Regression

March 24, 2016

```
In [206]: ##importing the required libariries##
          import pandas as pd
          import numpy as np
          import matplotlib.pyplot as plt
          from sklearn import svm
          from sklearn import preprocessing
          from sklearn.cross_validation import train_test_split
          from sklearn.decomposition import PCA
          from sklearn.ensemble.forest import RandomForestRegressor
          from sklearn.cross_validation import cross_val_score
          import operator
          %pylab inline
```

```
Populating the interactive namespace from numpy and matplotlib
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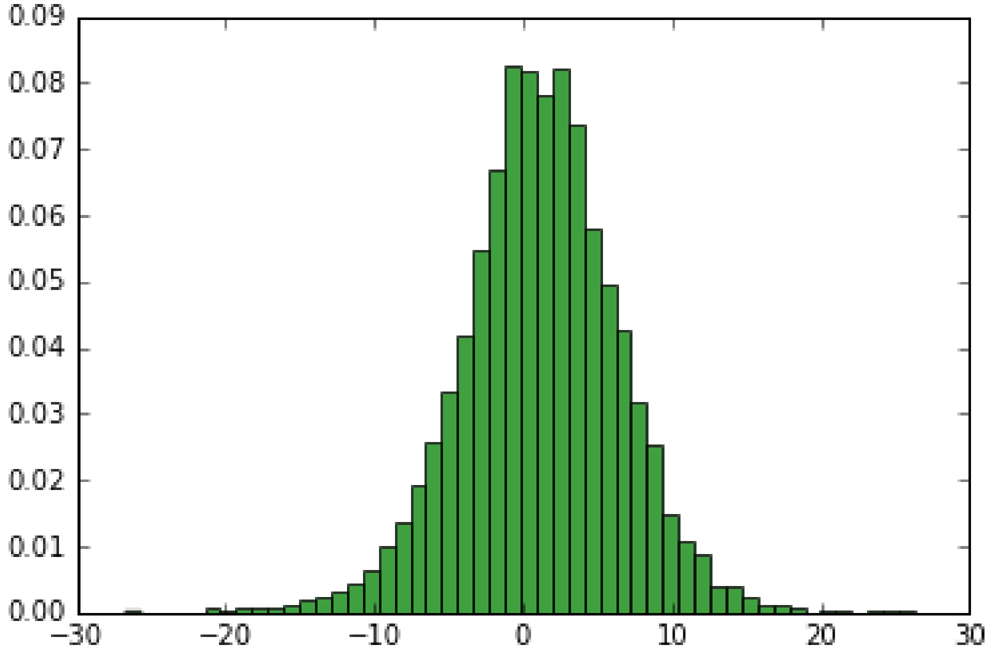
```
In [207]: ##importing the data into a pandas data frame##
          train_DF=pd.read_csv('codetest_train.txt', delimiter='\t')
```

```
In [208]: ##getting the statistics of the target values to get a better feeling of the proper learning
          n, bins, patches = plt.hist(train_DF['target'], 50, normed=1, facecolor='green', alpha=0.75)
          train_DF['target'].describe()
```

```
Out[208]: count    5000.000000
          mean        1.143878
          std         5.259896
          min       -26.705570
          25%        -2.034383
          50%         1.166835
          75%         4.439549
          max        26.347818
          Name: target, dtype: float64
```




```
In [209]: ##splitting the data into train/test set to have a set for performance evaluation##
          X_train, X_test, y_train, y_test = train_test_split(train_DF.iloc[:,1:255], train_DF['target']

In [210]: ##data_refine function will: 1-find the non-numeric columns, 2- fill the NaN in non-numeric c
          #the most used element 3- transform the non-numeric columns to numeric values using LabelEnco
          #from SKLearn, 4- fill the NaN values in the numeric columns using the mean value of them##
          def data_refine(train_DF):
              #1-find the non-numeric columns#
              real_or_str=train_DF.applymap(np.isreal).all(0)
              non_num_feature=real_or_str[~real_or_str].keys()
              le = preprocessing.LabelEncoder()
              for col in non_num_feature:
                  #2- fill the NaN in non-numeric columns with the most used element#
                  train_DF[col].fillna(train_DF[col].describe().top, inplace=True)
                  #3- transform the non-numeric columns to numeric values using LabelEncoder method fro
                  train_DF[col]=le.fit_transform(train_DF[col])
              #4- fill the NaN values in the numeric columns using the mean value of them
              train_DF.fillna(train_DF.mean(), inplace=True)
              return train_DF

          X_train_refined=data_refine(X_train)
          X_test_refined=data_refine(X_test)

In [211]: ##Using a Support Vector Regressor as our learning technique##
          clf = svm.SVR(C=1, epsilon=0.2)
          clf.fit(X_train_refined, y_train)
          print ("MSE on the training set is:\n"), mean_squared_error(y_train, clf.predict(X_train_refi
          print ("MSE on the test set is:\n"), mean_squared_error(y_test, clf.predict(X_test_refined))
```

```
MSE on the training set is:
12.3070075645
```

```
MSE on the test set is:
17.1043249591
```

```
In [212]: ##Using another learning technique (Random Forrest Regressor) on our data##
          rfr = RandomForestRegressor(n_estimators=10, random_state=0)
          rfr.fit(X_train_refined, y_train)
          print ("MSE on the training set is:\n"), mean_squared_error(y_train, rfr.predict(X_train_refi
          print ("MSE on the test set is:\n"), mean_squared_error(y_test, rfr.predict(X_test_refined))
```

```
MSE on the training set is:
2.60464066103
MSE on the test set is:
14.9156790445
```

As we can see, both of these models tend to overfit the training set. Linear Regressors/K Nearest Neighbor/Neural Networks yield the same performance and all tend to overfit as well. We will try two different method to overcome overfitting.

```
1- We will try to use PCA to reduce the number of features
2- We will pick Random Forrest Regressor as our model and using the k-fold cross validation technique f
```

```
In [214]: from sklearn.metrics import mean_squared_error
          ##Trying PCA and reducing the number of features and checking if the performance on the test 
          for n in [50,100,150,200]:
              pca = PCA(n_components=n)
              rfr.fit(pca.fit_transform(X_train_refined),y_train)
              print "With %d features, %f of variance is preserved and the MSE on the test set is %f"\
              %(n, pca.explained_variance_ratio_.sum(), mean_squared_error(y_test, rfr.predict(pca.fit_
```

```
With 50 features, 0.281928 of variance is preserved and the MSE on the test set is 41.294929
With 100 features, 0.509517 of variance is preserved and the MSE on the test set is 41.554494
With 150 features, 0.702944 of variance is preserved and the MSE on the test set is 40.473818
With 200 features, 0.866646 of variance is preserved and the MSE on the test set is 40.398843
```

We can see that almost all of the columns are containing significant amount of variance/data and even using 200 features we are still losing around 15% of the data. Also the performance of our model doesn't improve by using less features and it still overfit. So, next we try to fine tune the parameters of our RFR model using a 5-fold cross-validation

```
In [159]: ##trying different values for n_estimators parameters (number of trees in the forrest) and ev
          #using a 5-folded cross validation on the training set##
          est_list=[10,20,50,100,200]
          score={}
          for est in est_list:
              rfr = RandomForestRegressor(n_estimators=est, random_state=0)
              rfr.fit(X_train_refined, y_train)
              score[est]=cross_val_score(rfr, X_train_refined, y_train, cv=5).mean()
```

```
In [215]: ##finding the optimal value of n_estimators##
          n_est=max(score.iteritems(), key=operator.itemgetter(1))[0]
          print "the optimal value of n_estimators=%d"%(n_est)
```

```
the optimal value of n_estimators=200
```

```
In [216]: ##Using a Random Forest Regressor with the optimal C and epsilon parameters##
          rfr = RandomForestRegressor(n_estimators=n_est, random_state=0)
```

```python
rfr.fit(X_train_refined, y_train)
print ("score on the training set using optimal value of n_estimators is:\n"),\
mean_squared_error(y_train, rfr.predict(X_train_refined))
print ("score on the test set using optimal value of n_estimators is:\n"), \
mean_squared_error(y_test, rfr.predict(X_test_refined))
```

```
score on the training set using optimal value of n_estimators is:
1.74381333677
score on the test set using optimal value of n_estimators is:
13.6636416961
```

As we can see the performance improvement using a larger number of trees was marginal

In [217]:
```python
##predicting the target on the given test set and writing the output into a text file##
final_test_DF=pd.read_csv('codetest_test.txt', delimiter='\t')
X_test_final_refined=data_refine(final_test_DF)
predictions=rfr.predict(X_test_final_refined)
f = open('predicted_target_test.txt', 'w')
for pre in predictions:
    f.writelines(str(pre)+'\n')
f.close()
```