CSE258_HW2

February 5, 2017

1 CSE258 HW2

```
In [1]: import urllib
        import scipy.optimize
        import random
        import numpy
        from math import exp
        from math import log
        import matplotlib.pyplot as plt
        from sklearn.decomposition import PCA
        from sklearn.metrics import mean_squared_error
```

1.0.1 Task 1

After reshuffling the data, the train/validate/test performance are shown below:
lambda = 0; train=0.748774509804; validate=0.757501530925; test=0.738518064911
lambda = 0.01; train=0.748774509804; validate=0.756889161053; test=0.738518064911
lambda = 1.0; train=0.729166666667; validate=0.753827311696; test=0.72933251684
lambda = 100.0; train=0.66237745098; validate=0.681567666871; test=0.680342927128
We see the accuracy for train and validate part increase a little while the test accuracy decreases a little bit

```
In [2]: random.seed(0)

        def parseData(fname):
            for l in urllib.urlopen(fname):
                yield eval(l)

        print "Reading data..."
        dataFile = open("winequality-white.csv")
        header = dataFile.readline()
        fields = ["constant"] + header.strip().replace('"','').split(';')
        featureNames = fields[:-1]
        labelName = fields[-1]
        lines = [[1.0] + [float(x) for x in l.split(';')] for l in dataFile]
        random.shuffle(lines)
        X = [l[:-1] for l in lines]
```

```
y = [l[-1] > 5 for l in lines]
print "done"

def inner(x,y):
    return sum([x[i]*y[i] for i in range(len(x))])

def sigmoid(x):
    return 1.0 / (1 + exp(-x))

##################################################
# Logistic regression by gradient ascent         #
##################################################

# NEGATIVE Log-likelihood
def f(theta, X, y, lam):
    loglikelihood = 0
    for i in range(len(X)):
        logit = inner(X[i], theta)
        loglikelihood -= log(1 + exp(-logit))
        if not y[i]:
            loglikelihood -= logit
    for k in range(len(theta)):
        loglikelihood -= lam * theta[k]*theta[k]
    # for debugging
    # print "ll =", loglikelihood
    return -loglikelihood

# NEGATIVE Derivative of log-likelihood
def fprime(theta, X, y, lam):
    dl = [0]*len(theta)
    for i in range(len(X)):
        logit = inner(X[i], theta)
        for k in range(len(theta)):
            dl[k] += X[i][k] * (1 - sigmoid(logit))
            if not y[i]:
                dl[k] -= X[i][k]
    for k in range(len(theta)):
        dl[k] -= lam*2*theta[k]
    return numpy.array([-x for x in dl])

X_train = X[:int(len(X)/3)]
y_train = y[:int(len(y)/3)]
X_validate = X[int(len(X)/3):int(2*len(X)/3)]
y_validate = y[int(len(y)/3):int(2*len(y)/3)]
X_test = X[int(2*len(X)/3):]
y_test = y[int(2*len(X)/3):]

##################################################
```

```python
# Train                                            #
####################################################

def train(lam):
    theta,_,_ = scipy.optimize.fmin_l_bfgs_b(f, [0]*len(X[0]), fprime, pgtc
    return theta

####################################################
# Predict                                          #
####################################################

def performance(theta):
    scores_train = [inner(theta,x) for x in X_train]
    scores_validate = [inner(theta,x) for x in X_validate]
    scores_test = [inner(theta,x) for x in X_test]

    predictions_train = [s > 0 for s in scores_train]
    predictions_validate = [s > 0 for s in scores_validate]
    predictions_test = [s > 0 for s in scores_test]

    correct_train = [(a==b) for (a,b) in zip(predictions_train,y_train)]
    correct_validate = [(a==b) for (a,b) in zip(predictions_validate,y_vali
    correct_test = [(a==b) for (a,b) in zip(predictions_test,y_test)]

    acc_train = sum(correct_train) * 1.0 / len(correct_train)
    acc_validate = sum(correct_validate) * 1.0 / len(correct_validate)
    acc_test = sum(correct_test) * 1.0 / len(correct_test)
    return acc_train, acc_validate, acc_test

####################################################
# Validation pipeline                              #
####################################################

for lam in [0, 0.01, 1.0, 100.0]:
    theta = train(lam)
    acc_train, acc_validate, acc_test = performance(theta)
    print("lambda = " + str(lam) + ";\ttrain=" + str(acc_train) + "; valida
```

```
Reading data...
done
lambda = 0;         train=0.748774509804; validate=0.757501530925; test=0.73851806649
lambda = 0.01;         train=0.748774509804; validate=0.756889161053; test=0.738518(
lambda = 1.0;         train=0.729166666667; validate=0.753827311696; test=0.72933251
lambda = 100.0;         train=0.66237745098; validate=0.681567666871; test=0.6803429
```

1.0.2 Task 2

The number of
true positives = 1129; true negatives = 145; false positives = 321; false negatives = 38
The Balanced Error Rate is 0.360701663412

In [3]:
```
random.seed(0)

def parseData(fname):
    for l in urllib.urlopen(fname):
        yield eval(l)

print "Reading data..."
dataFile = open("winequality-white.csv")
header = dataFile.readline()
fields = ["constant"] + header.strip().replace('"','').split(';')
featureNames = fields[:-1]
labelName = fields[-1]
lines = [[1.0] + [float(x) for x in l.split(';')] for l in dataFile]
# random.shuffle(lines)
X = [l[:-1] for l in lines]
y = [l[-1] > 5 for l in lines]
print "done"

def inner(x,y):
    return sum([x[i]*y[i] for i in range(len(x))])

def sigmoid(x):
    return 1.0 / (1 + exp(-x))

##################################################
# Logistic regression by gradient ascent         #
##################################################

# NEGATIVE Log-likelihood
def f(theta, X, y, lam):
    loglikelihood = 0
    for i in range(len(X)):
        logit = inner(X[i], theta)
        loglikelihood -= log(1 + exp(-logit))
        if not y[i]:
            loglikelihood -= logit
    for k in range(len(theta)):
        loglikelihood -= lam * theta[k]*theta[k]
    # for debugging
    # print "ll =", loglikelihood
    return -loglikelihood
```

```
# NEGATIVE Derivative of log-likelihood
def fprime(theta, X, y, lam):
    dl = [0]*len(theta)
    for i in range(len(X)):
        logit = inner(X[i], theta)
        for k in range(len(theta)):
            dl[k] += X[i][k] * (1 - sigmoid(logit))
            if not y[i]:
                dl[k] -= X[i][k]
    for k in range(len(theta)):
        dl[k] -= lam*2*theta[k]
    return numpy.array([-x for x in dl])

X_train = X[:int(len(X)/3)]
y_train = y[:int(len(y)/3)]
X_validate = X[int(len(X)/3):int(2*len(X)/3)]
y_validate = y[int(len(y)/3):int(2*len(y)/3)]
X_test = X[int(2*len(X)/3):]
y_test = y[int(2*len(X)/3):]

##################################################
# Train                                          #
##################################################

def train(lam):
    theta,_,_ = scipy.optimize.fmin_l_bfgs_b(f, [0]*len(X[0]), fprime, pgtc
    return theta

##################################################
# Predict                                        #
##################################################

def performance(theta):
    scores_train = [inner(theta,x) for x in X_train]
    scores_validate = [inner(theta,x) for x in X_validate]
    scores_test = [inner(theta,x) for x in X_test]

    predictions_train = [s > 0 for s in scores_train]
    predictions_validate = [s > 0 for s in scores_validate]
    predictions_test = [s > 0 for s in scores_test]

    correct_train = [(a==b) for (a,b) in zip(predictions_train,y_train)]
    correct_validate = [(a==b) for (a,b) in zip(predictions_validate,y_vali
    correct_test = [(a==b) for (a,b) in zip(predictions_test,y_test)]

    acc_train = sum(correct_train) * 1.0 / len(correct_train)
    acc_validate = sum(correct_validate) * 1.0 / len(correct_validate)
    acc_test = sum(correct_test) * 1.0 / len(correct_test)
```

```
        return acc_train, acc_validate, acc_test, predictions_test, scores_test

    ##################################################
    # Validation pipeline                            #
    ##################################################

    # for lam in [0, 0.01, 1.0, 100.0]:
    lam = 0.01
    theta = train(lam)
    acc_train, acc_validate, acc_test, predictions_test, scores_test = performa
    print("lambda = " + str(lam) + ";\ttrain=" + str(acc_train) + "; validate='
```

```
Reading data...
done
lambda = 0.01;        train=0.732230392157; validate=0.721984078383; test=0.7801592
```

```
In [5]: num_TP = sum([(a==1 and b==1) for (a,b) in zip(predictions_test,y_test)])
        num_TN = sum([(a==0 and b==0) for (a,b) in zip(predictions_test,y_test)])
        num_FP = sum([(a==1 and b==0) for (a,b) in zip(predictions_test,y_test)])
        num_FN = sum([(a==0 and b==1) for (a,b) in zip(predictions_test,y_test)])
        BER = 1.0/2 * ((num_FP * 1.0 / (num_FP + num_TN)) + (num_FN * 1.0 / (num_FN
        print("true positives = " + str(num_TP) + ";\ntrue negatives = " + str(num_
              + ";\nfalse positives = " + str(num_FP) + ";\nfalse negatives = " + s
        print("Balanced Error Rate: " + str(BER))
```

```
true positives = 1129;
true negatives = 145;
false positives = 321;
false negatives = 38
Balanced Error Rate: 0.360701663412
```

1.0.3 Task 3

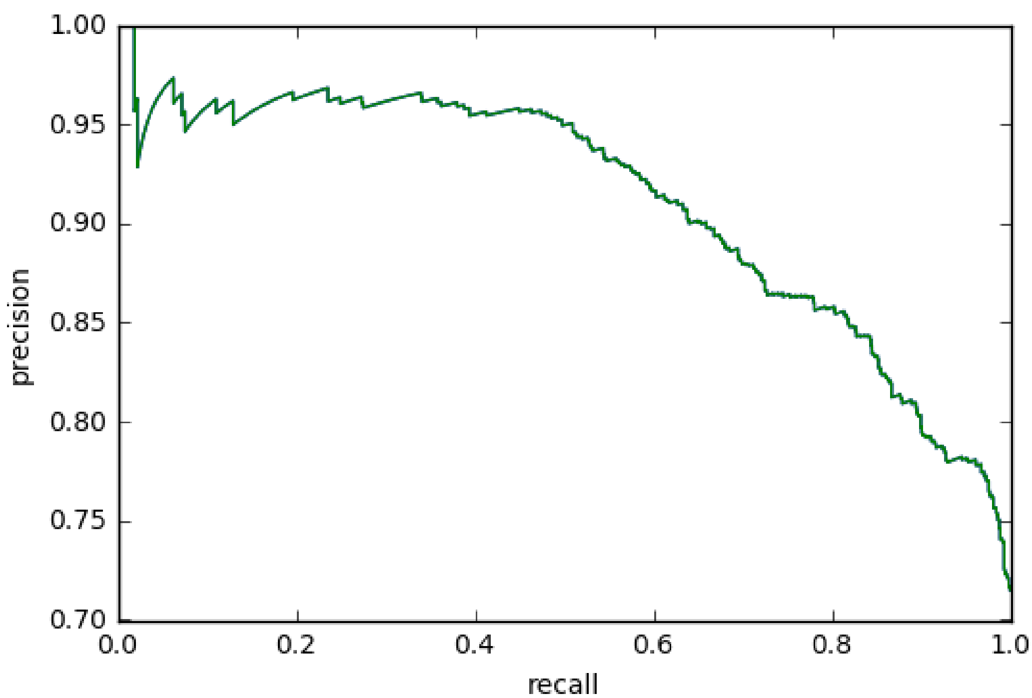
For top 10 predictions, precision = 1.0; recall = 0.00856898029135
For top 500 predictions, precision = 0.956; recall = 0.409597257926
For top 1000 predictions, precision = 0.864; recall = 0.740359897172

```
In [6]: confi_ordered = zip(scores_test, y_test)
        confi_ordered.sort(key = lambda x : x[0], reverse = True)

        for i in [10, 500, 1000]:
            data = confi_ordered[:i]
            trues = filter(lambda x : x[1] == True, data)
            precision = len(trues) * 1.0 / i
            recall = len(trues) * 1.0 / sum(y_test)
            print("For top " + str(i) + " predictions, precision = " + str(precisio
```

```
For top 10 predictions, precision = 1.0; recall = 0.00856898029135
For top 500 predictions, precision = 0.956; recall = 0.409597257926
For top 1000 predictions, precision = 0.864; recall = 0.740359897172
```

1.0.4 Task 4

```
In [8]: Precision = numpy.zeros(len(y_test)-1)
        Recall = numpy.zeros(len(y_test)-1)

        for i in range(1, len(y_test)):
            data = confi_ordered[:i]
            trues = filter(lambda x : x[1] == True, data)
            precision = len(trues) * 1.0 / i
            recall = len(trues) * 1.0 / sum(y_test)
            Precision[i-1] = precision
            Recall[i-1] = recall
        plt.plot(Recall, Precision)
        plt.xlabel("recall")
        plt.ylabel("precision")
        plt.ylim([0.7, 1])
        plt.show()
```



1.0.5 Task 5

The reconstruction error is 3675818.61688

```
In [9]: X_11d = [x[1:] for x in X_train]
        get_mean = numpy.mean(X_11d, axis = 0)
        diff = numpy.array([x - get_mean for x in X_11d])
        recon_error = numpy.sum(diff*diff)
        print "The reconstruction error is ", recon_error
```

```
The reconstruction error is  3675818.61688
```

1.0.6 Task 6

```
In [10]: pca = PCA(n_components = 11)
         pca.fit(X_11d)
         print pca.components_
```

```
[[  3.23636346e-04  -1.42201752e-04  -3.17030713e-04  -5.36390435e-02
   -9.30284526e-05  -2.54030965e-01  -9.65655009e-01  -3.19990241e-05
    2.95831396e-04  -3.84043646e-04   1.00526693e-02]
 [ -7.57985623e-03  -1.66366340e-03   1.04742899e-03   5.21677266e-02
    4.49425600e-05   9.65020304e-01  -2.56793964e-01   7.90089050e-06
    5.24900596e-04  -1.09699394e-03  -2.89827657e-03]
 [  1.82124420e-02   2.54680710e-03   3.31838657e-03   9.93221259e-01
   -1.51888372e-04  -6.42297821e-02  -3.91682592e-02   4.30929482e-04
   -6.93199060e-03  -2.85216045e-03  -8.62920933e-02]
 [ -1.56811999e-01  -3.28220652e-03  -1.66866136e-02  -8.28549640e-02
    6.91822288e-03  -1.13029682e-03  -5.39110108e-03   9.49080503e-04
   -2.68027305e-03  -1.30498102e-03  -9.83955205e-01]
 [ -9.81360642e-01   1.45890108e-02  -5.92643662e-02   3.17546064e-02
   -5.07483182e-04  -8.43759364e-03   1.77578042e-03  -6.03725221e-04
    9.05011239e-02   9.35630845e-03   1.54417839e-01]
 [ -7.76578401e-02   2.37665885e-01  -2.23406619e-02  -5.04113878e-03
    1.43564098e-02   2.14210997e-04   2.22913844e-04  -3.36617054e-03
   -8.77254205e-01  -4.08570175e-01   1.54145486e-02]
 [ -7.36289612e-02  -2.61563804e-01   9.43067566e-01  -2.14514264e-03
    1.19104298e-02  -1.68808905e-03   1.42294158e-04  -1.17203197e-04
   -1.45895558e-01   1.23868963e-01  -2.88797236e-03]
 [  1.37617196e-02  -2.11129619e-01   1.16514121e-01  -5.30670319e-04
   -1.05181628e-02  -1.36446528e-03   8.21179429e-04  -3.09221855e-04
    3.58358431e-01  -9.01728510e-01  -3.27758247e-03]
 [ -1.74575775e-02  -9.10890084e-01  -3.04081497e-01   2.89763923e-03
   -2.34615054e-02  -1.17406025e-03   3.85957239e-04  -1.23176271e-03
   -2.68927937e-01   6.70756658e-02   1.12101920e-02]
 [  2.31513441e-03  -2.38717789e-02  -1.67445603e-02   8.92206499e-04
    9.99462734e-01  -9.81109101e-05  -3.32812875e-05   4.14235255e-03
    1.18483756e-02  -3.51543098e-03   6.92344110e-03]
```

```
[  7.48312160e-04   3.08204153e-04   2.55232500e-04   3.49846801e-04
   4.12943179e-03  -6.96565372e-06   4.16951216e-06  -9.99984215e-01
   3.17948604e-03   1.53436134e-03  -1.10029138e-03]]
```

1.0.7 Task 7

The reconstruction error for 4-dimension PCA is 1345.4755741

It's just the rest of variance we lost when we do 4-dimension PCA. We see the total variance with 4 components is 3674473.1413. Sum of them is just the total variance in 11 dimensions in Task 5.

```
In [11]: print "The reconstruction error for 4-dimension PCA is ", numpy.sum(pca.ex

The reconstruction error for 4-dimension PCA is  1345.4755741


In [12]: pca = PCA(n_components = 4)
         pca.fit(X_11d)
         print numpy.sum(pca.explained_variance_[:])*len(X_train)
         transform = pca.components_

3674473.1413
```

1.0.8 Task 8

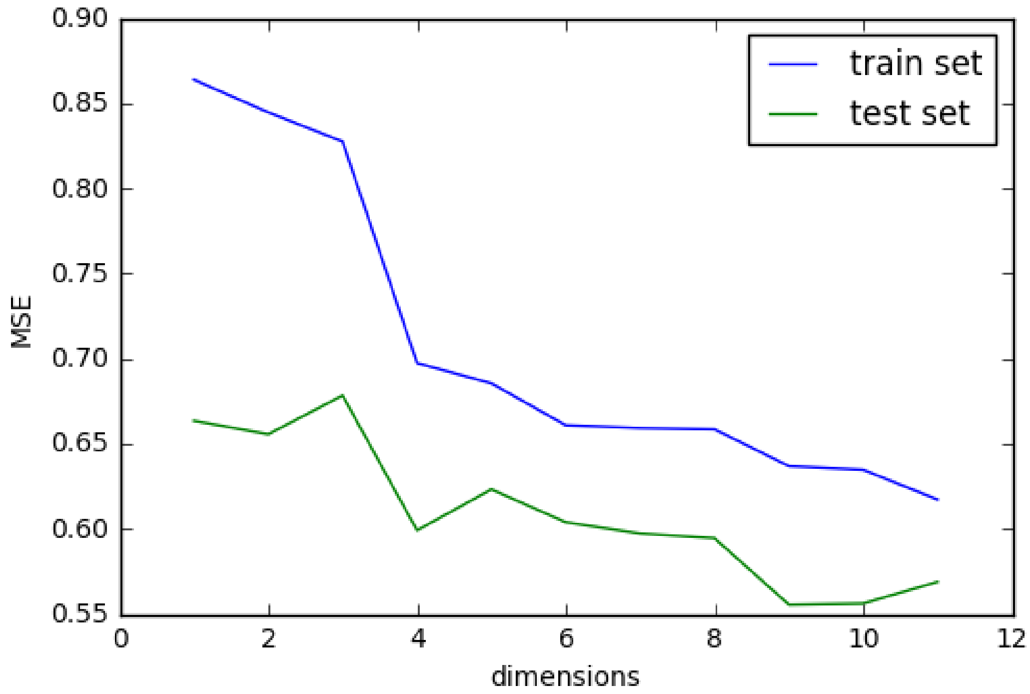
The MSE goes down as more and more dimensions are used

The MSE change on the train set is: [0.86384243973592434, 0.84466943185576071, 0.82751611558520088, 0.69738327887529172, 0.68550155987923889, 0.66085398898873275, 0.65919451154521747, 0.65848602461025896, 0.63685661427823248, 0.63468781914815453, 0.61721175854356825]

THe MSE change on the test set is: [0.66348348996669526, 0.6555874931669381, 0.67835915193077811, 0.59909062198092344, 0.62319815648296806, 0.60387838007105377, 0.5972799592490402, 0.59450622441189893, 0.55550509614578347, 0.55620192020640657, 0.56887177280462198]

```
In [27]: y_train_pca = [l[-1] for l in lines[:int(len(lines)/3)]]
         y_test_pca = [l[-1] for l in lines[int(2*len(lines)/3):]]

In [28]: MSE_train = []
         MSE_test = []
         for i in range(1,12):
             pca = PCA(n_components = i)
             X_deduced = numpy.concatenate((numpy.ones((len(X_train),1)), pca.fit_t
             result = numpy.linalg.lstsq(X_deduced, numpy.array(y_train_pca))
             MSE_train.append(result[1][0] / len(y_train_pca))
             test_deduced = numpy.concatenate((numpy.ones((len(X_test),1)), pca.tra
             MSE_test.append(mean_squared_error(numpy.dot(test_deduced, result[0]),
```

```
In [29]: dim = numpy.arange(1,12,1)
         train, = plt.plot(dim, MSE_train)
         test, = plt.plot(dim, MSE_test)
         plt.xlabel('dimensions')
         plt.ylabel('MSE')
         plt.legend([train, test], ["train set", "test set"])
         plt.show()
```




```
In [30]: print "The MSE change on the train set is: ", MSE_train
         print "THe MSE change on the test set is: ", MSE_test
```

```
The MSE change on the train set is:  [0.86384243973592434, 0.84466943185576071, 0.8
THe MSE change on the test set is:  [0.66348348996669526, 0.6555874931669381, 0.678
```

```
In [ ]:
```