1f.XGBoost

November 2, 2024

[1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error
import xgboost as xgb
from sklearn.model_selection import GridSearchCV
```

[2]:
```
# from google.colab import drive
# drive.mount('/content/drive', readonly=True)
```

[3]:
```
url = "https://ddc-datascience.s3.amazonaws.com/boston.csv"
boston = pd.read_csv( url, index_col = 0 )
```

[4]:
```
boston.head()
```

[4]:

	per_cap_crime	res_zoning_prop	business_prop	river_front	nitric_oxide_conc	num_rooms	units_before_1940	distance_to_employment	distance_to_hwy	prop_tax	pupil_teacher_ratio	perc_lower_status
0	0.00632	18.0	2.31	0.0	0.538	6.575	65.2	4.0900	1.0	296.0	15.3	4.98
1	0.02731	0.0	7.07	0.0	0.469	6.421	78.9	4.9671	2.0	242.0	17.8	9.14
2	0.02729	0.0	7.07	0.0	0.469	7.185	61.1	4.9671	2.0	242.0	17.8	4.03
3	0.03237	0.0	2.18	0.0	0.458	6.998	45.8	6.0622	3.0	222.0	18.7	2.94
4	0.06905	0.0	2.18	0.0	0.458	7.147	54.2	6.0622	3.0	222.0	18.7	5.33

```
   med_home_value
0            24.0
1            21.6
2            34.7
3            33.4
4            36.2
```

[5]:
```
boston.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 490 entries, 0 to 505
Data columns (total 13 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   per_cap_crime           490 non-null    float64
 1   res_zoning_prop         490 non-null    float64
 2   business_prop           490 non-null    float64
 3   river_front             490 non-null    float64
 4   nitric_oxide_conc       490 non-null    float64
 5   num_rooms               490 non-null    float64
 6   units_before_1940       490 non-null    float64
 7   distance_to_employment  490 non-null    float64
 8   distance_to_hwy         490 non-null    float64
 9   prop_tax                490 non-null    float64
 10  pupil_teacher_ratio     490 non-null    float64
 11  perc_lower_status       490 non-null    float64
 12  med_home_value          490 non-null    float64
dtypes: float64(13)
memory usage: 53.6 KB
```

Recall that with a decision tree we got an RMSE of about $3800, and with a random forest with got an RMSE of about $2850.

#XGBoost

Here we are fitting an XGBoost model without specifying any hyperparameters.

[6]:
```
X = boston.drop('med_home_value', axis = 1)
y = boston['med_home_value']
```

[7]:
```
numLoops = 100
mse_xgb  = np.zeros(numLoops)

for idx in range(0,numLoops):
  X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.15)
  xgbr = xgb.XGBRegressor(objective ='reg:squarederror', verbosity=0, seed = 10)
  xgbr.fit(X_train,y_train)
  y_pred_xgb = xgbr.predict(X_test)
  mse_xgb[idx] = mean_squared_error(y_test,y_pred_xgb)
```

```
print(f'RMSE: {np.sqrt(mse_xgb).mean()*1000}')
```

```
RMSE: 3016.021905965499
```

[8]:
```
y_pred_xgb[0]
```

[8]:
```
9.611709
```

[20]:
```
y_test.to_numpy()[0]
```

[20]:
```
11.0
```

[21]:
```
my_house = X_test[:3]
my_house
```

[21]:

	per_cap_crime	res_zoning_prop	business_prop	river_front	\
428	7.36711	0.0	18.10	0.0	
287	0.03871	52.5	5.32	0.0	
452	5.09017	0.0	18.10	0.0	

	nitric_oxide_conc	num_rooms	units_before_1940	distance_to_employment	\
428	0.679	6.193	78.1	1.9356	
287	0.405	6.209	31.3	7.3172	
452	0.713	6.297	91.8	2.3682	

	distance_to_hwy	prop_tax	pupil_teacher_ratio	perc_lower_status
428	24.0	666.0	20.2	21.52
287	6.0	293.0	16.6	7.14
452	24.0	666.0	20.2	17.27

[22]:
```
xgbr.predict(my_house)
```

[22]:
```
array([ 9.611709, 23.009007, 15.251231], dtype=float32)
```

0.1 XGBoost with Parameters

Now we will see if we can improve performance by changing some parameters.

[23]:
```
# Specify the parameters you want to try and their ranges.
param_test = {
 'max_depth'     : [ 3, 4, 5, 6, 7 ],
 'learning_rate' : [ 0.1, 0.2, 0.3, 0.4 ],
 'n_estimators'  : [ 20, 40, 60, 80, 100, 120, 140 ],
}

# Perform the grid search
gsearch = GridSearchCV(
```

```
    estimator = xgb.XGBRegressor( objective = 'reg:squarederror', seed = 10 ),
    param_grid = param_test,
    scoring = 'neg_mean_squared_error',
    cv = 5,
)

# Fit to training data
X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.05,␣
 ↪random_state = 42 )
model = gsearch.fit(X_train,y_train)

# See grid search results
print(model.best_params_)
```

```
{'learning_rate': 0.2, 'max_depth': 3, 'n_estimators': 100}
```

Now we will fit our XGBoost model with the best parameters

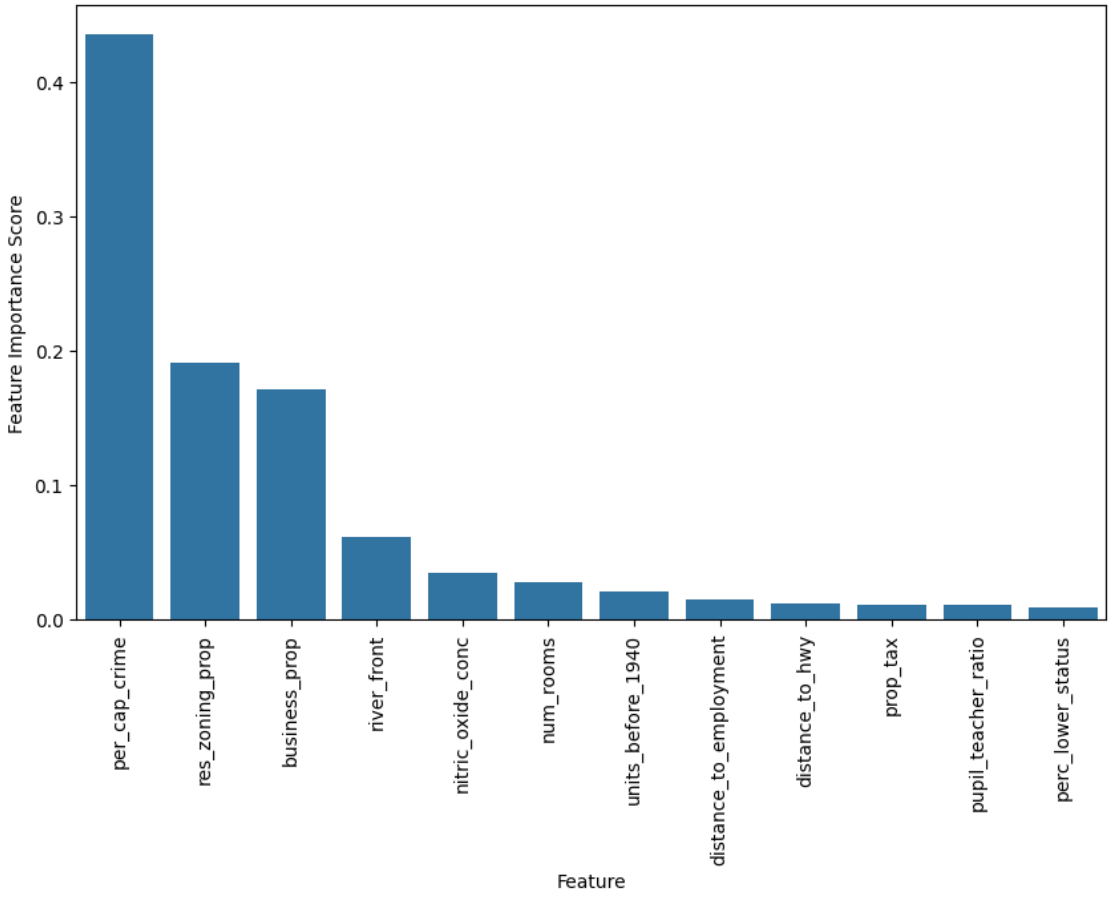
[24]:
```
numLoops = 100
mse_xgb  = np.zeros(numLoops)

for idx in range(0,numLoops):
  X_train, X_test, y_train, y_test = train_test_split( X, y, test_size = 0.15 )
  xgbr = xgb.XGBRegressor(
      objective ='reg:squarederror',
      verbosity=0,
      learning_rate = 0.2,
      max_depth = 3,
      n_estimators = 100,
      seed = 10,
  )
  xgbr.fit(X_train,y_train)
  y_pred_xgb = xgbr.predict(X_test)
  mse_xgb[idx] = mean_squared_error(y_test,y_pred_xgb)

print(f'RMSE: {np.sqrt(mse_xgb).mean()*1000}')
```

```
RMSE: 2769.0589582935277
```

[25]:
```
feat_imp = pd.Series(xgbr.feature_importances_, index=X.columns)
plt.figure(figsize = (10,6))
# ax = sns.barplot(x = feat_imp.index, y = feat_imp.values)
ax = sns.barplot(x = feat_imp.index, y = feat_imp.sort_values( ascending =␣
 ↪False ).values )
ax.set_xticklabels( ax.get_xticklabels(), rotation = 90 )
plt.xlabel('Feature')
plt.ylabel('Feature Importance Score') ;
```

```
<ipython-input-25-16d4b8a6cfd6>:5: UserWarning: FixedFormatter should only be
```

```
used together with FixedLocator
  ax.set_xticklabels( ax.get_xticklabels(), rotation = 90 )
```



[26]:
```
(feat_imp.sort_values( ascending = False )*100).cumsum()
```

[26]:
```
perc_lower_status          43.552254
num_rooms                  62.683205
pupil_teacher_ratio        79.776871
nitric_oxide_conc          85.915344
prop_tax                   89.433220
per_cap_crime              92.179024
distance_to_employment     94.283508
distance_to_hwy            95.770103
units_before_1940          96.949837
business_prop              98.067436
res_zoning_prop            99.148567
river_front               100.000008
dtype: float32
```