```
Ridge Regression Using UCI Dataset
In [1]:
         import pandas as pd
         import numpy as np
          # Communities and Crime dataset for regression
          # https://archive.ics.uci.edu/ml/datasets/Communities+and+Crime+Unnormalized
         crime datafile = 'E:\Protfolio\Ridge Regression Using UCI Dataset/CommViolPredUnnormalizedData.txt'
         crime = pd.read table(crime datafile, sep=',', na values='?')
         crime.head()
Out[1]:
                                                 communityCode fold
                                                                     population householdsize racepctblack racePctWhite racePctAsian
                  communityname
                                 state
                                      countyCode
                                                          5320.0
          0 BerkeleyHeightstownship
                                   NJ
                                             39.0
                                                                         11980
                                                                                        3.10
                                                                                                    1.37
                                                                                                               91.78
                                                                                                                            6.50
                                                         47616.0
          1
                    Marpletownship
                                   PA
                                             45.0
                                                                   1
                                                                         23123
                                                                                        2.82
                                                                                                    0.80
                                                                                                               95.57
                                                                                                                            3.44
          2
                        Tigardcity
                                  OR
                                             NaN
                                                           NaN
                                                                         29344
                                                                                        2.43
                                                                                                    0.74
                                                                                                               94.33
                                                                                                                            3.43
          3
                    Gloversvillecity
                                  NY
                                             35.0
                                                         29443.0
                                                                   1
                                                                         16656
                                                                                        2.40
                                                                                                    1.70
                                                                                                               97.35
                                                                                                                            0.50
                       Bemidjicity
                                  MN
                                              7.0
                                                          5068.0
                                                                         11245
                                                                                        2.76
                                                                                                    0.53
                                                                                                               89.16
                                                                                                                            1.17
         5 rows × 147 columns
In [2]:
         # remove features with poor coverage or lower relevance, and keep ViolentCrimesPerPop target column
         columns to keep = ([5, 6] + list(range(11, 26)) + list(range(32, 103)) + [145])
         crime = (crime[crime.columns[columns to keep]].dropna().reset index(drop=True))
         crime.head()
Out[2]:
             population
                      householdsize agePct12t21 agePct12t29
                                                           agePct16t24 agePct65up numbUrban pctUrban medIncome pctWWage
          0
                 11980
                               3.10
                                          12.47
                                                     21.44
                                                                 10.93
                                                                            11.33
                                                                                      11980
                                                                                                100.0
                                                                                                          75122
                                                                                                                    89.24
          1
                 23123
                               2.82
                                          11.01
                                                     21.30
                                                                10.48
                                                                           17.18
                                                                                      23123
                                                                                                100.0
                                                                                                          47917
                                                                                                                    78.99
                 29344
                                                     25.88
                                                                                      29344
          2
                               2.43
                                          11.36
                                                                 11.01
                                                                            10.28
                                                                                                100.0
                                                                                                          35669
                                                                                                                    82.00
          3
                 16656
                               2.40
                                          12.55
                                                     25.20
                                                                12.19
                                                                            17.57
                                                                                                 0.0
                                                                                                          20580
                                                                                                                    68.15 ...
                140494
                               2.45
                                          18.09
                                                     32.89
                                                                20.04
                                                                            13.26
                                                                                     140494
                                                                                                100.0
                                                                                                          21577
                                                                                                                    75.78
         5 rows × 89 columns
In [3]:
         #splitting features
         X=crime.iloc[:,0:88]
Out[3]:
                                                                         agePct65up
               population
                          householdsize
                                       agePct12t21 agePct12t29
                                                              agePct16t24
                                                                                    numbUrban
                                                                                               pctUrban medIncome
                                                                                                                   pctWWage
                                                        21.44
             0
                   11980
                                                                   10.93
                                                                                                 100.00
                                  3.10
                                            12.47
                                                                              11.33
                                                                                         11980
                                                                                                             75122
                                                                                                                       89.24
             1
                   23123
                                  2.82
                                            11.01
                                                        21.30
                                                                   10.48
                                                                              17.18
                                                                                         23123
                                                                                                 100.00
                                                                                                             47917
                                                                                                                       78.99 ...
                                                                                                                       82.00 ...
             2
                   29344
                                  2.43
                                            11.36
                                                        25.88
                                                                   11.01
                                                                              10.28
                                                                                         29344
                                                                                                 100.00
                                                                                                             35669
             3
                   16656
                                  2.40
                                            12.55
                                                        25.20
                                                                   12.19
                                                                              17.57
                                                                                            0
                                                                                                   0.00
                                                                                                             20580
                                                                                                                       68.15 ...
                  140494
                                  2.45
                                            18.09
                                                        32.89
                                                                   20.04
                                                                                        140494
                                                                                                 100.00
                                                                              13.26
                                                                                                             21577
                                                                                                                       75.78 ...
          1989
                                  3.07
                   56216
                                            15.46
                                                        30.16
                                                                   14.34
                                                                               8.08
                                                                                         56216
                                                                                                 100.00
                                                                                                             24727
                                                                                                                       75.05 ...
          1990
                   12251
                                  2.68
                                            17.36
                                                        31.23
                                                                   16.97
                                                                              12.57
                                                                                         12251
                                                                                                 100.00
                                                                                                             20321
                                                                                                                       75.06 ...
          1991
                   32824
                                  2.46
                                            11.81
                                                        20.96
                                                                    9.53
                                                                              20.73
                                                                                         32824
                                                                                                 100.00
                                                                                                             27182
                                                                                                                       59.79 ...
          1992
                   13547
                                  2.89
                                            17.16
                                                        30.01
                                                                   14.73
                                                                              10.42
                                                                                            0
                                                                                                   0.00
                                                                                                             19899
                                                                                                                       71.67 ...
          1993
                   28898
                                  2.61
                                            12.99
                                                                                         28664
                                                                                                             23287
                                                        25.21
                                                                    11.63
                                                                              12.12
                                                                                                  99.19
                                                                                                                       68.89 ...
         1994 rows × 88 columns
In [4]:
         #splitting level
         y=crime['ViolentCrimesPerPop']
Out[4]: 0
                   41.02
         1
                  127.56
                  218.59
         2
                  306.64
         3
                  442.95
                   . . .
         1989
                  545.75
         1990
                  124.10
         1991
                  353.83
         1992
                  691.17
         1993
                  918.89
         Name: ViolentCrimesPerPop, Length: 1994, dtype: float64
In [5]: #plitting train and test set
         from sklearn.linear_model import Ridge
         from sklearn.model_selection import train_test_split
         X_train, X_test, y_train, y_test = train_test_split(X,y,random_state=0)
In [6]: | #fit rdge regreesion on train set
         linridge = Ridge(alpha = 20.0)
         linridge.fit(X_train, y_train)
Out[6]: Ridge(alpha=20.0)
In [7]: | print('Crime dataset')
         print('ridge regression linear model intercept: {}'
               .format(linridge.intercept ))
         print('ridge regression linear model coeff:\n{}'
               .format(linridge.coef ))
         print('R-squared score (training): {:.3f}'
               .format(linridge.score(X_train, y_train)))
         print('R-squared score (test): {:.3f}'
               .format(linridge.score(X test, y test)))
         print('Number of non-zero features: {}'
               .format(np.sum(linridge.coef != 0)))
         Crime dataset
         ridge regression linear model intercept: -3352.4230358457785
         ridge regression linear model coeff:
         [ 1.95091438e-03 2.19322667e+01 9.56286607e+00 -3.59178973e+01
            6.36465325e+00 -1.96885471e+01 -2.80715856e-03 1.66254486e+00
           -6.61426604 \\ e-03 -6.95450680 \\ e+00 \\ 1.71944731 \\ e+01 -5.62819154 \\ e+00
           8.83525114e+00 6.79085746e-01 -7.33614221e+00 6.70389803e-03
           9.78505502e-04 5.01202169e-03 -4.89870524e+00 -1.79270062e+01
           9.17572382e+00 -1.24454193e+00 1.21845360e+00 1.03233089e+01
          -3.78037278e+00 -3.73428973e+00 4.74595305e+00 8.42696855e+00
```

```
2.41917002e+01 -1.32497562e+01 -4.20113118e-01 -3.59710660e+01  
1.29786751e+01 -2.80765995e+01   4.38513476e+01   3.86590044e+01  
-6.46024046e+01 -1.63714023e+01   2.90397330e+01   4.15472907e+00  
5.34033563e+01   1.98773191e-02   -5.47413979e-01   1.23883518e+01  
1.03526583e+01 -1.57238894e+00   3.15887097e+00   8.77757987e+00  
-2.94724962e+01 -2.33551881e-04   3.13528914e-04   -4.13071930e-04  
-1.80407541e-04   -5.74054527e-01   -5.17742507e-01   -4.20670930e-01  
1.53383594e-01   1.32725423e+00   3.84863158e+00   3.03024594e+00  
-3.77692644e+01   1.37933464e-01   3.07676522e-01   1.57128807e+01  
3.31418306e-01   3.35994414e+00   1.61265911e-01   -2.67619878e+00]
```

3.09250005e+01 1.18644167e+01 -2.05183675e+00 -3.82210450e+01 1.85081589e+01 1.52510829e+00 -2.20086608e+01 2.46283912e+00 3.29328703e-01 4.02228467e+00 -1.12903533e+01 -4.69567413e-03 4.27046505e+01 -1.22507167e-03 1.40795790e+00 9.35041855e-01 -3.00464253e+00 1.12390514e+00 -1.82487653e+01 -1.54653407e+01

from sklearn.preprocessing import MinMaxScaler

Ridge Regression with feature normalization

```
scaler = MinMaxScaler()
#normalize the train and test set
```

Here using MinMaxScaler for the preprocessing

R-squared score (training): 0.671 R-squared score (test): 0.494 Number of non-zero features: 88

```
X train scaled = scaler.fit_transform(X_train)
        X test scaled = scaler.fit transform(X test)
        #fit ridge model in scaled train set
        linridge2 = Ridge(alpha = 20.0).fit(X train scaled, y train)
In [13]:
        print('Crime dataset')
        print('ridge regression linear model intercept: {}'
             .format(linridge2.intercept ))
        print('ridge regression linear model coeff:\n{}'
             .format(linridge2.coef_))
        print('R-squared score (training): {:.3f}'
             .format(linridge2.score(X train scaled, y train)))
        print('R-squared score (test): {:.3f}'
             .format(linridge2.score(X test scaled, y test)))
        print('Number of non-zero features: {}'
             .format(np.sum(linridge2.coef != 0)))
        Crime dataset
        ridge regression linear model intercept: 933.390638504413
        ridge regression linear model coeff:
        -2.27674244 87.74108514 150.94862182 18.8802613 -31.05554992
          -43.13536109 -189.44266328 -4.52658099 107.97866804 -76.53358414
            2.86032762 34.95230077 90.13523036 52.46428263 -62.10898424
          115.01780357 2.66942023 6.94331369 -5.66646499 -101.55269144
                       -8.7053343 29.11999068 171.25963057 99.36919476
          -36.9087526
           75.06611841 123.63522539 95.24316483 -330.61044265 -442.30179004
         -284.49744001 -258.37150609 17.66431072 -101.70717151 110.64762887
          523.13611718 24.8208959
                                    4.86533322 -30.46775619 -3.51753937
           50.57947231 10.84840601 18.27680946 44.11189865 58.33588176
           67.08698975 -57.93524659 116.1446052 53.81163718 49.01607711
           -7.62262031 55.14288543 -52.08878272 123.39291017 77.12562171
           45.49795317 184.91229771 -91.35721203 1.07975971 234.09267451
```

 10.3887921
 94.7171829
 167.91856631
 -25.14025088
 -1.18242839

 14.60362467
 36.77122659
 53.19878339
 -78.86365997
 -5.89858411

 26.04790298
 115.1534917
 68.74143311
 68.28588166
 16.5260514

 -97.90513652
 205.20448474
 75.97304123
 61.3791085
 -79.83157049

67.26700741 95.67094538 -11.88380569]

R-squared score (training): 0.615 R-squared score (test): 0.620 Number of non-zero features: 88

In [12]: