ENSE 885AY

Application of Deep Learning in Computer Vision

Assignment A04

Scene recognition with bag of words

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1. Introduction

1.1. Overview (Key points from the assignment description) [1]

Assignment Subject:

Scene recognition with bag of words

Assignment objectives:

- The goal of this project is to get familiar with image recognition.

Steps to local feature matching between two images (image1 & image 2):

1. Represent images using:
    - ⇨ get_tiny_images()
    - ⇨ build_vocabulary()
    - ⇨ get_bags_of_sifts()

2. Classify images using:
    - ⇨ nearest_neighbor_classify()
    - ⇨ svm_classify()

2. Student Code

2.1. Represent images using tiny images (get_tiny_images())

Algorithm of get_tiny_images() [1]:

feats = get_tiny_images(image_paths)

1. Define feature dimension:
    a. feat_dim = 16

for each image path in {image_paths}:

2. Load image as grayscale
3. Resize image to 16x16 (according to feat_dim)
4. Normalize image

    a. Norm_img = (img - np.mean(img))/np.std(img)
5. Return resized & normalized image as tiny_image feature

2.2. Represent images using bags_of_sifts (build_vocabulary() & get_bags_of_sifts())

Algorithm of build_vocabulary() [1]:

vocab = build_vocabulary(image_paths, vocab_size)

for each image path in {image_paths}:

1. Load image as grayscale
2. Normalize image
    a. Norm_img = (img - np.mean(img))/np.std(img)
3. Obtain descriptor using "vlfeat.sift.dsift" function
    a. _, descriptors = vlfeat.sift.dsift(img, step=[50,50], fast=True)
4. Append image descriptors to bag_of_features
5. Cluster bag_of_features using "vlfeat.kmeans.kmeans"
    a. vocab = vlfeat.kmeans.kmeans(bag_of_features, vocab_size, initialization="PLUSPLUS")
6. Return cluster centroids as vocab

Remark on step size:

The choice of step=[50,50] is through trying different step sizes. This value results in about 42000 descriptor which is a reasonable number.

Algorithm of get_bags_of_sifts() [1]:

feats = get_bags_of_sifts(image_paths, vocab_filename):

1. Load vocab from saved files

    for each image path in {image_paths}:

2. Load image as grayscale
3. Normalize image
    a. Norm_img = (img - np.mean(img))/np.std(img)

4. Obtain descriptor using “vlfeat.sift.dsift” function
    a. _, descriptors = vlfeat.sift.dsift(img, step=[9,9], fast=True)
5. Assign each descriptor vector to nearest cluster center using “vlfeat.kmeans.kmeans_quantize” function
    a. assignments = vlfeat.kmeans.kmeans_quantize(descriptors.astype(np.float32), vocab)
6. Obtain histogram of features using “np.histogram” function
    a. histo, _ = np.histogram(assignments, range(len(vocab)+1))
7. Normalize histogram and append to feats
    a. feats.append(histo / np.linalg.norm(histo))
8. Return histograms of descriptor as feats

Remark on step size:

The choice of step=[9, 9] is through trying different step sizes. This value results in about 0.1 of the step size which was used in build_vocabulary() function.

2.3. Classify images using KNN (nearest_neighbor_classify())

Algorithm of nearest_neighbor_classify() [1]:

test_labels = nearest_neighbor_classify(train_image_feats, train_labels, test_image_feats, metric='euclidean'):

1. Define k for KNN
    a. k = 16
2. Computes the distance matrix D between all pairs of test & train images
    a. D = sklearn_pairwise.pairwise_distances(test_image_feats, train_image_feats, 'euclidean')
3. Find the K nearest features (train images) to each test image feature by sorting D matrix along every row
    a. Row [i] of matrix D is corresponding to distances between test image [i] and all train images

For each test image [i]:

4. Obtain the labels for K nearest train images to test image [i]
5. Predict the label of test image [i] by voting among K labels
6. Return predicted labels as test_labels

Remark on K:

The choice of K = 16 is through trying different values. This value ensures that labels will be predicted by obtaining at least 2 votes (not by chance).

2.4. Classify images using 1 vs. All SVM (svm_classify())

Algorithm of svm_classify() [1]:

test_labels = svm_classify(train_image_feats, train_labels, test_image_feats, lambd=3)

1. Obtain list of categories
2. Construct 1 vs all SVMs for each category:
    a. svms = {cat: LinearSVC(random_state=0, tol=1e-3, loss='hinge', C=lambd, max_iter=10000) for cat in categories}

One vs. All SVC:

for each category[k]:

3. Obtain binary train labels (by setting the category label to "1" and all other labels to "0")
4. Fit SVC on binary train data
    a. svc.fit(train_image_feats, train_labels_binary)
5. Obtain prediction confidence for test images using the trained svc
    a. pred_conf[:,cat_idx] = svc.decision_function(test_image_feats)

for each test image[i]:

6. Obtain the highest prediction confidence and its corresponding category
7. Predict the label according to the label with highest confidence
8. Return predicted labels as test_labels

3. Experiment Design

3.1. Cross Validation with Different Vocabulary Sizes

Cross validation experiment summary:

- Number of experiments: exp_num = 10
- Dataset:

    - Train dataset: 150 random images from original train dataset
    - Test dataset: 150 random images from original test dataset
- Varying parameters:
    - vocab_zize = [10, 20, 50, 100, 200, 400, 1000, 10000]
- Approaches:
    - KNN on tiny_images
    - KNN on bags_of_sifts
    - SVM on bags_of_sifts
- Total number of experiments: 10 * (1 + 8 + 8) = 170
- Results:
    - Accuracy average per approach, per vocab_size
    - Accuracy standard deviation, per approach per vocab_size

Cross validation experiment algorithm:

1. Define constant and varying parameters

   exp_number = 10

   cv_size = 150

2. Define output matrices

   CV_acc_knn_tiny: Prediction accuracy for KNN on tiny_images

   CV_acc_knn_sift: Prediction accuracy for KNN on bags_of_sifts

   CV_acc_svm_sift: Prediction accuracy for SVM on bags_of_sifts

Experiment on random train & test datasets:

for exp_idx = [0 10):

3. Generating random indexes for trainCV & testCV datasets
4. Obtain trainCV & testCV dataset by indexing

KNN on tiny_images:

5. Obtain tiny_images features for trainCV & testCV dataset
6. Apply KNN on tiny_images
7. Save accuracy

KNN on bags_of_sifts:

for vocab_size = [10, 20, 50, 100, 200, 400, 1000, 10000]:

8. Obtain bags_of_sifts features for trainCV & testCV dataset
9. Apply KNN on bags_of_sifts
10. Save accuracy

SVM on bags_of_sifts:

for vocab_size = [10, 20, 50, 100, 200, 400, 1000, 10000]:

11. Obtain bags_of_sifts features for trainCV & testCV dataset
12. Apply KNN on bags_of_sifts
13. Save accuracy

Obtain average accuracy among experiments:

CV_acc_knn_tiny_mean

CV_acc_knn_sift_mean

CV_acc_svm_sift_mean

Obtain standard deviation of accuracy among experiments:

CV_acc_knn_tiny_std

CV_acc_knn_sift_std

CV_acc_svm_sift_std

3.2. Validation with Different Vocabulary Sizes and Different SVM Lambda Values

Validation experiment summary:

- Number of experiments: 1
- Dataset:
  - Train dataset: 1050 images from original train dataset (70 images per class)
  - validation dataset: 450 images from original train dataset (30 images per class)

- Varying parameters:
  - vocab_zize = [10, 20, 50, 100, 200, 400, 1000, 10000]
  - svm_lambda = [0.1, 0.5, 1, 3, 5, 7]
- Approaches:
  - KNN on tiny_images
  - KNN on bags_of_sifts
  - SVM on bags_of_sifts
- Total number of experiments: exp_num = 1 * (1 + 8 + 8*6) = 57
- Results:
  - Accuracy per approach, per vocab_size, per svm_lambda

Validation experiment algorithm:

1. Define constant and varying parameters
   N_trainV = 1050 images from original train dataset (70 images per class)

   N_validation = 450 images from original train dataset (30 images per class)

2. Generating indexes for trainV & validation datasets (uniform number of samples per class)
3. Obtain trainV & validation dataset by indexing
4. Define output matrices

   val_knn_tiny: Prediction accuracy for KNN on tiny_images

   val_knn_sift: Prediction accuracy for KNN on bags_of_sifts

   val_svm_sift: Prediction accuracy for SVM on bags_of_sifts

Experiment on train & validation datasets:

KNN on tiny_images:

5. Obtain tiny_images features for trainV & validation dataset
6. Apply KNN on tiny_images
7. Save accuracy

KNN on bags_of_sifts:

for vocab_size = [10, 20, 50, 100, 200, 400, 1000, 10000]:

8. Obtain bags_of_sifts features for trainV & validation dataset
9. Apply KNN on bags_of_sifts
10. Save accuracy

SVM on bags_of_sifts:

for vocab_size = [10, 20, 50, 100, 200, 400, 1000, 10000]:

for lambda = [0.1, 0.5, 1, 3, 5, 7]:

11. Obtain bags_of_sifts features for trainV & validation dataset
12. Apply KNN on bags_of_sifts
13. Save accuracy

Return validation accuracy:

val_knn_tiny

val_knn_sift

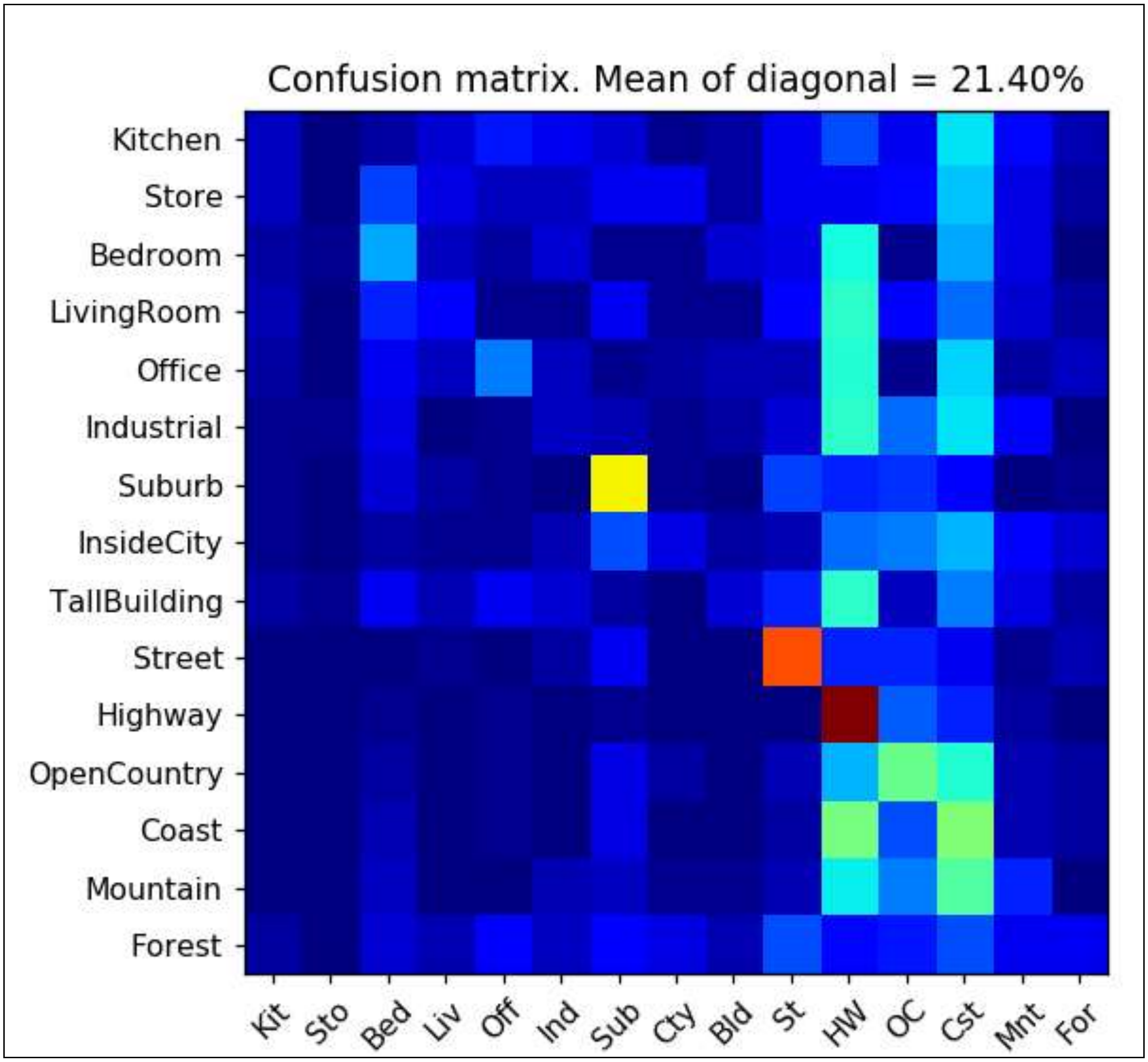
val_svm_sift

4. Results and Discussion

4.1. Results for KNN on tiny_images

Table 1: KNN on tiny_images (K = 16)

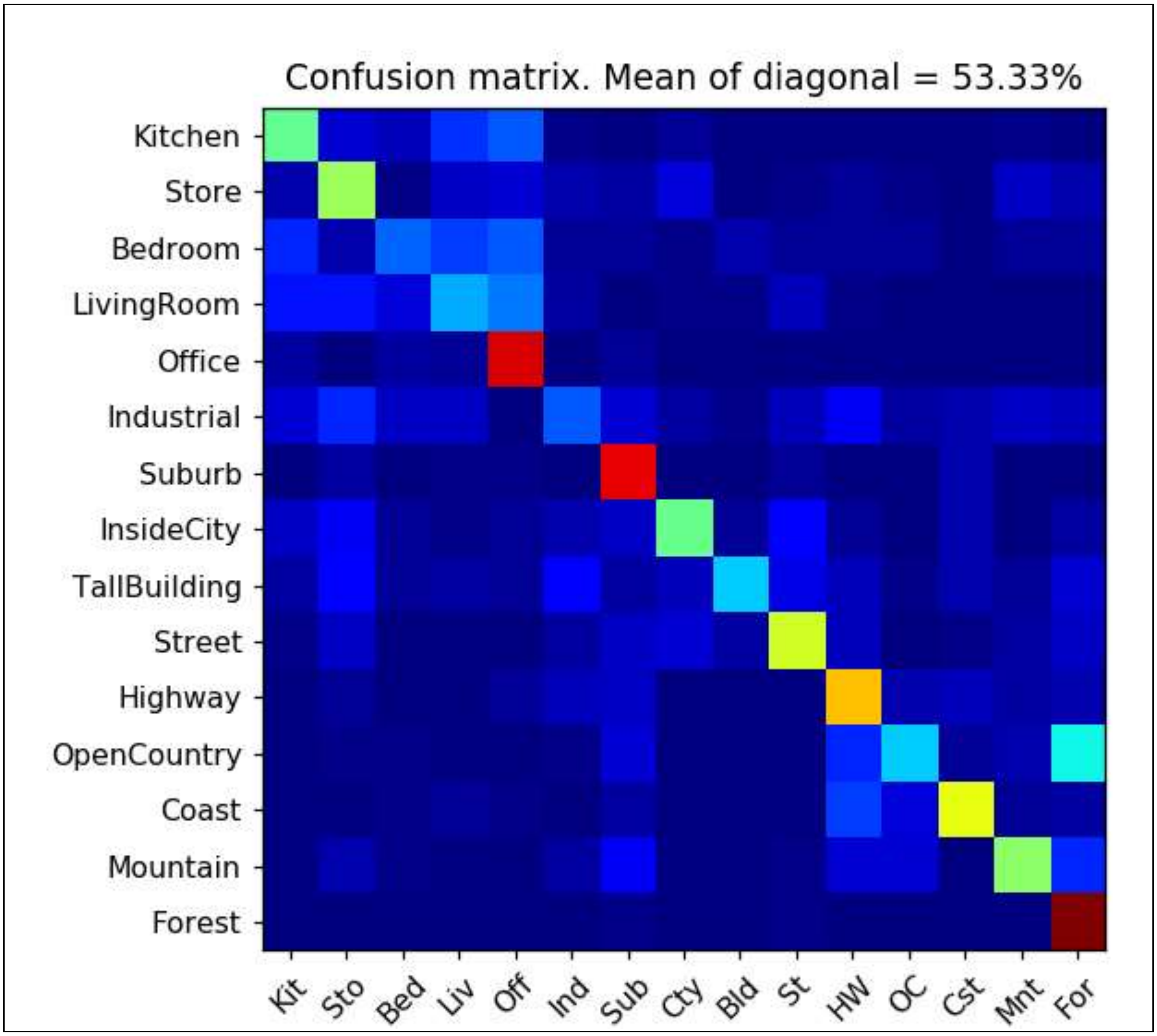
KNN on tiny_images
K = 16
Accuracy = 21.4 %



4.2. Results for KNN on bags_of_sifts

Table 2: KNN on bags_of_sifts (K = 16)

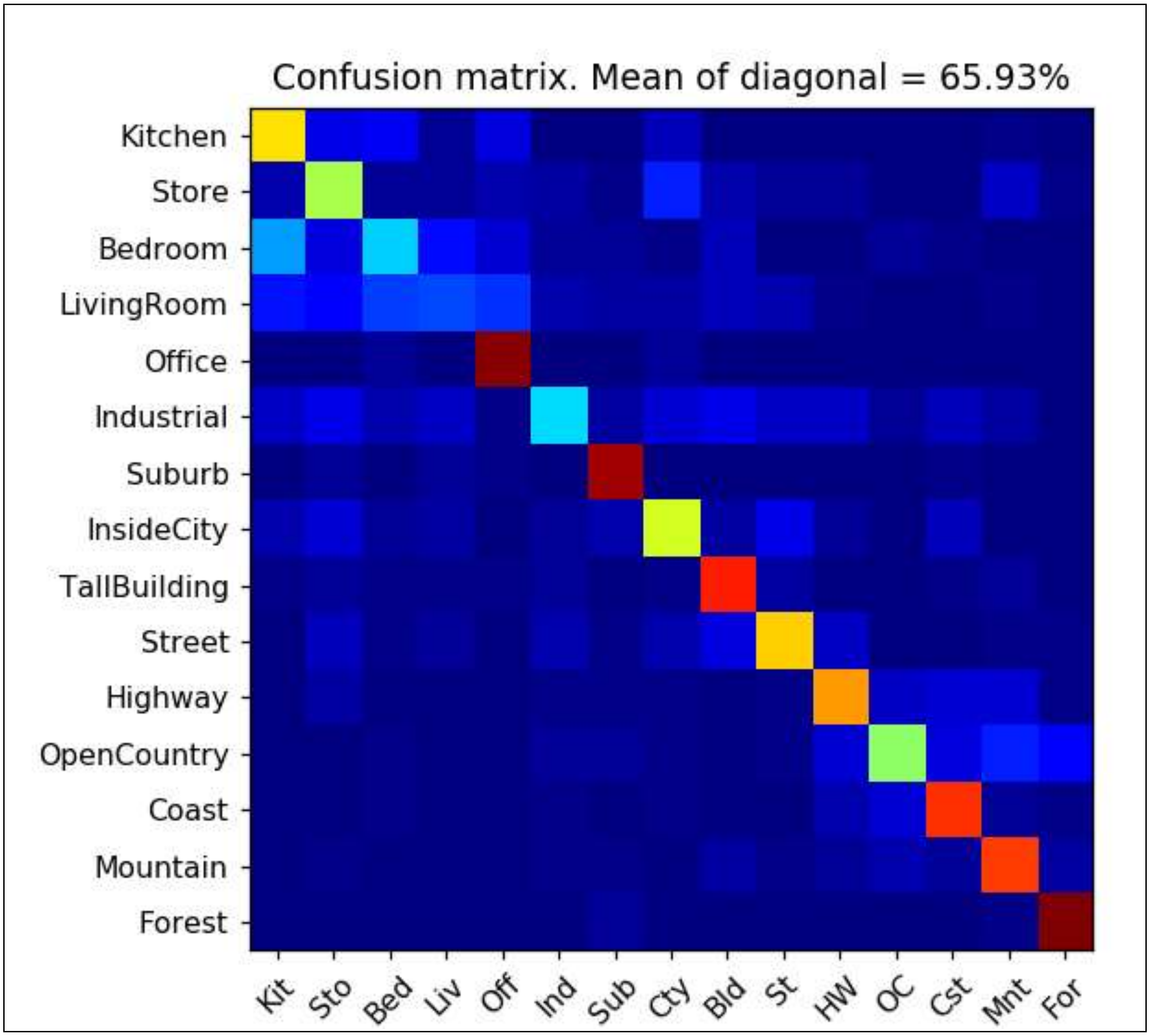
KNN on bags_of_sifts
Vocab_size = 200 & K = 16
Accuracy = 53.33%



4.3. Results for SVM on bags_of_sifts

Table 3: SVM on bags_of_sifts (K = 16)

SVM on bags_of_sifts
Vocab_size = 200 & SVM_Lambda = 3
Accuracy = 65.93%



4.4. Results for Cross Validation with Different Vocabulary Sizes

Table 4: Results for Cross Validation with Different Vocabulary Sizes

Cross validation results		Vocab size							
		10	**20**	**50**	**100**	**200**	**400**	**1000**	**10,000**
KNN on tiny_images	**Accuracy Average**	0.13							
	Accuracy Std.	0.011							

KNN on bags_of_sifts	**Accuracy Average**	0.30	0.31	0.33	0.32	0.34	0.36	0.33	0.33
	Accuracy Std.	0.051	0.044	0.050	0.032	0.052	0.039	0.033	0.034
SVM on bags_of_sifts	**Accuracy Average**	0.30	0.37	0.41	0.44	0.46	0.47	0.48	0.46
	Accuracy Std.	0.030	0.014	0.037	0.050	0.045	0.050	0.049	0.067

Table 5: Cross Validation Results: Average Prediction Accuracy vs. Vocab Size & Approach

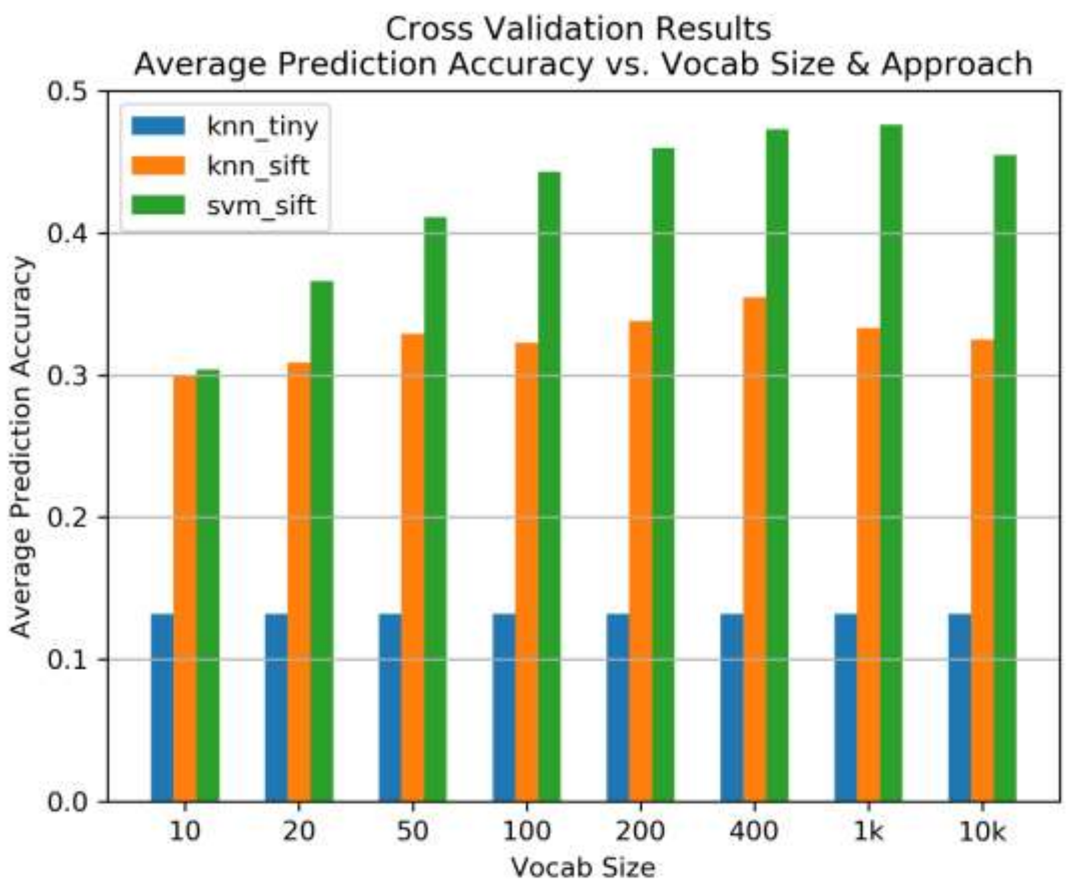
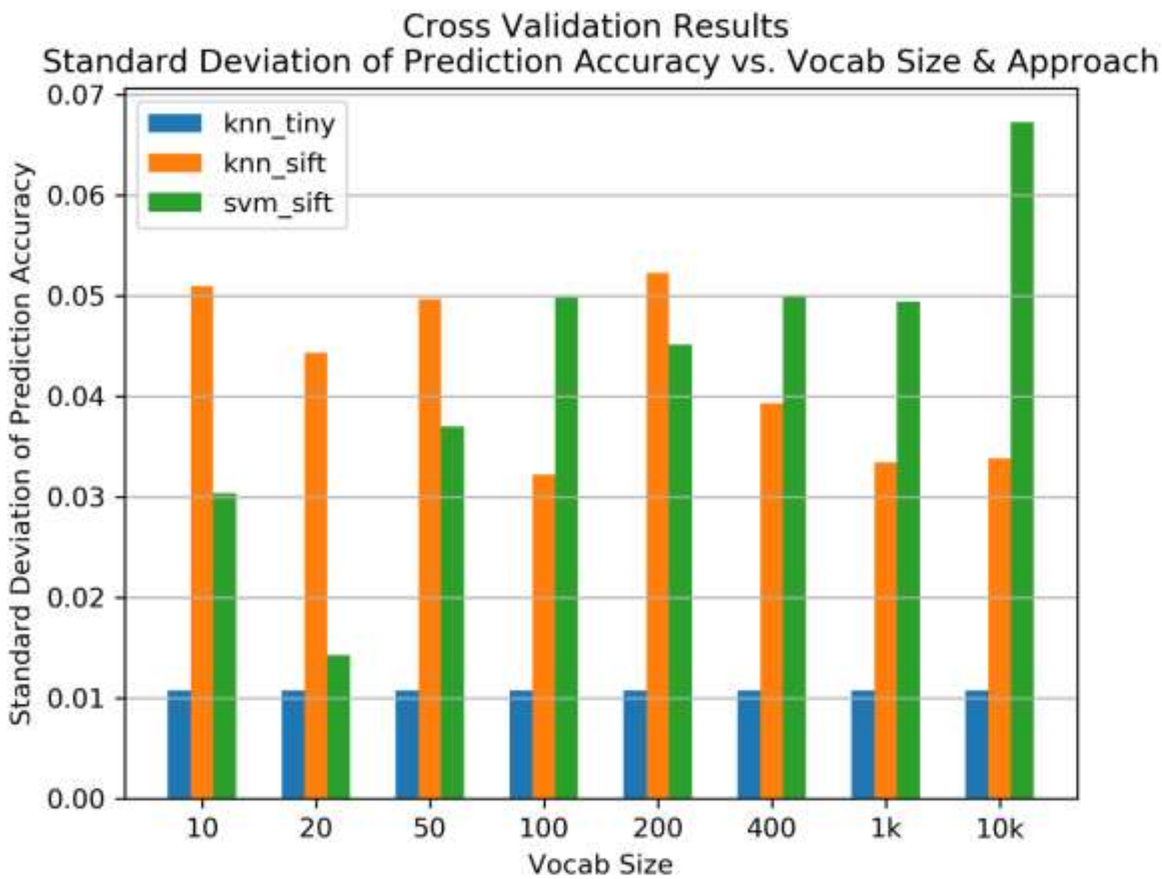


Table 6: Cross Validation Results: Standard Deviation of Prediction Accuracy vs. Vocab Size & Approach



Remarks on the cross-validation results:

Experiment design summary (rewritten here for convenience of reader):

- Number of experiments: exp_number = 10
- Dataset:
  - Train dataset: 150 random images from original train dataset
  - Test dataset: 150 random images from original test dataset
- Varying parameters:
  - vocab_size = [10, 20, 50, 100, 200, 400, 1000, 10000]
- Approaches:
  - KNN on tiny_images
  - KNN on bags_of_sifts
  - SVM on bags_of_sifts
- Total number of experiments: 10 * (1 + 8 + 8) = 170
- Results:
  - Accuracy average per approach, per vocab_size

- Accuracy standard deviation, per approach per vocab_size

Accuracy average vs. approach:

- It is worth mentioning that for KNN on tiny_images, accuracy is a single value, independent of vocab_size (all blue bars in the plot are identical).
- As expected, the average accuracy for KNN on tiny_images is the least value (13% ±1%);
- Next accuracy is obtained by KNN on bags_of_sifts (average: 33% ± 4%).
- The highest accuracy is obtained by SVM on bags_of_sifts (average: 42% ± 4%).

Accuracy average vs. vocab_size:

- When using bags_of_sifts features, the accuracy might also depend on vocab_size:
- For SVM on bags_of_sifts, average cross validation accuracy is increasing proportional to vocab_size until vocab_size = 1k; and then slightly decreases for vocab_size = 10k.
- However, for KNN on bags_of_sifts, average cross validation accuracy is almost independent of vocab_size.

Accuracy standard deviation vs. approach:

- As expected, the standard deviation for KNN on tiny_images is the least value (±1%);
- The average standard deviation is almost equal for KNN/SVM on bags_of_sifts (± 4%).

Accuracy standard deviation vs. vocab_size:

- While standard deviation is varying for different vocab_size, there does not seem to be a significant relationship between standard deviation of accuracy and vocab_size.

Overall conclusion from cross-validation results:

- bags_of_sifts are stronger features than tiny_images.
- SVM is stronger approach than KNN.
- For SVM on bags_of_sifts, accuracy is almost proportional to vocab_size (up to vocab_size = 1k).

4.5. Results for Validation with Different Vocabulary Sizes and Different SVM Lambda Values

Table 7: Results for Validation with Different Vocabulary Sizes and Different SVM Lambda Values

Validation results		**Vocab size**							
	Lambda	**10**	**20**	**50**	**100**	**200**	**400**	**1000**	**10,000**
KNN on tiny_images	**NA**	0.21							
KNN on bags_of_sifts	**NA**	0.40	0.47	0.48	0.49	**0.52**	0.51	0.50	0.43
SVM on bags_of_sifts	**0.1**	0.25	0.41	0.47	0.53	0.60	0.60	0.63	0.61
	0.5	0.29	0.42	0.50	0.56	0.60	0.61	0.65	0.62
	1	0.33	0.45	0.51	0.58	0.61	0.65	0.67	0.66
	3	0.40	0.48	0.54	0.60	0.66	0.67	0.70	0.67
	5	0.31	0.47	0.55	0.62	0.64	0.65	0.68	0.68
	7	0.38	0.49	0.56	0.63	0.64	0.64	0.68	0.68
	Average	**0.33**	**0.45**	**0.52**	**0.59**	**0.63**	**0.64**	**0.67**	**0.65**

Table 8: Validation Results: KNN on tiny_images & bags_of_sifts | Prediction Accuracy vs. Vocab Size

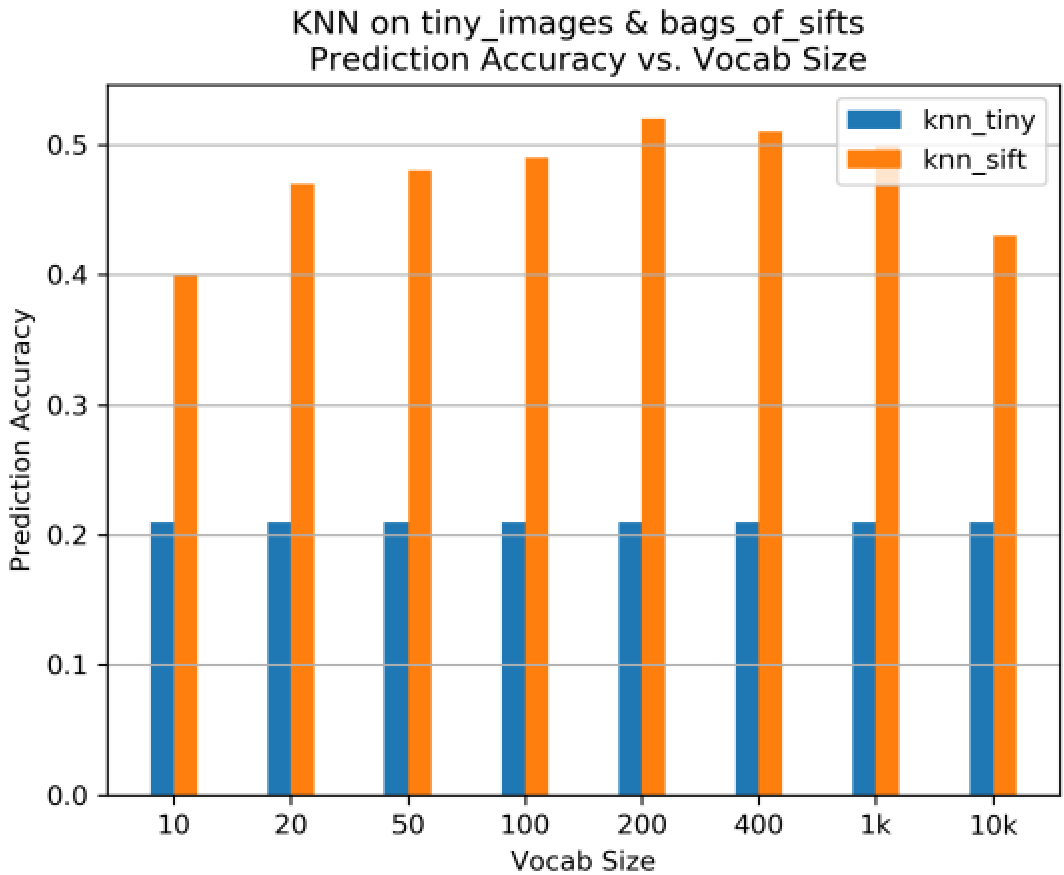
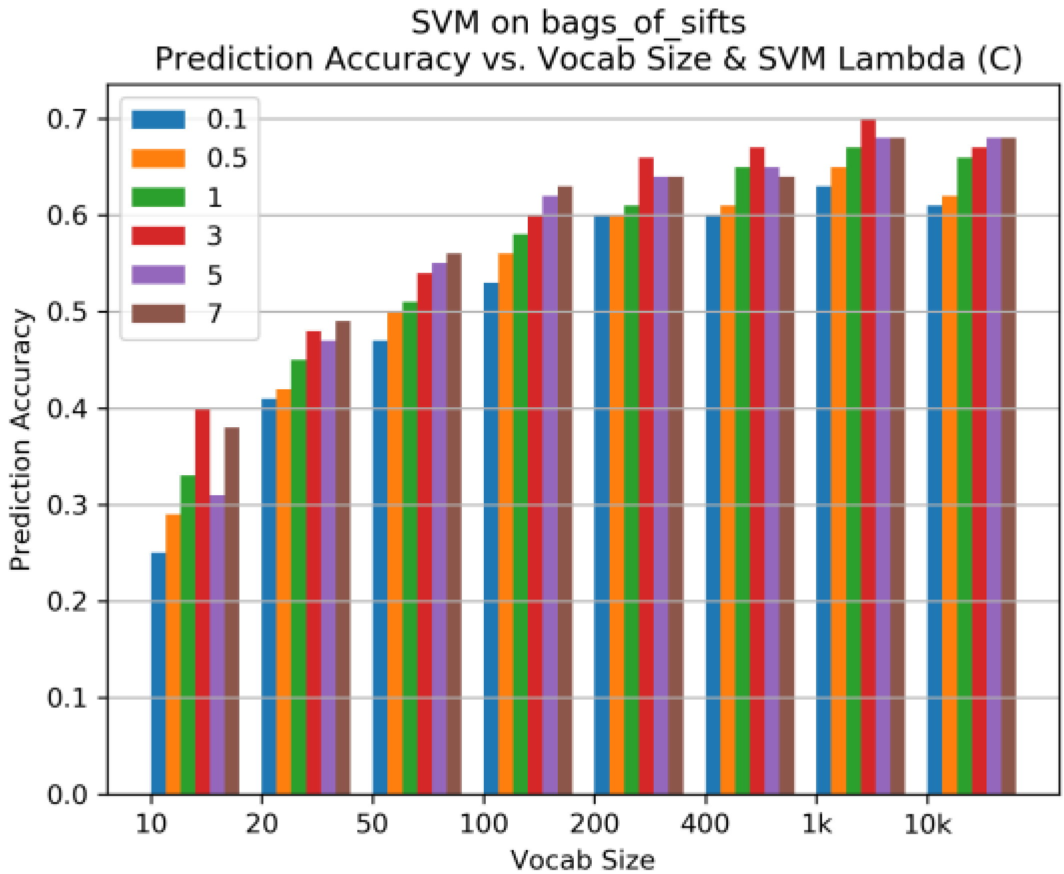


Table 9: Validation Results: SVM on bags_of_sifts | Prediction Accuracy vs. Vocab Size & SVM Lambda (C)



Remarks on the validation results:

Experiment design summary (rewritten here for convenience of reader):

- Number of experiments: 1
- Dataset:
  - Train dataset: 1050 images from original train dataset (70 images per class)
  - validation dataset: 450 images from original train dataset (30 images per class)
- Varying parameters:
  - vocab_zize = [10, 20, 50, 100, 200, 400, 1000, 10000]
  - svm_lambda = [0.1, 0.5, 1, 3, 5, 7]
- Approaches:
  - KNN on tiny_images
  - KNN on bags_of_sifts
  - SVM on bags_of_sifts
- Total number of experiments: exp_num = 1 * (1 + 8 + 8*6) = 57
- Results:

- Accuracy per approach, per vocab_size, per svm_lambda

Accuracy vs. approach:

- It is worth mentioning that for KNN on tiny_images, accuracy is a single value, independent of vocab_size (all blue bars in the plot are identical).
- As expected, the average accuracy for KNN on tiny_images is the least value (21%);
- Next accuracy is obtained by KNN on bags_of_sifts (average: 48%).
- The highest accuracy is obtained by SVM on bags_of_sifts when using appropriate vocab_size (accuracy from 33% (vocab_size = 10) to 67% (vocab_size =1000)).

Accuracy vs. vocab_size:

- When using bags_of_sifts features, the accuracy might also depend on vocab_size:
- For SVM on bags_of_sifts, validation accuracy is increasing proportional to vocab_size until vocab_size = 1k; and then slightly decreases for vocab_size = 10k.
- For KNN on bags_of_sifts, validation accuracy is also related to vocab_size but not as significant as SVM. The accuracy increases with vocab_size until reaches its maximum (52%) at vocab_size = 200 and then slowly decreases.

Accuracy vs. SVM lambda:

- When using SVM on bags_of_sifts, the accuracy might also depend on lambda:
- For most cases (vocab_sizes), validation accuracy is increasing proportional to lambda.
- For those cases where validation accuracy is not increasing proportional to lambda, it is mostly maximum at lambda = 3

Overall conclusion from validation results:

- bags_of_sifts are stronger features than tiny_images.
- SVM is stronger approach than KNN.
- For KNN on bags_of_sifts, accuracy is maximum for vocab_size = 200.
- For SVM on bags_of_sifts, accuracy is almost proportional to vocab_size (up to vocab_size = 1k).
- SVM accuracy is maximum with lambda = 5 for smaller vocab_size and lambda = 3 for higher vocab_size.

Extra Works

Following functions and code were done outside student_code.py predefined functions and proj4.ipynb:

- Function show_results_R1 saved in student_code.py
- Experiment code for cross validation and validation saved in proj4_experiment.ipynb

References

[1] Assignment 04 description by Dr. Kin-Choong Yow

[2] Szeliski, R. (2010). Computer vision: algorithms and applications. Springer Science & Business Media.