Machine Learning: Mini Project II

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Kernel Perceptron

Description:

Kernelized perceptron (polynomial kernel) using ECOC to classify the mnist dataset.

Notes:

With this algorithm, I've noticed that the # of iterations is quite important. Unfortunately, those iterations ask a lot of computing power, which I do not have available at the time. Below you can see How my algorithm increased after raising the #of iterations.

<u>Training and testing accuracies + confusion matrix:</u>

with # of iterations = 10:

```
Training Accuracy = 71.0%
2522 test case predicted.
1651 are correct.
Testing Accuracy = 65.0%
[[194
       0
            4
                0
                   0
                       0
                            0
                                0
                                  39
                   1
                                0 10 177]
   0
      89
                3
                       0
                            0
            6
        0 224 14
                   0
                       0
                            6
                                1
                                    2
                                        1]
    1
   1
       0
           25 211
                   0
                       1
                            1
                               12
                                    1
                                        2]
       0
          15
                1 129
                       6
                           22
                                3 62
                                       18]
        2
           14
              14
                   32
                       68
                            4
                               22
                                  46
                                       26]
       0
           22
                   1
                       0 208
                                0
                                    1
   4
                0
                                        0]
              65
                       6
                            9 179
                                       14]
   0
       0
                   1
                                    4
       0 43
              8
                   0
                       0
                            1
                                0 168 10]
   0
       0
           4 20
                   0
                       6
                            0
                                4 31 181]]
   0
```

with # of iterations = 30:

```
Training Accuracy = 83.0%
6000 test case predicted.
4732 are correct.
Testing Accuracy = 79.0%
        0
            5
                2
                    1
                        0
                             2
                                0
                                     5
                                         0]
                    0
                                     1
                                        22]
   4 615
            1
               24
                        2
                            1
                                1
   9
        0 499
               53
                    0
                        1
                           12
                                2
                                     5
                                         0]
           14 538
                    0
                        2
                             2
                                     2
                                        19]
   1
        6
                                20
       11
           14
                5 332 111
                            32
                                12
                                    40
                                        43]
  19
  22
       67
               47
                   12 283
                             6
                                45
                                     6
                                        27]
        0
           17
                3
                    4
                        2 563
                                4
                                     2
                                         0]
   8
           11 72
                    6 11
                             9 492
                                     2
                                        13]
            5
               23
                       26
                             0
```

Kernel Perceptron Code:

```
import numpy as np
     from numpy import linalg
     import matplotlib
     import matplotlib.pyplot as plt
     from libsvm.svmutil import svm_read_problem
     from sklearn.model selection import train test split
     from sklearn.metrics import confusion matrix, classification report
     def decToBin(array):
         result = {
11
12
             0: [0, 0, 0, 0],
             1: [0, 0, 0, 1],
13
             2: [0, 0, 1, 0],
             3: [0, 0, 1, 1],
             4: [0, 1, 0, 0],
             5: [0, 1, 0, 1],
             6: [0, 1, 1, 0],
             7: [0, 1, 1, 1],
             8: [1, 0, 0, 0],
21
             9: [1, 0, 0, 1]
         return np.array([result[number] for number in array])
24
     def binToDec(array):
         result = np.array([num[0]*8 + num[1] * 4 + num[2]
                           * 2 + num[3] for num in array])
         if result > 9:
             return np.array([num[0]*0 + num[1] * 4 + num[2]
                              * 2 + num[3] for num in array])
         else:
            return result
34
     def kernel(a, x, z, p, lr):
         result = np.sum(a*(1+(lr*(np.dot(x, z)))**p))
         return result
```

```
class perceptron:
    def __init__(self, learning_rate=0.001, n iters=30):
       self.lr = learning rate
        self.n iters = n iters
       self.weights = None
       self.bias = None
        self.alpha = None
   def fit(self, X, y):
        self.alpha = np.zeros(len(X))
       pred = []
        for i in range(self.n iters):
            for j in range(len(X)):
                val = kernel(self.alpha, X, X[j], p=3, lr=0.001)
                result = np.sign(val)
                pred.append(result)
                if result != y[j]:
                    self.alpha[j] = self.alpha[j] + self.lr*y[j]
    def predict(self, X, Xi):
       val = kernel(self.alpha, X, Xi, p=5, lr=0.005)
       result = np.sign(val)
       if result <= 0:
           return 0
       else:
           return 1
```

```
# reading in the data
70
     y raw, x raw = svm read problem('mnist.scale')
71
     y = np.array(y raw)
     x = np.zeros((len(y raw), 780))
74 v for i in range(len(y_raw)):
         line = x raw[i]
76 ~
         for k, v in line.items():
             x[i][k-1] = v
78
     x train, x test, y train, y test = train test split(x, y, test size=0.5)
     y trainAcc = y train
82
     y_train = decToBin(y_train)
     y train = np.where(y train == 0, -1, 1)
     #splitting digits of binary number
     y train1 = np.copy(y train[:, 0])
     y_train2 = np.copy(y_train[:, 1])
     y_train3 = np.copy(y_train[:, 2])
     y train4 = np.copy(y train[:, 3])
```

```
perceptron1 = perceptron()
      perceptron1.fit(x train, y train1)
      perceptron2 = perceptron()
      perceptron2.fit(x train, y train2)
      perceptron3 = perceptron(learning rate=0.1)
      perceptron3.fit(x train, y train3)
      perceptron4 = perceptron(learning rate=0.05)
      perceptron4.fit(x train, y train4)
      # Calculating training accuracy
      predicted = np.zeros(len(y trainAcc))
      for i in range(len(y trainAcc)):
          pred = np.zeros(4)
110
          pred[0] = perceptron1.predict(x train, x train[i])
111
          pred[1] = perceptron2.predict(x train, x train[i])
          pred[2] = perceptron3.predict(x train, x train[i])
112
113
          pred[3] = perceptron4.predict(x train, x train[i])
114
          predicted[i] = binToDec([pred])
115
      correct num = np.sum(predicted == y trainAcc)
      print('Training Accuracy = ', np.round(
116.
          correct num * 100 / len(predicted)), '%', sep='')
117
118
119
120
      # Calculating testing accuracy
121
      predicted = np.zeros(len(y test))
122
      for i in range(len(y test)):
123
          pred = np.zeros(4)
124
          pred[0] = perceptron1.predict(x train, x test[i])
125
          pred[1] = perceptron2.predict(x train, x test[i])
          pred[2] = perceptron3.predict(x train, x test[i])
126
127
          pred[3] = perceptron4.predict(x_train, x_test[i])
          predicted[i] = binToDec([pred])
128
129
      correct num = np.sum(predicted == y test)
130
      print('Testing Accuracy = ', np.round(
131
          correct num * 100 / len(predicted)), '%', sep='')
      # printing confusion matrix:
      print(confusion_matrix(y_test, predicted))
134
```

Pegasos SVM

Description:

Pegasos SVM written with ECOC to classify the mnist dataset.

<u>Training and testing accuracies + confusion matrix:</u>

```
Training Accuracy = 74.0%

Testing Accuracy = 69.0%

[[47  4  3  0  3  1  0  1  1  0]

[ 2  65  0  1  0  2  0  1  1  0]

[14  1  46  4  1  0  5  4  0  0]

[ 1  12  2  40  0  1  2  3  2  1]

[ 3  1  0  0  53  12  2  0  1  1]

[ 2  13  0  2  6  25  1  2  2  0]

[ 7  0  4  0  4  0  48  1  0  0]

[ 0  5  0  6  2  20  0  44  0  0]

[ 5  1  1  2  3  0  0  0  43  4]

[ 2  4  0  0  2  9  0  2  2  43]
```

Note: this is the highest achieved accuracy. Average accuracy of 10 runs was 66.53%.

Code for pegasos_SVM:

```
import numpy as np
     from numpy import linalg
     import math
    from random import randint
    import matplotlib
     import matplotlib.pyplot as plt
     from libsvm.svmutil import svm_read_problem
     from sklearn.model selection import train test split
     from sklearn.metrics import confusion matrix
     # function to change decimal to binary array
     def decToBin(array):
         result = {
             0: [0, 0, 0, 0],
             1: [0, 0, 0, 1],
             2: [0, 0, 1, 0],
             3: [0, 0, 1, 1],
             4: [0, 1, 0, 0],
             5: [0, 1, 0, 1],
             6: [0, 1, 1, 0],
22
             7: [0, 1, 1, 1],
             8: [1, 0, 0, 0],
             9: [1, 0, 0, 1]
         return np.array([result[number] for number in array])
```

```
29
     # function to change binary array to decimal
     def binToDec(array):
         result = np.array([num[0]*8 + num[1] * 4 + num[2]
                          * 2 + num[3] for num in array])
         if result > 9:
34
             return np.array([num[0]*0 + num[1] * 4 + num[2]
                              * 2 + num[3] for num in array])
         else:
             return result
     # pegasos part of the algorithm
     def pegasos(x, y, weights=None, iterations=2000, lam=0.001):
         if type(weights) == type(None):
             weights = np.zeros(x[0].shape)
         num S = len(y)
         for i in range(iterations):
             it = randint(0, num S-1)
             step = 1/(lam*(i+1))
             decision = y[it] * weights @ x[it].T
             if decision < 1:
                 weights = (1 - step*lam) * weights + step*y[it]*x[it]
             else:
                 weights = (1 - step*lam) * weights
         return weights
```

```
class SVM:
   def init (self, learning rate=0.0005, lambda param=0.01, n iters=100):
       self.lr = learning rate
       self.lam = lambda param
       self.n iters = n iters
       self.weights = None
       self.b = None
   def fit(self, X, y):
       self.weights = pegasos(x=X, y=y, iterations=self.n iters)
   def predict(self, X):
       approx = np.dot(X, self.weights)
       sign_approx = np.sign(approx)
       if sign_approx <= 0:
           return 0
       else:
           return 1
```

```
# reading in the data
76
     y_raw, x_raw = svm_read_problem('mnist.scale')
77
     y = np.array(y_raw)
     x = np.zeros((len(y_raw), 780))
     for i in range(len(y_raw)):
         line = x_raw[i]
         for k, v in line.items():
             x[i][k - 1] = v
     x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.3)
     # converting label to binary and splitting them up
     y trainAcc = y train
     y trainzeroOne = decToBin(y train)
90
     y_train = np.where(y_trainzero0ne == 0, 1, -1)
     y_train1 = np.copy(y_train[:, 0])
94
     y_train2 = np.copy(y_train[:, 1])
     y train3 = np.copy(y train[:, 2])
     y train4 = np.copy(y train[:, 3])
```

```
98
      #training 4 algorithms for each binary digit
      svm1 = SVM()
      svm1.fit(x train, y train1)
      svm2 = SVM()
      svm2.fit(x train, y train2)
103
      svm3 = SVM()
104
      svm3.fit(x train, y train3)
105
      svm4 = SVM()
      svm4.fit(x train, y train4)
107
108
109
      # training accuracy
110
      predicted = np.zeros(len(y trainAcc))
111 v for i in range(len(y trainAcc)):
112
          pred = np.zeros(4)
113
          pred[0] = svm1.predict(x train[i])
114
          pred[1] = svm2.predict(x train[i])
115
          pred[2] = svm3.predict(x train[i])
116
          pred[3] = svm4.predict(x train[i])
117
          predicted[i] = binToDec([pred])
          # print("binary answer: ", pred, " | decimal prediction: ",
118
119
120
      print(len(predicted), ' test case predicted.', sep='')
      correct_num = np.sum(predicted == y_trainAcc)
121
```

```
128
      # Testing accuracy
129
      predicted = np.zeros(len(y_test))
130
      for i in range(len(y test)):
131
          pred = np.zeros(4)
132
          pred[0] = svm1.predict(x_test[i])
133
          pred[1] = svm2.predict(x test[i])
134
          pred[2] = svm3.predict(x_test[i])
          pred[3] = svm4.predict(x test[i])
135
          predicted[i] = binToDec([pred])
136
          print("binary answer: ", pred, " | decimal prediction: ",
137
                predicted[i], " | correct prediction: ", y_test[i])
138
      print(len(predicted), ' test case predicted.', sep='')
139
140
      correct_num = np.sum(predicted == y_test)
      print(correct_num, ' are correct.', sep='')
141
      print('Accuracy = ', np.round(correct_num * 100 / len(predicted)), '%', sep='')
142
```

Neural Network:

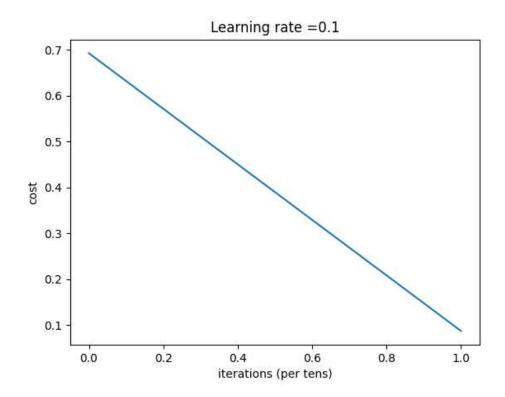
Description:

Neural Net to classify the mnist dataset.

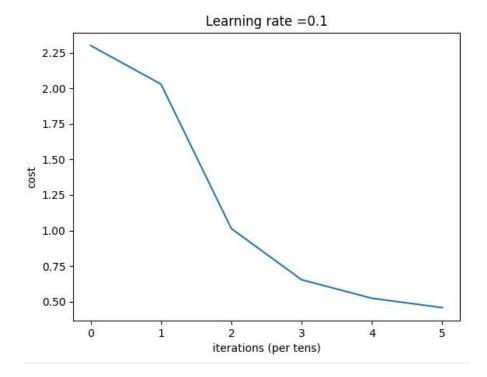
<u>Training and testing accuracies + confusion matrix:</u>

```
===== Binary (Digit 1 and 2) ======
Cost after iteration 0: 0.6926057785748851
Cost after iteration 50: 0.08490423769633489
Training Accuracy:
8890 test case predicted.
8890 are correct.
Accuracy = 1.0
Testing Accuracy:
3810 test case predicted.
3810 are correct.
Accuracy = 1.0
===== Multi-class ======
Cost after iteration 0: 2.302454060157147
Cost after iteration 50: 2.0319194764807524
Cost after iteration 100: 1.0125986456112632
Cost after iteration 150: 0.6517215378108929
Cost after iteration 200: 0.5212031076333735
Cost after iteration 250: 0.45508607556340214
Training Accuracy:
42000 Test case predicted.
41383 are correct.
Accuracy = 0.98530952381
Testing Accuracy:
18000 test case predicted.
15961 are correct.
Accuracy = 0.886722222222222
[[1690
                   4 39 15 13
      0
            26 9
                                     7 9]
                     6
    0 1881
            41
                14
                         15
                             7 34
                                      36
                                          13]
        9 1553
   9
                44
                    11
                       14 38 34 29 13]
      9 43 1549 0 69 1 5 68 30]
  10
       2 36 2 1563 16 24 16 8 99]
    5
  31
       8 3
                91 3 1358 28 2 63 8]
                    26
   13
        4 54
                4
                         37 1674 0
                                         2]
                                      18
       6 21 26 1 13 0 1676 3
   2
                                          80]
   12 29 54 50 12
                            11 7 1445
                                          22]
                         64
                22 114
                         27
                              0
                                 75
                                     52 1572]]
```

Cost/Iteration for the Binary:



Cost/Iteration for the multiclass:



Code for the Neural Net:

```
import numpy as np
     from numpy import linalg
     import matplotlib
     import matplotlib.pyplot as plt
     from libsvm.svmutil import svm read problem
     from sklearn.model_selection import train_test_split
     from sklearn.metrics import confusion matrix
 9 v def oneHot(array):
         result = np.zeros((len(array),10))
         for number in range(len(array)):
             result[number][int(array[number])] = 1
         return result
15 v def softmax(Z):
         Z_shift = Z - np.max(Z, axis=0)
         A = np.exp(Z_shift) / np.sum(np.exp(Z_shift), axis=0)
         cache = Z_shift
         return A, cache
23 v def relu(Z):
         A = np.maximum(0, Z)
         assert (A.shape == Z.shape)
         cache = Z
         return A, cache
29 v def initialize parameters(n_x, n_h, n_y):
         np.random.seed(1)
         W1 = np.random.randn(n_h, n_x) * 0.01
         b1 = np.zeros((n_h, 1))
         W2 = np.random.randn(n_y, n_h) * 0.01
         b2 = np.zeros((n_y, 1))
         assert (W1.shape == (n_h, n_x))
         assert (b1.shape == (n_h, 1))
         assert (W2.shape == (n y, n h))
         assert (b2.shape == (n_y, 1))
         parameters = { "W1": W1,
                        "b1": b1,
                       "W2": W2,
45
                       "b2": b2}
         return parameters
```

```
def linear forward(A, W, b):
    Z = np.dot(W, A) + b
    assert (Z.shape == (W.shape[0], A.shape[1]))
    cache = (A, W, b)
    return Z, cache
def linear_activation_forward(A_prev, W, b, activation):
    if activation == "softmax":
       # Inputs: "A_prev, W, b". Outputs: "A, activation_cache".
       Z, linear cache = linear forward(A prev, W, b)
       A, activation cache = softmax(Z)
    elif activation == "relu":
       # Inputs: "A prev, W, b". Outputs: "A, activation_cache".
       Z, linear_cache = linear_forward(A_prev, W, b)
       A, activation_cache = relu(Z)
    assert (A.shape == (W.shape[0], A prev.shape[1]))
    cache = (linear_cache, activation_cache)
    return A, cache
def compute_cost(AL, Y):
   m = Y.shape[1]
    cost = -(np.sum(Y * np.log(AL))) / float(m)
    # cost = np.squeeze(cost)
    assert (cost.shape == ())
    return cost
def linear backward(dZ, cache):
    A prev, W, b = cache
   m = A prev.shape[1]
    dW = np.dot(dZ, A prev.T) / float(m)
    db = np.sum(dZ, axis=1, keepdims=True) / float(m)
    dA prev = np.dot(W.T, dZ)
    assert (dA prev.shape == A prev.shape)
    assert (dW.shape == W.shape)
    assert (db.shape == b.shape)
    return dA_prev, dW, db
```

```
94 v def relu_backward(dA, cache):
          Z = cache
          dZ = np.array(dA, copy=True)
          dZ[Z \leftarrow 0] = 0
          assert (dZ.shape == Z.shape)
100
          return dZ
103 v def softmax backward(Y, cache):
104
          Z = cache
          s = np.exp(Z) / np.sum(np.exp(Z), axis=0)
          dZ = s - Y
          assert (dZ.shape == Z.shape)
110
111
          return dZ
112
113 v def linear activation backward(dA, cache, activation):
114
          linear_cache, activation_cache = cache
115
          if activation == "relu":
116 ~
117
              dZ = relu backward(dA, activation cache)
118
              dA prev, dW, db = linear backward(dZ, linear cache)
119
          elif activation == "softmax":
120 ~
121
              dZ = softmax backward(dA, activation cache)
              dA prev, dW, db = linear backward(dZ, linear cache)
122
123
124
          return dA_prev, dW, db
```

```
def update_parameters(parameters, grads, learning_rate):
    L = len(parameters) // 2 # number of layers in the neural network

# Update rule for each parameter. Use a for loop.
for l in range(1, L + 1):
    parameters['W' + str(l)] -= learning_rate * grads['dW' + str(l)]

parameters['b' + str(l)] -= learning_rate * grads['db' + str(l)]

return parameters
```

```
def two_layer_model(X, Y, layers_dims, learning_rate=0.1, num_iterations=3000, print_cost=False):
   np.random.seed(1)
   grads = \{\}
   costs = [] # to keep track of the cost
   m = X.shape[1] # number of examples
   (n_x, n_h, n_y) = layers_dims
   # Initialize parameters dictionary, by calling one of the functions you'd previously implemented
   parameters = initialize_parameters(n_x, n_h, n_y)
   # Get W1, b1, W2 and b2 from the dictionary parameters.
   W1 = parameters["W1"]
   b1 = parameters["b1"]
   W2 = parameters["W2"
   b2 = parameters["b2"]
   # Loop (gradient descent)
   for i in range(0, num_iterations):
       A1, cache1 = linear_activation_forward(X, W1, b1, activation='relu')
       A2, cache2 = linear_activation_forward(A1, W2, b2, activation='softmax')
       cost = compute_cost(A2, Y)
       # Backward propagation
       dA1, dW2, db2 = linear activation backward(Y, cache2, activation='softmax')
       dA0, dW1, db1 = linear_activation_backward(dA1, cache1, activation='relu')
       grads['dW1'] = dW1
       grads['db1'] = db1
       grads['dW2'] = dW2
       grads['db2'] = db2
       # Update parameters.
       parameters = update_parameters(parameters, grads, learning_rate)
       W1 = parameters["W1"]
       b1 = parameters["b1"]
       W2 = parameters["W2"]
       b2 = parameters["b2"]
```

```
183
              # Print the cost every 100 training example
184
              if i % 50 == 0:
                  print("Cost after iteration {}: {}".format(i, np.squeeze(cost)))
186
                  costs.append(cost)
187
188
189
          plt.plot(np.squeeze(costs))
191
          plt.ylabel('cost')
          plt.xlabel('iterations (per tens)')
193
          plt.title("Learning rate =" + str(learning_rate))
          plt.show()
          return parameters
```

```
198 v def predict(X, y, parameters):
           m = X.shape[1]
           W1 = parameters["W1"]
           b1 = parameters["b1"]
203
           W2 = parameters["W2"]
           b2 = parameters["b2"]
           A1, _ = linear_activation_forward(X, W1, b1, activation='relu')
           probs, _ = linear_activation_forward(A1, W2, b2, activation='softmax')
           predicted = np.argmax(probs, axis=0)
           # print ("predictions: " + str(p))
           print(m, ' test case predicted.', sep='')
           correct_num = np.sum(predicted == y)
           print(correct_num, ' are correct.', sep='')
#print('Accuracy = ', np.round(correct_num * 100 / len(predicted)), '%', sep='')
           print("Accuracy = " + str(correct_num / float(m)), sep='')
           return predicted
      y_raw, x_raw = svm_read_problem('mnist.scale')
      y = np.array(y_raw)
      x = np.zeros((len(y_raw), 780))
225 v for i in range(len(y_raw)):
           line = x_raw[i]
           for k, v in line.items():
               x[i][k-1] = v
       x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.3)
      y_train = oneHot(y_train)
234
      print('===== Binary (Digit 1 and 2) ======')
      y_{\text{bin}} = \text{np.concatenate}((y[y==1],[0]*sum(y==2)))
      temp = np.zeros((len(y_bin), 2))
238 v for number in range(len(y_bin)):
           temp[number][int(y_bin[number])] = 1
      y_bin = temp
      x_bin = np.concatenate((x[y==1],x[y==2]))
      x train bin, x test bin, y train bin, y test bin = train test split(x bin, y bin, test size=0.3)
      parameters_bin = two_layer_model(x_train_bin.T, y_train_bin.T, (780, 100, 2), 0.1, 100, True)
       print("Training Accuracy:")
       training prediction = predict(x train bin.T, y train bin.T, parameters bin)
      prediction_bin = predict(x_test_bin.T, y_test_bin.T, parameters_bin)
      print('===== Multi-class ======')
       parameters = two_layer_model(x_train.T, y_train.T, (780, 100, 10), 0.1, 300, True)
       print("Training Accuracy:")
       training pred = predict(x_train.T, y_train.T, parameters)
       print("Testing Accuracy:")
       prediction = predict(x_test.T, y_test.T, parameters)
      print(confusion_matrix(prediction, y_test))
```