HOMEWORK 1: SPATIAL PYRAMID MATCHING FOR SCENE CLASSIFICATION

16-720A Computer Vision (Spring 2023)
https://canvas.cmu.edu/courses/32966

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Instructor: Deva Ramanan
TAs: Kangle Deng, Vidhi Jain, Xiaofeng Guo, Chung Hee Kim, Ingrid Navarro Anaya

Figure 0.1: **Scene Classification:** Given an image, can a computer program determine where it was taken? In this homework, you will build a representation based on bags of visual words and use spatial pyramid matching for classifying the scene categories.

START HERE: Instructions

- Please refer to the course logistics page for information on the **Collaboration Policy** and **Late Submission Policy**.
- **Submitting your work:** There will be two submission slots for this homework on **Gradescope**: Written and Programming.
  - For written problems such as short answer, multiple choice, derivations, proofs, or plots, we will be using the written submission slot. Please use this provided template. **We don't accept handwritten submissions.** Each answer should be completed in the boxes provided below the question. You are allowed to adjust the size of these boxes, but **make sure to link your answer to each question when submitting to Gradescope**. Otherwise, your submission will not be graded.
  - You are also required to upload your code, which you wrote to solve this homework, to the Programming submission slot. Your code may be run by TAs so please make sure it is in a

workable state. The assignment must be completed using Python 3.7 or newer. We recommend setting up a conda environment, but you are free to set up your environment however you like.

- Regrade requests can be made after the homework grades are released, however this gives the TA the opportunity to regrade your entire paper, meaning if additional mistakes are found then points will be deducted.

- **Start early!** This homework may take a long time to complete.

- **Attempt to verify your implementation as you proceed.** If you don't verify that your implementation is correct on toy examples, you will risk having a huge mess when you put everything together. Here are two tips:

  (1) Once you write a function, uncomment the corresponding lines in `main.py` to verify whether the function executes correctly.

  (2) To debug your logic within a function, use `print()` or `breakpoint()`.

- Follow the guidelines in Section 5: HW Checklist for writeup and code. If you have any questions or need clarifications, please post in Slack or visit the TAs during office hours.

Overview

Bag-of-words (BoW) can be applied to many problems in computer vision, including object recognition [5, 7] and scene classification [6, 8][1]. This homework will explore classic BoW along with extensions, such as pyramid matching [2, 4] and feature encoding [1]. Fig 0.2 provides an overview. Section 1 builds a dictionary of visual words from a training set of images by clustering. Section 2 builds a representation for a particular image as a histogram over visual words, or BoW. Finally, you will build a scene recognition system that classifies a test image by comparing it to a training library of images in BoW space (e.g., nearest-neighbor classification).

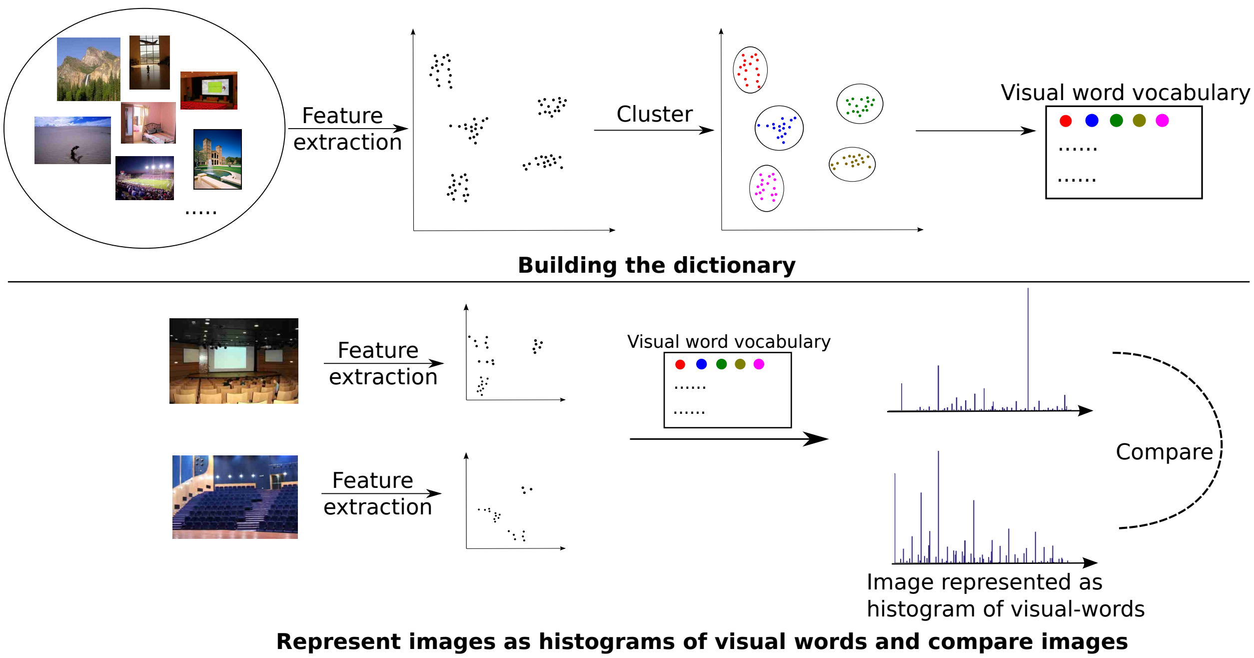


Figure 0.2: An overview of the bags-of-words approach to be implemented in the homework. First, given the training set of images, we extract the visual features of the images. In our case, we will use the filter responses of the pre-defined filter bank as the visual features. Next, we build visual words, *i.e.* a dictionary, by finding the centers of clusters of the visual features. To classify new images, we first represent each image as a vector of visual words, and then compare new images to old ones in the visual-word vector space – the nearest match provides a label!

What you will be doing: You will implement a scene classification system that uses the bag-of-words approach with its spatial pyramid extension. The paper that introduced the pyramid matching kernel [2] is

> K. Grauman and T. Darrell. *The Pyramid Match Kernel: Discriminative Classification with Sets of Image Features*. ICCV 2005. http://www.cs.utexas.edu/~grauman/papers/grauman_darrell_iccv2005.pdf

Spatial pyramid matching [4] is presented in

> S. Lazebnik, C. Schmid, and J. Ponce, *Beyond Bags of Features: Spatial Pyramid Matching for Recognizing Natural Scene Categories*, CVPR 2006. http://www.di.ens.fr/willow/pdfs/cvpr06b.pdf

[1] This homework is largely self-contained, but reading the listed papers (or even just skimming them) will likely be helpful.

You will be working with a subset of the SUN database[2]. The data set contains 1600 images from various scene categories like "aquarium, "desert" and "kitchen". And to build a recognition system, you will:

- take responses of a filter bank on images and build a dictionary of visual words, and then
- learn a model for images based on the bag of words (with spatial pyramid matching [4]), and use nearest-neighbor to predict scene classes in a test set.

In terms of number of lines of code, this assignment is fairly small. However, it may take *a few hours* to finish running the baseline system, so make sure you start early so that you have time to debug things. Try printing statements within long-running functions to verify that the function did not hang. Also, try **each component** on **a subset of the data set** first before putting everything together. We provide you with a number of functions and scripts in the hopes of alleviating some tedious or error-prone sections of the implementation. You can find a list of files provided in Section 4. *Though not necessary, you are recommended to implement a multi-processing*[3] *version to make use of multiple CPU cores to speed up the code*. Functions with `n_worker` as input can benefit greatly from parallel processing.

Hyperparameters: We provide you with a basic set of hyperparameters, which might not be optimal. You will be asked in Q3.1 to tune the system you built and we suggest you to keep the defaults before you get to Q3.1. All hyperparameters can be found in a single configuration file `opts.py`.

[2] http://groups.csail.mit.edu/vision/SUN/

[3] Note that multi-threading in python does not make use of multiple CPU cores. It may not work on windows jupyter notebook.

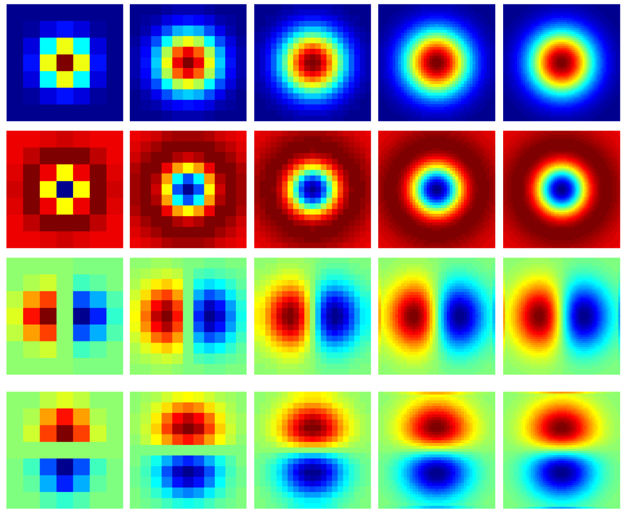


Figure 1.1: Multi-scale filter bank

1 Representing the World with Visual Words

1.1 Extracting Filter Responses

We want to run a filter bank on an image by convolving each filter in the bank with the image and concatenating all the responses into a vector for each pixel. In our case, we will be using 4 types of filters of multiple scales (`opts.filter_scales`). The filters are: (1) Gaussian, (2) Laplacian of Gaussian, (3) derivative of Gaussian in the x direction, and (4) derivative of Gaussian in the y direction.

Q1.1.1 (5 points): (a) What properties do each of the filter functions pick up? (See Fig 1.1) Try to group the filters into broad categories (*e.g.* all the Gaussians).

(b) Why do we need multiple scales of filter responses?

Q1.1.1 (a)(b)

(a) Gaussian Filter: Maintains edges of the image while reducing white noise
Laplace of Gaussian Filter: Helps identify changes in image intensity which typically indicate the presence of an edge
Derivative of Gaussian in the x direction: enhances vertical edges in the image
Derivative of Gaussian in the y direction: enhances horizontal edges in the image

(b) Multiple scales of filter responses are needed in order to fully capture the image edges. As can be seen in Figure 1.2, the less blurry images (smaller filter scales) have some trouble distinguishing certain edges, while the more blurry images (larger filter scales) are able to establish these edges. Conversely, the smaller filter scales are able to pick up on certain fine features that the large filter scales cannot.

Q1.1.2 (10 points): For the code, loop through the filters and the scales to extract responses. Since color images have 3 channels, you are going to have a total of $3F$ filter responses per pixel if the filter bank is of size F. Note that in the given dataset, there are some gray-scale images. For those gray-scale images, you can simply duplicate them into three channels. Then output the result as a $3F$ channel image. Image

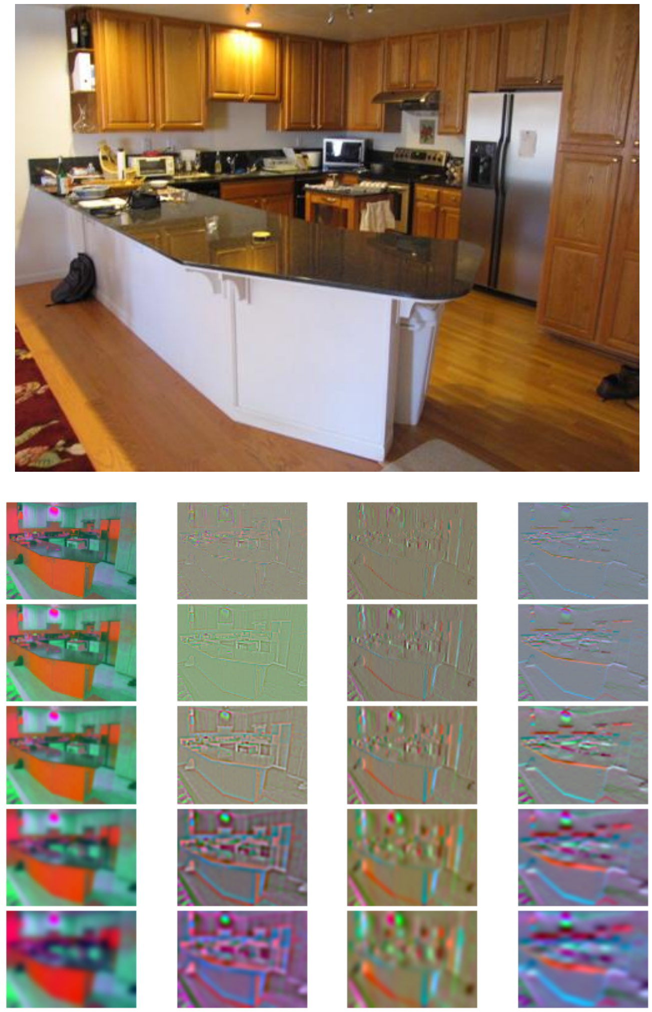


Figure 1.2: An input image and filter responses for all of the filters in the filter bank. **Top:** The input image. **Bottom:** The filter responses in Lab colorization, corresponding to the filters in Fig 1.1 (Transposed).

`laundromat/sun_afrrjykuhhlwiwun.jpg` has 4 channels instead of 3. Discard the last channel. Try to first iterate across scales and then for each scale, iterate across each channel (i.e. Scale$_1$ {Gaussian {R,G,B}, Laplacian {R, G, B}, ...}, Scale$_2$ {Gaussian{R,G,B}, Laplace{R, G, B}, ...}). Use zero-padding if necessary. Normalize the input before passing the image to extract_filter_responses. Complete the function

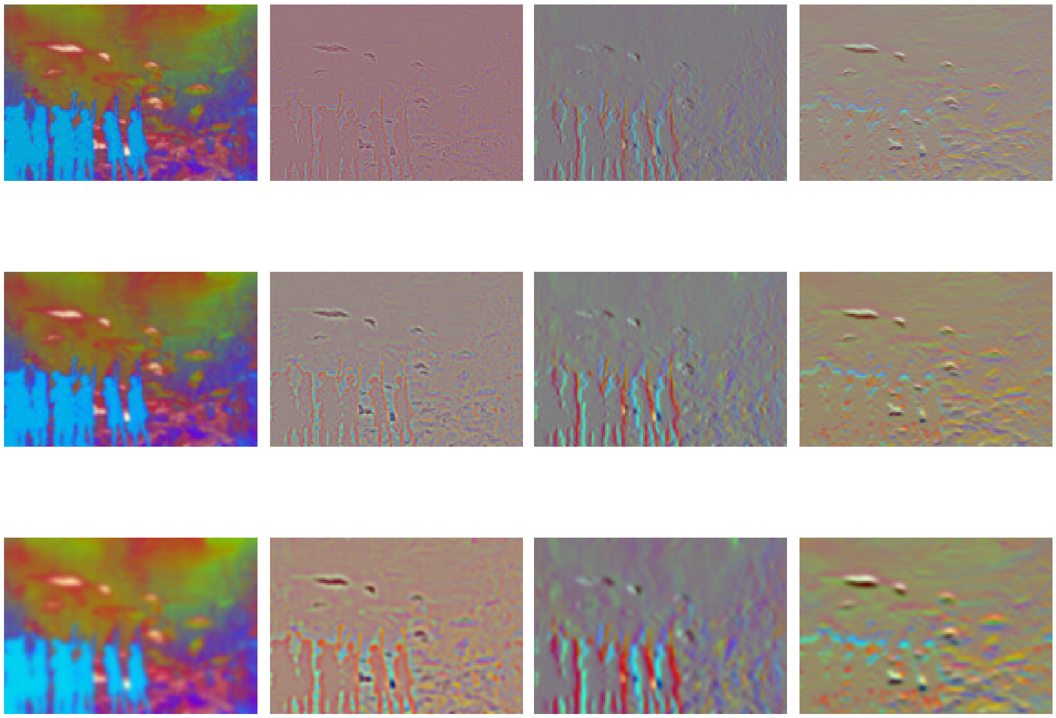
```
visual_words.extract_filter_responses(opts, img)
```

and return the responses as `filter_responses`. We have provided you with template code, with detailed instructions commented inside. The convolution routine function `scipy.ndimage.convolve()` can be used with user-defined filters, but the functions `scipy.ndimage.gaussian_filter()` and `scipy.ndimage.gaussian_laplace()` may be useful here for improved efficiency. Note that by default `scipy.ndimage` applies filters to all dimensions including channels. Therefore you might want to filter each channel separately. You can also pass in a parameter indicating you want either the x or y derivative.

Remember to check the input argument `image` to make sure it is a floating point type with range $[0, 1]$, and convert it if necessary. Be sure to check the number of input image channels and convert it to 3-channel if it is not. Before applying the filters, use the function `skimage.color.rgb2lab()` to convert your image into the `Lab` color space, which is designed to more effectively quantify color differences with respect to human perception. (See **here** for more information.) If the input `image` is an $M \times N \times 3$ matrix, then `filter_responses` should be a matrix of size $M \times N \times 3F$. Make sure your convolution function call handles image padding along the edges sensibly.

Apply all 4 filters at least 3 scales on `aquarium/sun_aztvjgubyrgvirup.jpg`, and visualize the responses as an image collage as shown in Fig 1.2. To plot the collage, you can use the included helper function `util.display_filter_responses` by providing a list of filter responses with those of the Lab channels grouped together with shape $M \times N \times 3$. We provide the skeleton code from line 17-21 in `main.py`. You can get the results by running `python main.py --filter-scales 1 2 4`.

Q1.1.2



1.2 Creating Visual Words

You will now create a dictionary of visual words from the filter responses using k-means. After applying k-means, similar filter responses will be represented by the same visual word. You will use a dictionary with a fixed size. Instead of using all of the filter responses (**which might exceed the memory capacity of your computer**), you will use responses at α random pixels. If there are T training images, then you should collect a matrix `filter_responses` over all the images that is $\alpha T \times 3F$, where F is the filter bank size. Then, to generate a visual words dictionary with K words (`opts.K`), you will cluster the responses with k-means using the function `sklearn.cluster.KMeans` as follows:

```
kmeans = sklearn.cluster.KMeans(n_clusters=K).fit(filter_responses)
```

```
dictionary = kmeans.cluster_centers_
```

If you like, you can pass the `n_jobs` argument into the `KMeans()` object to utilize parallel computation.

Q1.2 (10 points): Write the functions

`visual_words.compute_dictionary(opts, n_worker)`,
`visual_words.compute_dictionary_one_image(args)` (optional, multi-processing),

Given a dataset, these functions generate a dictionary. The overall goal of `compute_dictionary()` is to load the training data, iterate through the paths to the image files to read the images, and extract αT filter responses over the training files, and call k-means. This can be slow to run; however, the images can be processed independently and in parallel. Inside `compute_dictionary_one_image()`, you should read an image, extract the responses, and save to a temporary file. Here `args` is a collection of arguments passed into the function. Inside `compute_dictionary()`, you should load all the training data and create subprocesses to call `compute_dictionary_one_image()`. After all the subprocesses finish, load the temporary files back, collect the filter responses, and run k-means. A list of training images can be found in `data/train_files.txt`.

Finally, execute `compute_dictionary()`, and go do some push-ups while you wait for it to complete. If all goes well, you will have a file named `dictionary.npy` (with size of $K \times 3F$) that contains the dictionary of visual words. If the clustering takes too long, reduce the number of clusters and samples. You can start with a tiny subset of training images for debugging. We provide the skeleton code from line 24-25 in `main.py`. You can get the results by running `python main.py --filter-scales 1 2 4 --feat-dir TMP_OUT_DIR_FOR_EACH_IMG --out-dir FINAL_OUT_DIR`.

Include your implemented functions within the `minted` block below `compute_dictionary`, and optionally, `compute_dictionary_one_image` or other customized functions).

Q1.2

```
# Copy and paste your code here.
def compute_dictionary(opts, n_worker=1):


    ”””
    Creates the dictionary of visual words by clustering using k-means.
    [input] * opts : options
    * n_worker : number of workers to process in parallel
    [saved]
    * dictionary : numpy.ndarray of shape (K,3F)
    ”””


    data_dir = opts.data_dir
    feat_dir = opts.feat_dir
    out_dir = opts.out_dir
    K = opts.K
    alpha = opts.alpha
    train_files = open(join(data_dir, ”train_files.txt”)).read().splitlines()


    filter_scales = opts.filter_scales
    response_ext = np.empty((alpha * len(train_files), 3 * 4 *len(filter_scales))) #(alpha * T, 3 * F)


    for j in range(len(train_files)):
        img_path = join(data_dir, train_files[j])
        img = Image.open(img_path)
        img = np.array(img).astype(np.float32) / 255 #Normalizing image
        filter_responses = extract_filter_responses(opts, img)


        for k in range(alpha):
            row = np.random.randint(0, filter_responses.shape[0] - 1)
            column = np.random.randint(0, filter_responses.shape[1] - 1)
            response_ext[k * j,:] = filter_responses[row, column, :]


        if j % 50 == 0:
            print(”Image Number: ”, j)
    kmeans = KMeans(n_clusters=K).fit(response_ext) #KMeans clustering
    dictionary = kmeans.cluster_centers_
    np.save(join(out_dir, ’dictionary.npy’), dictionary)

pass
```

1.3 Computing Visual Words

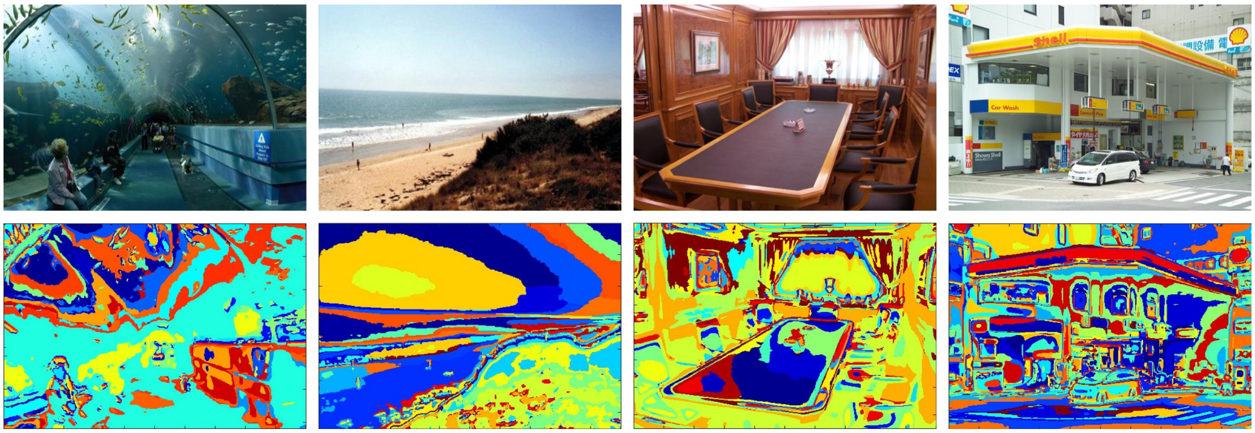


Figure 1.3: Visual words over images. You will use the spatially unordered distribution of visual words in a region (a bag of visual words) as a feature for scene classification, with some coarse information provided by spatial pyramid matching [4].

Q1.3 (10 points): We want to map each pixel in the image to its closest word in the dictionary. Complete the following function to do this:

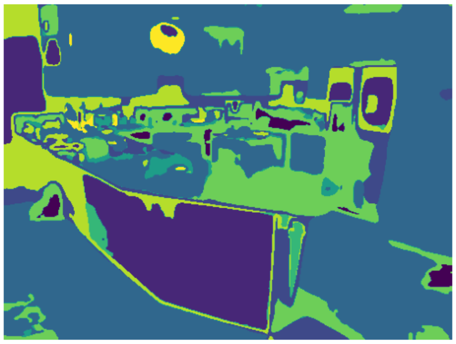
`visual_words.get_visual_words(opts, img, dictionary)`

and return `wordmap`, a matrix with the same width and height as `img`, where each pixel in `wordmap` is assigned the closest visual word of the filter response at the respective pixel in `img`. We will use the standard Euclidean distance to do this; to do this efficiently, use the function `scipy.spatial.distance.cdist()`. Some sample results are shown in Fig 1.3.

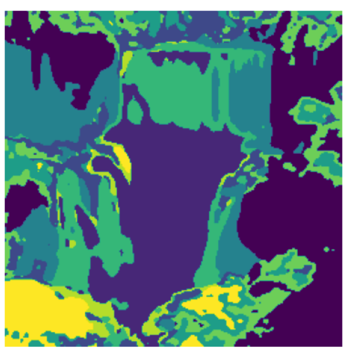
Visualize wordmaps for three images. Include some comments on these visualizations: do the "word" boundaries make sense to you? The visualizations should look similar to the ones in Fig 1.3. Don't worry if the colors don't look the same, newer `matplotlib` might use a different color map.

We provide the skeleton code from line 28-33 in `main.py`. You can get the results by running `python main.py --filter-scales 1 2 4 --feat-dir TMP_OUT_DIR_FOR_EACH_IMG --out-dir FINAL_OUT_DIR`.

Q1.3








The visualizations make sense to me as the wordmaps are consistent with the types of features they represent.

2 Building a Recognition System

We have formed a convenient representation for recognition. We will now produce a basic recognition system with spatial pyramid matching. The goal of the system is presented in Fig 0.1: given an image, classify (i.e., recognize/name) the scene depicted in the image.

Traditional classification problems follow two phases: training and testing. At training time, the computer is given a pile of formatted data (*i.e.*, a collection of feature vectors) with corresponding labels (*e.g.*, "desert", "park") and then builds a model of how the data relates to the labels (*e.g.*, "if green, then park"). At test time, the computer takes features and uses these rules to infer the label (*e.g.*, "this is green, therefore it is a park").

In this assignment, we will use the simplest classification method: nearest neighbor. At test time, we will simply look at the query's nearest neighbor in the training set and transfer that label. In this example, you will be looking at the query image and looking up its nearest neighbor in a collection of training images whose labels are already known. This approach works surprisingly well given a huge amount of data. (For a cool application, see the work by Hays & Efros [3]).

The key components of any nearest-neighbor system are:

- features (how do you represent your instances?) and
- similarity (how do you compare instances in the feature space?).

You will implement both.

2.1 Extracting Features

We will first represent an image with a bag of words. In each image, we simply look at how often each word appears.

Q2.1 (10 points): Write the function

```
visual_recog.get_feature_from_wordmap(opts, wordmap)
```

that extracts the histogram (`numpy.histogram()`) of visual words within the given image (*i.e.*, the bag of visual words). As output, the function will return `hist`, an "L_1 normalized" `dict_size`-length histogram The L_1 normalization makes the sum of the histogram equal to 1. You may wish to load a single visual word map, visualize it, and verify that your function is working correctly before proceeding.

Include your implemented functions within the `minted` block below.

Q2.1

```
# Copy and paste your code here.
def get_feature_from_wordmap(opts, wordmap):

    """
    Compute histogram of visual words.
    [input]
    * opts : options
    * wordmap : numpy.ndarray of shape (H,W)
    [output]
    * hist: numpy.ndarray of shape (K)
    """

    K = opts.K

    # —— TODO ——

    hist, bin_edges = np.histogram(wordmap, bins = range(K+1), density = True)
    hist = hist / np.sum(hist) #Normalizing histogram


    return hist
```

2.2 Multi-resolution: Spatial Pyramid Matching

A bag of words is simple and efficient, but it discards information about the spatial structure of the image and this information is often valuable. One way to alleviate this issue is to use spatial pyramid matching [4]. The general idea is to divide the image into a small number of cells, and concatenate the histogram of each of these cells to the histogram of the original image, with a suitable weight.

Here we will implement a popular scheme that chops the image into $2^l \times 2^l$ cells where l is the layer number. We treat each cell as a small image and count how often each visual word appears. This results in a histogram for every single cell in every layer. Finally to represent the entire image, we concatenate all the histograms together after normalization by the total number of features in the image. If there are $L+1$ layers and K visual words, the resulting vector has dimension $K \sum_{l=0}^{L} 4^l = K\left(4^{(L+1)} - 1\right)/3$.

Now comes the weighting scheme. Note that when concatenating all the histograms, histograms from different levels are assigned different weights. Typically (and in the original work [4]), a histogram from layer l gets half the weight of a histogram from layer $l+1$, with the exception of layer 0, which is assigned a weight equal to layer 1. A popular choice is to set the weight of layers 0 and 1 to 2^{-L}, and set the rest of the weights to 2^{l-L-1} (*e.g.*, in a three layer spatial pyramid, $L = 2$ and weights are set to $1/4$, $1/4$ and $1/2$ for layer 0, 1 and 2 respectively. See Fig 2.1 for an illustration of a spatial pyramid. Note that the L_1 norm (absolute values of all dimensions summed up together) for the final vector is 1.

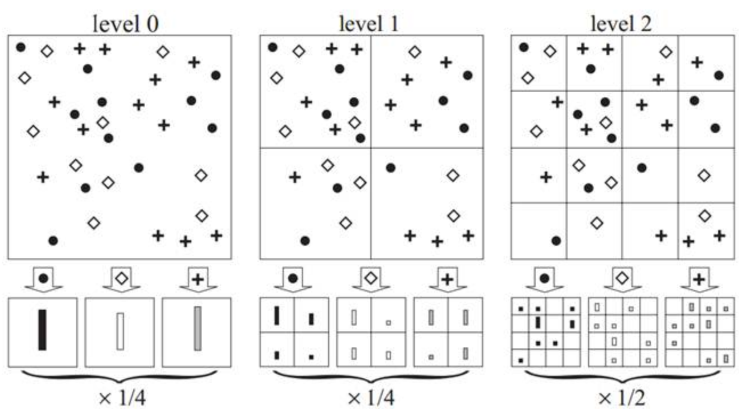


Figure 2.1: **Spatial Pyramid Matching:** From [4]. Toy example of a pyramid for L = 2. The image has three visual words, indicated by circles, diamonds, and crosses. We subdivide the image at three different levels of resolution. For each level of resolution and each channel, we count the features that fall in each spatial bin. Finally, weight each spatial histogram.

Q2.2 (15 points): Create a function `get_feature_from_wordmap_SPM` that forms a multi-resolution representation of the given image.

```
visual_recog.get_feature_from_wordmap_SPM(opts, wordmap)
```

You need to specify the layers of pyramid in `opts.L` (Note there are $L+1$ layers in total). As output, the function will return `hist_all`, a vector that is L_1 normalized.

One small hint for efficiency: a lot of computation can be saved if you first compute the histograms of the *finest* layer, because the histograms of coarser layers can then be aggregated from finer ones. Make sure you normalize the histogram after aggregation.

Include your implemented functions within the `minted` block below.

Q2.2

```
# Copy and paste your code here.
def get_feature_from_wordmap_SPM(opts, wordmap):
    """
    Compute histogram of visual words using spatial pyramid matching.
    [input]
    * opts : options
    * wordmap : numpy.ndarray of shape (H,W)

    [output]
    * hist_all: numpy.ndarray of shape K * (4 **(L + 1) - 1)/3
    """

    K = opts.K
    L = opts.L
    # ----- TODO -----
    weights = np.empty(L+1)
    for l_w in range(len(weights)):
        if l_w <= 1:
            weights[l_w] = 2**(-L)  else:
            weights[l_w] = 2**(l_w - L - 1)

    count = 0 #counter variable for hist_all array creation
    for l_hist in range(L, -1, -1):
        #splitting wordmap across rows
        cell_split = 2**l_hist block_split_row = int(np.ceil(wordmap.shape[0] / cell_split))

        #splitting wordmap across columns
        block_split_col = int(np.ceil(wordmap.shape[1] / cell_split))

        for i in range(0, wordmap.shape[0], block_split_row):
            for j in range(0, wordmap.shape[1], block_split_col):
                block = wordmap[i:i + block_split_row, j:j + block_split_col]
                hist_block = get_feature_from_wordmap(opts, block) * weights[l_hist]
                hist_block = np.reshape(hist_block, (K,1))
                if i == 0 and j == 0 and count == 0:
                    hist_all = hist_block
                    count = 1

                else:

                    #appending the block histograms to hist_all
                    hist_all = np.vstack((hist_all, hist_block))

    hist_all = hist_all / np.sum(hist_all) #Normalizing full histogram
    return hist_all
```

2.3 Comparing images

We need a way to compare images, to find the "nearest" instance in the training data. In this assignment, we'll use the histogram intersection similarity. The histogram intersection similarity between two histograms is the sum of the minimum value of each corresponding bins. This is a similarity score: the *largest* value indicates the "nearest" instance.

Q2.3 (10 points): Create the function

`visual_recog.distance_to_set(word_hist, histograms)`

where `word_hist` is a $K\left(4^{(L+1)}-1\right)/3$ vector and `histograms` is a $T \times K\left(4^{(L+1)}-1\right)/3$ matrix containing T features from T training samples concatenated along the rows. This function computes the histogram intersection similarity between `word_hist` and each training sample as a vector of length T and returns one minus the above quantity as a distance measure (distance is the inverse of similarity). Since this is called every time you look up a classification, you will want this to be fast! (Doing a for-loop over tens of thousands of histograms is a bad idea.) Note: `laundromat/sun_afrrjykuhhlwiwun.jpg` has 4 channels instead of 3. Discard the last channel.

Include your implemented functions within the `minted` block below.

Q2.3

```
# Copy and paste your code here.
def distance_to_set(word_hist, histograms):
    """
    Compute distance between a histogram of visual words with all training image histograms.
    [input]
    * word_hist: numpy.ndarray of shape (K)
    * histograms: numpy.ndarray of shape (N,K)

    [output]
    * dist: numpy.ndarray of shape (N)
    """
    # ----- TODO -----

    sim = np.sum(np.minimum(word_hist.flatten(), histograms.T), axis = 1)
    dist = 1 - sim #Distance is the inverse of similarity

    return dist
```

2.4 Building A Model of the Visual World

Now that we've obtained a representation for each image, and defined a similarity measure to compare two spatial pyramids, we want to put everything up to now together.

Simple I/O code has been provided in the respective functions, which include loading the training images specified in `data/train_files.txt` and the filter bank and visual word dictionary from `dictionary.npy`, and also saving the learned model to `trained_system.npz`. Specifically in `trained_system.npz`, you should have:

1. `dictionary`: your visual word dictionary.
2. `features`: an $N \times K\left(4^{(L+1)}-1\right)/3$ matrix containing all of the histograms of the N training images in the data set.
3. `labels`: an N vector containing the labels of each of training images. (`features[i]` will correspond to label `labels[i]`).
4. `SPM_layer_num`: the number of spatial pyramid layers you used to extract the features for the training images.

Do not use the testing images for training!

The table below lists the class names that correspond to the label indices:

0	1	2	3	4	5	6	7
aquarium	desert	highway	kitchen	laundromat	park	waterfall	windmill

Q2.4 (15 points): Implement the function

`visual_recog.build_recognition_system()`

that produces `trained_system.npz`. You may include any helper functions you write in `visual_recog.py`.

Implement

`visual_recog.get_image_feature(opts, img_path, dictionary)`

that loads an image, extract word map from the image, computes the SPM, and returns the computed feature. Use this function in your `visual_recog.build_recognition_system()`.

We provide the skeleton code from line 36-37 in `main.py`. You can train the model by running `python main.py --filter-scales 1 2 4 --feat-dir TMP_OUT_DIR_FOR_EACH_IMG --out-dir FINAL_OUT_DIR`.

Include your implemented functions within the `minted` block below.

Q2.4

```
# Copy and paste your code here.
def build_recognition_system(opts, n_worker=1):
    """
    Creates a trained recognition system by generating training features from all training images.
    [input]
    * opts : options
    * n_worker : number of workers to process in parallel
    [saved]
    * features: numpy.ndarray of shape (N,M)
    * labels: numpy.ndarray of shape (N)
    * dictionary: numpy.ndarray of shape (K,3F)
    * SPM_layer_num: number of spatial pyramid layers
    """
    data_dir = opts.data_dir
    out_dir = opts.out_dir
    SPM_layer_num = opts.L
    train_files = open(join(data_dir, "train_files.txt")).read().splitlines()
    train_labels = np.loadtxt(join(data_dir, "train_labels.txt"), np.int32)
    dictionary = np.load(join(out_dir, "dictionary.npy"))

    # ----- TODO -----
    for i in range(len(train_files)):
        img_path = join(opts.data_dir, train_files[i])
        if i == 0:
            features = get_image_feature(opts, img_path, dictionary)
        else:
            features = np.hstack((features, get_image_feature(opts, img_path, dictionary)))
        if i % 50 == 0:
            print("Image number:", i)

    np.savez_compressed(join(out_dir, 'trained_system.npz'), features=features, labels=train_labels,
    dictionary=dictionary, SPM_layer_num=SPM_layer_num,)

    pass
```

2.5 Quantitative Evaluation

Qualitative evaluation is all well and good (and very important for diagnosing performance gains and losses), but we want some hard numbers.

Load the test images and their labels, and compute the predicted label of each one. That is, compute the test image's distance to every image in the training set, and return the label of the closest training image. To quantify the accuracy, compute a confusion matrix `C`. In a classification problem, the entry `C(i,j)` of a confusion matrix counts the number of instances of class `i` that were predicted as class `j`. When things are going well, the elements on the diagonal of `C` are large, and the off-diagonal elements are small. Since there are 8 classes, `C` will be 8×8. The accuracy, or percent of correctly classified images, is given by the trace of `C` divided by the sum of `C`. **Hint:** The accuracy with default parameters is 50%.

Q2.5 (10 points): Implement the function

`visual_recog.evaluate_recognition_system()`

that tests the system and outputs the confusion matrix. **Report the (a) confusion matrix and your (b) overall accuracy.** This does not have to be formatted prettily: *e.g.*, you can simply copy/paste it into a `verbatim` environment.

Q2.5 (a) (b)

(a)

32 1 2 1 4 3 5 2
0 26 6 6 4 2 2 4
1 7 26 2 0 5 2 7
3 4 1 30 11 0 1 0
0 2 3 16 16 6 5 2
2 0 5 1 4 30 6 2
4 0 1 1 9 7 26 2
5 6 7 1 3 4 0 24

(b) Accuracy = 52.5%

2.6 Find the failures

There are some classes/samples that are more difficult to classify than the rest using the bags-of-words approach. As a result, they are classified incorrectly into other categories.

Q2.6 (5 points): Include some images of these hard classes/samples, and discuss why they are more difficult than the rest.

Q2.6

Laundromats appear to have some difficulty being classified correctly. As can be seen in 2.5 (a), they are classified as kitchens as many times as they are classified as laundromats. This is likely due to the fact that kitchens and laundromats share similar characteristics in color and appliance shapes/sizes.

The image on the left is from a laundromat and the image on the right is from the kitchen label. Depending on the parameters used to define the histogram size, misclassifying laundromat images as kitchen images is a distinct possibility.

3 Improving performance

3.1 Hyperparameter tuning

Now we have a full-fledged recognition system plus an evaluation system, it's time to boost up the performance. In practice, it is most likely that a model will not work well out-of-the-box. It is important to know how to tune a visual recognition system for the task at hand.

Q3.1 (15 points): Tune the system you build to reach around 65% accuracy on the provided test set (`data/test_files.txt`). A list of hyperparameters you should tune is provided below. They can all be found in `opts.py`.

- `filter_scales`: a list of filter scales used in extracting filter response;
- `K`: the number of visual words and also the size of the dictionary;
- `alpha`: the number of sampled pixels in each image when creating the dictionary;
- `L`: the number of spatial pyramid layers used in feature extraction.

(a) Include a table of ablation study containing at least 3 major steps (changing parameter X to Y achieves accuracy Z%). (b) Also, describe why you think changing a particular parameter should increase or decrease the overall performance in the table you show.

Q3.1 (a) (b)

(a)

Iteration	Change	Accuracy (%)
1	Default Values*	52.50
2	K = 70	62.75
3	K = 90	65.25

*Default Values:
filter_scales = 1 2 4
K = 10
L = 1
alpha = 25
The other iterations were performed with only changing K
(b) As can be observed changing K usually results in an increase in accuracy. This is because increasing K means increasing the number of visual words being compared. More data being stored typically results in more accurate results.
Alpha was also increased in a subsequent test (from 25 to 50). This test only resulted in a small increase in accuracy from 52.5% to 53.5%. I did expect an increase in accuracy as we are increasing the size of the filter responses being sampled, but thought the increase would be higher.
The number of filter scales were then reduced to two and resulted in a dip in accuracy (to 51.75%) which made sense as we now had less data to compare. This drop was not as large as I was expecting. With other parameter changes using fewer filter scales could be an option to improve execution runtime. Consequently this shows that increasing the number of filter scales should increase the accuracy.
When L was increased from 1 to 3 there was a 2% increase in accuracy which is good but further increases would take more computation time as I am looping over each block for my SPM function.
All accuracy values and Confusion Matrices can be found in the data folder labelled according to which parameter was changed (i.e., change in filter scale is labeled as confmat_fs2 meaning a filter scale of length 2 was implemented.

3.2 [Extra Credit] Further improvement

Q3.2 (10 points): Can you improve your classifier, in terms of accuracy or speed? Be creative! Or be well-informed, and cite your sources! For some quick ideas, try resizing the images, subtracting the mean color, changing the structure or weights of the spatial pyramid, or replacing the histogram intersection with some other similarity score. Whatever you do, explain:

(1) what you did,

(2) what you expected would happen, and

(3) what actually happened.

Include these results in the report and submit the code.

Q3.2

My classifiers speed can be improved by using pooling and multiprocessing. I was unable to implement it in this assignment and this resulted in my classifier needing around an hour to build and test the recognition system. Attempts were made to get regular pooling to work as can be seen in the visual_words function, but were unsuccessful.
A quick search shows that using Starmap would be a promising solution to my speed issue. More information can be found at this link: https://superfastpython.com/multiprocessing-pool-starmap/

Accuracy wise, we could change the distance is measured. Instead of using the intersection method we could use Bhattacharyya distance. I attempted implementing this method and was able to achieve an accuracy of 64% with the same parameters that provided an accuracy of 65.25% in the previous method. I was hoping that this method would yield a better accuracy which it unfortunately was unable to do.
However, unlike the prior method, it was able to distinguish between the kitchen and laundromat cases better than the previous attempt as can be seen in the confmat_extracred file. But this method requires the addition of a for loop and should, theoretically, be slower than the previous method, despite being close accuracy wise.
The attempt can be found in the main_extracred.py and visual_recog_extracred.py files (located in the distance_to_set function)
https://stats.stackexchange.com/questions/7400/how-to-assess-the-similarity-of-two-histograms
https://docs.opencv.org/3.4/d8/dc8/tutorial_histogram_comparison.html
https://www.researchgate.net/post/What_is_the_range_of_Bhattacharya_coefficient_value
https://github.com/meshgi/Histogram_of_Color_Advancements/blob/master/distance/dist_bhattacharyya.m

4 HW1 Distribution Checklist

After unpacking `hw1.zip`, you should have a folder `hw1` containing one folder for the data (`data`), one for your code (`code`), and one for the report (`latex`). In the `code` folder, where you will primarily work, you will find:

- `visual_words.py`: function definitions for extracting visual words.
- `visual_recog.py`: function definitions for building a visual recognition system.
- `util.py`: some utility functions
- `main.py`: main function for running the system

The data folder contains:

- `data/`: a directory containing `.jpg` images from the SUN database.
- `data/train_files.txt`: a text file containing a list of training images.
- `data/train_labels.txt`: a text file containing a list of training labels.
- `data/test_files.txt`: a text file containing a list of testing images.
- `data/test_labels.txt`: a text file containing a list of testing labels.

5 HW1 submission checklist

Submit your write-up and code to Gradescope.

- **Writeup.** Please use this provided template for your writeup. The write-up should be a pdf file named <**AndrewId**>**_hw1.pdf**. **You must select the pages of the writeup that correspond to each question**.
- **Code.** The code should be submitted as a zip file named <**AndrewId**>**_hw1.zip**. By extracting the zip file, it should have the following files in the structure defined below.

  When you submit, remove the folder `data/` **and** `feat/` **if applicable, as well as any large temporary files that we did not ask you to create.**

  - <**andrew_id**>**/** # A directory inside .zip file
    - `code/`
      - `dictionary.npy`
      - `trained_system.npz`
      - <!– all of your .py files >
    - `<andrew_id>_hw1.pdf` make sure you upload this pdf file to Gradescope. Please assign the locations of answers to each question on Gradescope.

References

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[7] J. Winn, A. Criminisi, and T. Minka. Object categorization by learned universal visual dictionary. In *Computer Vision (ICCV), 2005 IEEE International Conference on*, volume 2, pages 1800–1807 Vol. 2, 2005.

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