY DATA ANALYSIS (EDA)

[3]:
```
df.head()
```

[3]:
```
      CRIM    ZN  INDUS  CHAS    NOX     RM   AGE     DIS  RAD  TAX  PTRATIO  \
0  0.00632  18.0   2.31     0  0.538  6.575  65.2  4.0900  1.0  296     15.3
1  0.02731   0.0   7.07     0  0.469  6.421  78.9  4.9671  2.0  242     17.8
2  0.02729   0.0   7.07     0  0.469  7.185  61.1  4.9671  2.0  242     17.8
3  0.03237   0.0   2.18     0  0.458  6.998  45.8  6.0622  3.0  222     18.7
4  0.06905   0.0   2.18     0  0.458  7.147  54.2  6.0622  3.0  222     18.7

        B  LSTAT  MEDV
0  396.90   4.98  24.0
1  396.90   9.14  21.6
2  392.83   4.03  34.7
3  394.63   2.94  33.4
4  396.90   5.33  36.2
```

[4]:
```
df.tail()
```

[4]:
```
        CRIM   ZN  INDUS  CHAS    NOX     RM   AGE     DIS  RAD  TAX  PTRATIO  \
504  0.06263  0.0  11.93     0  0.573  6.593  69.1  2.4786  1.0  273     21.0
```

```
505  0.04527  0.0  11.93     0  0.573  6.120  76.7  2.2875  1.0  273     21.0
506  0.06076  0.0  11.93     0  0.573  6.976  91.0  2.1675  1.0  273     21.0
507  0.10959  0.0  11.93     0  0.573  6.794  89.3  2.3889  1.0  273     21.0
508  0.04741  0.0  11.93     0  0.573  6.030  80.8  2.5050  1.0  273     21.0

          B  LSTAT  MEDV
504  391.99   9.67  22.4
505  396.90   9.08  20.6
506  396.90   5.64  23.9
507  393.45   6.48  22.0
508  396.90   7.88  11.9
```

[5]:
```
##CHECKING THE SHAPE OF THE DATASET
df.shape
```

[5]:
```
(509, 14)
```

[6]:
```
##CHECKING THE COLUMNS NAMES
col = df.columns
col
```

[6]:
```
Index(['CRIM', 'ZN', 'INDUS', 'CHAS', 'NOX', 'RM', 'AGE', 'DIS', 'RAD', 'TAX',
       'PTRATIO', 'B', 'LSTAT', 'MEDV'],
      dtype='object')
```

[7]:
```
df.describe(include='all')
```

[7]:
```
             CRIM          ZN       INDUS        CHAS         NOX          RM  \
count  509.000000  509.000000  506.000000  509.000000  507.000000  509.000000
mean     3.707516   11.296660   11.198281    0.068762    0.555216    6.279845
std      8.732089   23.269781    6.856713    0.253298    0.115633    0.703449
min      0.006320    0.000000    0.460000    0.000000    0.385000    3.561000
25%      0.082210    0.000000    5.190000    0.000000    0.449000    5.880000
50%      0.261690    0.000000    9.690000    0.000000    0.538000    6.202000
75%      3.693110   12.500000   18.100000    0.000000    0.624000    6.619000
max     88.976200  100.000000   27.740000    1.000000    0.871000    8.780000

              AGE         DIS         RAD         TAX     PTRATIO           B  \
count  508.000000  509.000000  508.000000  509.000000  509.000000  509.000000
mean    68.579134    3.787705    9.610236  409.216110   18.463851  356.664892
std     28.114744    2.101852    8.735069  168.814161    2.161553   91.562469
min      2.900000    1.129600    1.000000  187.000000   12.600000    0.320000
25%     45.075000    2.100700    4.000000  279.000000   17.400000  375.330000
50%     77.150000    3.182700    5.000000  330.000000   19.100000  391.450000
75%     94.100000    5.118000   24.000000  666.000000   20.200000  396.240000
max    100.000000   12.126500   24.000000  711.000000   22.000000  396.900000
```

```
       LSTAT        MEDV
count  508.000000  509.000000
mean    12.705276   22.501572
std      7.131979    9.183497
min      1.730000    5.000000
25%      7.092500   17.000000
50%     11.430000   21.200000
75%     16.992500   25.000000
max     37.970000   50.000000
```

[8]:
```
df.dtypes
```

[8]:
```
CRIM       float64
ZN         float64
INDUS      float64
CHAS         int64
NOX        float64
RM         float64
AGE        float64
DIS        float64
RAD        float64
TAX          int64
PTRATIO    float64
B          float64
LSTAT      float64
MEDV       float64
dtype: object
```

[9]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 509 entries, 0 to 508
Data columns (total 14 columns):
 #   Column   Non-Null Count  Dtype
---  ------   --------------  -----
 0   CRIM     509 non-null    float64
 1   ZN       509 non-null    float64
 2   INDUS    506 non-null    float64
 3   CHAS     509 non-null    int64
 4   NOX      507 non-null    float64
 5   RM       509 non-null    float64
 6   AGE      508 non-null    float64
 7   DIS      509 non-null    float64
 8   RAD      508 non-null    float64
 9   TAX      509 non-null    int64
 10  PTRATIO  509 non-null    float64
 11  B        509 non-null    float64
```

```
 12  LSTAT    508 non-null    float64
 13  MEDV     509 non-null    float64
dtypes: float64(12), int64(2)
memory usage: 55.8 KB
```

[10]:
```python
df.nunique()
```

[10]:
```
CRIM       503
ZN          26
INDUS       76
CHAS         2
NOX         81
RM         446
AGE        354
DIS        411
RAD          9
TAX         66
PTRATIO     46
B          356
LSTAT      453
MEDV       228
dtype: int64
```

[11]:
```python
##CHECKING DUPLICATE
df.duplicated().sum()
```

[11]: 4

[12]:
```python
##DELETE DUPLICATE
df = df.drop_duplicates()
```

[13]:
```python
df.duplicated().sum()
```

[13]: 0

[14]:
```python
##CHECKING MISSING VALUES
df.isna().sum()
```

[14]:
```
CRIM       0
ZN         0
INDUS      3
CHAS       0
NOX        2
RM         0
AGE        1
DIS        0
RAD        1
```

```
TAX         0
PTRATIO     0
B           0
LSTAT       1
MEDV        0
dtype: int64
```

MISSING VALUE

[15]:
```
df.dropna().shape
```

[15]:
```
(497, 14)
```

[16]:
```
##SET THE VALUES
df["INDUS"] = df["INDUS"].fillna(df["INDUS"].median())
```

[17]:
```
##SET THE VALUES
df["NOX"] = df["NOX"].fillna(df["NOX"].median())
```

[18]:
```
##SET THE VALUES
df["AGE"] = df["AGE"].fillna(df["AGE"].median())
```

[19]:
```
##SET THE VALUES
df["RAD"] = df["RAD"].fillna(df["RAD"].median())
```

[20]:
```
##SET THE VALUES
df["LSTAT"] = df["LSTAT"].fillna(df["LSTAT"].median())
```

[21]:
```
df.isna().sum()
```

[21]:
```
CRIM        0
ZN          0
INDUS       0
CHAS        0
NOX         0
RM          0
AGE         0
DIS         0
RAD         0
TAX         0
PTRATIO     0
B           0
LSTAT       0
MEDV        0
dtype: int64
```

[22]:
```
##CHECKING THE DTYPES DETAIL WISE
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 505 entries, 0 to 508
Data columns (total 14 columns):
 #   Column   Non-Null Count  Dtype
---  ------   --------------  -----
 0   CRIM     505 non-null    float64
 1   ZN       505 non-null    float64
 2   INDUS    505 non-null    float64
 3   CHAS     505 non-null    int64
 4   NOX      505 non-null    float64
 5   RM       505 non-null    float64
 6   AGE      505 non-null    float64
 7   DIS      505 non-null    float64
 8   RAD      505 non-null    float64
 9   TAX      505 non-null    int64
 10  PTRATIO  505 non-null    float64
 11  B        505 non-null    float64
 12  LSTAT    505 non-null    float64
 13  MEDV     505 non-null    float64
dtypes: float64(12), int64(2)
memory usage: 59.2 KB
```

[23]:
```
# CONVERT TYPE
df["AGE"] = df["AGE"].astype(int)
df["ZN"] = df["ZN"].astype(int)
df["RAD"] = df["RAD"].astype(int)
df["TAX"] = df["TAX"].astype(int)
```

[24]:
```
## AFTER CHANGE TYPE
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 505 entries, 0 to 508
Data columns (total 14 columns):
 #   Column   Non-Null Count  Dtype
---  ------   --------------  -----
 0   CRIM     505 non-null    float64
 1   ZN       505 non-null    int32
 2   INDUS    505 non-null    float64
 3   CHAS     505 non-null    int64
 4   NOX      505 non-null    float64
 5   RM       505 non-null    float64
 6   AGE      505 non-null    int32
 7   DIS      505 non-null    float64
 8   RAD      505 non-null    int32
```

```
 9   TAX      505 non-null    int32
 10  PTRATIO  505 non-null    float64
 11  B        505 non-null    float64
 12  LSTAT    505 non-null    float64
 13  MEDV     505 non-null    float64
dtypes: float64(9), int32(4), int64(1)
memory usage: 51.3 KB
```

[25]:
```
##STATISTICAL SUMMARY OF THE DATASET
df.describe().T
```

[25]:

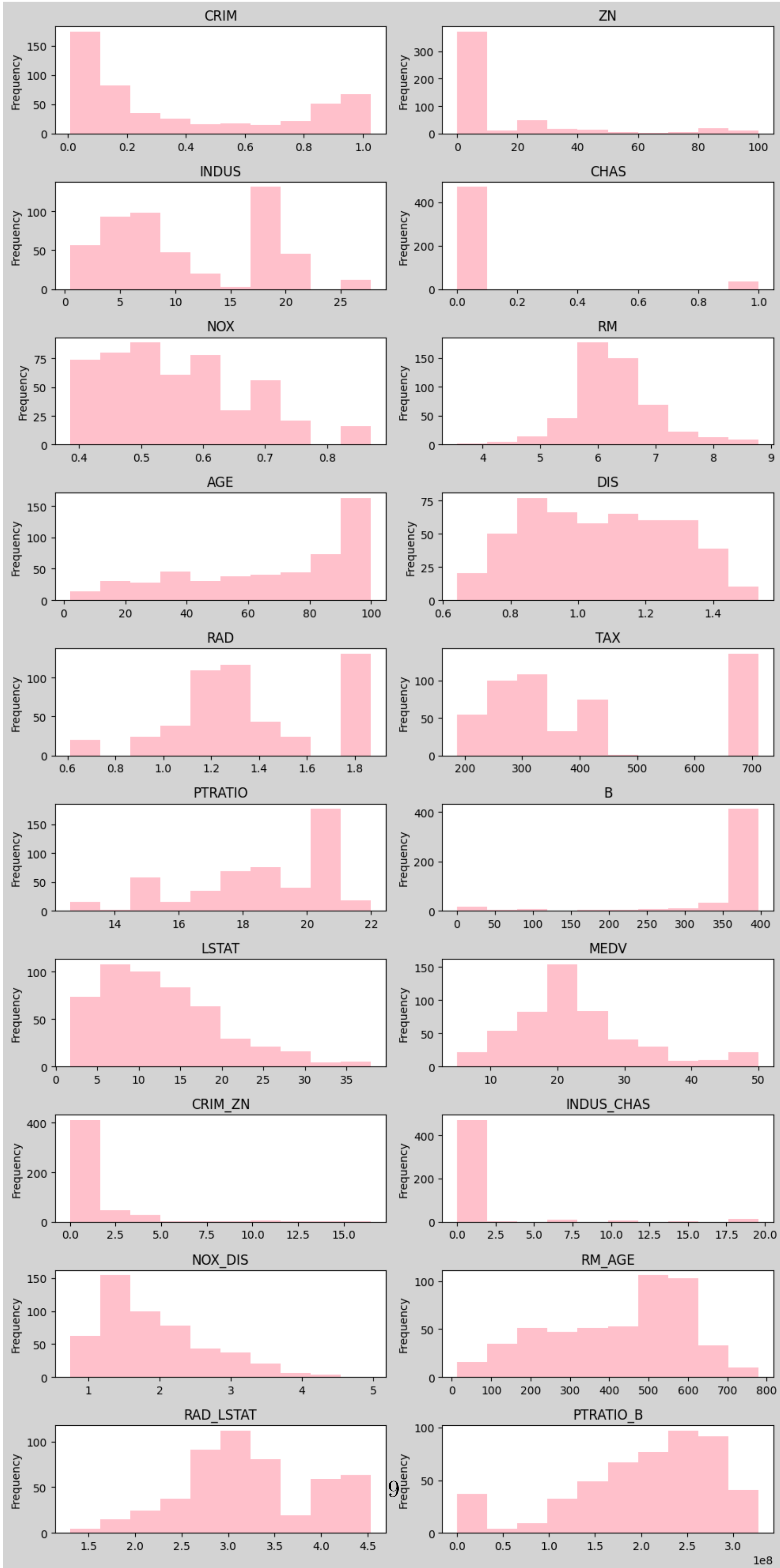
	count	mean	std	min	25%	50%
CRIM	505.0	3.606091	8.608447	0.00632	0.08199	0.25387
ZN	505.0	11.370297	23.328220	0.00000	0.00000	0.00000
INDUS	505.0	11.151307	6.843323	0.46000	5.19000	9.69000
CHAS	505.0	0.069307	0.254227	0.00000	0.00000	0.00000
NOX	505.0	0.554679	0.115693	0.38500	0.44900	0.53800
RM	505.0	6.284816	0.703302	3.56100	5.88500	6.20900
AGE	505.0	68.114851	28.216754	2.00000	45.00000	77.00000
DIS	505.0	3.798725	2.106167	1.12960	2.10070	3.21570
RAD	505.0	9.522772	8.690899	1.00000	4.00000	5.00000
TAX	505.0	407.726733	168.312294	187.00000	279.00000	330.00000
PTRATIO	505.0	18.452079	2.165696	12.60000	17.40000	19.00000
B	505.0	357.188772	90.647420	0.32000	375.52000	391.45000
LSTAT	505.0	12.654079	7.121604	1.73000	7.01000	11.36000
MEDV	505.0	22.555644	9.191851	5.00000	17.10000	21.20000

	75%	max
CRIM	3.67367	88.9762
ZN	12.00000	100.0000
INDUS	18.10000	27.7400
CHAS	0.00000	1.0000
NOX	0.62400	0.8710
RM	6.62500	8.7800
AGE	94.00000	100.0000
DIS	5.21190	12.1265
RAD	24.00000	24.0000
TAX	666.00000	711.0000
PTRATIO	20.20000	22.0000
B	396.23000	396.9000
LSTAT	16.94000	37.9700
MEDV	25.00000	50.0000

[27]:
```
def plot_hist(df):
    cols = (
        df
        .select_dtypes(include=[int, float])
```

```
        .columns
    )
    ncols = 2
    nrows = np.ceil(len(cols) / ncols).astype(int)
    vertical_figsize = 2 * nrows
    fig, axs = plt.subplots(nrows, ncols, figsize=[10, vertical_figsize])
    fig.patch.set_facecolor('lightgray')
    axs = axs.flatten()
    for col, ax in zip(cols, axs):
        df[col].plot.hist(title=col, ax=ax, color='pink')
    plt.tight_layout()
    plt.show()
```

[111]:
```
plot_hist(df)
```


CRIM
ZN
INDUS
CHAS
NOX
RM
AGE
DIS
RAD
TAX
PTRATIO
B
LSTAT
MEDV
CRIM_ZN
INDUS_CHAS
NOX_DIS
RM_AGE
RAD_LSTAT
PTRATIO_B
Frequency
1e8

PROCESSING

[28]:
```python
target = 'TAX'
target = 'MEDV'
```

[29]:
```python
df['CRIM_ZN'] = df['CRIM'] * df['ZN']
df['INDUS_CHAS'] = df['INDUS'] * df['CHAS']
df['NOX_DIS'] = df['NOX'] * df['DIS']
df['RM_AGE'] = df['RM'] * df['AGE']
df['RAD_LSTAT'] = df['RAD'] * df['LSTAT']
df['PTRATIO_B'] = df['PTRATIO'] * df['B']
```

[30]:
```python
skew_res = df.select_dtypes([int, float]).skew().abs().
 ↪sort_values(ascending=False)
skew_cols = skew_res.loc[lambda x: (x>=1) & (x.index!=target)].index

print(skew_res)
print('-'*50)
print('Cols that are skewed:')
print(', '.join(skew_cols))
```

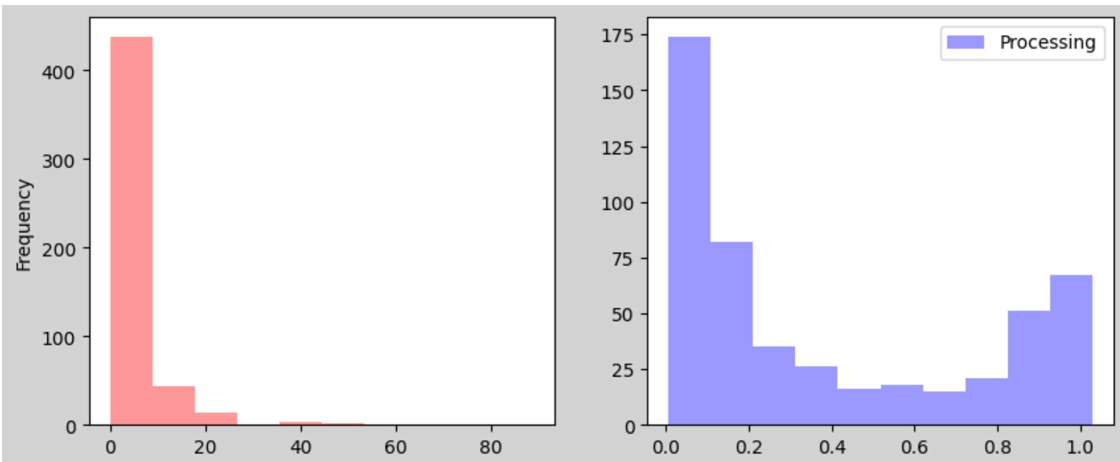
```
CRIM          5.223410
INDUS_CHAS    4.289043
CRIM_ZN       3.866274
CHAS          3.401726
B             2.928761
ZN            2.224261
PTRATIO_B     2.078090
RAD_LSTAT     1.660685
MEDV          1.108662
RAD           1.012819
DIS           1.009242
NOX_DIS       0.939629
LSTAT         0.918150
PTRATIO       0.799325
NOX           0.735879
TAX           0.675963
AGE           0.593229
RM_AGE        0.445334
RM            0.402463
INDUS         0.294479
dtype: float64
--------------------------------------------------
Cols that are skewed:
CRIM, INDUS_CHAS, CRIM_ZN, CHAS, B, ZN, PTRATIO_B, RAD_LSTAT, RAD, DIS
```

[31]:
```
def best_transformation(data) -> tuple:
    functions = [np.log1p, np.sqrt, stats.yeojohnson]
    results = []

    for func in functions:
        transformed_data = func(data)
        if type(transformed_data) == tuple:
            vals, _ = transformed_data
            results.append(vals)
        else:
            results.append(transformed_data)

    abs_skew_results = [np.abs(stats.skew(val)) for val in results]
    lowest_skew_index = abs_skew_results.index(min(abs_skew_results))
    return functions[lowest_skew_index], results[lowest_skew_index]
```

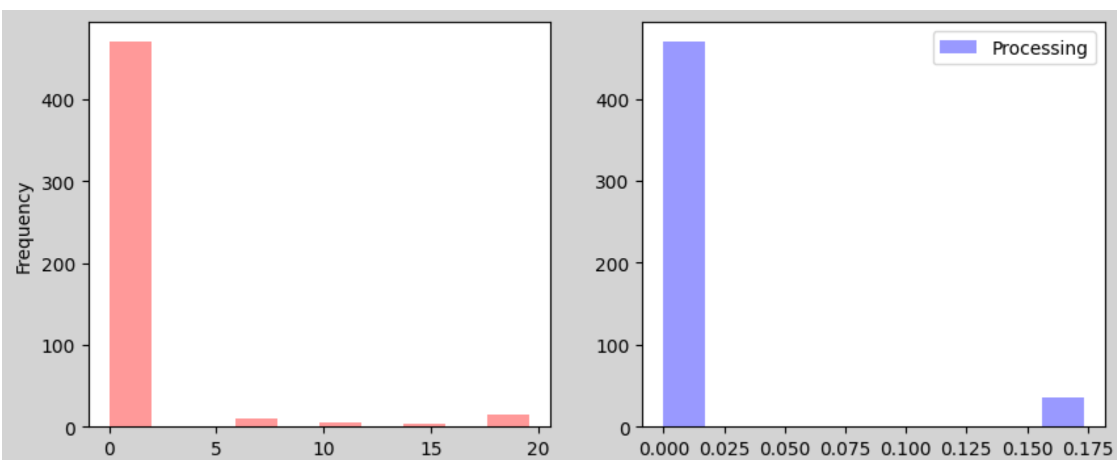
[32]:
```
def unskew(col):
    global best_transformation
    print('-' * 100)
    col_skew = stats.skew(col)
    col_name = col.name
    print('{} skew is: {}'.format(col_name, col_skew))
    fig, (ax1, ax2) = plt.subplots(1, 2, figsize=[10, 4])
    fig.patch.set_facecolor('lightgray')
    col.plot.hist(color='red', alpha=0.4, label='pre-skew', ax=ax1)

    if np.abs(col_skew) >= 1.:
        result_skew, data = best_transformation(col)
        new_col_skew = stats.skew(data)
        print(f'Best function {result_skew} and the skew results:␣
↪{new_col_skew}')
        ax2.hist(data, label='Processing', color='blue', alpha=0.4)
        ax2.legend()
        plt.show()

        if np.abs(new_col_skew) >= 1.:
            print(f'Transformation was not successful for {col_name}, returning␣
↪original data')
            return col

        return data

    plt.show()

skew_cols = ['CRIM', 'INDUS_CHAS', 'CRIM_ZN', 'CHAS', 'B', 'ZN', 'PTRATIO_B',␣
↪'RAD_LSTAT', 'RAD', 'DIS']  # LIST OF COLUMNS TO CHANGE
```

```
df[skew_cols] = df[skew_cols].apply(unskew)
```


CRIM skew is: 5.207882130237598
Best function <function yeojohnson at 0x000001FAFF986520> and the skew results: 0.5971108677374487

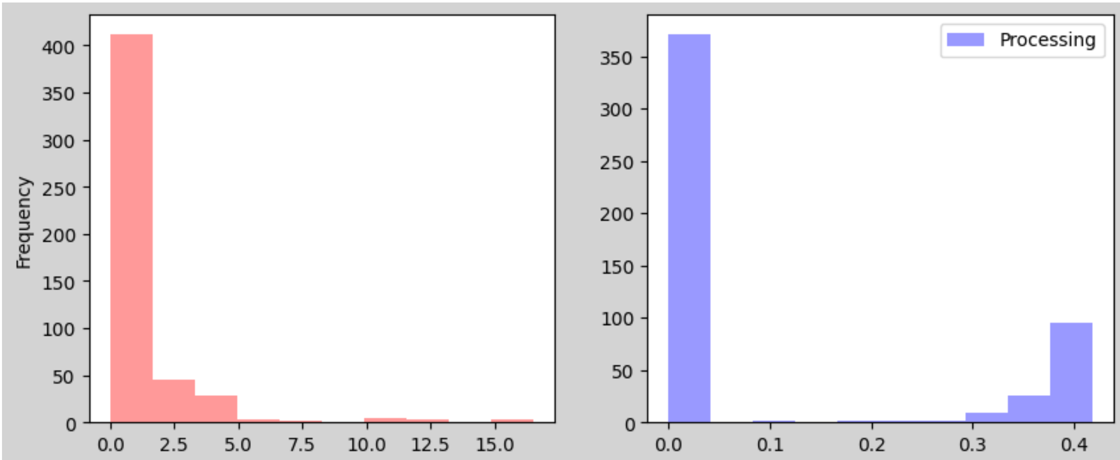


INDUS_CHAS skew is: 4.27629231640458
Best function <function yeojohnson at 0x000001FAFF986520> and the skew results: 3.3916316839780345



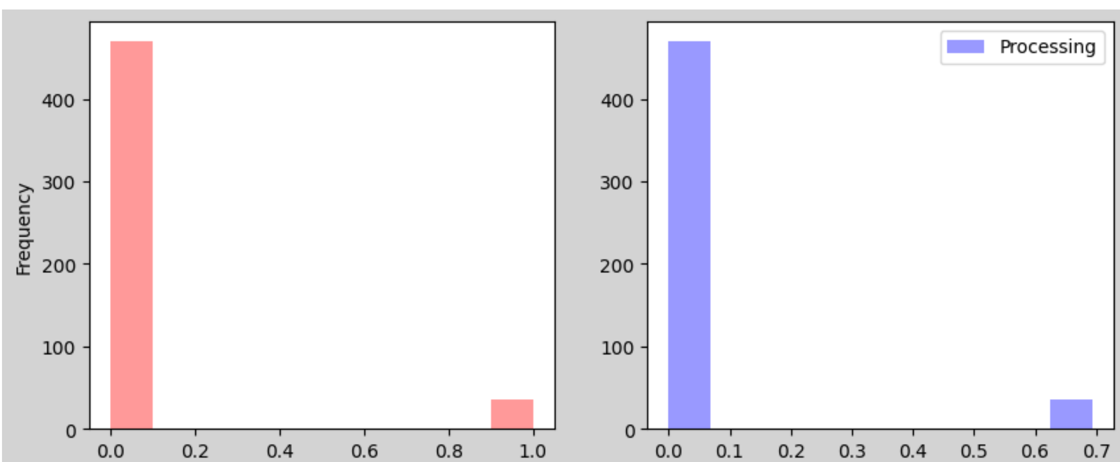
Transformation was not successful for INDUS_CHAS, returning original data
----

CRIM_ZN skew is: 3.8547806172795185
Best function <function yeojohnson at 0x000001FAFF986520> and the skew results: 1.107145826307136



Transformation was not successful for CRIM_ZN, returning original data
----

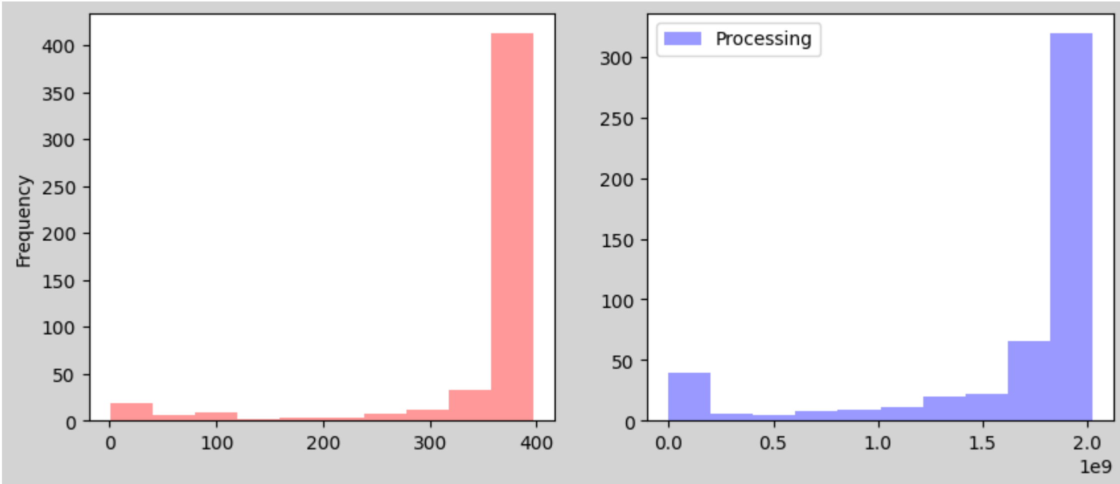
CHAS skew is: 3.3916131137967094
Best function <ufunc 'log1p'> and the skew results: 3.3916131137967094



Transformation was not successful for CHAS, returning original data
----

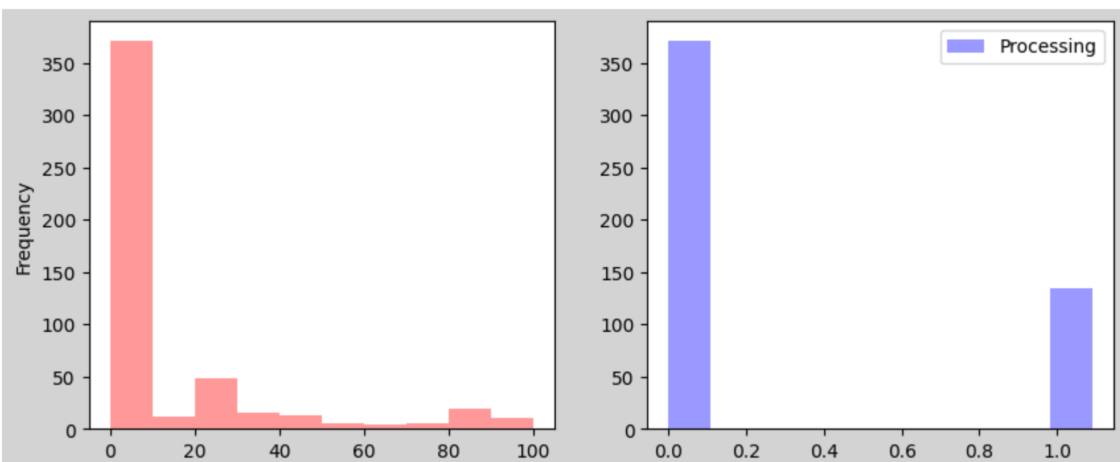
B skew is: -2.9200540251712503
Best function <function yeojohnson at 0x000001FAFF986520> and the skew results:

-1.9134669715515502



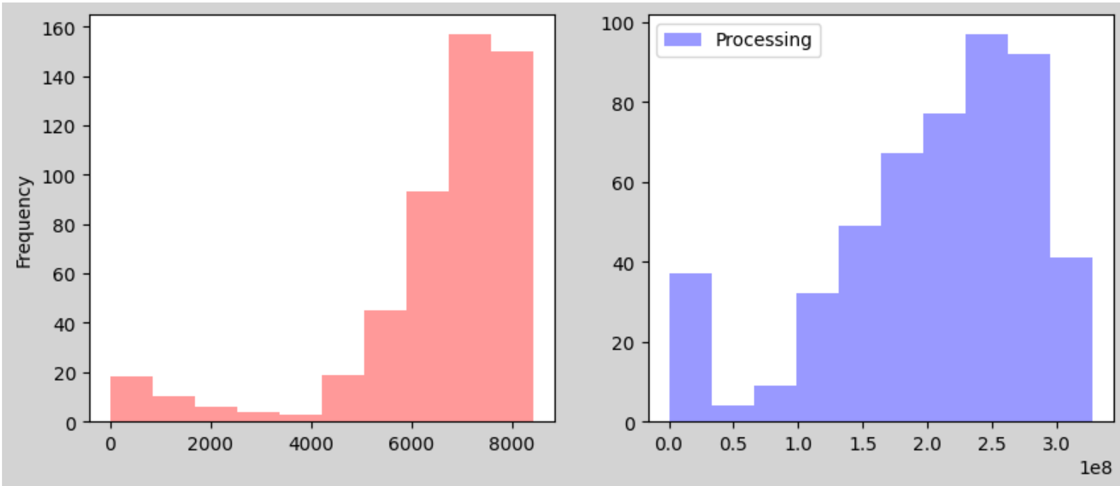
Transformation was not successful for B, returning original data
----

ZN skew is: 2.2176485715362144
Best function <function yeojohnson at 0x000001FAFF986520> and the skew results:
1.0656202518570272

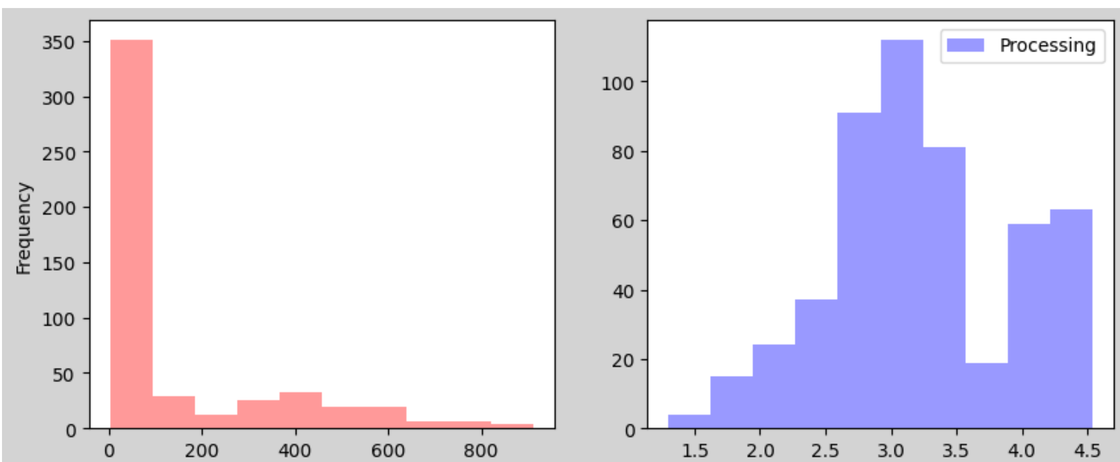


Transformation was not successful for ZN, returning original data
----

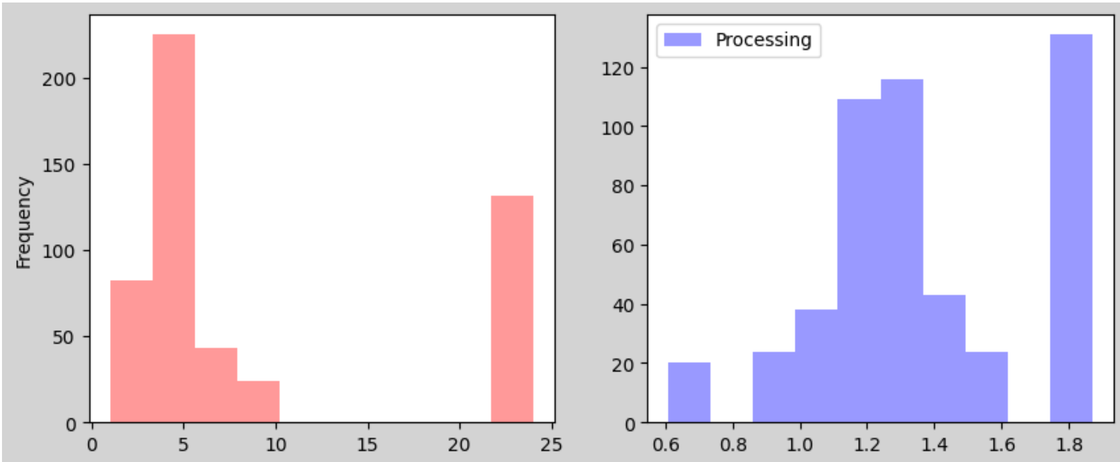
PTRATIO_B skew is: -2.0719125268867025
Best function <function yeojohnson at 0x000001FAFF986520> and the skew results:
-0.8842448562512275



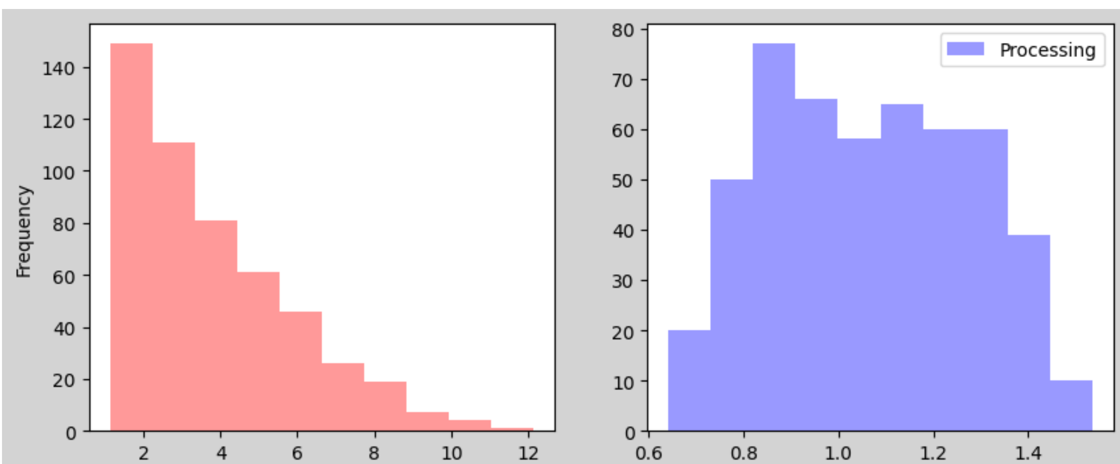

```
--------------------------------------------------------------------------------
--------------------
RAD_LSTAT skew is: 1.655748342768243
Best function <function yeojohnson at 0x000001FAFF986520> and the skew results:
0.036112577705346025
```




```
--------------------------------------------------------------------------------
--------------------
RAD skew is: 1.0098085122259308
Best function <function yeojohnson at 0x000001FAFF986520> and the skew results:
0.06475239131344185
```

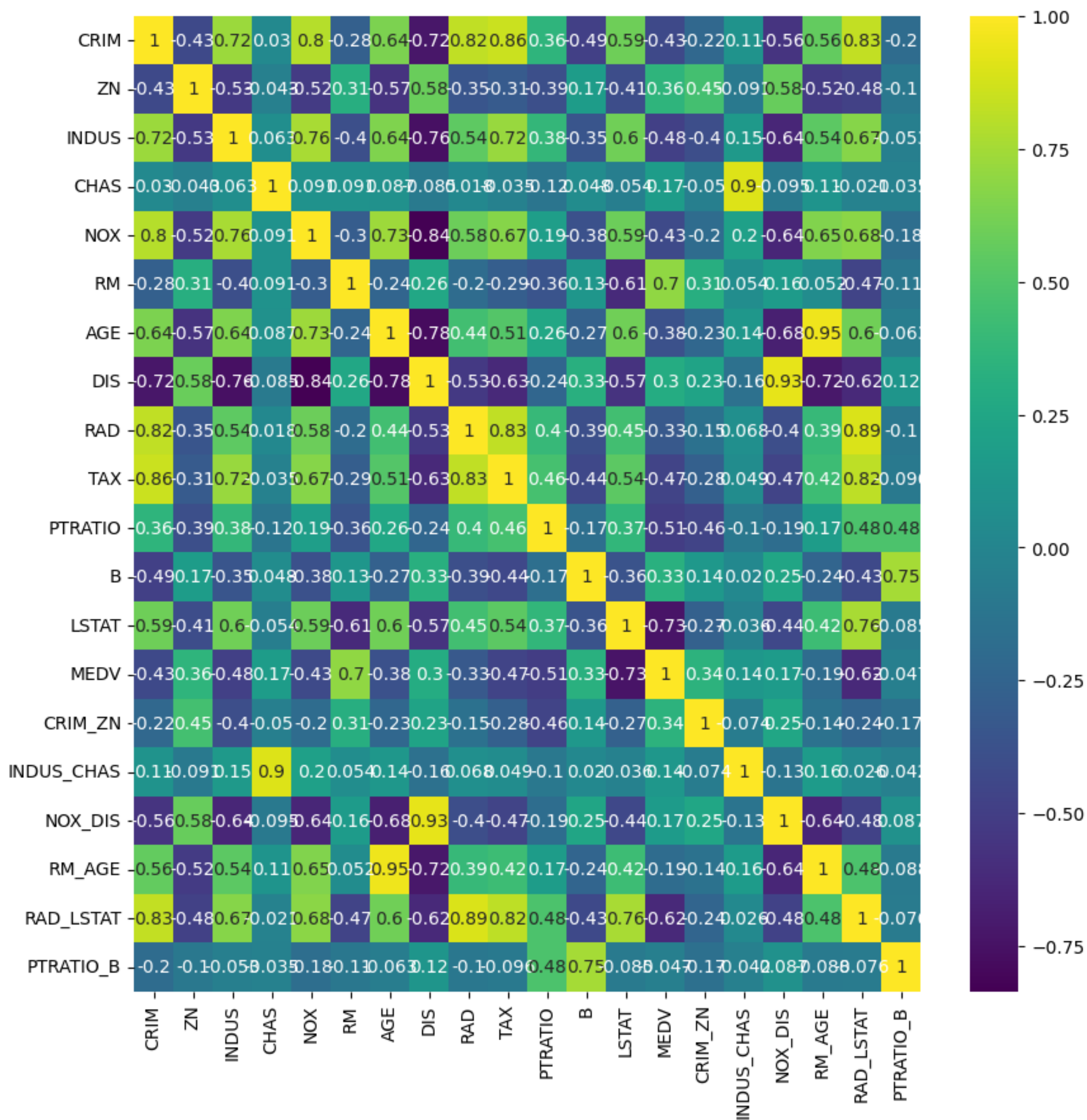



```
--------------------------------------------------------------------------------
--------------------
DIS skew is: 1.0062415748072984
Best function <function yeojohnson at 0x000001FAFF986520> and the skew results:
0.06606618319401818
```



[34]:
```
##FEATURE SLECTION
corr_ranking = (
    df
    .drop(target, axis=1)
    .corrwith(df[target])
    .abs()
    .sort_values(ascending=False)
)
```

```
[113]: plt.figure(figsize=(10,10))
heatmap = sns.heatmap(df.corr(), annot=True, cmap="viridis")
plt.show()
```



A correlation whose magnitude is between 0.9 and 1.0 can be considered very highly correlated. A correlation whose magnitude is between 0.7 and 0.9 can be considered highly correlated. Correlation whose magnitude is between 0.5 and 0.7 indicates a variable that can be considered moderately correlated. Correlation whose size is between 0.3 and 0.5 indicates a variable that has a low correlation. Correlation whose magnitude is less than 0.3 has a small (linear) correlation if any.

```
[63]: ##TAKES ALL VALUES FROM LARGEST TO SMALLEST
threshold = 0.0
```

```
chosen_cols = corr_ranking[corr_ranking>=threshold]
print(chosen_cols)
chosen_cols = chosen_cols.index.to_list()
```

```
LSTAT          0.734954
RM             0.696134
RAD_LSTAT      0.624044
PTRATIO        0.506899
INDUS          0.484554
TAX            0.466541
CRIM           0.426657
NOX            0.426326
AGE            0.376773
ZN             0.360016
CRIM_ZN        0.343270
B              0.329548
RAD            0.327940
DIS            0.295066
RM_AGE         0.192451
CHAS           0.174868
NOX_DIS        0.167917
INDUS_CHAS     0.139211
PTRATIO_B      0.047279
dtype: float64
```

TRAIN TEST SPLIT

[64]:
```
X = df[chosen_cols]
y = df[target]
```

[65]:
```
X.shape, y.shape
```

[65]:
```
((505, 19), (505,))
```

[68]:
```
from sklearn.model_selection import train_test_split
```

[69]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y)
```

[70]:
```
X_train.dtypes
```

[70]:
```
LSTAT          float64
RM             float64
RAD_LSTAT      float64
PTRATIO        float64
INDUS          float64
TAX              int32
CRIM           float64
NOX            float64
```

```
AGE             int32
ZN              int32
CRIM_ZN       float64
B             float64
RAD           float64
DIS           float64
RM_AGE        float64
CHAS            int64
NOX_DIS       float64
INDUS_CHAS    float64
PTRATIO_B     float64
dtype: object
```

SCALING

[71]:
```
from sklearn.preprocessing import StandardScaler
```

[72]:
```
scaler = StandardScaler()

cols = X_train.select_dtypes([float, int]).columns.to_list()

X_train[cols] = scaler.fit_transform(X_train)
X_test[cols] = scaler.transform(X_test)
```

REGRESSION

[74]:
```
from sklearn.linear_model import LinearRegression
from sklearn.ensemble import RandomForestRegressor
from xgboost import XGBRegressor

from sklearn.experimental import enable_halving_search_cv
from sklearn.model_selection import HalvingGridSearchCV
```

[75]:
```
n_features = X_train.shape[1]
```

[76]:
```
linear_reg_params = {
    'fit_intercept': [True, False],
}
```

[77]:
```
random_forest_params = {
    'n_estimators': np.sort(np.random.default_rng().choice(500, size=10,␣
 ↪replace=False)),
    'max_features': np.sort(np.random.default_rng().choice(n_features, size=5,␣
 ↪replace=False)),
    'max_depth': [1, 5, 10],
}
```

```
[78]: xgb_params = {
    'objective': ['reg:squarederror'],
    'max_depth': [2, 5,],
    'min_child_weight': np.arange(1, 5, 2),
    'n_estimators': np.sort(np.random.default_rng().choice(500, size=3,␣
 ↪replace=False)),
    'learning_rate': [1e-1, 1e-2,],
    'gamma': np.sort(np.random.default_rng().choice(20, size=3, replace=False)),
    'reg_lambda': [0, 1.0, 10.0],
    'scale_pos_weight': [1, 3, 5],
    'n_jobs': [-1],
}
```

```
[79]: best_mode_params = {
    LinearRegression(): {'fit_intercept': True},
    RandomForestRegressor(): {'max_depth': 10, 'max_features': 9,␣
 ↪'n_estimators': 378},
    XGBRegressor(): {'gamma': 18, 'learning_rate': 0.1, 'max_depth': 2,␣
 ↪'min_child_weight': 3, 'n_estimators': 461, 'n_jobs': -1, 'objective': 'reg:
 ↪squarederror', 'reg_lambda': 0, 'scale_pos_weight': 1},
}
```

```
[80]: from sklearn.metrics import mean_squared_error, r2_score
```

```
[81]: b_models = []
model_results = []

for model in best_mode_params.keys():
    params = best_mode_params[model]
    model.set_params(**params)
    model.fit(X_train, y_train)
    b_models.append(model)

    y_pred = model.predict(X_test)
    mse = mean_squared_error(y_test, y_pred)
    rmse = np.sqrt(mse)
    r2 = r2_score(y_test, y_pred)

    model_name = re.search(r'\w+', str(model))[0]
    results = pd.Series({'MSE': mse, 'RMSE': rmse, 'R2': r2}, name=model_name)
    model_results.append(results)
```

RESULTS

```
[82]: pd.concat(model_results, axis=1)
```

[82]:

	LinearRegression	RandomForestRegressor	XGBRegressor
MSE	14.699898	7.331241	7.450094
RMSE	3.834045	2.707626	2.729486
R2	0.826901	0.913671	0.912271

[109]:

```
feature_imp = []
for model in b_models:
    try:
        model_name = re.search(r'\w+', str(model))[0]
        feature_imp.append(
            pd.Series(
                {
                    col: importance
                    for col, importance in zip(cols, model.feature_importances_)
                },
                name = model_name
            )
        )
    except AttributeError:
        pass

pd.concat(feature_imp, axis=1).sort_values(by='XGBRegressor', ascending=False)
```

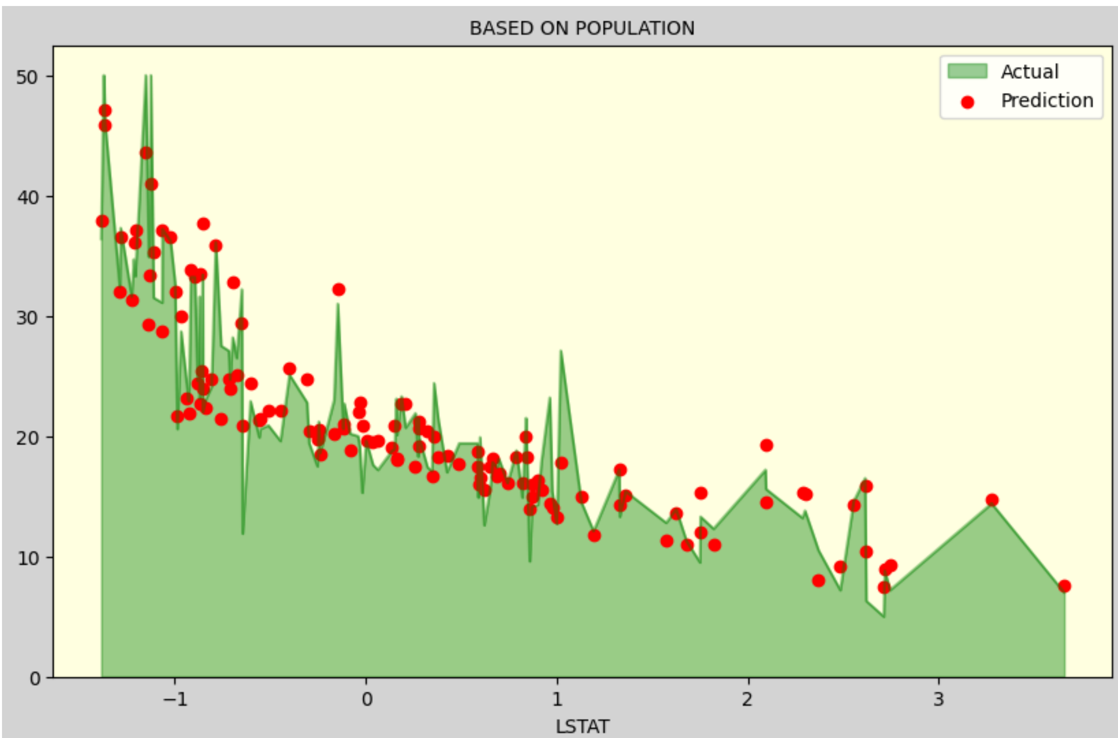
[109]:

	RandomForestRegressor	XGBRegressor
LSTAT	0.288331	0.298713
RM	0.324429	0.273483
RAD_LSTAT	0.096810	0.104293
DIS	0.041650	0.065250
NOX	0.027767	0.045835
PTRATIO	0.039474	0.040784
CRIM	0.023212	0.039476
PTRATIO_B	0.018802	0.030594
NOX_DIS	0.052029	0.025307
CHAS	0.000631	0.017719
TAX	0.013327	0.014512
INDUS	0.016677	0.012836
RAD	0.004206	0.009553
B	0.009682	0.008944
RM_AGE	0.017325	0.007867
AGE	0.015307	0.004835
CRIM_ZN	0.005276	0.000000
INDUS_CHAS	0.002783	0.000000
ZN	0.002283	0.000000

[177]:

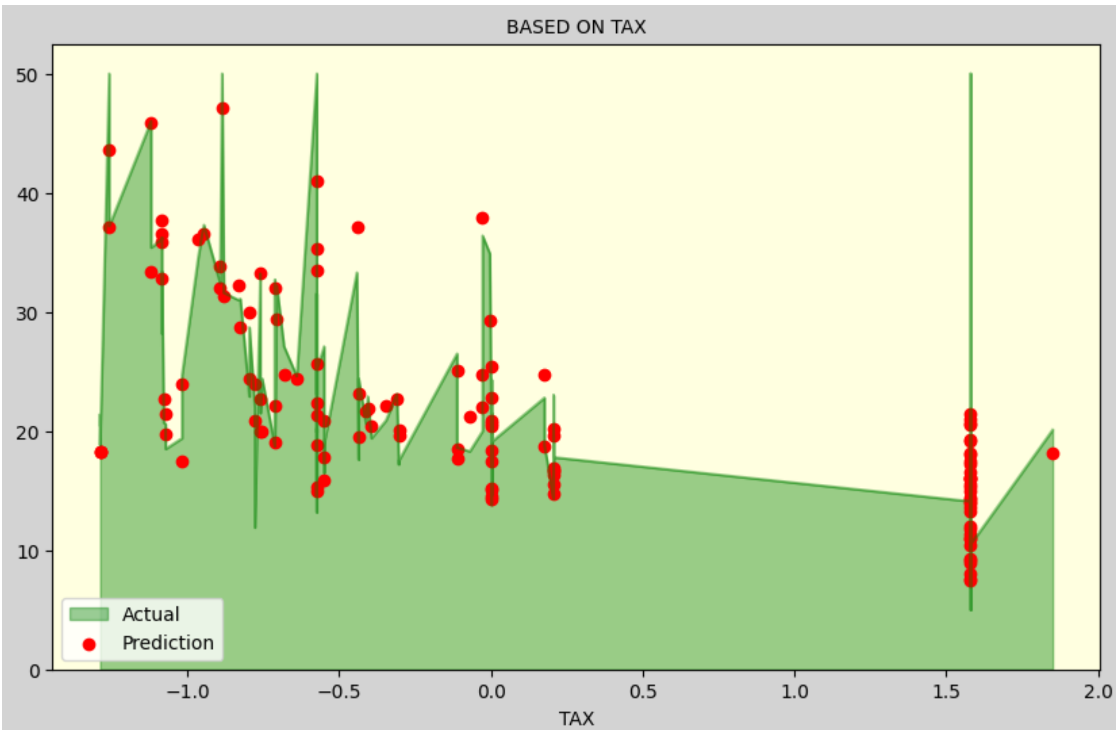
```
xgb_model = b_models[2]
col = 'LSTAT'
y_pred = xgb_model.predict(X_test.sort_values(by=col))
```

```
fig, ax = plt.subplots(figsize=(10, 6))
fig.patch.set_facecolor('lightgray')

(
    pd.concat([X_test[col], y_test], axis=1)
    .sort_values(by=col)
    .plot.area(x=col, y='MEDV', color='green', alpha=0.4, label='Actual', ax=ax)
)

plt.scatter(X_test[col].sort_values(), y_pred, color='red', label='Prediction')
plt.legend()
plt.title("BASED ON POPULATION", size=10)
ax.set_facecolor('lightyellow')
plt.show()
```



[178]:
```
xgb_model = b_models[2]
col = 'TAX'
y_pred = xgb_model.predict(X_test.sort_values(by=col))

fig, ax = plt.subplots(figsize=(10, 6))
fig.patch.set_facecolor('lightgray')
```

```
(
    pd.concat([X_test[col], y_test], axis=1)
    .sort_values(by=col)
    .plot.area(x=col, y='MEDV', color='green', alpha=0.4, label='Actual', ax=ax)
)

plt.scatter(X_test[col].sort_values(), y_pred, color='red', label='Prediction')
plt.legend()
plt.title("BASED ON TAX", size=10)
ax.set_facecolor('lightyellow')
plt.show()
```



[179]:

```
xgb_model = b_models[2]
col = 'RM'
y_pred = xgb_model.predict(X_test.sort_values(by=col))

fig, ax = plt.subplots(figsize=(10, 6))
fig.patch.set_facecolor('lightgray')

(
    pd.concat([X_test[col], y_test], axis=1)
    .sort_values(by=col)
    .plot.area(x=col, y='MEDV', color='green', alpha=0.4, label='Actual', ax=ax)
```

```
)

plt.scatter(X_test[col].sort_values(), y_pred, color='red', label='Prediction')
plt.legend()
plt.title("BASED ON THE NUMBER OF ROOMS PER OCCUPANCY", size=10)
ax.set_facecolor('lightyellow')
plt.show()
```