

ECE 661 Homework 8

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The task of this homework is to implement a simple image classifier using the Gram matrix for texture characterization and Support Vector Machines (SVM) for the classification.

1 Logic

1.1 Gram matrix

In order to extract the features from the image, we convolve the image with C different convolutional kernels. The resulting outputs are called feature maps.

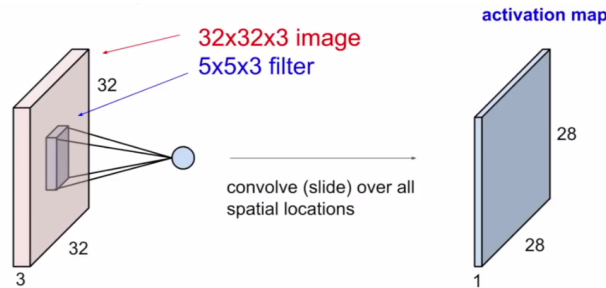


Figure 1: Convolution operation

Considering each feature map as a vector (Flatten the feature map), we take the dot product between the two vectors. The dot product us the information about the relation between them. If the dot product is high it means that the two features are closely related (similar kinds of feature) whereas if the dot product is small , it means that the features are different from each other.

In other words, the lesser the product, the lesser the two features co-occur and the greater it is, the more they occur together. This in a sense gives information about an image's style(texture).

The dot product between the features can be stored in a $C \times C$ matrix known as the Gram matrix.

$$G_{i,j} = F_i \cdot F_j$$

where $G_{i,j}$ is the (i,j) element of the Gram matrix and F is the feature vector.

Therefore every image in the dataset can be represented as a feature in the $C^2/2$ dimensional feature space. These features can now be used to train a classifier network. In this exercise, we use the Support Vector Machine (SVM) for the classification task.

The best results were achieved for $C = 256$. Above this value there was no change in the accuracy.

2 Results

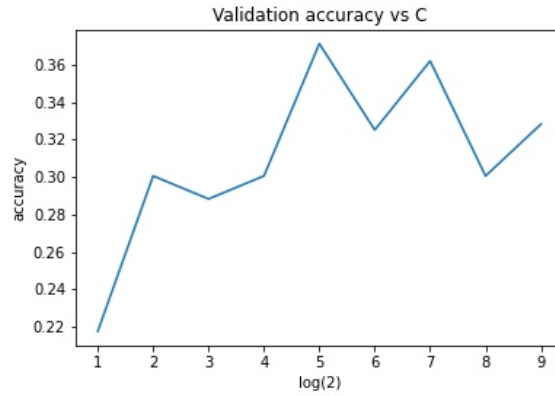


Figure 2: Validation accuracy

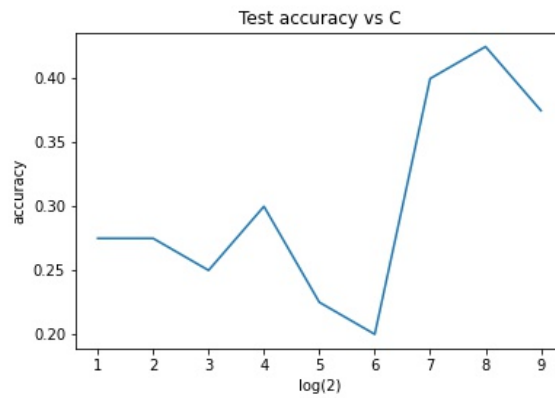


Figure 3: Test accuracy

From the two plots we can assume that the best test accuracy is achieved for $C = 256$. However the validation accuracy for $C = 256$ is lower than $C=128$.

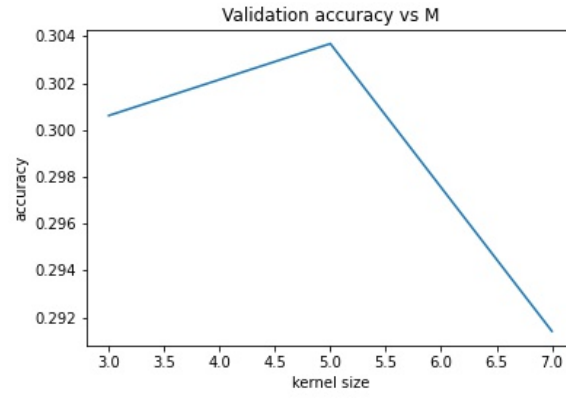


Figure 4: Validation accuracy

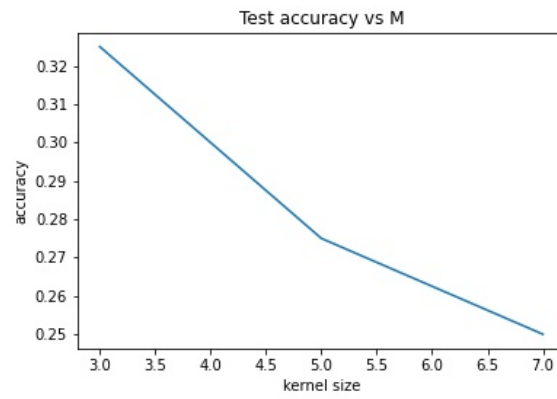


Figure 5: Test accuracy

From this we can see that the best performance is achieved for $M = 3$.

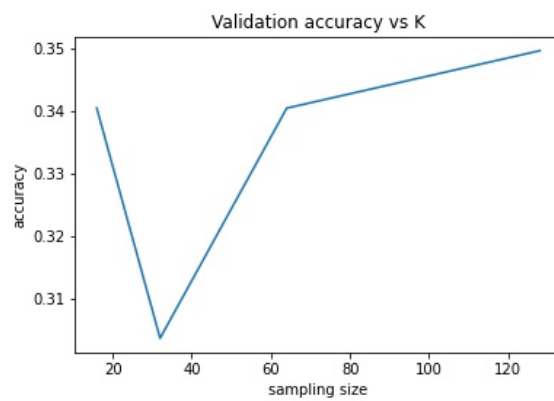


Figure 6: Validation accuracy

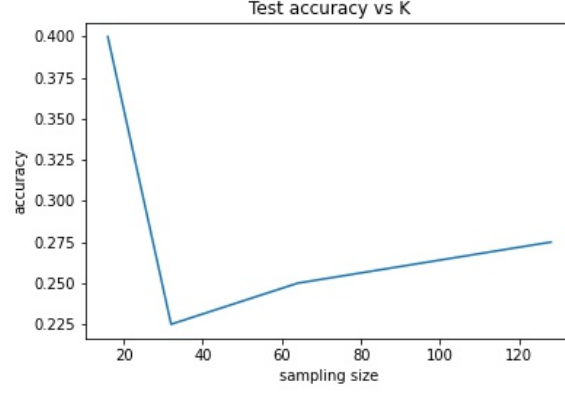


Figure 7: Test accuracy

The results obtained by $K=16$ and 64 are the same for validation data. The validation accuracy is very high for $K=128$ but performs poorly on the test data indicating overfitting. Hence $k = 16$ is the best choice.

2.1 Best model confusion matrix

Feature extractor parameters

1. $C = 256$
2. $M = 3$
3. $K = 16$

Classifier parameters:

1. $C = 100$
2. $\text{gamma} = \text{'scale'}$
3. $\text{kernel} = \text{'rbf'}$

2.1.1 Validation

$$\text{ConfMat} = \begin{bmatrix} \text{True/Predicted} & \text{Cloudy} & \text{Rain} & \text{Shine} & \text{Sunrise} \\ \text{Cloudy} & 23 & 23 & 11 & 37 \\ \text{Rain} & 0 & 42 & 0 & 18 \\ \text{Shine} & 14 & 16 & 7 & 25 \\ \text{Sunrise} & 21 & 30 & 9 & 50 \end{bmatrix}$$

2.1.2 Testing

$$\text{ConfMat} = \begin{bmatrix} \text{True/Predicted} & \text{Cloudy} & \text{Rain} & \text{Shine} & \text{Sunrise} \\ \text{Cloudy} & 3 & 2 & 0 & 5 \\ \text{Rain} & 0 & 8 & 0 & 2 \\ \text{Shine} & 0 & 2 & 3 & 5 \\ \text{Sunrise} & 1 & 4 & 1 & 4 \end{bmatrix}$$

3 Observations

1. It can be seen from the testing confusion matrix that the classifier performed really well on classifying rain images. However it did not fare well on other classes.
2. One reason might be due to grayscaling the image. Color plays an important role in differentiating between classes however most of the grayscale images have similar intensity (for shine,cloudy and sunrise). That is why most of the shine and cloudy are classified as sunrise.
3. Another reason that I think might be the center cropping of the images. Most of the images contain clouds in them. And center cropping leaves the pixels of the clouds almost always.
4. Another reason is the random initialization of the convolution kernels everytime. The kernel weights are not the optimal values and hence the features extracted may not be the correct representation of the image.

3.1 False Positives and False Negatives

3.2 Cloudy



Figure 8: False Negative (Predicted Rain)

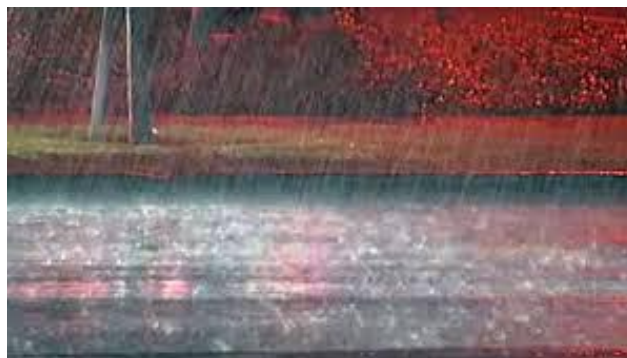


Figure 9: False Positive (Rain but predicted Cloudy)

3.3 Rain



Figure 10: False Negative (Predicted Shine)



Figure 11: False Positive (Shine but predicted Rain)

3.4 Shine



Figure 12: False Negative (Predicted Rain)



Figure 13: False Positive (Rain but predicted Shine)

3.5 Sunrise



Figure 14: False Negative (Predicted Cloudy)

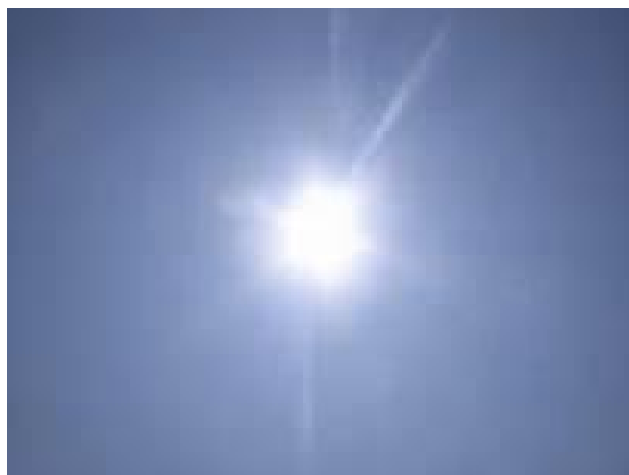


Figure 15: False Positive (Shine but predicted Sunrise)

4 Code Listings

```
1 # -*- coding: utf-8 -*-
2 """hw8_Suyash_Ail.ipynb
3
4 Automatically generated by Colaboratory.
5
6 Original file is located at
7     https://colab.research.google.com/drive/1WR_TlB6XFLfP-2D4EGBtOCur2TrOlkNn
8 """
9
10 # import all the necessary libraries
11 import numpy as np
12 import cv2
13 import matplotlib.pyplot as plt
14 import os
15 import re
16 import pickle
17 from sklearn.pipeline import make_pipeline
18 from sklearn.preprocessing import StandardScaler
19 from sklearn.svm import SVC
20 from sklearn.model_selection import train_test_split
21 from sklearn.metrics import accuracy_score, confusion_matrix
22
23 training_dir = '/content/drive/My Drive/imagesDatabaseHW8/training/'
24 testing_dir = '/content/drive/My Drive/imagesDatabaseHW8/testing/'
25
26 # function to load images and get class labels
27 def get_images(dir):
28     filenames = os.listdir(dir)
29     images = []
30     #class labels dictionary
31     labels = {'cloudy':0,
32              'rain':1,
33              'shine':2,
34              'sunrise':3
35              }
36     for filename in filenames:
37
38         image_dir = dir + filename
39         img = plt.imread(image_dir)
40
41         classname=re.split('(\d+)',filename)[0]
42         classlabel = labels[classname]
43         images.append([img, classlabel])
44     return images
45
46 # get the training and test images
47 train_images = get_images(training_dir)
48 test_images = get_images(testing_dir)
49
50 # function to get the gram matrix
51 def gram_matrix(image, C=16, M=3, K=16):
52     # convert to grayscale if not already in
53     if len(image.shape)>2:
54         image = cv2.cvtColor(image, cv2.COLOR_BGR2GRAY)
55
56     #image = cv2.resize(image,(K,K)) #rescaling didnt work out good
```



```

57 h,w = image.shape
58 image = image[h//2-K//2:h//2+K//2,w//2-K//2:w//2+K//2] #center crop
59 #print(image.shape)
60 img_vector = []
61 # run for C times to get C channel maps
62 for i in range (C):
63     # get random kernel
64     w = a = np.random.rand(M,M)
65     w = w - np.sum(w)/M**2
66     filtered_img = cv2.filter2D(image,-1,w)
67     filtered_vector = filtered_img.flatten()
68     img_vector.append(filtered_vector)
69
70 gram_mat = np.zeros ((C,C))
71 for i in range(len(img_vector)):
72     for j in range(i+1):
73         #for j in range(len(img_vector)): #trying to see if full matrix helps
74         #improve accuracy but no
75         dot = np.dot(img_vector[i],img_vector[j])
76         gram_mat[i,j] = dot
77
78 return gram_mat
79
80 # full classification pipeline including finding gram vectors and
81 # classification using SVM
82
83 def classification(train_image_list,test_image_list,C,M,K):
84     input = np.array([x[0] for x in train_image_list])
85     label = [x[1] for x in train_image_list]
86     #print(input[0].shape)
87     #print(label)
88
89     test_input = [x[0] for x in test_image_list]
90     test_label = [x[1] for x in test_image_list]
91     train_gram_list=[]
92     # get gram matrix for all training images
93     for img in input:
94         gm = gram_matrix(img,C,M,K)
95         gm = np.array(gm).flatten()
96         train_gram_list.append(gm)
97     #print(train_gram_list)
98     test_gram_list=[]
99     # get gram matrix for all testing images
100     for img in test_input:
101         gm = gram_matrix(img,C,M,K)
102         gm = np.array(gm).flatten()
103         test_gram_list.append(gm)
104
105     ##### Start the Classification task #####
106     X_train,X_val,y_train,y_val = train_test_split(train_gram_list,label,
107         test_size = 0.3,shuffle=True)
108     X_test,y_test = test_gram_list, test_label
109
110     clf = make_pipeline(StandardScaler(),SVC(C=100,gamma='scale',kernel='rbf'))
111     clf.fit(X_train, y_train)
112     y_pred = clf.predict(X_val)
113     acc = accuracy_score(y_val,y_pred)
114     y_test_pred = clf.predict(X_test)

```

```

112     test_acc = accuracy_score(y_test, y_test_pred)
113     return acc, test_acc
114
115 #C = [2,4,8,16,32,64,128,256,512]
116 M = [3,5,7]
117 acc_list = []
118 test_acc_list = []
119 for m in M:
120     print("current C=", c)
121     acc, test_acc = classification(train_images, test_images, 256, m, 16)
122     acc_list.append(acc)
123     test_acc_list.append(test_acc)
124
125 acc, test_acc
126
127 plt.plot(range(1,10), acc_list)
128 plt.xlabel('log(2)')
129 plt.ylabel('accuracy')
130 plt.title('Validation accuracy vs C')
131 plt.savefig("/content/drive/My Drive/imagesDatabaseHW8/val_acc.jpg")
132
133 plt.plot(range(1,10), test_acc_list)
134 plt.xlabel('log(2)')
135 plt.ylabel('accuracy')
136 plt.title('Test accuracy vs C')
137 plt.savefig("/content/drive/My Drive/imagesDatabaseHW8/test_acc.jpg")

```