Machine Learning Final Project

December 18, 2017

1 Study on Communities and Crime Data Set

1.1 Data Set Description

Abstract: Communities within the United States. The data combines socio-economic data from the 1990 US Census, law enforcement data from the 1990 US LEMAS survey, and crime data from the 1995 FBI UCR.

Data Set Description	
Data Set Characteristics:	Multivariate
Number of Instances:	1994
Area:	Social
Number of Attributes:	128
Date Donated	2009-07-13
Associated Tasks:	Regression

1.2 Load Data Set and Library

We generate the attributes names list for loading the data by doing some tricks on the meta data of the data set. Load the data as pandas dataframe.

```
In [88]: import pandas as pd
         import numpy as np
         from sklearn import linear_model
         import math
         import matplotlib.pyplot as plt
         %matplotlib inline
```

```
In [89]: # Attribute names extract from meta data
         names = ['state', 'county', 'community', 'communityname', 'fold', 'population',
                  'householdsize', 'racepctblack', 'racePctWhite', 'racePctAsian', 'racePctHisp'
                  'agePct12t21', 'agePct12t29', 'agePct16t24', 'agePct65up', 'numbUrban', 'pctUr
                  'medIncome', 'pctWWage', 'pctWFarmSelf', 'pctWInvInc', 'pctWSocSec', 'pctWPubA
                  'pctWRetire', 'medFamInc', 'perCapInc', 'whitePerCap', 'blackPerCap', 'indianP
                  'AsianPerCap', 'OtherPerCap', 'HispPerCap', 'NumUnderPov', 'PctPopUnderPov',
                  'PctLess9thGrade', 'PctNotHSGrad', 'PctBSorMore', 'PctUnemployed', 'PctEmploy'
                  'PctEmplManu', 'PctEmplProfServ', 'PctOccupManu', 'PctOccupMgmtProf', 'MalePct
```

```
'MalePctNevMarr', 'FemalePctDiv', 'TotalPctDiv', 'PersPerFam', 'PctFam2Par',
'PctKids2Par', 'PctYoungKids2Par', 'PctTeen2Par', 'PctWorkMomYoungKids', 'PctW
'NumIlleg', 'PctIlleg', 'NumImmig', 'PctImmigRecent', 'PctImmigRec5', 'PctImmi
'PctImmigRec10', 'PctRecentImmig', 'PctRecImmig5', 'PctRecImmig8', 'PctRecImmi
'PctSpeakEnglOnly', 'PctNotSpeakEnglWell', 'PctLargHouseFam', 'PctLargHouseOcc
'PersPerOccupHous', 'PersPerOwnOccHous', 'PersPerRentOccHous', 'PctPersOwnOccu
'PctPersDenseHous', 'PctHousLess3BR', 'MedNumBR', 'HousVacant', 'PctHousOccup'
'PctHousOwnOcc', 'PctVacantBoarded', 'PctVacMore6Mos', 'MedYrHousBuilt',
'PctHousNoPhone', 'PctWOFullPlumb', 'OwnOccLowQuart', 'OwnOccMedVal',
'OwnOccHiQuart', 'RentLowQ', 'RentMedian', 'RentHighQ', 'MedRent',
'MedRentPctHousInc', 'MedOwnCostPctInc', 'MedOwnCostPctIncNoMtg',
'NumInShelters', 'NumStreet', 'PctForeignBorn', 'PctBornSameState',
'PctSameHouse85', 'PctSameCity85', 'PctSameState85', 'LemasSwornFT',
'LemasSwFTPerPop', 'LemasSwFTFieldOps', 'LemasSwFTFieldPerPop', 'LemasTotalReq
'LemasTotReqPerPop', 'PolicReqPerOffic', 'PolicPerPop', 'RacialMatchCommPol',
'PctPolicWhite', 'PctPolicBlack', 'PctPolicHisp', 'PctPolicAsian', 'PctPolicMi
'OfficAssgnDrugUnits', 'NumKindsDrugsSeiz', 'PolicAveOTWorked', 'LandArea',
'PopDens', 'PctUsePubTrans', 'PolicCars', 'PolicOperBudg', 'LemasPctPolicOnPat
'LemasGangUnitDeploy', 'LemasPctOfficDrugUn', 'PolicBudgPerPop',
'ViolentCrimesPerPop']

# Load the data
df = pd.read_csv("http://archive.ics.uci.edu/ml/machine-learning-databases/communities/
                 delim_whitespace=False, na_values='?', names=names)
```

Attribute Information: (122 predictive, 5 non-predictive, 1 goal)

First 5 attributes are not predictive, so we start from the 6th to the 122nd attribute. The last one is goal.

As we can see, there are NaN values in the data. We just fill the empty blocks with mean value of that column.

```
In [155]: df.head(6)
```

```
Out[155]:    state  county  community       communityname  fold  population  \
          0      8     NaN        NaN         Lakewoodcity     1        0.19
          1     53     NaN        NaN          Tukwilacity     1        0.00
          2     24     NaN        NaN         Aberdeentown     1        0.00
          3     34     5.0    81440.0  Willingborotownship     1        0.04
          4     42    95.0     6096.0    Bethlehemtownship     1        0.01
          5      6     NaN        NaN    SouthPasadenacity     1        0.02

             householdsize  racepctblack  racePctWhite  racePctAsian  \
          0           0.33          0.02          0.90          0.12
          1           0.16          0.12          0.74          0.45
          2           0.42          0.49          0.56          0.17
          3           0.77          1.00          0.08          0.12
          4           0.55          0.02          0.95          0.09
          5           0.28          0.06          0.54          1.00
```

```
         ...           LandArea  PopDens  PctUsePubTrans  PolicCars  \
0        ...               0.12     0.26            0.20       0.06
1        ...               0.02     0.12            0.45        NaN
2        ...               0.01     0.21            0.02        NaN
3        ...               0.02     0.39            0.28        NaN
4        ...               0.04     0.09            0.02        NaN
5        ...               0.01     0.58            0.10        NaN

  PolicOperBudg  LemasPctPolicOnPatr  LemasGangUnitDeploy  \
0          0.04                  0.9                  0.5
1           NaN                  NaN                  NaN
2           NaN                  NaN                  NaN
3           NaN                  NaN                  NaN
4           NaN                  NaN                  NaN
5           NaN                  NaN                  NaN

  LemasPctOfficDrugUn  PolicBudgPerPop  ViolentCrimesPerPop
0                0.32             0.14                 0.20
1                0.00              NaN                 0.67
2                0.00              NaN                 0.43
3                0.00              NaN                 0.12
4                0.00              NaN                 0.03
5                0.00              NaN                 0.14

[6 rows x 128 columns]
```

In [91]:
```
# goal
y = df['ViolentCrimesPerPop']
# 122 predictive attributes
X = df.loc[:, 'population': 'PolicBudgPerPop'].fillna(df.mean()).values
# First 5 not predictive attributes
X_info = df.loc[:, 'state']
```

1.3 L1 Regularization

We first calculate the RSS of linear regression with different alphas. We use the range from log-5 to 0.1. K fold cross validation is used to get a accurate result of the RSS.

In [92]:
```
import sklearn.model_selection

# kfold
nfold = 10
kf = sklearn.model_selection.KFold(n_splits=nfold, shuffle=True)

# alpha value from 10**-5 to 10**-1, 10 samples
nalpha = 50
alpha_test = np.logspace(-5, -1, nalpha)
```

```
# create linear regression model with L1 regulation
reg = linear_model.Lasso(warm_start=True)

# define RSS
RSS = np.zeros((nalpha, nfold))

for isplit, Ind in enumerate(kf.split(X)):
    print("fold = %d" % isplit)
    Itr, Its = Ind
    Xtr = X[Itr, :]
    ytr = y[Itr]
    Xts = X[Its, :]
    yts = y[Its]
    for it, a in enumerate(alpha_test):
        reg.alpha = a
        reg.fit(Xtr, ytr);
        yhat = reg.predict(Xts)
        RSS[it, isplit] = np.mean((yhat - yts) ** 2)
```

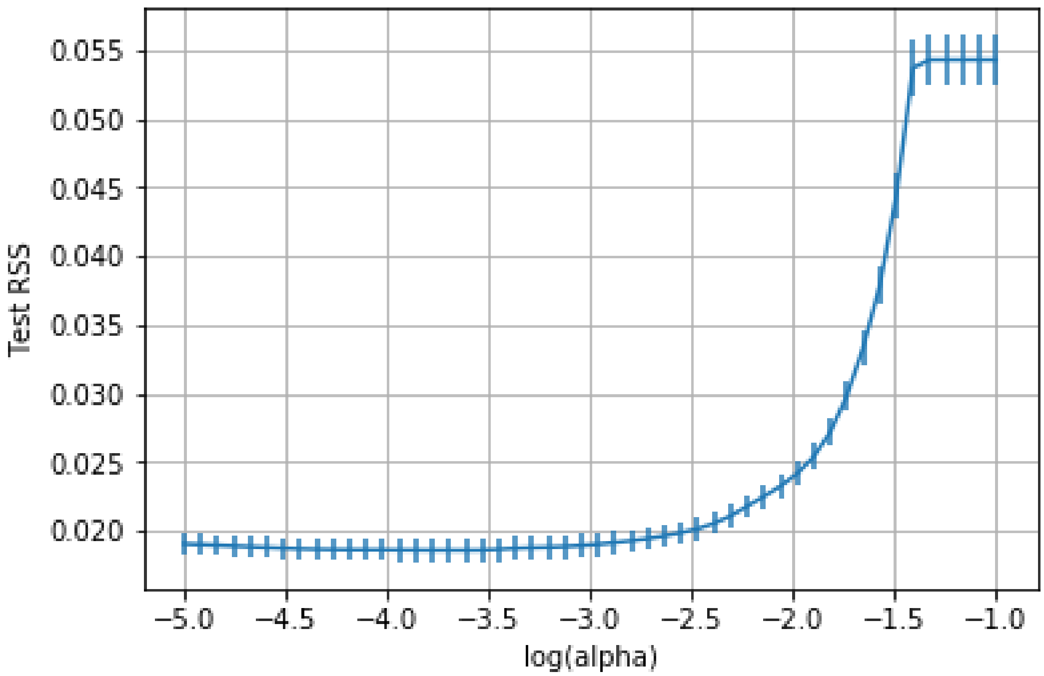
```
fold = 0
fold = 1
fold = 2
fold = 3
fold = 4
fold = 5
fold = 6
fold = 7
fold = 8
fold = 9
```

1.3.1 1 Standard Error Rule

Plot the RSS with respect to different alpha. And we calculate the standard deviation of RSS for next step to apply 1 SE rule. As we can see, the lowest RSS is in the middle of the range.

In [93]:
```
# mean RSS with respect to 10 fold
RSS_mean = np.mean(RSS, axis=1)
# standard error
RSS_std = np.std(RSS, axis=1) / np.sqrt(nfold)
# Plot the graph
plt.errorbar(np.log10(alpha_test), RSS_mean, yerr=RSS_std)
plt.grid()
plt.xlabel('log(alpha)')
plt.ylabel('Test RSS')
```

Out[93]:
```
Text(0,0.5,'Test RSS')
```



To simplify the model while retain as much attributes, 1 SE rule is applied. And we can get the optimal alpha value and its corresponding RSS.

In [94]:
```
# index of least RSS
imin = np.argmin(RSS_mean)
# least RSS
alpha_min = alpha_test[imin]
# 1 standard deviation rule
RSS_tgt = RSS_mean[imin] + RSS_std[imin]
iopt = np.where(RSS_mean <= RSS_tgt)[0][-1]
alpha_opt = alpha_test[iopt]

print("The optimal alpha = %12.4e" % alpha_opt)
print("Mean test RSS = %f" % RSS_mean[iopt])
```

```
The optimal alpha =   1.9307e-03
Mean test RSS = 0.019412
```

Do the model fitting using the optimal alpha we get in previous step, and print out the attribute names whose coefficient is not zero. These attributes have a more influential to the predictable goal attribute.

In [95]:
```
# try model fitting using optimal alpha
model = linear_model.Lasso(alpha=alpha_opt, warm_start=True)
model.fit(X, y)
```

```
# print the attributes whose coefficient is not 0
coef = model.coef_
# index is extracted from the 6th attributes, so +5
l1_coe = np.where(coef != 0)[0] + 5
related_para = df.columns[l1_coe]
nn_in = related_para.size
print(related_para)
```

```
Index(['racepctblack', 'racePctWhite', 'pctUrban', 'MalePctDivorce',
       'PctKids2Par', 'PctWorkMom', 'PctIlleg', 'PctPersDenseHous',
       'HousVacant', 'PctHousOccup', 'PctVacantBoarded', 'NumStreet',
       'LemasPctOfficDrugUn'],
      dtype='object')
```

Sort the dominant attributes by its coefficient values, we get a rank of these attributes from the lowest influence to the highest.

```
In [129]: ind = np.argsort(np.abs(coef[l1_coe-5]))
          related_para[ind]
          #np.sort(np.abs(coef[l1_coe-5]))
```

```
Out[129]: Index(['NumStreet', 'LemasPctOfficDrugUn', 'PctVacantBoarded', 'PctWorkMom',
                 'PctHousOccup', 'pctUrban', 'racepctblack', 'PctPersDenseHous',
                 'MalePctDivorce', 'HousVacant', 'racePctWhite', 'PctIlleg',
                 'PctKids2Par'],
                dtype='object')
```

1.4 SVR and Linear Regression

We do linear regression, support vector regressionon and nueral network one by one on the whole data set with the selected attributes.

```
In [12]: # Assign the data of dominant attributes into X and the goal attribute in y. X_info is
         # first 5 unpredictive attributes.
         X = np.array(df[related_para])
         X_info = np.array(X_info)
         y = np.array(y)

         # Doing linear regression and print out the total loss
         linear = linear_model.LinearRegression()
         linear.fit(X, y)
         y_pre_linear = linear.predict(X)
         loss_linear = np.mean((y_pre_linear - y) ** 2)
         print("Loss of linear regression is {}. ".format(loss_linear))

         # Doing support vector regression
         from sklearn import svm
```

```
# Calculate for optimal C
C_range = np.linspace(10, 50, 100)
C_loss = []
for c in C_range:
    svr = svm.SVR(C=c)
    svr.fit(X, y)
    y_pre_svr = svr.predict(X)
    loss_svr = np.mean((y_pre_svr - y) ** 2)
    C_loss.append(loss_svr)

c_arg_min = np.argmin(C_loss)
C_opt = C_range[c_arg_min]

# Run support vector regression with the optimal c and print the loss
svr = svm.SVR(C=C_opt)
svr.fit(X, y)
y_pre_svr = svr.predict(X)
loss_svr = np.mean((y_pre_svr - y) ** 2)
print("Loss of SVM is {}".format(loss_svr))
```

```
Loss of linear regression is 0.018421184024430454.
Loss of SVM is 0.015925207413192612
```

1.5 2 Layers Neural Network

We use keras with tensorflow as backend to do neural network. There are 2 layers in the model, one hidden layer and one output layer. The output number of the hidden layer is the same as the input. And in the output layer, there is only one output.

```
In [16]: import keras
         from keras.models import Sequential
         from keras.layers import Dense

         nin = related_para.shape[0]
         model = Sequential()
         model.add(Dense(nin, input_dim=nin, kernel_initializer='normal', activation='relu'))
         model.add(Dense(1, kernel_initializer='normal'))
         # Compile model
         model.compile(loss='mean_squared_error', optimizer='adam')
```

```
In [46]: for step in range(5001):
             cost = model.train_on_batch(X, y)
             if step % 500 == 0:
                 print("After %d trainings, the cost: %f" % (step, cost))
```

```
After 0 trainings, the cost: 0.013871
After 500 trainings, the cost: 0.013869
After 1000 trainings, the cost: 0.013869
```

```
After 1500 trainings, the cost: 0.013874
After 2000 trainings, the cost: 0.013873
After 2500 trainings, the cost: 0.013868
After 3000 trainings, the cost: 0.013867
After 3500 trainings, the cost: 0.013876
After 4000 trainings, the cost: 0.013867
After 4500 trainings, the cost: 0.013872
After 5000 trainings, the cost: 0.013867
```

```
In [127]: # Print the loss of nn
          y_pre_nn = model.predict(X)
          print(np.mean((y_pre_nn - y)**2))
```

```
0.019101400758822194
```

1.6 Visualization of the Results

To visualize the predict value of each model, we export the results to a 'csv' file and plot the figure in our web page.

```
In [137]: # Generate predict data and actual data refer to state
          import warnings
          import csv
          warnings.filterwarnings("ignore")
          index = ['state', 'population']
          Loop = ['sample', 'linear', 'svr', 'nn']
          filename = 'y_data.json'
          for s in Loop:
              data = df[index]
              if (s == 'linear'):
                  filename = 'y_data_linear.csv'
                  data.loc[:, 'ViolentCrimesPerPop'] = pd.Series(y_pre_linear, index=df.index).v
                  data['ViolentCrimesPerPop'] = data['ViolentCrimesPerPop'] * data['population']
              elif (s == 'svr'):
                  filename = 'y_data_svr.csv'
                  data.loc[:, 'ViolentCrimesPerPop'] = pd.Series(y_pre_svr, index=df.index).valu
                  data['ViolentCrimesPerPop'] = data['ViolentCrimesPerPop'] * data['population']
              elif (s == 'nn'):
                  filename = 'y_data_nn.csv'
                  data.loc[:, 'ViolentCrimesPerPop'] = pd.Series(y_pre_nn, index=df.index).value
                  data['ViolentCrimesPerPop'] = data['ViolentCrimesPerPop'] * data['population']
              else:
                  filename = 'y_data.csv'
                  data.loc[:, 'ViolentCrimesPerPop'] = df['ViolentCrimesPerPop'] * df['populatio
              data = data.groupby(['state']).sum()
              data['ViolentCrimesPerPop'] = data['ViolentCrimesPerPop'] / data['population']
              data = data[['ViolentCrimesPerPop']]
```

```
data['state'] = data.index
data = data[['state', 'ViolentCrimesPerPop']]
y_out = data.to_csv(sep = ' ', header = False, index = False)
with open(filename,'w') as file:
    for lines in y_out:
        file.write(lines)
```

1.7 Reference

U. S. Department of Commerce, Bureau of the Census, Census Of Population And Housing 1990 United States: Summary Tape File 1a & 3a (Computer Files),

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