Feature Selection- With Correlation In this step we will be removing the features which are highly correlated from sklearn.datasets import load_boston import pandas as pd import matplotlib.pyplot as plt In [61]: data=load_boston() data.feature_names Out[62]: array(['CRIM', 'ZN', 'INDUS', 'CHAS', 'NOX', 'RM', 'AGE', 'DIS', 'RAD', 'TAX', 'PTRATIO', 'B', 'LSTAT'], dtype='<U7') In [63]: df=pd.DataFrame(data.data,columns=data.feature_names) df.head() DIS RAD TAX PTRATIO B LSTAT Out[64]: CRIM ZN INDUS CHAS NOX RM AGE **0** 0.00632 18.0 0.0 0.538 6.575 65.2 4.0900 1.0 296.0 15.3 396.90 4.98 2.31 **1** 0.02731 0.0 7.07 0.0 0.469 6.421 78.9 4.9671 2.0 242.0 17.8 396.90 9.14 0.0 0.469 7.185 61.1 4.9671 2.0 242.0 4.03 **2** 0.02729 0.0 7.07 17.8 392.83 **3** 0.03237 0.0 2.18 0.0 0.458 6.998 45.8 6.0622 3.0 222.0 18.7 394.63 2.94 **4** 0.06905 0.0 2.18 0.0 0.458 7.147 54.2 6.0622 3.0 222.0 5.33 18.7 396.90 In [65]: df['MEDV']=data.target In [66]: df.head() CRIM ZN INDUS CHAS NOX RM AGE DIS RAD TAX PTRATIO B LSTAT MEDV Out[66]: **0** 0.00632 18.0 2.31 0.0 0.538 6.575 65.2 4.0900 1.0 296.0 15.3 396.90 24.0 2.0 242.0 **1** 0.02731 0.0 7.07 0.0 0.469 6.421 78.9 4.9671 17.8 396.90 9.14 21.6 **2** 0.02729 0.0 7.07 0.0 0.469 7.185 61.1 4.9671 2.0 242.0 17.8 392.83 4.03 34.7 **3** 0.03237 0.0 2.18 0.0 0.458 6.998 45.8 6.0622 3.0 222.0 18.7 394.63 2.94 33.4 0.0 0.458 7.147 54.2 6.0622 3.0 222.0 **4** 0.06905 0.0 2.18 18.7 396.90 5.33 36.2 In [67]: x=df.drop('MEDV',axis=1) y=df['MEDV'] In [68]: from sklearn.model_selection import train_test_split xtrain,xtest,ytrain,ytest=train_test_split(x,y,random_state=0,test_size=.30) In [70]: import seaborn as sns import matplotlib.pyplot as plt plt.figure(figsize=(12,10)) sns.heatmap(xtrain.corr(), annot=True, cmap=plt.cm.CMRmap_r) Out[70]: <AxesSubplot:> 0.38 -0.049 0.42 -0.19 0.33 -0.36 0.6 0.56 0.26 -0.3 0.44 -0.31 -0.33 -0.39 0.16 -0.43 - 0.8 0.75 **-0.39** 0.63 **-0.69** 0.58 0.72 0.39 **-0.33** 0.6 0.38 - 0.6 CHAS - 0.4 0.74 -0.77 0.63 0.68 0.18 -0.37 0.42 -0.52 -0.24 0.18 -0.18 -0.28 -0.39 0.16 -0.62 0.32 -0.39 0.088 -0.28 - 0.2 -0.76 0.44 0.5 0.24 -0.25 0.61 -0.58 0.63 0.067 0.74 - 0.0 -0.77 -0.47 -0.52 -0.18 0.25 -0.5 0.66 0.58 0.022 0.63 -0.42 0.44 -0.18 0.44 -0.47 0.91 0.44 - -0.2 -0.28 0.5 -0.52 0.91 1 -0.41 0.52 -0.33 0.72 -0.017 0.68 0.45 - -0.4 0.26 -0.39 0.39 -0.073 0.18 -0.39 0.24 -0.18 0.44 0.45 -0.15 0.39 - -0.6 -0.62 0.44 0.52 0.39 CRIM ZN INDUS CHAS NOX RM AGE DIS RAD TAX PTRATIO B LSTAT # with the following function we can select highly correlated features # it will remove the first feature that is correlated with anything other feature def correlation(dataset, threshold): col_corr = set() # Set of all the names of correlated columns corr_matrix = dataset.corr() for i in range(len(corr_matrix.columns)): for j in range(i): if abs(corr_matrix.iloc[i, j]) > threshold: # we are interested in absolute coeff value colname = corr_matrix.columns[i] # getting the name of column col_corr.add(colname) return col_corr corr_features=correlation(xtrain, 0.7) In [73]: len(corr_features) Out[73]: 4 In [74]: corr_features Out[74]: {'AGE', 'DIS', 'NOX', 'TAX'} xtrain.drop(corr_features,axis=1)

CRIM ZN INDUS CHAS RM RAD PTRATIO B LSTAT Out[75]: **141** 1.62864 0.0 21.89 0.0 5.019 4.0 21.2 396.90 34.41 **272** 0.11460 20.0 6.96 0.0 6.538 3.0 18.6 394.96 7.73 **135** 0.55778 0.0 21.89 0.0 6.335 4.0 21.2 394.67 16.96 14.8 368.24 4.97 **298** 0.06466 70.0 2.24 0.0 6.345 5.0 **122** 0.09299 0.0 25.65 0.0 5.961 2.0 19.1 378.09 17.93 **323** 0.28392 0.0 7.38 0.0 5.708 5.0 19.6 391.13 11.74 **192** 0.08664 45.0 3.44 0.0 7.178 5.0 15.2 390.49 2.87 **117** 0.15098 0.0 10.01 0.0 6.021 6.0 17.8 394.51 10.30 **47** 0.22927 0.0 6.91 0.0 6.030 3.0 17.9 392.74 18.80 16.6 396.90 14.69 **172** 0.13914 0.0 4.05 0.0 5.572 5.0 354 rows × 9 columns

In [76]: xtest.drop(corr_features,axis=1)

152 rows × 9 columns

Out[76]: CRIM ZN INDUS CHAS RM RAD PTRATIO B LSTAT **329** 0.06724 0.0 3.24 0.0 6.333 4.0 16.9 375.21 7.34 **371** 9.23230 0.0 18.10 0.0 6.216 24.0 20.2 366.15 9.53 **219** 0.11425 0.0 13.89 1.0 6.373 5.0 16.4 393.74 10.50 **403** 24.80170 0.0 18.10 0.0 5.349 24.0 20.2 396.90 19.77 **78** 0.05646 0.0 12.83 0.0 6.232 5.0 18.7 386.40 12.34 **4** 0.06905 0.0 2.18 0.0 7.147 3.0 18.7 396.90 5.33 **428** 7.36711 0.0 18.10 0.0 6.193 24.0 20.2 96.73 21.52 **385** 16.81180 0.0 18.10 0.0 5.277 24.0 20.2 396.90 30.81 **308** 0.49298 0.0 9.90 0.0 6.635 4.0 18.4 396.90 4.54 **5** 0.02985 0.0 2.18 0.0 6.430 3.0 18.7 394.12 5.21