MBA_Demo

February 13, 2019

1 Mini-Batch AUC Optimization (MBA)

A comparison of Mini-Batch AUC Optimization (MBA) with Online Logistic Regression (ONLR) on a sample dataset.

In [1]:
```
import numpy as np
import matplotlib.pyplot as plt
from sklearn.datasets import load_svmlight_file
from sklearn.metrics import roc_auc_score
from tqdm import tqdm
```

In [2]:
```
#load svmguide dataset
#this data has 21 features
train_path, test_path, no_feat = './data/data_train', './data/data_test', 21
X_train, y_train = load_svmlight_file(train_path, no_feat)
X_test, y_test = load_svmlight_file(test_path, no_feat)

X_train = np.asarray( X_train.todense() )
X_test = np.asarray( X_test.todense() )

y_train_01 = .5*(y_train+1)
y_test_01 = .5*(y_test+1)
```

In [3]:
```
#Online logistic regression
class ONLR:
    def __init__(self, no_feat, lam2):
        self.weig = np.zeros(no_feat + 1)
        self.lam2 = lam2
        self.err = []


    def predict(self, x):
        x_aug = np.append(x, 1.0)
        return 1.0 / ( 1.0 + np.exp(-np.dot(self.weig, x_aug)) )


    def update(self, x, y, step_size):
        x_aug = np.append( x , 1.0 ) #add bias term to end
```

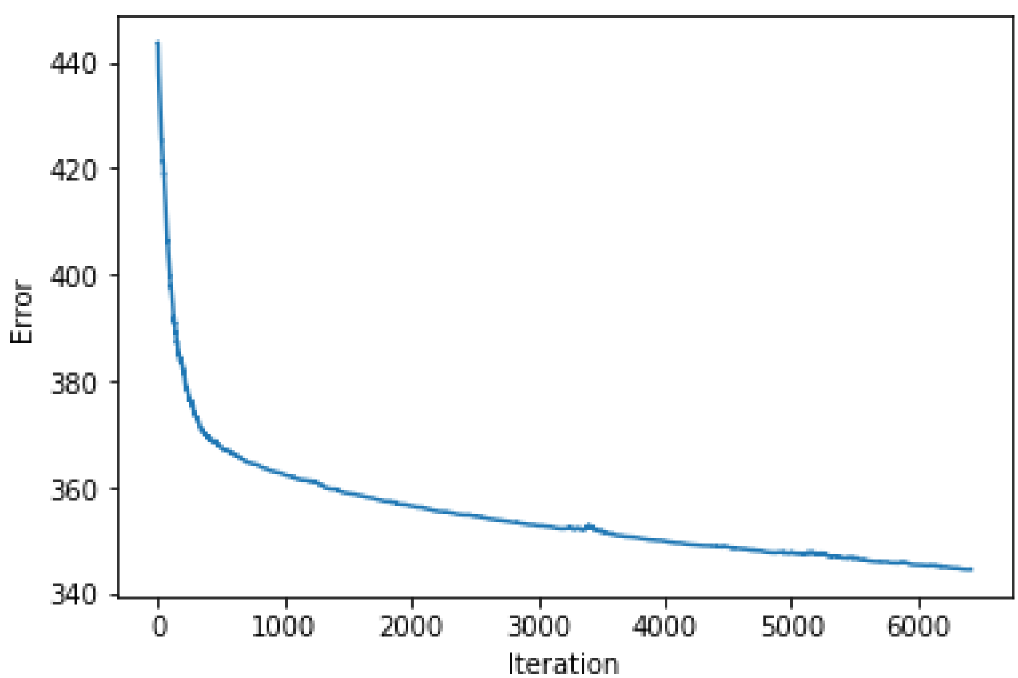
```
            y_hat = self.predict(x)
            grd = (y_hat-y)*x_aug + self.lam2*self.weig
            self.weig = self.weig - step_size*grd


        def rec_err(self, X_train, y_train):
            Xw = X_train.dot(self.weig[:-1]) + self.weig[-1]
            p1, p2 = np.log(1 + np.exp(-Xw)), np.log(1 + np.exp(Xw))
            self.err.append( np.dot(y_train, p1) + np.dot(1-y_train, p2) )
```

```
In [55]: clf = ONLR(no_feat, 1e-4) #L2 regularization set from paper
         #for the best performance use slow learning rate and large number of iterations
         #the problem is convex so there is a unique solution
         step_size = 1e-3
         for i in tqdm(xrange(100*X_train.shape[0])):
             sel = np.random.choice(X_train.shape[0])
             clf.update(X_train[sel,:], y_train_01[sel], step_size)
             if (i+1)%10==0:
                 clf.rec_err(X_train,y_train_01)
```

```
100%|| 64200/64200 [00:02<00:00, 28444.84it/s]
```

```
In [56]: plt.figure()
         plt.plot(clf.err)
         plt.xlabel('Iteration')
         plt.ylabel('Error')
         plt.show()
```



```
In [57]: print('AUC of ONLR')
         y_test_hat = np.array([])
         for i in range(X_test.shape[0]):
             y_test_hat = np.append(y_test_hat, clf.predict(X_test[i,:]))
         print(roc_auc_score(y_test,y_test_hat))
```

```
AUC of Logistic Regression
0.660320002002
```

```
In [128]: #Mini-Batch AUC Optimization

          class MBA:
              def __init__(self, lam2, mb_size, no_iter):
                  self.lam2 = lam2
                  self.mb_size = mb_size
                  self.no_iter = no_iter
                  self.apprx_mean = None
                  self.apprx_cov = None
                  self.weig = None

              def apprx_moments(self, Xp, Xm):
                  apprx_mean = np.zeros(Xp.shape[0])
                  apprx_cov = np.zeros((Xp.shape[0], Xp.shape[0]))
                  for i in xrange(self.no_iter):
                      Xp_sub = Xp[:, np.random.choice(Xp.shape[1], self.mb_size, replace=True)
                      Xm_sub = Xm[:, np.random.choice(Xm.shape[1], self.mb_size, replace=True)
                      Xdif = Xp_sub - Xm_sub
                      apprx_mean = apprx_mean + (1.0/self.mb_size)*np.sum(Xdif, axis=1)
                      apprx_cov = apprx_cov + (1.0/self.mb_size)*np.dot(Xdif,Xdif.T)
                  apprx_mean = (1.0/self.no_iter)*apprx_mean
                  apprx_cov = (1.0/self.no_iter)*apprx_cov
                  self.apprx_mean = apprx_mean
                  self.apprx_cov = apprx_cov


              def train(self, Xp, Xm):
                  self.apprx_moments(Xp, Xm)
                  self.weig = np.linalg.inv(self.lam2*np.eye(self.apprx_cov.shape[0]) + \
                                       self.apprx_cov).dot(self.apprx_mean)


              def predict(self, x):
                  return np.dot(self.weig, x)
```

```
In [132]: #split positive and negative instances
          Xp, Xm = X_train[np.where(y_train > 0)].T, X_train[np.where(y_train < 0)].T
```

```
          clf = MBA(1e-6, X_train.shape[0], 1) #L2 regularization set from paper
          clf.train(Xp, Xm)
```

```
<type 'numpy.ndarray'>
```

```
In [134]: print('AUC of MBA')
          y_test_hat = np.array([])
          for i in range(X_test.shape[0]):
              y_test_hat = np.append(y_test_hat, clf.predict(X_test[i,:]))
          print(roc_auc_score(y_test,y_test_hat))
```

```
AUC of MBA
0.804008156423
```

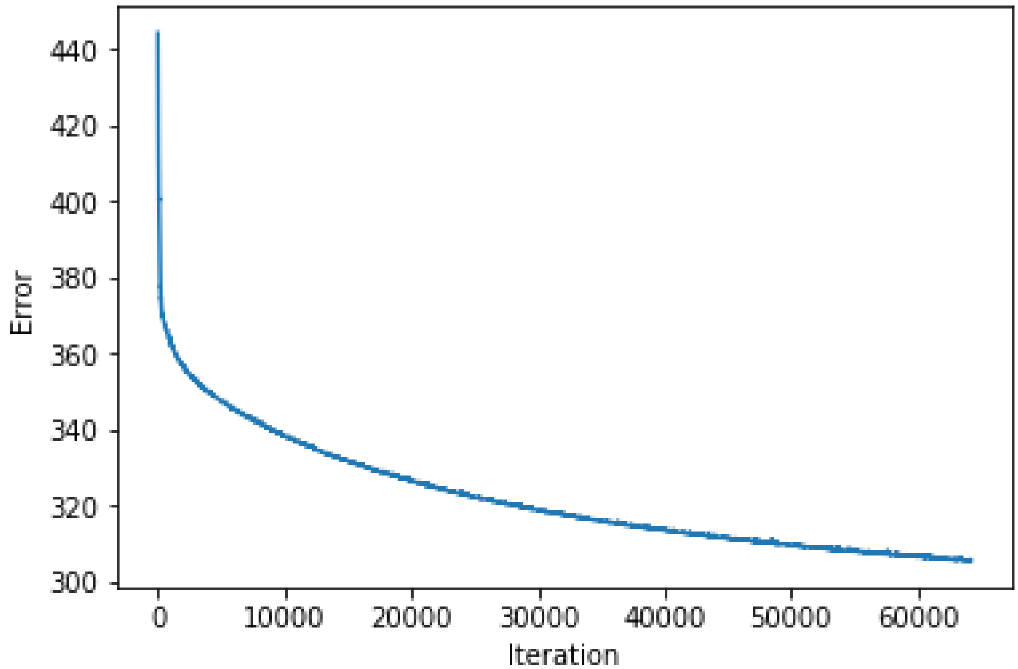
2 Conclusion

- AUC of ONLR = 66 %
- AUC of MBA = 80%
- MBA achieves 14% better AUC compared to ONLR.
- ONLR requires 100 times more samples than MBA to reach 66%.
- ONLR can get competitive performance if we use 1000 more samples!

```
In [135]: #Demo with 1000x samples
          clf = ONLR(no_feat, 1e-4) #L2 regularization set from paper
          #for the best performance use slow learning rate and large number of iterations
          #the problem is convex so there is a unique solution
          step_size = 1e-3
          for i in tqdm(xrange(1000*X_train.shape[0])):
              sel = np.random.choice(X_train.shape[0])
              clf.update(X_train[sel,:], y_train_01[sel], step_size)
              if (i+1)%10==0:
                  clf.rec_err(X_train,y_train_01)
```

```
100%|| 642000/642000 [00:22<00:00, 29169.88it/s]
```

```
In [136]: plt.figure()
          plt.plot(clf.err)
          plt.xlabel('Iteration')
          plt.ylabel('Error')
          plt.show()
```




```
In [137]: print('AUC of ONLR with 1000x Samples')
          y_test_hat = np.array([])
          for i in range(X_test.shape[0]):
              y_test_hat = np.append(y_test_hat, clf.predict(X_test[i,:]))
          print(roc_auc_score(y_test,y_test_hat))
```

```
AUC of ONLR with 1000x Samples
0.781202697124
```