

In [7]:

```
1 import math
2 import multiprocessing
3 import os
4 from copy import copy
5 from os.path import join
6
7 import numpy as np
8 import pandas as pd
9 import scipy.ndimage
10 import skimage.color
11 import matplotlib.pyplot as plt
12 from PIL import Image
13 from sklearn.cluster import KMeans
14 from tqdm.autonotebook import tqdm
15
16 import imageio
17 from skimage import io
```

16-720 Computer Vision: Homework 1 (Spring 2022)

Spatial Pyramid Matching for Scene Classification

```
In [8]: 1 class Opts(object):
2         def __init__(
3             self,
4             data_dir="../data",
5             feat_dir="../feat",
6             out_dir=".",
7             filter_scales=(1, 2, 4, 8, 8*np.sqrt(2)),
8             K=10,
9             alpha=25,
10            L=1,
11        ):
12            '''
13            Manage tunable hyperparameters.
14
15            You can also add your own additional hyperparameters.
16
17            [input]
18            * data_dir: Data directory.
19            * feat_dir: Feature directory.
20            * out_dir: Output directory.
21            * filter_scales: A list of scales for all the filters.
22            * K: Number of words.
23            * alpha: Subset of alpha pixels in each image.
24            * L: Number of layers in spatial pyramid matching (SPM).
25
26            '''
27            self.data_dir = data_dir
28            self.feat_dir = feat_dir
29            self.out_dir = out_dir
30            self.filter_scales = list(filter_scales)
31            self.K = K
32            self.alpha = alpha
33            self.L = L
34
35        opts = Opts()
```

```

In [9]: 1 # utils
2
3 def get_num_CPU():
4     '''
5     Counts the number of CPUs available in the machine.
6     '''
7     return multiprocessing.cpu_count()
8
9
10 def display_filter_responses(opts, response_maps):
11     '''
12     Visualizes the filter response maps.
13
14     [input]
15     * response_maps: a numpy.ndarray of shape (H,W,3F)
16     '''
17
18     n_scale = len(opts.filter_scales)
19     plt.figure()
20
21     for i in range(n_scale * 4):
22         plt.subplot(n_scale, 4, i + 1)
23         resp = response_maps[:, :, i * 3:i * 3 + 3]
24         resp_min = resp.min(axis=(0, 1), keepdims=True)
25         resp_max = resp.max(axis=(0, 1), keepdims=True)
26         resp = (resp - resp_min) / (resp_max - resp_min)
27         plt.imshow(resp)
28         plt.axis("off")
29
30     plt.subplots_adjust(left=0.05, right=0.95, top=0.95,
31                        bottom=0.05, wspace=0.05, hspace=0.05)
32     plt.show()
33
34
35 def visualize_wordmap(original_image, wordmap, out_path=None):
36     fig = plt.figure(figsize=(12.8, 4.8))
37     ax = fig.add_subplot(1, 2, 1)
38     ax.imshow(original_image)
39     plt.axis("off")
40     ax = fig.add_subplot(1, 2, 2)
41     ax.imshow(wordmap)
42     plt.axis("off")
43     plt.show()
44     if out_path:
45         plt.savefig(out_path, pad_inches=0)
46

```

Question 1

Q1.1.1

The filters in these filter banks are Gaussian filter, Laplacian of Gaussian filter, the derivative of

Gaussian filter in x-direction and derivative of Gaussian filter in the y-direction.

Gaussian Filter: It is a smoothing low-pass filter. It removes high-frequencies from the image and allows for the lower frequencies to pass through it.

Laplacian of Gaussian Filter: It is a second derivative filter which gives zero response for uniform regions in an image and positive/negative response in regions where there are changes. These filters are commonly used to detect blob-like features in images.

Gaussian x-derivative: Captures the vertical edges in the image.

Gaussian y-derivative: Captures the horizontal edges in the image.

We need multiple scales of filter responses because we don't know the scale of the point of interest. A line in one scale can be represented as a point on another scale. So, with multiple scales of filter, we will be able to better represent the features.

Q1.1.2

In []:

1

In []:

1

```

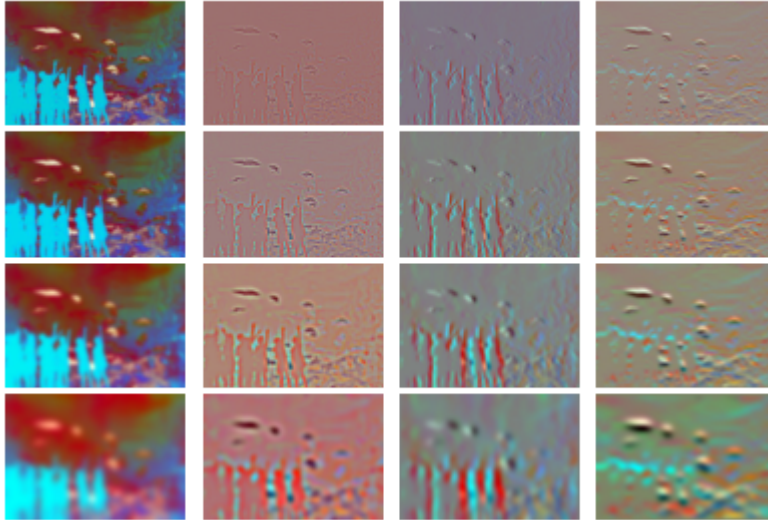
In [10]: 1 def extract_filter_responses(opts, img):
2         '''
3         Extracts the filter responses for the given image.
4
5         [input]
6         * opts      : options
7         * img       : numpy.ndarray of shape (H,W) or (H,W,3)
8         [output]
9         * filter_responses: numpy.ndarray of shape (H,W,3F)
10        '''
11
12        filter_scales = opts.filter_scales
13        # ----- TODO -----
14
15        F = 4
16
17        if len(img.shape) < 3:
18            C = 1
19            H, W = img.shape
20        else:
21            H, W, C = img.shape
22
23        if C == 1:
24            img = np.expand_dims(img, axis = 2)
25            img = np.tile(img, (1,1,3))
26            H, W, C = img.shape
27
28        if C == 4:
29            img = img[:, :, 0:3]
30            H, W, C = img.shape
31
32        img = img.astype('float')/255.
33        img = skimage.color.rgb2lab(img)
34        filter_responses = np.zeros((H, W, C*F*len(filter_scales)))
35
36
37        for i in range(3):
38            count = i
39            for j in range(4):
40                filter_responses[:, :, count] = scipy.ndimage.filters.gaussian_fil
41                filter_responses[:, :, count + 3] = scipy.ndimage.filters.gaussian
42                filter_responses[:, :, count + 6] = scipy.ndimage.filters.gaussian
43                filter_responses[:, :, count + 9] = scipy.ndimage.filters.gaussian
44                count += C*F
45            count = i+1
46        # filter_responses = np.dstack(filter_responses)
47
48        return filter_responses

```

In [11]:

```
1 def extract_filter_responses(opts, img):
2     '''
3     Extracts the filter responses for the given image.
4
5     [input]
6     * opts      : options
7     * img       : numpy.ndarray of shape (H,W) or (H,W,3)
8     [output]
9     * filter_responses: numpy.ndarray of shape (H,W,3F)
10    '''
11
12
13    filter_scales = opts.filter_scales
14    # ----- TODO -----
15
16    F = 4
17
18    if len(img.shape) < 3:
19        C = 1
20        H, W = img.shape
21    else:
22        H, W, C = img.shape
23
24    if C == 1:
25        img = np.expand_dims(img, axis = 2)
26        img = np.tile(img, (1,1,3))
27        H, W, C = img.shape
28
29    if C == 4:
30        img = img[:, :, 0:3]
31        H, W, C = img.shape
32
33    img = img.astype('float')/255.
34    img = skimage.color.rgb2lab(img)
35    filter_responses = []
36
37    for sigma in filter_scales:
38        for i in range(3):
39            filter_responses.append(scipy.ndimage.filters.gaussian_filter(im
40
41        for i in range(3):
42            filter_responses.append(scipy.ndimage.filters.gaussian_laplace(i
43
44        for i in range(3):
45            filter_responses.append(scipy.ndimage.filters.gaussian_filter(im
46
47        for i in range(3):
48            filter_responses.append(scipy.ndimage.filters.gaussian_filter(im
49
50    filter_responses = np.dstack(filter_responses)
51
52    return filter_responses
```

```
In [12]: 1 # Should have filters for at least 3 scales.  
2  
3 opts.filter_scales = [1, 2, 4, 8]  
4 img_path = join(opts.data_dir, 'aquarium/sun_aztvjgubyrgrup.jpg')  
5 img = plt.imread(img_path) / 255  
6 filter_responses = extract_filter_responses(opts, img)  
7 display_filter_responses(opts, filter_responses)
```



Q1.2

In [13]:

```

1  from numpy.random import default_rng
2
3  def compute_dictionary_one_image(img_path, opts):
4      """
5          Extracts a random subset of filter responses of an image and save it to
6          This is a worker function called by compute_dictionary
7
8          Your are free to make your own interface based on how you implement comp
9      """
10     #     opts, idx, img_path = args
11     # ----- TODO -----
12
13     alpha = opts.alpha
14
15     img = imageio.imread('../data/' + img_path)
16     img = img.astype('float')/255
17
18     filter_responses = extract_filter_responses(opts, img)
19     H, W, C = filter_responses.shape
20
21     responses = np.reshape(filter_responses, (H*W, C))
22
23     #     random = default_rng()
24     joints = np.random.randint(H*W, size=alpha)
25
26     responses = responses[joints, :]
27
28     return responses
29
30     np.save('%s%d'%(sample_response_path, i), np.asarray(responses))
31
32
33 def compute_dictionary(opts, n_worker=1):
34     """
35     Creates the dictionary of visual words by clustering using k-means.
36
37     [input]
38     * opts          : options
39     * n_worker      : number of workers to process in parallel
40
41     [saved]
42     * dictionary : numpy.ndarray of shape (K,3F)
43     """
44
45     data_dir = opts.data_dir
46     feat_dir = opts.feat_dir
47     out_dir = opts.out_dir
48     K = opts.K
49
50     train_files = open(join(data_dir, "train_files.txt")).read().splitlines(
51     # ----- TODO -----
52
53     img_response=compute_dictionary_one_image(os.path.join(opts.data_dir, (tr
54     img_stack=np.zeros((0,img_response.shape[1]))
55     for i in range(len(train_files)):
56         img_response=compute_dictionary_one_image(os.path.join(opts.data_dir

```



```
57     img_stack=np.vstack((img_stack,img_response))
58     #     print(img_stack.shape)
59
60     kmeans = KMeans(n_clusters=K,n_jobs=-1).fit(img_stack)
61     dictionary = kmeans.cluster_centers_
62     np.save('dictionary.npy',dictionary)
63
64     return dictionary
```

In [14]:

```
1 print('abc')
2 n_cpu = get_num_CPU()
3 print(n_cpu)
4 compute_dictionary(opts, n_worker=n_cpu)
5 print('abc')
```

abc
12

C:\ProgramData\Anaconda3\lib\site-packages\sklearn\cluster_kmeans.py:792: FutureWarning: 'n_jobs' was deprecated in version 0.23 and will be removed in 1.0 (renaming of 0.25).

warnings.warn("'n_jobs' was deprecated in version 0.23 and will be"

abc

Q1.3

The wordmap shows the contours in each image. Words change along the edges and tend to stay the same for homogenous regions.

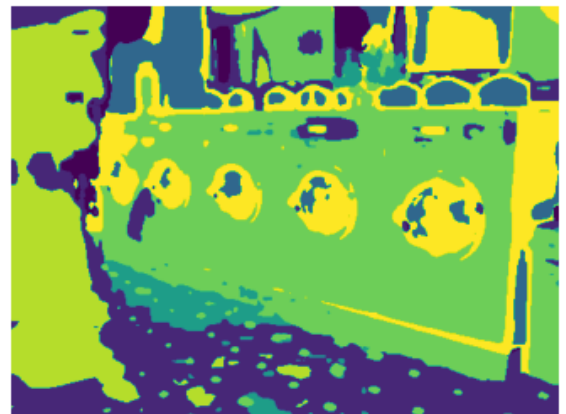
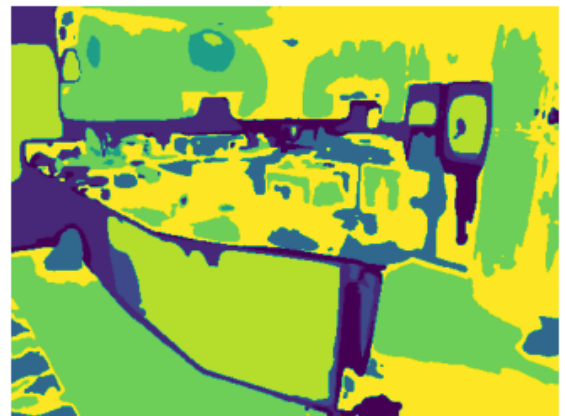
```
In [15]: 1 def get_visual_words(opts, img, dictionary):
2         """
3         Compute visual words mapping for the given img using the dictionary of v
4
5         [input]
6         * opts      : options
7         * img       : numpy.ndarray of shape (H,W) or (H,W,3)
8
9         [output]
10        * wordmap: numpy.ndarray of shape (H,W)
11        """
12
13        # ----- TODO -----
14        filter_response = extract_filter_responses(opts, img)
15
16        H, W, C = filter_response.shape
17        filter_response = filter_response.reshape(H*W, C)
18
19        distance = scipy.spatial.distance.cdist(filter_response, dictionary, met
20        wordmap = np.argmin(distance, axis = 1)
21        wordmap = wordmap.reshape(H, W)
22
23        return wordmap
24
```

```
In [16]: 1 dictionary = np.load(join(opts.out_dir, 'dictionary.npy'))
```

```

In [17]: 1 img_path = join(opts.data_dir, 'kitchen/sun_aasmevtpkslccptd.jpg')
2 img = plt.imread(img_path) / 255.
3 wordmap = get_visual_words(opts, img, dictionary)
4 visualize_wordmap(img, wordmap)
5
6 img_path = join(opts.data_dir, 'highway/sun_ailjxpgyepocjdos.jpg')
7 img = plt.imread(img_path) / 255.
8 wordmap = get_visual_words(opts, img, dictionary)
9 visualize_wordmap(img, wordmap)
10
11 img_path = join(opts.data_dir, 'laundromat/sun_aabvooxzwmzzvws.jpg')
12 img = plt.imread(img_path) / 255.
13 wordmap = get_visual_words(opts, img, dictionary)
14 visualize_wordmap(img, wordmap)
15

```



Here we can see the images of kitchen, highway and the laundromat. The visualization does make sense but it varies from scene to scene. Consider the highway image, it has less defined features relative to the laundromat image, making the highway image harder to make sense without the

actual reference image next to it.

Q2.1

```
In [18]: 1 def get_feature_from_wordmap(opts, wordmap):
2         '''
3         Compute histogram of visual words.
4
5         [input]
6         * opts      : options
7         * wordmap    : numpy.ndarray of shape (H,W)
8
9         [output]
10        * hist: numpy.ndarray of shape (K)
11        '''
12
13        K = opts.K
14        # ----- TODO -----
15        H, W = wordmap.shape
16        wordmap = np.reshape(wordmap, (1, H*W))
17        hist, edges = np.histogram(wordmap, np.linspace(0, K, K+1, endpoint = Tr
18        hist = hist/np.linalg.norm(hist, ord=1)
19        hist = np.reshape(hist, (1, K))
20
21        return hist
```

```
In [19]: 1 get_feature_from_wordmap(opts, wordmap)
```

```
Out[19]: array([[2.48213333e-02, 2.05957333e-01, 1.49333333e-04, 6.73546667e-02,
0.00000000e+00, 3.59200000e-02, 0.00000000e+00, 3.74906667e-01,
1.35264000e-01, 1.55626667e-01]])
```

Q2.2

In [101]:

```
1 def get_feature_from_wordmap_SPM(opts, wordmap):
2     """
3     Compute histogram of visual words using spatial pyramid matching.
4
5     [input]
6     * opts      : options
7     * wordmap    : numpy.ndarray of shape (H,W)
8
9     [output]
10    * hist_all: numpy.ndarray of shape (K*(4^L-1)/3)
11    """
12
13    K = opts.K
14    L = opts.L
15    # ----- TODO -----
16    H, W = wordmap.shape
17
18    hist_all = []
19    norm_factor = H*W
20
21    for i in range(L+1):
22
23        if i == 0 or i == 1:
24            weight = 2**(-L)
25        else:
26            weight = 2**(L-i-1)
27
28        cell_num = 2**i
29
30        x = np.array_split(wordmap, cell_num, axis=0)
31        for r in x:
32            y = np.array_split(r, cell_num, axis=1)
33            for c in y:
34                hist, bin_edges = np.histogram(c, bins=K)
35                hist_all = np.append(hist_all, hist / norm_factor * weight)
36
37
38
39    return hist_all
```

```
In [21]: 1 img_path = join(opts.data_dir, 'kitchen/sun_aasmevtpkslccptd.jpg')
2 img = plt.imread(img_path) / 255.
3 wordmap = get_visual_words(opts, img, dictionary)
4 hist = get_feature_from_wordmap_SPM(opts, wordmap)
5 print(hist)
```

```
[0.02398133 0.04710933 0.005872 0.03305333 0. 0.004328
0. 0.16242933 0.07177867 0.151448 0.00380533 0.022856
0. 0.005672 0. 0.004328 0. 0.04239467
0.01204267 0.03423467 0.00819733 0.008128 0.00028267 0.01006133
0. 0. 0. 0.03782667 0.00543467 0.05540267
0.00256533 0.01257867 0.00271467 0.00686667 0. 0.
0. 0.04837067 0.03905867 0.012512 0.00941333 0.00354667
0.00287467 0.01045333 0. 0. 0. 0.03383733
0.01524267 0.04929867]
```

Q2.3

```
In [22]: 1 def distance_to_set(word_hist, histograms):
2         """
3         Compute the distance between a histogram of visual words with all traini
4
5         [input]
6         * word_hist: numpy.ndarray of shape (K)
7         * histograms: numpy.ndarray of shape (N,K)
8
9         [output]
10        * dists: numpy.ndarray of shape (N)
11        """
12
13        # ----- TODO -----
14        dists = None
15
16        d = np.minimum(word_hist, histograms)
17        dists = np.sum(d, axis = 1)
18
19        return dists
```

```
In [23]: 1 word_hist = [1, 2]
2 histograms = [[1, 2],[0,4]]
3 distance_to_set(word_hist, histograms)
```

```
Out[23]: array([3, 2])
```

Q2.4

```
In [24]: 1 def get_image_feature(opts, img_path, dictionary):
2         """
3         Extracts the spatial pyramid matching feature.
4
5         [input]
6         * opts      : options
7         * img_path   : path of image file to read
8         * dictionary: numpy.ndarray of shape (K, 3F)
9
10
11         [output]
12         * feature: numpy.ndarray of shape (K)
13         """
14
15         # ----- TODO -----
16         #     feature = None
17         image = io.imread(img_path)
18         image = image.astype('float')/255
19         wordmap = get_visual_words(opts, image, dictionary)
20         feature = get_feature_from_wordmap_SPM(opts, wordmap)
21         #     print(np.shape(wordmap), wordmap)
22         return feature
```

```
In [ ]: 1
```

```

In [76]: 1 def build_recognition_system(opts, n_worker=1):
2         """
3         Creates a trained recognition system by generating training features fro
4
5         [input]
6         * opts          : options
7         * n_worker      : number of workers to process in parallel
8
9         [saved]
10        * features: numpy.ndarray of shape (N,M)
11        * labels: numpy.ndarray of shape (N)
12        * dictionary: numpy.ndarray of shape (K,3F)
13        * SPM_layer_num: number of spatial pyramid layers
14        """
15
16        data_dir = opts.data_dir
17        out_dir = opts.out_dir
18        SPM_layer_num = opts.L
19
20        train_files = open(join(data_dir, "train_files.txt")).read().splitlines(
21        train_labels = np.loadtxt(join(data_dir, "train_labels.txt"), np.int32)
22        dictionary = np.load(join(out_dir, "dictionary.npy"))
23
24        # ----- TODO -----
25        K = opts.K
26        L = opts.L
27        #     labels = []
28        train_data = np.asarray(train_files)
29        length_train = train_data.shape[0]
30
31        hist_features = []
32
33        for i in range(0, length_train ):
34            image_path = os.path.join(data_dir, train_files[i])
35            features = get_image_feature(opts, image_path, dictionary)
36            #         print(features)
37            #         print("Shape of Feature: ", np.shape(hist_features))
38            hist_features.append(features)
39
40
41        # example code snippet to save the learned system
42        np.savez_compressed(join(out_dir, 'trained_system.npz'),
43                            features=hist_features,
44                            labels=train_labels,
45                            dictionary=dictionary,
46                            SPM_layer_num=SPM_layer_num,
47        )
48

```


In [26]:

```
1 build_recognition_system(opts, n_worker=n_cpu)
```

```
2
```

```
Shape of Feature: (1114, 50)
Shape of Feature: (1115, 50)
Shape of Feature: (1116, 50)
Shape of Feature: (1117, 50)
Shape of Feature: (1118, 50)
Shape of Feature: (1119, 50)
Shape of Feature: (1120, 50)
Shape of Feature: (1121, 50)
Shape of Feature: (1122, 50)
Shape of Feature: (1123, 50)
Shape of Feature: (1124, 50)
Shape of Feature: (1125, 50)
Shape of Feature: (1126, 50)
Shape of Feature: (1127, 50)
Shape of Feature: (1128, 50)
Shape of Feature: (1129, 50)
Shape of Feature: (1130, 50)
```

In []:

```
1
```

Q2.5

```

In [79]: 1 def evaluate_recognition_system(opts, n_worker=1):
2         """
3         Evaluates the recognition system for all test images and returns the con
4
5         [input]
6         * opts          : options
7         * n_worker      : number of workers to process in parallel
8
9         [output]
10        * conf: numpy.ndarray of shape (8,8)
11        * accuracy: accuracy of the evaluated system
12        """
13
14        data_dir = opts.data_dir
15        out_dir = opts.out_dir
16
17        trained_system = np.load(join(out_dir, "trained_system.npz"))
18        dictionary = trained_system["dictionary"]
19
20        # using the stored options in the trained system instead of opts.py
21        test_opts = copy(opts)
22        test_opts.K = dictionary.shape[0]
23        test_opts.L = trained_system["SPM_layer_num"]
24        # print(test_opts.K, test_opts.L)
25
26        test_files = open(join(data_dir, "test_files.txt")).read().splitlines()
27        test_labels = np.loadtxt(join(data_dir, "test_labels.txt"), np.int32)
28
29        # ----- TODO -----
30        conf, accuracy = None, None
31
32        trained_features = trained_system['features']
33        train_labels = trained_system['labels']
34        test_labels = np.asarray(test_labels)
35        # print(np.shape(trained_features), np.shape(test_labels))
36        conf = np.zeros((8,8))
37        pred_label=list()
38        # count = 0
39        for i in range(len(test_files)):
40            image_path = os.path.join(data_dir, test_files[i])
41            hist_all = get_image_feature(opts, image_path, dictionary)
42            # print(np.shape(hist_all))
43            # print(trained_features)
44            distance = distance_to_set(hist_all, trained_features)
45            pred_index = np.argmax(distance)
46            # p = train_labels[pred_index]
47            # pred_label.append(p)
48            # print(pred_index)
49            pred_label = train_labels[pred_index]
50            conf[test_labels[i], pred_label] += 1
51            # if(pred_label[i] == test_labels[i]):
52            # count+=1
53            # accuracy = count/len(test_labels)
54            accuracy = np.trace(conf)/np.sum(conf)
55            print("{} accuracy: {}".format(i, accuracy))
56

```

```
57     return conf, accuracy
```

In []:

```
1
```

In []:

```
1
```

Initial Case

```
filter_scales = [1, 2, 4, 8]
```

```
K = 10
```

```
alpha = 25
```

```
L = 1
```

Accuracy achieved: 49.25%

Confusion Matrix:

```
[[34. 0. 1. 2. 2. 3. 5. 3.]
```

```
 [ 0. 23. 8. 8. 5. 1. 1. 4.]
```

```
 [ 0. 6. 26. 3. 3. 3. 2. 7.]
```

```
 [ 4. 3. 0. 25. 12. 4. 2. 0.]
```

```
 [ 1. 4. 0. 11. 16. 8. 6. 4.]
```

```
 [ 2. 0. 7. 2. 4. 27. 6. 2.]
```

```
 [ 3. 1. 1. 5. 8. 5. 22. 5.]
```

```
 [ 0. 3. 7. 4. 1. 7. 4. 24.]]
```

```
In [28]: 1 conf, accuracy = evaluate_recognition_system(opts, n_worker=n_cpu)
2
3 print("Accuracy:", accuracy)
4 classes = [
5     "aquarium", "desert", "highway", "kitchen",
6     "laundromat", "park", "waterfall", "windmill",
7 ]
8 df = pd.DataFrame(conf, columns=classes)
9 df.insert(0, "", classes)
10 df
```

```
397 accuracy: 0.49246231155778897
398 accuracy: 0.49122807017543857
399 accuracy: 0.4925
Accuracy: 0.4925
```

Out[28]:

		aquarium	desert	highway	kitchen	laundromat	park	waterfall	windmill
0	aquarium	34.0	0.0	1.0	2.0	2.0	3.0	5.0	3.0
1	desert	0.0	23.0	8.0	8.0	5.0	1.0	1.0	4.0
2	highway	0.0	6.0	26.0	3.0	3.0	3.0	2.0	7.0
3	kitchen	4.0	3.0	0.0	25.0	12.0	4.0	2.0	0.0
4	laundromat	1.0	4.0	0.0	11.0	16.0	8.0	6.0	4.0
5	park	2.0	0.0	7.0	2.0	4.0	27.0	6.0	2.0
6	waterfall	3.0	1.0	1.0	5.0	8.0	5.0	22.0	5.0
7	windmill	0.0	3.0	7.0	4.0	1.0	7.0	4.0	24.0

```
In [29]: 1 print(conf)
```

```
[[34.  0.  1.  2.  2.  3.  5.  3.]
 [ 0. 23.  8.  8.  5.  1.  1.  4.]
 [ 0.  6. 26.  3.  3.  3.  2.  7.]
 [ 4.  3.  0. 25. 12.  4.  2.  0.]
 [ 1.  4.  0. 11. 16.  8.  6.  4.]
 [ 2.  0.  7.  2.  4. 27.  6.  2.]
 [ 3.  1.  1.  5.  8.  5. 22.  5.]
 [ 0.  3.  7.  4.  1.  7.  4. 24.]]
```

Q2.6

We can see that there are some pairs which have more intersection than others, signifying that these are some of the hard classes to classify.

From the confusion matrix, we can infer some of these pairs as: (laundromat, kitchen); (waterfall, park); (windmill, highway)

The reason for this can be more than one. Some of which include: Small number of clusters, alpha number for the patches which might result in the classifier not having enough information to classify it to any class, etc



This is a laundromat image that was classified as kitchen. We can see how the model machine might have gotten confused between the two because the washing machines resemble a counter table of the kitchen and there is not much to differentiate with. Similar images of waterfall and park might have been detected as well since both the scenes have vast amount of similar structure, park has a grass scene and waterfall is an image filled with water, again making it hard for the system to actually find features to differentiate with.

Q3.1

Filter Scales	K	Alpha	L	Accuracy
[1, 2, 4, 8, 16]	50	100	2	55
[1, 2, 4, 8, 16]	100	150	2	59.75
[1, 2, 4, 8, 12]	75	125	2	60.75
[1, 2, 4, 8, 10]	100	200	3	59.75
[1, 2, 3, 5, 10]	200	200	2	56.25

The above table shows the multiple different test cases that were tried to improve the accuracy. The bold row is the one that received the maximum accuracy. I had tried more test cases with higher L values and different scales and alpha values, but the accuracy seemed to be stuck between 59-62 for some reason.

As the value of K increases the elements in a cluster reduces. So average distortion should decrease due to which classification accuracy increases.

When Layers (L) are increased, more details can be captured, making the classification easier and thus increasing accuracy.

Alpha increment provides more data and filter scales help you pick all the multi sized features, making it flexible.

Case1

filter_scales = [1, 2, 4, 8, 16]

K = 50

alpha = 100

L = 2

Accuracy achieved: 55%

Confusion Matrix:

[[33. 5. 0. 3. 1. 1. 1. 6.]

[0. 31. 5. 7. 4. 1. 0. 2.]

[2. 4. 25. 3. 0. 1. 7. 8.]

[4. 0. 1. 35. 9. 0. 1. 0.]

[1. 1. 1. 13. 25. 3. 6. 0.]

[1. 0. 2. 4. 2. 31. 6. 4.]

[3. 2. 4. 4. 1. 14. 19. 3.]

[1. 4. 9. 2. 1. 6. 6. 21.]]

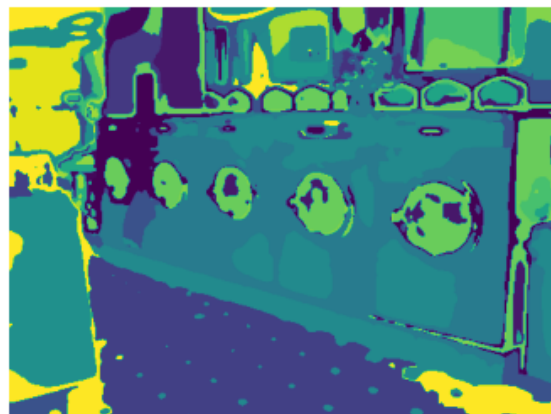
```
In [30]: 1 opts.filter_scales = [1, 2, 4, 8, 16]
2         opts.K = 50
3         opts.alpha = 100
4         opts.L = 2
5
6
7         compute_dictionary(opts, n_worker = n_cpu)
```

C:\ProgramData\Anaconda3\lib\site-packages\sklearn\cluster_kmeans.py:792: FutureWarning: 'n_jobs' was deprecated in version 0.23 and will be removed in 1.0 (renaming of 0.25).

warnings.warn("'n_jobs' was deprecated in version 0.23 and will be"

```
Out[30]: array([[ 1.15876212e-01,  4.36782268e-03,  4.05798567e-02, ...,
-5.21518768e-05,  1.86628810e-05,  4.52797306e-05],
[ 1.03455566e-01,  1.27282049e-03,  2.84666342e-03, ...,
-1.79602358e-04,  2.37297312e-05,  6.75507649e-05],
[ 2.28347684e-01, -3.85973657e-02, -4.56490844e-02, ...,
-1.20623188e-04,  4.59700828e-05,  3.01844266e-04],
...,
[ 5.75928270e-02, -8.56209810e-03, -7.30004015e-02, ...,
-1.87743934e-05,  7.62965416e-06,  1.34216587e-04],
[ 2.00365441e-01,  1.84316568e-03,  4.05263572e-02, ...,
-1.17066480e-04,  1.81136066e-05,  1.11786048e-04],
[ 9.29853627e-02,  1.10812091e-02, -2.14113370e-01, ...,
-9.38671153e-05,  2.16766730e-05,  2.72513921e-04]])
```

```
In [31]: 1 dictionary = np.load(join(opts.out_dir, 'dictionary.npy'))
2         # print(np.shape(dictionary))
3
4         img_path = join(opts.data_dir, 'laundromat/sun_aabvooxzwmzzvws.jpg')
5         img = plt.imread(img_path) / 255.
6         wordmap = get_visual_words(opts, img, dictionary)
7         visualize_wordmap(img, wordmap)
8
```



In [32]: 1 build_recognition_system(opts, n_worker = n_cpu)

```
Shape of Feature: (1158, 1050)
Shape of Feature: (1159, 1050)
Shape of Feature: (1160, 1050)
Shape of Feature: (1161, 1050)
Shape of Feature: (1162, 1050)
Shape of Feature: (1163, 1050)
Shape of Feature: (1164, 1050)
Shape of Feature: (1165, 1050)
Shape of Feature: (1166, 1050)
Shape of Feature: (1167, 1050)
Shape of Feature: (1168, 1050)
Shape of Feature: (1169, 1050)
Shape of Feature: (1170, 1050)
Shape of Feature: (1171, 1050)
Shape of Feature: (1172, 1050)
Shape of Feature: (1173, 1050)
Shape of Feature: (1174, 1050)

Shape of Feature: (1175, 1050)
Shape of Feature: (1176, 1050)
```

In [33]: 1 conf, accuracy = evaluate_recognition_system(opts, n_worker=n_cpu)
2
3 print("Accuracy:", accuracy)

```
381 accuracy: 0.5549758215855288
382 accuracy: 0.556135770234987
383 accuracy: 0.5546875
384 accuracy: 0.5532467532467532
385 accuracy: 0.5544041450777202
386 accuracy: 0.5529715762273901
387 accuracy: 0.5541237113402062
388 accuracy: 0.5526992287917738
389 accuracy: 0.5512820512820513
390 accuracy: 0.5498721227621484
391 accuracy: 0.548469387755102
392 accuracy: 0.549618320610687
393 accuracy: 0.5482233502538071
394 accuracy: 0.549367088607595
395 accuracy: 0.547979797979798
396 accuracy: 0.5465994962216625
397 accuracy: 0.5477386934673367
398 accuracy: 0.5488721804511278
399 accuracy: 0.55
Accuracy: 0.55
```



```
In [34]: 1 classes = [
2         "aquarium", "desert", "highway", "kitchen",
3         "laundromat", "park", "waterfall", "windmill",
4     ]
5     df = pd.DataFrame(conf, columns=classes)
6     df.insert(0, "", classes)
7     df
```

Out[34]:

		aquarium	desert	highway	kitchen	laundromat	park	waterfall	windmill
0	aquarium	33.0	5.0	0.0	3.0	1.0	1.0	1.0	6.0
1	desert	0.0	31.0	5.0	7.0	4.0	1.0	0.0	2.0
2	highway	2.0	4.0	25.0	3.0	0.0	1.0	7.0	8.0
3	kitchen	4.0	0.0	1.0	35.0	9.0	0.0	1.0	0.0
4	laundromat	1.0	1.0	1.0	13.0	25.0	3.0	6.0	0.0
5	park	1.0	0.0	2.0	4.0	2.0	31.0	6.0	4.0
6	waterfall	3.0	2.0	4.0	4.0	1.0	14.0	19.0	3.0
7	windmill	1.0	4.0	9.0	2.0	1.0	6.0	6.0	21.0

```
In [35]: 1 print(conf)
```

```
[[33.  5.  0.  3.  1.  1.  1.  6.]
 [ 0. 31.  5.  7.  4.  1.  0.  2.]
 [ 2.  4. 25.  3.  0.  1.  7.  8.]
 [ 4.  0.  1. 35.  9.  0.  1.  0.]
 [ 1.  1.  1. 13. 25.  3.  6.  0.]
 [ 1.  0.  2.  4.  2. 31.  6.  4.]
 [ 3.  2.  4.  4.  1. 14. 19.  3.]
 [ 1.  4.  9.  2.  1.  6.  6. 21.]]
```

```
In [ ]: 1
```

```
In [ ]: 1
```

Case2

filter_scales = [1, 2, 4, 8, 16]

K = 100

alpha = 150

L = 2

Accuracy achieved: 59.75%

Confusion Matrix:

```
[[33. 3. 5. 1. 2. 2. 3. 1.]
```

```
[ 1. 29. 6. 2. 4. 1. 1. 6.]
```

```
[ 2. 3. 25. 0. 3. 7. 4. 6.]
```

```
[ 4. 1. 1. 33. 6. 1. 2. 2.]
```

```
[ 1. 1. 2. 15. 26. 3. 2. 0.]
```

```
[ 3. 0. 3. 1. 2. 39. 2. 0.]
```

```
[ 1. 2. 4. 1. 3. 8. 28. 3.]
```

```
[ 0. 3. 7. 2. 0. 6. 6. 26.]]
```

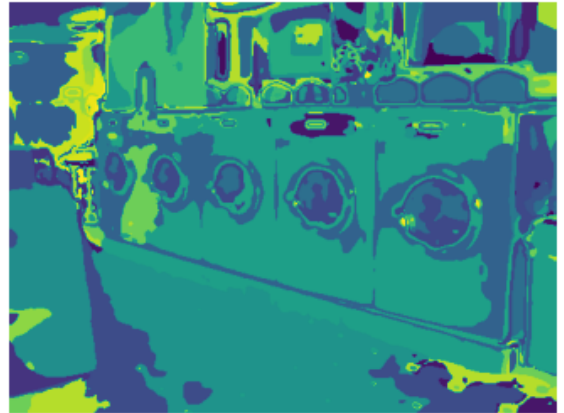
```
In [38]: 1 opts.filter_scales = [1, 2, 4, 8, 16]
          2 opts.K = 100
          3 opts.alpha = 150
          4 opts.L = 2
          5
          6
          7 compute_dictionary(opts, n_worker = n_cpu)
```

C:\ProgramData\Anaconda3\lib\site-packages\sklearn\cluster_kmeans.py:792: FutureWarning: 'n_jobs' was deprecated in version 0.23 and will be removed in 1.0 (renaming of 0.25).

warnings.warn("'n_jobs' was deprecated in version 0.23 and will be")

```
Out[38]: array([[ 9.51995574e-02, -3.02588995e-02,  3.89448314e-02, ...,
                  -9.82660421e-05, -2.41316505e-06,  1.13328688e-04],
                 [ 2.40745624e-01, -6.68988718e-03, -2.31454853e-02, ...,
                  -2.29451210e-04,  3.53342495e-05,  1.70943453e-04],
                 [ 1.34470733e-01, -1.08000023e-02, -7.34082026e-02, ...,
                  4.12280392e-05,  8.24376616e-06,  2.82038431e-04],
                 ...,
                 [ 1.46432668e-01, -8.96352498e-02,  1.14805161e-01, ...,
                  -5.12143211e-05, -2.21977612e-04,  2.11997921e-04],
                 [ 1.23446784e-01,  1.90365096e-02,  1.17470404e-01, ...,
                  -5.90639366e-05,  4.69625512e-06,  1.53943161e-05],
                 [ 1.87571906e-01, -2.51547342e-03,  4.91168370e-03, ...,
                  -1.88244007e-04, -1.66824016e-06,  4.72441652e-05]])
```

```
In [39]: 1 dictionary = np.load(join(opts.out_dir, 'dictionary.npy'))
2         # print(np.shape(dictionary))
3
4         img_path = join(opts.data_dir, 'laundromat/sun_aabvooxzwmzzvws.jpg')
5         img = plt.imread(img_path) / 255.
6         wordmap = get_visual_words(opts, img, dictionary)
7         visualize_wordmap(img, wordmap)
8
```



```
In [40]: 1 build_recognition_system(opts, n_worker = n_cpu)
```

```
Shape of Feature: (1158, 2100)
Shape of Feature: (1159, 2100)
Shape of Feature: (1160, 2100)
Shape of Feature: (1161, 2100)
Shape of Feature: (1162, 2100)
Shape of Feature: (1163, 2100)
Shape of Feature: (1164, 2100)
Shape of Feature: (1165, 2100)
Shape of Feature: (1166, 2100)
Shape of Feature: (1167, 2100)
Shape of Feature: (1168, 2100)
Shape of Feature: (1169, 2100)
Shape of Feature: (1170, 2100)
Shape of Feature: (1171, 2100)
Shape of Feature: (1172, 2100)
Shape of Feature: (1173, 2100)
Shape of Feature: (1174, 2100)

Shape of Feature: (1175, 2100)
Shape of Feature: (1176, 2100)
```

```
In [41]: 1 conf, accuracy = evaluate_recognition_system(opts, n_worker=n_cpu)
2
3 print("Accuracy:", accuracy)
381 accuracy: 0.6075238423313371
382 accuracy: 0.6057441253263708
383 accuracy: 0.6067708333333334
384 accuracy: 0.6051948051948052
385 accuracy: 0.6036269430051814
386 accuracy: 0.6020671834625323
387 accuracy: 0.6030927835051546
388 accuracy: 0.6015424164524421
389 accuracy: 0.6025641025641025
390 accuracy: 0.6035805626598465
391 accuracy: 0.6020408163265306
392 accuracy: 0.6030534351145038
393 accuracy: 0.6015228426395939
394 accuracy: 0.6
395 accuracy: 0.601010101010101
396 accuracy: 0.5994962216624685
397 accuracy: 0.5979899497487438
398 accuracy: 0.5989974937343359
399 accuracy: 0.5975
Accuracy: 0.5975
```

```
In [45]: 1 classes = [
2         "aquarium", "desert", "highway", "kitchen",
3         "laundromat", "park", "waterfall", "windmill",
4     ]
5 df = pd.DataFrame(conf, columns=classes)
6 df.insert(0, "", classes)
7 df
```

Out[45]:

		aquarium	desert	highway	kitchen	laundromat	park	waterfall	windmill
0	aquarium	33.0	3.0	5.0	1.0	2.0	2.0	3.0	1.0
1	desert	1.0	29.0	6.0	2.0	4.0	1.0	1.0	6.0
2	highway	2.0	3.0	25.0	0.0	3.0	7.0	4.0	6.0
3	kitchen	4.0	1.0	1.0	33.0	6.0	1.0	2.0	2.0
4	laundromat	1.0	1.0	2.0	15.0	26.0	3.0	2.0	0.0
5	park	3.0	0.0	3.0	1.0	2.0	39.0	2.0	0.0
6	waterfall	1.0	2.0	4.0	1.0	3.0	8.0	28.0	3.0
7	windmill	0.0	3.0	7.0	2.0	0.0	6.0	6.0	26.0

In [46]:

```
1 print(conf)

[[33.  3.  5.  1.  2.  2.  3.  1.]
 [ 1. 29.  6.  2.  4.  1.  1.  6.]
 [ 2.  3. 25.  0.  3.  7.  4.  6.]
 [ 4.  1.  1. 33.  6.  1.  2.  2.]
 [ 1.  1.  2. 15. 26.  3.  2.  0.]
 [ 3.  0.  3.  1.  2. 39.  2.  0.]
 [ 1.  2.  4.  1.  3.  8. 28.  3.]
 [ 0.  3.  7.  2.  0.  6.  6. 26.]]
```

In []:

1

In []:

1

Case3

filter_scales = [1, 2, 4, 8, 12]

K = 75

alpha = 125

L = 2

Accuracy achieved: 60.75%

Confusion Matrix:

```
[[31.  1.  2.  2.  6.  2.  3.  3.]
```

```
[ 1. 30.  3.  6.  4.  3.  3.  0.]
```

```
[ 1.  3. 30.  2.  5.  1.  3.  5.]
```

```
[ 2.  0.  1. 31. 15.  0.  1.  0.]
```

```
[ 0.  0.  0. 12. 30.  5.  2.  1.]
```

```
[ 3.  0.  4.  2.  2. 36.  3.  0.]
```

```
[ 2.  0.  1.  2.  5.  7. 30.  3.]
```

```
[ 1.  3.  5.  3.  4.  5.  4. 25.]]
```

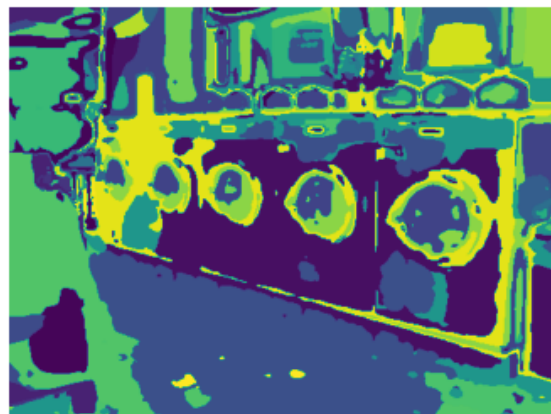
```
In [47]: 1 opts.filter_scales = [1, 2, 4, 8, 12]
2         opts.K = 75
3         opts.alpha = 125
4         opts.L = 2
5
6
7         compute_dictionary(opts, n_worker = n_cpu)
```

C:\ProgramData\Anaconda3\lib\site-packages\sklearn\cluster_kmeans.py:792: FutureWarning: 'n_jobs' was deprecated in version 0.23 and will be removed in 1.0 (renaming of 0.25).

warnings.warn("'n_jobs' was deprecated in version 0.23 and will be"

```
Out[47]: array([[ 5.95452137e-02,  6.96601560e-04,  3.76379443e-03, ...,
-3.08905703e-04,  3.31365833e-05,  1.23726408e-04],
[ 2.38887560e-01, -8.26069175e-04,  2.88026701e-03, ...,
-2.54312634e-04, -1.02548407e-05,  8.29625924e-05],
[ 1.36621767e-01, -2.59319951e-03, -3.56313909e-02, ...,
-2.86191823e-04,  1.74122237e-05,  2.45691422e-04],
...,
[ 1.74387705e-01, -1.67885017e-03,  4.37426562e-03, ...,
-1.31298074e-04,  1.58452824e-05,  6.76558440e-05],
[ 1.29279498e-01, -5.68756333e-04,  2.11790326e-02, ...,
-8.65162840e-05,  2.07977186e-05,  3.27904258e-05],
[ 2.27241325e-01, -4.47448141e-02,  9.42580553e-02, ...,
-2.09557101e-05, -1.19034273e-04,  1.81845101e-04]])
```

```
In [48]: 1 dictionary = np.load(join(opts.out_dir, 'dictionary.npy'))
2         # print(np.shape(dictionary))
3
4         img_path = join(opts.data_dir, 'laundromat/sun_aabvooxzwmzzvws.jpg')
5         img = plt.imread(img_path) / 255.
6         wordmap = get_visual_words(opts, img, dictionary)
7         visualize_wordmap(img, wordmap)
8
```



In [49]: 1 build_recognition_system(opts, n_worker = n_cpu)

```
Shape of Feature: (1158, 1575)
Shape of Feature: (1159, 1575)
Shape of Feature: (1160, 1575)
Shape of Feature: (1161, 1575)
Shape of Feature: (1162, 1575)
Shape of Feature: (1163, 1575)
Shape of Feature: (1164, 1575)
Shape of Feature: (1165, 1575)
Shape of Feature: (1166, 1575)
Shape of Feature: (1167, 1575)
Shape of Feature: (1168, 1575)
Shape of Feature: (1169, 1575)
Shape of Feature: (1170, 1575)
Shape of Feature: (1171, 1575)
Shape of Feature: (1172, 1575)
Shape of Feature: (1173, 1575)
Shape of Feature: (1174, 1575)

Shape of Feature: (1175, 1575)
Shape of Feature: (1176, 1575)
```

In [50]: 1 conf, accuracy = evaluate_recognition_system(opts, n_worker=n_cpu)
2
3 print("Accuracy:", accuracy)

```
381 accuracy: 0.6095470433730373
382 accuracy: 0.6109660574412533
383 accuracy: 0.6119791666666666
384 accuracy: 0.6103896103896104
385 accuracy: 0.6088082901554405
386 accuracy: 0.6098191214470284
387 accuracy: 0.6108247422680413
388 accuracy: 0.609254498714653
389 accuracy: 0.6102564102564103
390 accuracy: 0.6086956521739131
391 accuracy: 0.6071428571428571
392 accuracy: 0.6081424936386769
393 accuracy: 0.6065989847715736
394 accuracy: 0.6050632911392405
395 accuracy: 0.6035353535353535
396 accuracy: 0.6045340050377834
397 accuracy: 0.6055276381909548
398 accuracy: 0.606516290726817
399 accuracy: 0.6075
Accuracy: 0.6075
```

```
In [51]: 1 classes = [
2         "aquarium", "desert", "highway", "kitchen",
3         "laundromat", "park", "waterfall", "windmill",
4     ]
5     df = pd.DataFrame(conf, columns=classes)
6     df.insert(0, "", classes)
7     df
```

Out[51]:

		aquarium	desert	highway	kitchen	laundromat	park	waterfall	windmill
0	aquarium	31.0	1.0	2.0	2.0	6.0	2.0	3.0	3.0
1	desert	1.0	30.0	3.0	6.0	4.0	3.0	3.0	0.0
2	highway	1.0	3.0	30.0	2.0	5.0	1.0	3.0	5.0
3	kitchen	2.0	0.0	1.0	31.0	15.0	0.0	1.0	0.0
4	laundromat	0.0	0.0	0.0	12.0	30.0	5.0	2.0	1.0
5	park	3.0	0.0	4.0	2.0	2.0	36.0	3.0	0.0
6	waterfall	2.0	0.0	1.0	2.0	5.0	7.0	30.0	3.0
7	windmill	1.0	3.0	5.0	3.0	4.0	5.0	4.0	25.0

```
In [52]: 1 print(conf)
```

```
[[31.  1.  2.  2.  6.  2.  3.  3.]
 [ 1. 30.  3.  6.  4.  3.  3.  0.]
 [ 1.  3. 30.  2.  5.  1.  3.  5.]
 [ 2.  0.  1. 31. 15.  0.  1.  0.]
 [ 0.  0.  0. 12. 30.  5.  2.  1.]
 [ 3.  0.  4.  2.  2. 36.  3.  0.]
 [ 2.  0.  1.  2.  5.  7. 30.  3.]
 [ 1.  3.  5.  3.  4.  5.  4. 25.]]
```

```
In [ ]: 1
```

```
In [ ]: 1
```

Case4

filter_scales = [1, 2, 4, 8, 10]

K = 100

alpha = 200

L = 3

Accuracy achieved: 59.75%

Confusion Matrix:


```
[[31. 7. 0. 2. 3. 3. 2. 2.]
```

```
[ 1. 34. 8. 3. 1. 0. 1. 2.]
```

```
[ 3. 6. 26. 4. 1. 3. 0. 7.]
```

```
[ 2. 4. 2. 26. 14. 1. 1. 0.]
```

```
[ 0. 2. 0. 9. 31. 5. 2. 1.]
```

```
[ 1. 1. 1. 2. 3. 36. 4. 2.]
```

```
[ 1. 5. 2. 1. 4. 8. 28. 1.]
```

```
[ 0. 4. 6. 0. 1. 8. 4. 27.]]
```

```
In [53]: 1 opts.filter_scales = [1, 2, 4, 8, 10]
          2 opts.K = 100
          3 opts.alpha = 200
          4 opts.L = 3
          5
          6
          7 compute_dictionary(opts, n_worker = n_cpu)
```

C:\ProgramData\Anaconda3\lib\site-packages\sklearn\cluster_kmeans.py:792: FutureWarning: 'n_jobs' was deprecated in version 0.23 and will be removed in 1.0 (renaming of 0.25).

warnings.warn("'n_jobs' was deprecated in version 0.23 and will be")

```
Out[53]: array([[ 8.21060057e-02, -5.67046124e-04,  3.47494867e-03, ...,
                  -4.19657783e-04,  3.42027444e-07,  1.47033474e-04],
                 [ 5.34965995e-02, -1.22170931e-03,  2.49588810e-02, ...,
                  -7.21907379e-05,  1.74770369e-05,  1.18251574e-05],
                 [ 1.29752981e-01,  1.82200336e-02,  8.61959020e-02, ...,
                  -5.96709962e-05,  2.94634095e-05,  7.73447819e-05],
                 ...,
                 [ 1.29471524e-01, -2.84972263e-02, -1.08635313e-01, ...,
                  1.86785199e-04, -3.52658144e-05,  2.05732741e-04],
                 [ 1.59056442e-01, -3.59041763e-03,  2.36466965e-02, ...,
                  -1.58189172e-04,  1.67860724e-05,  5.21496198e-05],
                 [ 1.10161698e-01, -9.89226734e-02, -6.83617294e-02, ...,
                  -7.24628781e-05,  7.66037647e-05,  1.94375326e-04]])
```

```
In [54]: 1 dictionary = np.load(join(opts.out_dir, 'dictionary.npy'))
2         # print(np.shape(dictionary))
3
4         img_path = join(opts.data_dir, 'laundromat/sun_aabvooxzwmzzvws.jpg')
5         img = plt.imread(img_path) / 255.
6         wordmap = get_visual_words(opts, img, dictionary)
7         visualize_wordmap(img, wordmap)
```



```
In [55]: 1 build_recognition_system(opts, n_worker = n_cpu)
```

```
Shape of Feature: (1158, 8500)
Shape of Feature: (1159, 8500)
Shape of Feature: (1160, 8500)
Shape of Feature: (1161, 8500)
Shape of Feature: (1162, 8500)
Shape of Feature: (1163, 8500)
Shape of Feature: (1164, 8500)
Shape of Feature: (1165, 8500)
Shape of Feature: (1166, 8500)
Shape of Feature: (1167, 8500)
Shape of Feature: (1168, 8500)
Shape of Feature: (1169, 8500)
Shape of Feature: (1170, 8500)
Shape of Feature: (1171, 8500)
Shape of Feature: (1172, 8500)
Shape of Feature: (1173, 8500)
Shape of Feature: (1174, 8500)

Shape of Feature: (1175, 8500)
Shape of Feature: (1176, 8500)
```

```
In [56]: 1 conf, accuracy = evaluate_recognition_system(opts, n_worker=n_cpu)
2
3 print("Accuracy:", accuracy)
381 accuracy: 0.5972408370303331
382 accuracy: 0.5926892950391645
383 accuracy: 0.59375
384 accuracy: 0.5922077922077922
385 accuracy: 0.5932642487046632
386 accuracy: 0.5917312661498708
387 accuracy: 0.5927835051546392
388 accuracy: 0.5938303341902313
389 accuracy: 0.5948717948717949
390 accuracy: 0.5959079283887468
391 accuracy: 0.5969387755102041
392 accuracy: 0.5979643765903307
393 accuracy: 0.5964467005076142
394 accuracy: 0.5949367088607594
395 accuracy: 0.5959595959595959
396 accuracy: 0.5944584382871536
397 accuracy: 0.5954773869346733
398 accuracy: 0.5964912280701754
399 accuracy: 0.5975
Accuracy: 0.5975
```

```
In [57]: 1 classes = [
2         "aquarium", "desert", "highway", "kitchen",
3         "laundromat", "park", "waterfall", "windmill",
4     ]
5 df = pd.DataFrame(conf, columns=classes)
6 df.insert(0, "", classes)
7 df
```

Out[57]:

		aquarium	desert	highway	kitchen	laundromat	park	waterfall	windmill
0	aquarium	31.0	7.0	0.0	2.0	3.0	3.0	2.0	2.0
1	desert	1.0	34.0	8.0	3.0	1.0	0.0	1.0	2.0
2	highway	3.0	6.0	26.0	4.0	1.0	3.0	0.0	7.0
3	kitchen	2.0	4.0	2.0	26.0	14.0	1.0	1.0	0.0
4	laundromat	0.0	2.0	0.0	9.0	31.0	5.0	2.0	1.0
5	park	1.0	1.0	1.0	2.0	3.0	36.0	4.0	2.0
6	waterfall	1.0	5.0	2.0	1.0	4.0	8.0	28.0	1.0
7	windmill	0.0	4.0	6.0	0.0	1.0	8.0	4.0	27.0

In [58]:

```
1 print(conf)

[[31.  7.  0.  2.  3.  3.  2.  2.]
 [ 1. 34.  8.  3.  1.  0.  1.  2.]
 [ 3.  6. 26.  4.  1.  3.  0.  7.]
 [ 2.  4.  2. 26. 14.  1.  1.  0.]
 [ 0.  2.  0.  9. 31.  5.  2.  1.]
 [ 1.  1.  1.  2.  3. 36.  4.  2.]
 [ 1.  5.  2.  1.  4.  8. 28.  1.]
 [ 0.  4.  6.  0.  1.  8.  4. 27.]]
```

In []:

1

In []:

1

Case5

filter_scales = [1, 2, 3, 5, 10]

K = 200

alpha = 200

L = 2

Accuracy achieved: 56.25%

Confusion Matrix:

```
[[37. 0. 2. 0. 3. 0. 5. 3.]
 [ 1. 22. 8. 8. 4. 2. 2. 3.]
 [ 1. 4. 22. 3. 2. 3. 4. 11.]
 [ 3. 2. 1. 29. 13. 1. 1. 0.]
 [ 1. 1. 0. 15. 25. 4. 4. 0.]
 [ 0. 0. 3. 2. 2. 42. 1. 0.]
 [ 2. 1. 3. 1. 3. 14. 25. 1.]
 [ 1. 1. 6. 2. 4. 10. 3. 23.]]
```


In [65]: 1 build_recognition_system(opts, n_worker = n_cpu)

```
Shape of Feature: (1158, 4200)
Shape of Feature: (1159, 4200)
Shape of Feature: (1160, 4200)
Shape of Feature: (1161, 4200)
Shape of Feature: (1162, 4200)
Shape of Feature: (1163, 4200)
Shape of Feature: (1164, 4200)
Shape of Feature: (1165, 4200)
Shape of Feature: (1166, 4200)
Shape of Feature: (1167, 4200)
Shape of Feature: (1168, 4200)
Shape of Feature: (1169, 4200)
Shape of Feature: (1170, 4200)
Shape of Feature: (1171, 4200)
Shape of Feature: (1172, 4200)
Shape of Feature: (1173, 4200)
Shape of Feature: (1174, 4200)

Shape of Feature: (1175, 4200)
Shape of Feature: (1176, 4200)
```

In [66]: 1 conf, accuracy = evaluate_recognition_system(opts, n_worker=n_cpu)
2
3 print("Accuracy:", accuracy)

```
381 accuracy: 0.5634730201700105
382 accuracy: 0.5639686684073107
383 accuracy: 0.5651041666666666
384 accuracy: 0.5636363636363636
385 accuracy: 0.5621761658031088
386 accuracy: 0.5633074935400517
387 accuracy: 0.5644329896907216
388 accuracy: 0.5629820051413882
389 accuracy: 0.5641025641025641
390 accuracy: 0.5626598465473146
391 accuracy: 0.5612244897959183
392 accuracy: 0.5623409669211196
393 accuracy: 0.5609137055837563
394 accuracy: 0.5620253164556962
395 accuracy: 0.5606060606060606
396 accuracy: 0.5591939546599496
397 accuracy: 0.5603015075376885
398 accuracy: 0.5614035087719298
399 accuracy: 0.5625
Accuracy: 0.5625
```

```
In [67]: 1 classes = [
2         "aquarium", "desert", "highway", "kitchen",
3         "laundromat", "park", "waterfall", "windmill",
4     ]
5     df = pd.DataFrame(conf, columns=classes)
6     df.insert(0, "", classes)
7     df
```

Out[67]:

		aquarium	desert	highway	kitchen	laundromat	park	waterfall	windmill
0	aquarium	37.0	0.0	2.0	0.0	3.0	0.0	5.0	3.0
1	desert	1.0	22.0	8.0	8.0	4.0	2.0	2.0	3.0
2	highway	1.0	4.0	22.0	3.0	2.0	3.0	4.0	11.0
3	kitchen	3.0	2.0	1.0	29.0	13.0	1.0	1.0	0.0
4	laundromat	1.0	1.0	0.0	15.0	25.0	4.0	4.0	0.0
5	park	0.0	0.0	3.0	2.0	2.0	42.0	1.0	0.0
6	waterfall	2.0	1.0	3.0	1.0	3.0	14.0	25.0	1.0
7	windmill	1.0	1.0	6.0	2.0	4.0	10.0	3.0	23.0

```
In [68]: 1 print(conf)
```

```
[[37.  0.  2.  0.  3.  0.  5.  3.]
 [ 1. 22.  8.  8.  4.  2.  2.  3.]
 [ 1.  4. 22.  3.  2.  3.  4. 11.]
 [ 3.  2.  1. 29. 13.  1.  1.  0.]
 [ 1.  1.  0. 15. 25.  4.  4.  0.]
 [ 0.  0.  3.  2.  2. 42.  1.  0.]
 [ 2.  1.  3.  1.  3. 14. 25.  1.]
 [ 1.  1.  6.  2.  4. 10.  3. 23.]]
```

Q3.2

I did not get the time to implement this but my plan was to pass the images through the function `resize_image()` which will resize every image to a 256x256 size image, prior to making the dictionary and formulating trained_system. This method is proposed in multiple published papers. I took my inspiration from the following paper:

Ref: Torralba, Antonio, Rob Fergus, and William T. Freeman. "80 million tiny images: A large data set for nonparametric object and scene recognition." IEEE transactions on pattern analysis and machine intelligence 30.11 (2008): 1958-1970.

Prior to this, I also tried to reduce the weights for the images. I kept the hyperparameters fixed as to when I got the maximum accuracy and scaled down the weights assigned. Right now when in layer 3, weights are 1/4(layer 0), 1/4(layer 1) and 1/2(layer 2), I changed it down to 1/8, 1/8 and 1/4 respectively for layers 0, 1 and 2. Since I am scaling down all of the layers by the same factor, there should not be a massive jump in accuracy, but I expected a little bump since it follows a

similar idea as the IDF-TF suggested in 3.3. However, what I noticed was my accuracy had dipped to close to 56%. I think this happened because of improper assignment of weights to the 0th and 1st level, or maybe I should have had a combination of weights to adapt to every layer rather than just scaling it down by a single factor all throughout.

```
In [107]: 1 def resize_image():
2         data_dir = "../data"
3         train_files = open(join(data_dir, "train_files.txt")).read().splitlines()
4         imageFile = os.path.join(opts.data_dir, (train_files[0]))
5         im1 = Image.open(imageFile)
6         width = 256
7         height = 256
8         # use one of these filter options to resize the image
9         im2 = im1.resize((width, height), Image.NEAREST)      # use nearest neighbor
10        im3 = im1.resize((width, height), Image.BILINEAR)      # linear interpolation
11        im4 = im1.resize((width, height), Image.BICUBIC)       # cubic spline interpolation
12        im5 = im1.resize((width, height), Image.ANTIALIAS)
13
14        return im2
```

Alternatively, to increase the speed of the computation, we can implement multiprocessing - process based parallelism (using pool.map)

Its implementation will look somewhat similar to the following:

```
In [111]: 1 import multiprocessing
2
3 pool = multiprocessing.Pool(num_workers)
4 pool.map(compute_dictionary_one_image, arguments)
5 pool.close()
6 pool.join()
7
8 # Similarly for the other functions as well, where num_workers = n_cpu
```

```
In [ ]: 1
```

Q3.3 (Extra Credit)

The basic idea of this approach is to assign less weights to the patches of images that are very frequent and do not provide a lot of information about how to classify them into different classes. So when we weigh down these common patches and scale up the rare patches, we will have a better classification process, thus improving the accuracy.


```
In [ ]: 1 def compute_IDF(opts, n_worker=1):
        2     # YOUR CODE HERE
        3
        4     K value
        5
        6     if bins != 0, then new bin + 1
        7     np.log(1177/list) = weights[]
        8     pass
        9
    10 def evaluate_recognition_System_IDF(opts, n_worker=1):
    11     # YOUR CODE HERE
    12     pass
```