Monday, April 11, 2016

Running a Lasso Regression Analysis

Running a Lasso Regression Analysis

`Author: Samuel M.H. <samuel.mh@gmail.com> Date: 04-03-2016`

Instructions

This week's assignment involves running a lasso regression analysis. Lasso regression analysis is a shrinkage and variable selection method for linear regressior models. The goal of lasso regression is to obtain the subset of predictors that minimizes prediction error for a quantitative response variable. The lasso does this b imposing a constraint on the model parameters that causes regression coefficients for some variables to shrink toward zero. Variables with a regression coefficien equal to zero after the shrinkage process are excluded from the model. Variables with non-zero regression coefficients variables are most strongly associated witl the response variable. Explanatory variables can be either quantitative, categorical or both.

Your assignment is to run a lasso regression analysis using k-fold cross validation to identify a subset of predictors from a larger pool of predictor variables that be predicts a quantitative response variable.

What to Submit

Following completion of the steps described above, create a blog entry where you submit syntax used to run a lasso regression (copied and pasted from your program) along with corresponding output and a brief written summary. Please note that your reviewers should NOT be required to download any files in order to complete the review.

If your data set has a relatively small number of observations, you do not need to split into training and test data sets. You can provide your rationale for not splittir your data set in your written summary.

Intro

This week I will try to explain the average daily volume of ethanol consumed per person in past year with a LASSO regression model.

Dataset

- National Epidemiological Survey on Alcohol and Related Conditions (NESARC)
- CSV file (https://d396qusza40orc.cloudfront.net/phoenixassets/data-management-visualization/nesarc_pds.csv)
- File description (https://d396qusza40orc.cloudfront.net/phoenixassets/data-management-visualization/NESARC%20Wave%201%20Code%20Book%20w%20toc.pdf)

Variables

- **Response**:
  - ETOTLCA2 -> ETHANOL: average daily volume of ethanol consumed in past year (ounces).
- **Explanatory**:
  - AGE -> AGE: age (years).
  - S1Q24LB -> WEIGHT: weight (pounds).
  - NUMPERS -> HOUSE_PEOPLE: number of persons in household.
  - S1Q4A -> MARRAIGE: age at first marriage (years).
  - S1Q8D -> WORK: age when first worked full time, 30+ hours a week (years).
  - S1Q12A -> INCOME: total household income in last 12 months (dolars).
  - SEX -> MALE: gender (2 groups).
  - S10Q1A63 -> CHANGE_MIND: change mind about things depending on people you're with or what read or saw on tv (2 groups).

All used variables are quantitative.

In [16]:

```
%pylab inline

import numpy as np
import pandas as pd

from sklearn.cross_validation import train_test_split
import sklearn.metrics
from sklearn.linear_model import LassoLarsCV

#Visualization
import matplotlib.pylab as plt
import seaborn as sns

pylab.rcParams['figure.figsize'] = (15, 8)
```

```
Populating the interactive namespace from numpy and matplotlib
```

```
WARNING: pylab import has clobbered these variables: ['plt']
`%matplotlib` prevents importing * from pylab and numpy
```

Data

In [2]:

```
# Load data
data = pd.read_csv('../datasets/NESARC/nesarc_pds.csv', usecols=['ETOTLCA2','AGE','S1Q24LB','NUMPERS','S1Q4A','S1Q8D','S1Q12A','SEX','S10Q1
A63'])
```

In [17]:

```
# Custom dataframe
df = pd.DataFrame()

# Response variable
df['ETHANOL'] = data['ETOTLCA2'].replace(' ',np.NaN).astype(float)

# Explanatory variables
df['AGE'] = data['AGE'].replace(' ',np.NaN).replace('98',np.NaN).astype(float)
df['WEIGHT'] = data['S1Q24LB'].replace(' ',np.NaN).replace('999',np.NaN).astype(float)
df['HOUSE_PEOPLE'] = data['NUMPERS'].replace(' ',np.NaN).astype(float)
df['MARRIAGE'] = data['S1Q4A'].replace(' ',np.NaN).replace('99',np.NaN).astype(float)
df['WORK'] = data['S1Q8D'].replace(' ',np.NaN).replace('99',np.NaN).replace('0',np.NaN).astype(float)
df['INCOME'] = data['S1Q12A'].replace(' ',np.NaN).astype(float)
df['MALE'] = data['SEX'].replace(' ',np.NaN).replace('2','0').astype(float)
df['CHANGE_MIND'] = data['S10Q1A63'].replace(' ',np.NaN).replace('9',np.NaN).replace('2','0').astype(float)

df = df.dropna()
df.describe()
```

Out[17]:

	ETHANOL	AGE	WEIGHT	HOUSE_PEOPLE	MARRIAGE	WORK	INCOME	MALE	CHANGE_MIND
count	15307.000000	15307.000000	15307.000000	15307.000000	15307.000000	15307.000000	15307.000000	15307.000000	15307.000000
mean	0.490314	45.146338	174.669628	2.736199	23.537532	19.021297	62375.538642	0.503234	0.148559
std	1.211545	13.486408	40.473162	1.422247	5.078884	4.496707	70392.218489	0.500006	0.355665
min	0.000300	18.000000	78.000000	1.000000	14.000000	5.000000	24.000000	0.000000	0.000000
25%	0.016800	35.000000	145.000000	2.000000	20.000000	17.000000	29999.000000	0.000000	0.000000
50%	0.103700	43.000000	170.000000	2.000000	23.000000	18.000000	50000.000000	1.000000	0.000000
75%	0.475450	54.000000	198.500000	4.000000	26.000000	21.000000	76000.000000	1.000000	0.000000
max	29.676500	94.000000	450.000000	13.000000	63.000000	71.000000	3000000.000000	1.000000	1.000000

In [4]:

```
TARGET = 'ETHANOL'
PREDICTORS = list(df.columns)
PREDICTORS.remove(TARGET)

df_target = df[TARGET]
df_predictors = pd.DataFrame()
```

Standardize predictors

- 0 Mean
- 1 Standadrd deviation

In [5]:

```
for predictor in PREDICTORS:
    pred_data = df[predictor]
    df_predictors[predictor] = (df[predictor] - df[predictor].mean()) / df[predictor].std()
```

In [6]:

```
df_predictors.describe()
```

Out[6]:

	AGE	WEIGHT	HOUSE_PEOPLE	MARRIAGE	WORK	INCOME	MALE	CHANGE_MIND
count	1.530700e+04	1.530700e+04	1.530700e+04	1.530700e+04	1.530700e+04	1.530700e+04	1.530700e+04	1.530700e+04
mean	-1.290461e-16	-5.756014e-17	-6.127369e-17	1.559694e-16	-8.541181e-17	-1.114067e-17	7.519953e-17	4.270591e-17
std	1.000000e+00	1.000000e+00	1.000000e+00	1.000000e+00	1.000000e+00	1.000000e+00	1.000000e+00	1.000000e+00
min	-2.012866e+00	-2.388487e+00	-1.220744e+00	-1.877880e+00	-3.118126e+00	-8.857732e-01	-1.006456e+00	-4.176946e-01
25%	-7.523381e-01	-7.330692e-01	-5.176310e-01	-6.965176e-01	-4.495061e-01	-4.599449e-01	-1.006456e+00	-4.176946e-01
50%	-1.591483e-01	-1.153759e-01	-5.176310e-01	-1.058366e-01	-2.271212e-01	-1.758083e-01	9.935207e-01	-4.176946e-01
75%	6.564878e-01	5.887944e-01	8.885945e-01	4.848444e-01	4.400337e-01	1.935507e-01	9.935207e-01	-4.176946e-01
max	3.622437e+00	6.802789e+00	7.216609e+00	7.769910e+00	1.155928e+01	4.173223e+01	9.935207e-01	2.393937e+00

Split: train, test

In [7]:

```
train_target, test_target, train_predictors, test_predictors = train_test_split(df_target, df_predictors, test_size=0.3, random_state=42)

print('Samples train: {0}'.format(len(train_target)))
print('Samples test:  {0}'.format(len(test_target)))
```

```
Samples train: 10714
Samples test:  4593
```

Model

In [8]:

```
model1 = LassoLarsCV(cv=10,precompute=False)
model1.fit(train_predictors, train_target)
```

Out[8]:

```
LassoLarsCV(copy_X=True, cv=10, eps=2.2204460492503131e-16,
      fit_intercept=True, max_iter=500, max_n_alphas=1000, n_jobs=1,
      normalize=True, positive=False, precompute=False, verbose=False)
```

In [9]:

```
print('Alpha parameter: {0}'.format(model1.alpha))
```

```
Alpha parameter: 0.0
```

Regression coeficients

In [10]:

```
coefs = zip(df_predictors.columns,model1.coef_)
coefs.sort(key=lambda x: abs(x[1]), reverse=True)
print '\n'.join( '{0}: {1}'.format(var,coef) for var,coef in coefs)
```

```
MALE: 0.25510029979
HOUSE_PEOPLE: -0.0664057742071
CHANGE_MIND: 0.0554624412918
WEIGHT: -0.0550868686148
WORK: -0.0437114356411
AGE: -0.0349338129742
MARRIAGE: -0.0195949134257
INCOME: -0.0138293582608
```

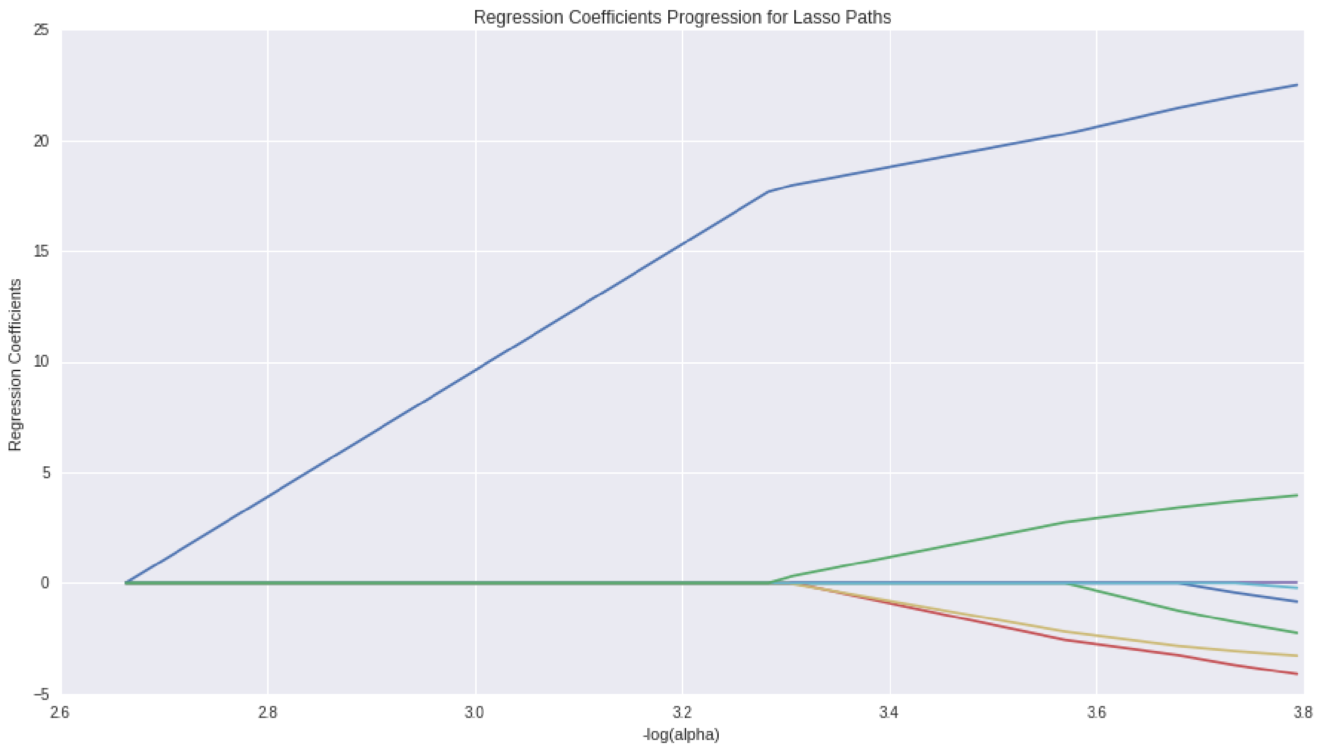
Plots

In [11]:

```
# plot coefficient progression
m_log_alphas = -np.log10(model1.alphas_)
ax = plt.gca()
plt.plot(m_log_alphas, model1.coef_path_.T)
plt.axvline(-np.log10(model1.alpha_), linestyle='--', color='k',label='alpha CV')
plt.ylabel('Regression Coefficients')
plt.xlabel('-log(alpha)')
plt.title('Regression Coefficients Progression for Lasso Paths')
```

Out[11]:

```
<matplotlib.text.Text at 0x7fc86aa34550>
```

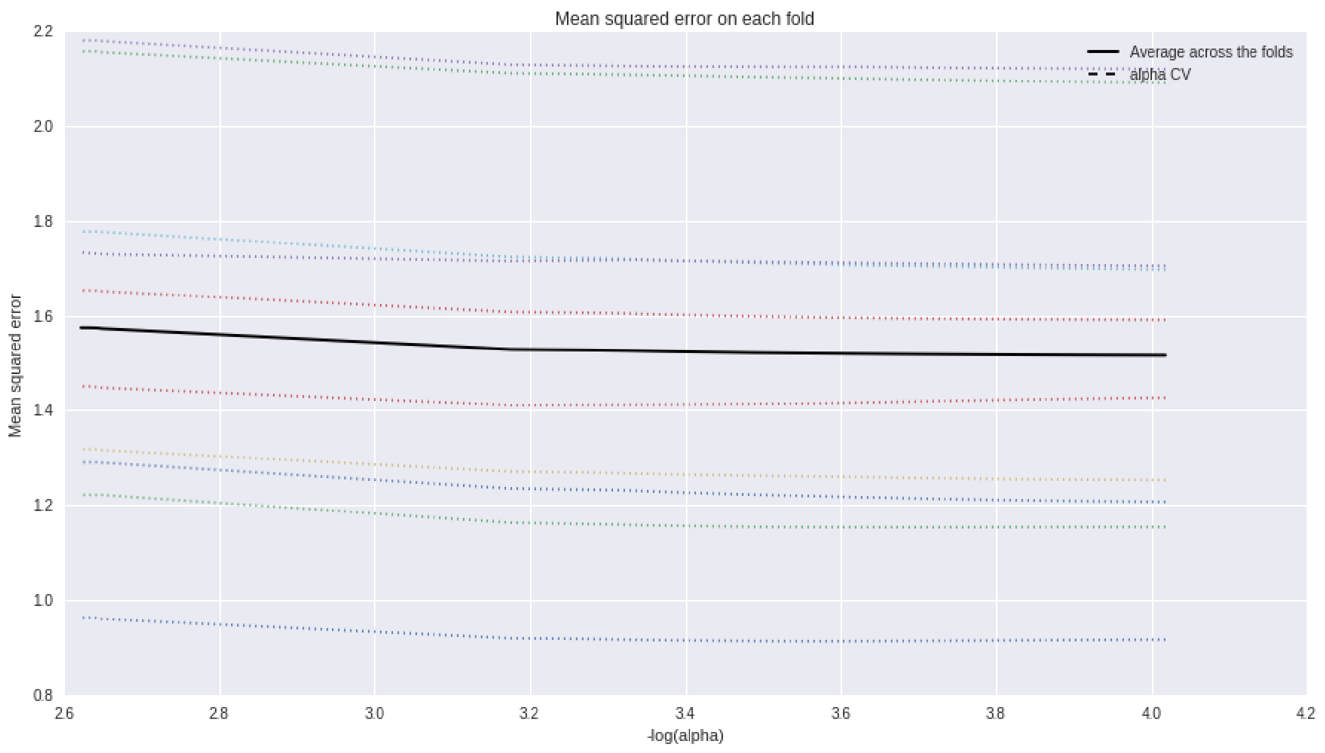


In [12]:

```
# plot mean square error for each fold
m_log_alphascv = -np.log10(model1.cv_alphas_)
plt.figure()
plt.plot(m_log_alphascv, model1.cv_mse_path_, ':')
plt.plot(m_log_alphascv, model1.cv_mse_path_.mean(axis=-1), 'k', label='Average across the folds', linewidth=2)
plt.axvline(-np.log10(model1.alpha_), linestyle='--', color='k', label='alpha CV')
plt.legend()
plt.xlabel('-log(alpha)')
plt.ylabel('Mean squared error')
plt.title('Mean squared error on each fold')
```

Out[12]:

```
<matplotlib.text.Text at 0x7fc86a8669d0>
```



Metrics

In [13]:

```
# MSE from training and test data
print ('MSE training: {0}'.format(sklearn.metrics.mean_squared_error(train_target, model1.predict(train_predictors))))
print ('MSE testing: {0}'.format(sklearn.metrics.mean_squared_error(test_target, model1.predict(test_predictors))))
```

```
MSE training: 1.51194970787
MSE testing: 1.15947090575
```

In [14]:

```
# R-square from training and test data
print ('R-square training: {0}'.format(model1.score(train_predictors,train_target)))
print ('R-square testing: {0}'.format(model1.score(test_predictors,test_target)))
```

```
R-square training: 0.0396962849816
R-square testing: 0.048380464543
```

Summary

In this assignment, the LASSO regression hasn't proved to be very valuable as the model can only explain a 4,8% of the variance (R-Squared value). It is surprising this value is higher in the test dataset than in the training one. It happens the same with the Mean Squared Error, it is lower in the testing dataset.

The prediction accuracy is pretty stable as the metric values are similar in training and testing datasets.

The most important variable to predict the alcohol ingest is MALE: 0.25510029979, followed by HOUSE_PEOPLE: -0.0664057742071 CHANGE_MIND: 0.0554624412918, WEIGHT: -0.0550868686148 and WORK: -0.0437114356411. Surprisingly, the income is not as relevant as the others but it is not discarded.

One bad thing about the results is getting an Alpha value of 0, this means no regularization has been done and an Ordinary Least Squares regression has been performed. This can be verified as no predictor has been discarded, every one has a coefficient bigger than one.

The LASSO regression is useful when there are few observations and a large number of predictors so it can be used for dimensionality reduction.

Posted by Samuel M.H. (https://www.blogger.com/profile/04166249124225549843) at 4/11/2016 01:44:00 PM (2016-04-11T13:44:00+02:00) (http://blog.samuelmh.com/2016/04/running-lasso-regression-analysis.html)

No comments:

Post a Comment

(https://www.blogger.com/comment-iframe.g?blogID=2349200133464300003&postID=1436093416831228428&blogspotRpcToken=4792959)

Enter your comment...

Comment as: anusha.mudiy: Sign out

Publish Preview Notify me

Newer Post (http://blog.samuelmh.com/2016/04/running-k-means-cluster-analysis.html) Home (http://blog.samuelmh.com/)
Older Post (http://blog.samuelmh.com/2016/04/running-random-forest.html)

Subscribe to: Post Comments (Atom) (http://blog.samuelmh.com/feeds/1436093416831228428/comments/default)

Blog Archive