HW2 task3 report

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1. A short description of the library you choose to use.

We are using the dlib library. The dlib library is a modern C++ toolkit containing machine learning algorithms and tools to solve real-world problems. It is used in both industry and academia in a wide range of domains including robotics, embedded devices, mobile phones, and large high performance computing environments.

2. The definition of your ϕ function. For simplicity you can adopt a simple option or adopt a more complex one such as enumerating more combinations of the neighboring labels.

I am reading x with 257 features per call of make_psi, and these 257 features are break into 3 parts: the bias term: mapped to the 0th element of psi. Indices 1-128 maps to the psi[1:2944] based on its label. If we have label 1 we will map it to psi[1:128]. If we have label 2, we will map it to psi[129:256]. Until we filled up all the 1:2944 spaces. Indices 129-256 maps to psi[2945:5890] based on its label. If we have label 1 we will map it to psi[2945:3072].If we have label 2, we will map it to psi[3073:3200] The same applies to all the rest until we filled up all 2945:5890 spaces.

3. A table of training and test accuracies for the corresponding window size.Due to the large overhead in training, you can just try a window size of 2

I am using a window size of 2. Training accuracy= 0.48675. Test accuracy= 0.43500000000000005

In [1]:
```
import warnings; warnings.simplefilter('ignore')
import numpy as np
from sklearn import preprocessing
le = preprocessing.LabelEncoder()
oe = preprocessing.OneHotEncoder()
import dlib
import re
import matplotlib.pyplot as plt
from matplotlib.pyplot import imshow
%matplotlib inline
import timeit
label_encoder = preprocessing.LabelEncoder()
import pickle
import random
```

Task 3: Structured SVM

In [2]:
```
# Windows Length
L = 2
# Number of examples
N = 5000
# Length of a feature
d = 128
# The hyper-parameter for icm search
Niter = 2
```

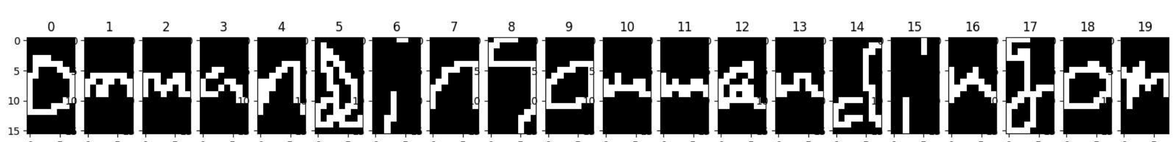
In [3]:
```
def l2i(a):
        return int(ord(a)-ord('a'))
def i2l(i):
    if i >= 0:
        return chr(i+ord('a'))
    else:
        return '_'
def iors(s):
    try:
        return int(s)
    except ValueError: # if it is a string, return a string
        return s
```

In [4]:
```
# Read the entire dataset into lists or list of lists
def read_OCR(filename, n_features):
    F = open(filename)
    dataset = {}
    dataset['ids'] = []#np.zeros(n_examples, dtype=int)
    dataset['labels'] = []#np.zeros(n_examples,dtype=int)
    dataset['labelDic'] = {} # To profile the distribution of labels
    dataset['next_ids'] = []#np.zeros(n_examples,dtype=int)
    dataset['word_ids'] = []#np.zeros(n_examples,dtype=int)
    dataset['positions'] = []#np.zeros(n_examples,dtype=int)
    dataset['folds'] = []#np.zeros(n_examples,dtype=int)
    dataset['features'] = []#np.zeros([n_examples,n_features])

    for str_line in F.readlines():
        #line0 = map(iors, filter(None, re.split('\t', str_line.strip())))
        ## ATTENTION: If you are using Python3, use the following line instea
        line0 = list(map(iors, filter(None, re.split('\t', str_line.strip()))


        dataset['ids'].append(int(line0.pop(0)))
        dataset['labels'].append(l2i(line0.pop(0))) # The label is converted
        if dataset['labels'][-1] in dataset['labelDic']:
            dataset['labelDic'][dataset['labels'][-1]] += 1
        else:
            dataset['labelDic'][dataset['labels'][-1]] = 1

        dataset['next_ids'].append(int(line0.pop(0)))
        dataset['word_ids'].append(int(line0.pop(0)))
        dataset['positions'].append(int(line0.pop(0)))
        dataset['folds'].append(int(line0.pop(0)))
        if len(line0) != 128:  # Sanity check of the length
            print (len(line0))
        dataset['features'].append(line0)

    return dataset
```

In [5]:
```
dataset1 = read_OCR('OCRdataset/letter.data', d)
```

In [6]:
```
# Understand the profile of OCR raw data
print ("max of labels=", max(dataset1['labels']), " min of labels=", min(data
print ("labelDic.keys()=", map(i2l, dataset1['labelDic'].keys()))
print ("Total number of lines=", len(dataset1['ids']))
print ("The shape of features:", np.array(dataset1['features']).shape)
#52152 the size of xi yi, 128 the number of k? =the size of wi..

print ("The first 10 ids:",dataset1['ids'][:10]) #id from 1 to 52152 (xi)
print ("ids[0]=",dataset1['ids'][0])
print ("labels[0]=", dataset1['labels'][0]) #the alphabetical label the lette
print("first 10 labels", dataset1['labels'][:10])
print ("The 1st letter is ", i2l(dataset1['labels'][0])) #i2l function conver
print ("next_ids[0]=",dataset1['next_ids'][0])
print ("The second letter is ", i2l(dataset1['labels'][1]))
# Show the matrix into an image
def showFeatures(features, num):
    plt.figure(figsize=(num, 6))

    for i in range(num):
        npfeature = np.array(features[i])
        plt.subplot(1,num,i+1)
        imshow(npfeature.reshape(16,8), cmap='gray')
        plt.title(i)

showFeatures(dataset1['features'],20)

# f1 = np.array(dataset1['features'])
# f1 = np.hstack([np.ones((f1.shape[0],1)), f1])
# print f1.shape
# dataset1['features'] = f1.tolist()
# d +=1
```

```
max of labels= 25  min of labels= 0 num of labels= 26
labelDic.keys()= <map object at 0x000001D3DD36EB30>
Total number of lines= 52152
The shape of features: (52152, 128)
The first 10 ids: [1, 2, 3, 4, 5, 6, 7, 8, 9, 10]
ids[0]= 1
labels[0]= 14
first 10 labels [14, 12, 12, 0, 13, 3, 8, 13, 6, 14]
The 1st letter is  o
next_ids[0]= 2
The second letter is  m
```



Options for Chopping

Concatenating and structurizing

version one:

(1) find 5000 words, split them into 4000 for training, and 1000 for testing.

(2) chop first 2 characters from each word

(3) then, you will have 4000 two-words pairs for training, and 1000 for testing.

(4) construct new structures data based on this pairs.

e.g.

apple => ap

banana => ba

version two:

(1) continue reading words from data until you have 4001 characters for training, and 1001 for testing

(2) concatenate characters together to form structure features.

(3) you will have the same amount structured data.

apple => ap, pp, pl, le

banana => ba, an, na, an, na

version three

(1) similar to version two, but add a dummy letter '_' between words.

apple_banana => ap, pp, pl, le, e_, _b, ba, an, na, an, na

version four

(1) similar, but window stride is 2 also, and pad a dummy letter '_', which will be represented as all 0 in the image.

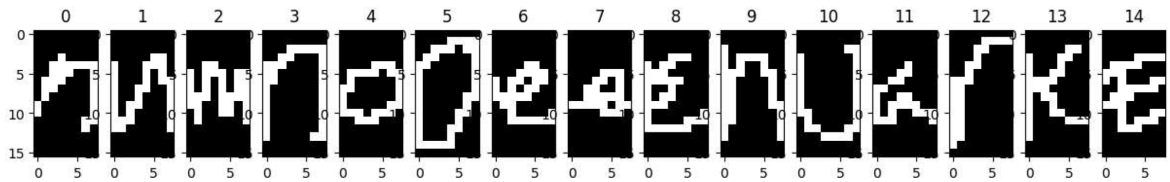
apple => ap, pl, e_

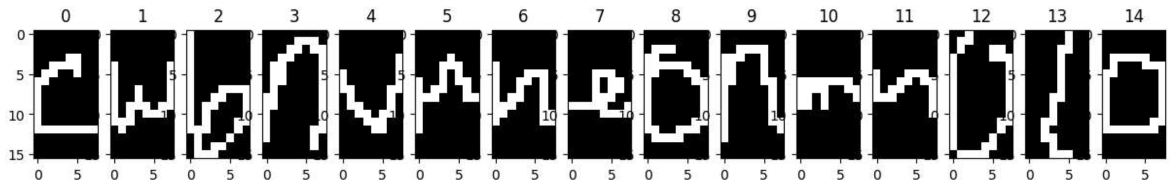
banana => ba, na, na

In [7]:
```
# Option 1: Extract the first L letters in a word
# You are welcome to try other options

def structurize1(dataset, N, L):
    d_features = len(dataset['features'][0])
    y = dataset['labels']
    X = dataset['features']
    next_id = dataset['next_ids']

    labels = np.zeros((N, L))
    features = np.zeros((N, L*d_features))

    # Extract only one structured example
    def extract(iN, loc):
        labels[iN] = y[loc:loc+L]
        features[iN] = np.array(X[loc:loc+L]).ravel().tolist()
        iN += 1
        return iN

    iN = 0
    iN = extract(iN, 0)

    for key, value in enumerate(y):
        if next_id[key] == -1:
            iN = extract(iN, key+1)

            if iN == N:
                break

    c = list(zip(labels, features))
    random.shuffle(c)
    labels, features = zip(*c)

    return np.array(labels), np.array(features)
```

In [8]:
```
labels1, features1 = structurize1(dataset1, N, L)

print (np.all(labels1[labels1==labels1[0]]))
print (labels1[:15].T)
showFeatures(features1[:,0:128],15)
showFeatures(features1[:,128:256],15)
```

```
True
[[13. 13. 12. 13. 14. 14.  4.  4.  4. 13. 20.  0. 17. 10.  4.]
 [ 2. 22.  1. 13. 21. 12. 13.  4. 14. 13. 12. 13. 14.  8. 14.]]
```





Use dlib to classify

In [9]:
```
print ('N=',N,'L=',L,'d=',d)
```

```
N= 5000 L= 2 d= 128
```

In [10]:
```
class ThreeClassProblem:
    C = 1

    def __init__(self, samples, labels, L, K, d):
        self.L = L #hyperparameter = 2
        self.K = K #23
        self.d = d #features = 128
        self.num_samples = len(samples)
        self.num_dimensions = (L*K*d+1) + (L-1) #5890
        self.samples = samples #4000
        self.labels = labels #4000
        self.loss_for_loop = True


    def make_psi(self, x, label):
        psi = dlib.vector()
        psi.resize(self.num_dimensions)  # 5890
        psi[0] = x[0]


        label_0 = label[0]
        psi_index = label_0
        psi[psi_index] = x[0]

        # Map the second part of x to psi based on label_0
        for i in range(128):
            psi_index = i + label_0 * 128 + 1
            psi[psi_index] = x[i + 1]

        # Map the third part of x to psi based on label_1
        label_1 = label[1]
        for i in range(128):
            psi_index = i + label_1 * 128 + 128 * 23 + 1
            psi[psi_index] = x[i + 129]

        return psi

    def get_truth_joint_feature_vector(self, idx):
        return self.make_psi(self.samples[idx], self.labels[idx])

    def separation_oracle(self, idx, current_solution):
        samp = self.samples[idx]
#         print(samp)
        psi = [0]*self.num_dimensions
        max1 = -1e10
        max_scoring_label = [0]*L # Initialize max_scoring_label for icm sear
        for k in range(Niter):
            for iL in range(self.L):   # Iterate over the window length
                for i in range(self.K):# Change different label for the searc
                    tmp_label = list(max_scoring_label)
                    tmp_label[iL] = i
                    tmp_psi = self.make_psi(samp, tmp_label)
                    score1 = dlib.dot(current_solution, tmp_psi)

                    loss1 = 0.0
                    if self.loss_for_loop:
                        for j in range(self.L):
```

```
                        if self.labels[idx][j] != tmp_label[j]:
                            loss1 += 1.0
                else:
                    if self.labels[idx] != tmp_label: # Add the condition
                        loss1 += 1.0

                if max1 < score1+loss1: # Search for the maximum and upda
                    max1 = score1 + loss1
                    loss = loss1
                    max_scoring_label[iL] = i
                    psi = tmp_psi

        return loss, psi
```

In [11]:

```
# half_index = 257 // 2
# print("halfindex",half_index)
# first_half = x[1:129]
# second_half = x[half_index+1:]
```

In [12]:

```
list1 = [1,1,1]
list2= [1,2,3,4,5]
list2[:3] = list1
list2
257//2
```

Out[12]: 128

In [13]:
```
def cal_accuracy(samples, labels, problem, weights, K):
    predictions = []
    for samp in samples:
        prediction = [0]*L # Initialize max_scoring_label for icm search
        Niter = 2                  # The hyper-parameter for icm search
        max1 = -1e10               # The max value during maximizing our targe
        for k in range(Niter):
            for iL in range(L):    # Iterate over the window length
                for i in range(K):# Change differnet label for the search of
                    tmp_label = list(prediction)    # Copy the current best p
                    tmp_label[iL] = i                # Modify the label at po
                    psi1 = problem.make_psi(samp, tmp_label)
                    score1 = dlib.dot(weights, psi1)

                    if max1 < score1:
                        max1 = score1
                        prediction[iL] = i
        predictions.append(prediction)


    errCnt = 0
    for i in range(len(predictions)):
        if predictions[i] != labels[i]:
            errCnt += 1

    return 1.0-float(errCnt)/float(len(predictions))
```

In [14]:
```
le1 = preprocessing.LabelEncoder()
nplabels1  = le1.fit_transform(labels1.ravel()).reshape(labels1.shape)
npsamples1 = np.hstack([np.ones((N,1)), features1]) # Add ones for bias
K1 = len(le1.classes_)
print ('K1=', K1)

tr_labels  = nplabels1[:int(N*0.8)].astype(int).tolist()
tr_samples = npsamples1[:int(N*0.8)].astype(int).tolist()
te_labels  = nplabels1[int(N*0.8):].astype(int).tolist()
te_samples = npsamples1[int(N*0.8):].astype(int).tolist()

def profiling(labels):
    TrDic = {}
    for i in np.array(labels).ravel():
        if i not in TrDic:
            TrDic[i] = 1
        else:
            TrDic[i] += 1
    return TrDic
print (profiling(tr_labels))
print (profiling(te_labels))
```

```
K1= 23
{12: 813, 2: 478, 19: 120, 11: 567, 1: 109, 13: 924, 18: 287, 4: 1045, 17: 6
37, 0: 673, 15: 296, 9: 118, 7: 370, 14: 330, 10: 202, 16: 112, 6: 227, 3: 1
19, 20: 120, 8: 60, 22: 208, 5: 104, 21: 81}
{12: 201, 19: 20, 4: 246, 15: 68, 13: 233, 18: 82, 0: 152, 11: 144, 1: 37, 1
4: 66, 6: 51, 7: 98, 3: 27, 17: 166, 10: 59, 2: 117, 9: 29, 16: 34, 20: 27,
5: 31, 22: 60, 21: 36, 8: 16}
```

In [15]:
```
# print(tr_labels)
# label = tr_labels
# print(len(tr_labels))
# print(label[0])
# print(label[0][1])

# print(tr_samples)
# print(len(tr_samples))
```

In [16]:
```
problem = ThreeClassProblem(tr_samples, tr_labels, L, K1, d)

start_train = timeit.default_timer()
weights = dlib.solve_structural_svm_problem(problem)
end_train = timeit.default_timer()
print ("Training time elapsed:", end_train - start_train, "s")
pickle.dump(weights, open('weights1_1.obj', 'wb'))
#pickle.dump(weights, open('weights1_1.obj', 'w'))
```

...

In [17]:
```
weights_load = pickle.load(open('weights1_1.obj','rb'))
#weights_load = pickle.load(open('weights1_1.obj','r'))

print ("Training accuracy=", cal_accuracy(tr_samples, tr_labels, problem, wei
print ("Test accuracy=", cal_accuracy(te_samples, te_labels, problem, weights_
```

```
Training accuracy= 0.48675
Test accuracy= 0.43500000000000005
```

In [ ]: