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Course: 14:332:472
Robotic & Computer Vision Project 4
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```
%run('/Users/e.kim4/Documents/MATLAB/vlfeat-0.9.20/toolbox/vl_setup')
%vl_version verbose
```

1: Bag Of Words

```
clear;

close all;
clc;

imgDir = '/Users/e.kim4/Documents/MATLAB/RCV_project4/vision_dataset';
imds = imageDatastore(imgDir, 'IncludeSubfolders', true, 'LabelSource',
'foldernames');
%split into testing vs train images: split is 5,5
[testImages,trainImages] = splitEachLabel(imds,5);
%label the trainImages 1~10
trainlabels = grp2idx(trainImages.Labels);
sizelabels = size(trainlabels);
concatDesTrain = [];

for i = 1:sizelabels(1)
    train{i} = imread(trainImages.Files{i});
    test{i} = imread(testImages.Files{i});
    %read each train images % test images
    if size(train{i},3) ~= 3
        train{i} = imresize(train{i},[300,300]);
    elseif size(train{i},3) == 3
        test{i} = imresize(test{i},[300,300]);
    else
        train{i} = rgb2gray(imresize(train{i},[300,300]));
        test{i} = rgb2gray(imresize(test{i},[300,300]));
    end

    %format them as single (just to run it on vl_sift)
    %singleTrain{i} = single(train{i});
    %singleTest{i} = single(test{i});

    %For a subset of all the interstpoints in training image, clustering
    %the descriptors using k-means clustering:
    %output as k-visual words with each word has an associated 128x1
    %centroids
    %%USING VL_SIFT: find interest points and descriptor for testing and train images
    %[interestTrain{i}, desTrain{i}] = vl_sift(singleTrain{i});
    %[interestTest{i}, desTest{i}] = vl_sift(singleTest{i});

    %USING MATLAB BUILT IN FUNCTION
    interestTrain{i} = detectSURFFeatures(train{i});
    %getOnly 150 strongest interestpoint to compute
    interestTrain{i} = interestTrain{i}.selectStrongest(100);
```

```

[desTrain{i}, validPTrain{i}] = extractFeatures(train{i},
interestTrain{i}, 'SURFSize',128);

interestTest{i} = detectSURFFeatures(test{i});
interestTest{i} = interestTest{i}.selectStrongest(100);
[desTest{i}, validPTest{i}] = extractFeatures(test{i},
interestTest{i}, 'SURFSize',128);

%put all the descriptors in one matrix for testing and train images
concatDesTrain = [concatDesTrain desTrain{i}'];
%concatDesTest = [concatDesTest desTest{i}'];
end;

```

For K=300 clustering

```

K = 300;

%so in here, assignments = closest centroids for each of Descriptor.
[centroid, assignTrain] = vl_kmeans(double(concatDesTrain), K);

%seperate each assigned descriptors into each classes.
for i = 1:sizelabels(1)
    [closestToCentroidsTrain{i}, distanceTrain{i}] = knnsearch(centroid',desTrain{i});
end

for i = 1:sizelabels(1)
    [closestToCentroidsTest{i}, distanceTest{i}] = knnsearch(centroid',desTest{i});
end

concatFVTrain = [];
for i = 1:sizelabels(1)
    featureVectorTrain{i} = zeros(1,K);
    featureVectorTest{i} = zeros(1,K);
    %can be either size of Test or Train
    sizeDescript = size(closestToCentroidsTest{i});
    for j=1:sizeDescript(1)
        featureVectorTrain{i}(1,closestToCentroidsTrain{i}(j,1)) =
featureVectorTrain{i}(1,closestToCentroidsTrain{i}(j,1)) + 1;
        featureVectorTest{i}(1,closestToCentroidsTest{i}(j,1)) =
featureVectorTest{i}(1,closestToCentroidsTest{i}(j,1)) + 1;
    end
    % concatFVTrain's each row contains histogram of eachImages
    concatFVTrain(i,:) = [featureVectorTrain{i}];
    concatFVTest(i,:) = [featureVectorTest{i}];
end
%%show similar histograms
figure(1)
for i = 1:4
    if i <= 2
        subplot(2,2,i)

```

```

        bar(featureVectorTrain{45+i});
        %featureVectorTest{trackTrain} = dummyTrain.Values;
        hold on;
        axis([0 K+1 0 15])
        title(sprintf('Similarity: class %d Train image %d: Zebra',10,45+i));
        hold off;
    else
        subplot(2,2,i)
        bar(featureVectorTest{45+i});
        %featureVectorTest{trackTest} = dummyTest.Values;
        hold on;
        axis([0 K+1 0 15])
        title(sprintf('Similarity: class %d Test image %d: Zebra',10,45+i));
        hold off;
    end
end

%%show different histogram
figure(2)
for i = 1:4
    if i <= 2
        subplot(2,2,i)
        bar(featureVectorTrain{45+i});
        %featureVectorTest{trackTrain} = dummyTrain.Values;
        hold on;
        axis([0 K+1 0 15])
        title(sprintf('Similarity: class %d Train image %d: Zebra',10,45+i));
        hold off;
    else
        subplot(2,2,i)
        bar(featureVectorTest{1+i});
        %featureVectorTest{trackTest} = dummyTest.Values;
        hold on;
        axis([0 K+1 0 15])
        title(sprintf('Similarity: class %d Test image %d: baseball',1,1+i));
        hold off;
    end
end

%%TrainHistogram vs TestHistogram
%compared a set of concatTrainHistogram with TestingHistogram(1).
[concatFVTestLabel, concatFVTestDistance] = knnsearch(concatFVTest,concatFVTrain);

for i = 1:size(concatFVTestLabel,1)
    if concatFVTestLabel(i,1) >= 1 && concatFVTestLabel(i,1) < 6
        concatFVTestLabel(i) = 1;
    elseif concatFVTestLabel(i,1) >= 6 && concatFVTestLabel(i,1) < 11
        concatFVTestLabel(i) = 2;
    elseif concatFVTestLabel(i,1) >= 11 && concatFVTestLabel(i,1) < 16
        concatFVTestLabel(i) = 3;
    elseif concatFVTestLabel(i,1) >= 16 && concatFVTestLabel(i,1) < 21

```

```

        concatFVTestLabel(i) = 4;
elseif concatFVTestLabel(i,1) >= 21 && concatFVTestLabel(i,1) < 26
    concatFVTestLabel(i) = 5;
elseif concatFVTestLabel(i,1) >= 26 && concatFVTestLabel(i,1) < 31
    concatFVTestLabel(i) = 6;
elseif concatFVTestLabel(i,1) >= 31 && concatFVTestLabel(i,1) < 36
    concatFVTestLabel(i) = 7;
elseif concatFVTestLabel(i,1) >= 36 && concatFVTestLabel(i,1) < 41
    concatFVTestLabel(i) = 8;
elseif concatFVTestLabel(i,1) >= 41 && concatFVTestLabel(i,1) < 46
    concatFVTestLabel(i) = 9;
else
    concatFVTestLabel(i) = 10;
end
end
%%ERROR CHECKING
errorclass = zeros(10,1);
for i = 1:size(concatFVTestLabel,1)
    if i>=1 && i <6 && concatFVTestLabel(i) ~= 1
        errorclass(1) = errorclass(1) + 1/5;
    elseif i >= 6 && i < 11 && concatFVTestLabel(i) ~= 2
        errorclass(2) = errorclass(2) + 1/5;
    elseif i >= 11 && i < 16 && concatFVTestLabel(i) ~= 3
        errorclass(3) = errorclass(3) + 1/5;
    elseif i >= 16 && i < 21 && concatFVTestLabel(i) ~= 4
        errorclass(4) = errorclass(4) + 1/5;
    elseif i >= 21 && i < 26 && concatFVTestLabel(i) ~= 5
        errorclass(5) = errorclass(5) + 1/5;
    elseif i >= 26 && i < 31 && concatFVTestLabel(i) ~= 6
        errorclass(6) = errorclass(6) + 1/5;
    elseif i >= 31 && i < 36 && concatFVTestLabel(i) ~= 7
        errorclass(7) = errorclass(7) + 1/5;
    elseif i >= 36 && i < 41 && concatFVTestLabel(i) ~= 8
        errorclass(8) = errorclass(8) + 1/5;
    elseif i >= 41 && i < 46 && concatFVTestLabel(i) ~= 9
        errorclass(9) = errorclass(9) + 1/5;
    elseif i >= 46 && i < 51 && concatFVTestLabel(i) ~= 10
        errorclass(10) = errorclass(10) + 1/5;
    end
end
end
%%confusion matrix
%idk if the confusionmatrix is correct
stats = confusionmatStats(trainlabels,concatFVTestLabel);
%plotting the interest points
%showing the class butterfly(3),carplate(4),watch(9)
colors = distinguishable_colors(50);
figure(11)
for i = 1:4
    subplot(2,2,i)
    imshow(train{10+i})
end

```

```

        hold on;
        plot(interestTrain{10+i});
        title(sprintf('trainImage: butterfly%d with interest points',i))
        hold off;
    end
    figure(12)
    for i = 1:4
        subplot(2,2,i)
        imshow(train{15+i})
        hold on;
        plot(interestTrain{15+i});
        title(sprintf('trainImage: carplate%d with interest points',i))
        hold off;
    end
    figure(13)
    for i = 1:4
        subplot(2,2,i)
        imshow(train{40+i})
        hold on;
        plot(interestTrain{40+i});
        title(sprintf('trainImage: carplate%d with interest points',i))
        hold off;
    end
    %plot(interestTrain{1}.Location(11,1),interestTrain{1}.Location(11,2),'*');
    %plot(interestTrain{1}.Location(244,1),interestTrain{1}.Location(258,2),'*')

```

For K=200 clustering

```

K200 = 200;

%so in here, assignments = closest centroids for each of Descriptor.
[centroid200, assignTrain200] = vl_kmeans(double(concatDesTrain), K200);

%seperate each assigned descriptors into each classes.
for i = 1:sizelabels(1)
    [closestToCentroidsTrain200{i}, distanceTrain200{i}] =
    knnsearch(centroid200',desTrain{i});
end

for i = 1:sizelabels(1)
    [closestToCentroidsTest200{i}, distanceTest200{i}] =
    knnsearch(centroid200',desTest{i});
end

concatFVTrain200 = [];
for i = 1:sizelabels(1)
    featureVectorTrain200{i} = zeros(1,K200);
    featureVectorTest200{i} = zeros(1,K200);
    %can be either size of Test or Train

```

```

sizeDescript200 = size(closestToCentroidsTest200{i});
for j=1:sizeDescript200(1)
    featureVectorTrain200{i}(1,closestToCentroidsTrain200{i}(j,1)) =
featureVectorTrain200{i}(1,closestToCentroidsTrain200{i}(j,1)) + 1;
    featureVectorTest200{i}(1,closestToCentroidsTest200{i}(j,1)) =
featureVectorTest200{i}(1,closestToCentroidsTest200{i}(j,1)) + 1;
end
% concatFVTrain's each row contains histogram of eachImages
concatFVTrain200(i,:) = [featureVectorTrain200{i}];
concatFVTest200(i,:) = [featureVectorTest200{i}];
end

%%TrainHistogram vs TestHistogram
%compared a set of concatTrainHistogram with TestingHistogram(1).
[concatFVTestLabel200, concatFVTestDistance200] =
knnsearch(concatFVTest200,concatFVTrain200);

for i = 1:size(concatFVTestLabel200,1)
    if concatFVTestLabel200(i,1) >= 1 && concatFVTestLabel200(i,1) < 6
        concatFVTestLabel200(i) = 1;
    elseif concatFVTestLabel200(i,1) >= 6 && concatFVTestLabel200(i,1) < 11
        concatFVTestLabel200(i) = 2;
    elseif concatFVTestLabel200(i,1) >= 11 && concatFVTestLabel200(i,1) < 16
        concatFVTestLabel200(i) = 3;
    elseif concatFVTestLabel200(i,1) >= 16 && concatFVTestLabel200(i,1) < 21
        concatFVTestLabel200(i) = 4;
    elseif concatFVTestLabel200(i,1) >= 21 && concatFVTestLabel200(i,1) < 26
        concatFVTestLabel200(i) = 5;
    elseif concatFVTestLabel200(i,1) >= 26 && concatFVTestLabel200(i,1) < 31
        concatFVTestLabel200(i) = 6;
    elseif concatFVTestLabel200(i,1) >= 31 && concatFVTestLabel200(i,1) < 36
        concatFVTestLabel200(i) = 7;
    elseif concatFVTestLabel200(i,1) >= 36 && concatFVTestLabel200(i,1) < 41
        concatFVTestLabel200(i) = 8;
    elseif concatFVTestLabel200(i,1) >= 41 && concatFVTestLabel200(i,1) < 46
        concatFVTestLabel200(i) = 9;
    else
        concatFVTestLabel200(i) = 10;
    end
end

%%ERROR CHECKING
errorclass200 = zeros(10,1);
for i = 1:size(concatFVTestLabel200,1)
    if i>=1 && i <6 && concatFVTestLabel200(i) ~= 1
        errorclass200(1) = errorclass200(1) + 1/5;
    elseif i >= 6 && i < 11 && concatFVTestLabel200(i) ~= 2
        errorclass200(2) = errorclass200(2) + 1/5;
    elseif i >= 11 && i < 16 && concatFVTestLabel200(i) ~= 3
        errorclass200(3) = errorclass200(3) + 1/5;

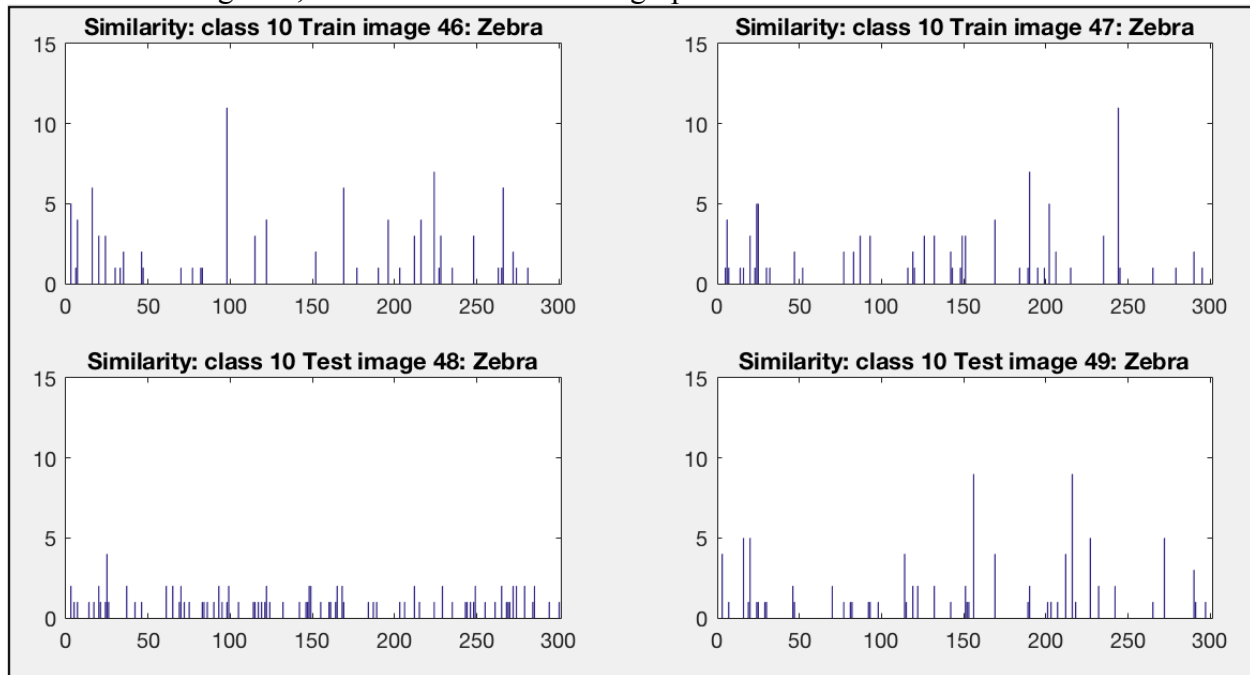
```

```

elseif i >= 16 && i < 21 && concatFVTestLabel200(i) ~= 4
    errorclass200(4) = errorclass200(4) + 1/5;
elseif i >= 21 && i < 26 && concatFVTestLabel200(i) ~= 5
    errorclass200(5) = errorclass200(5) + 1/5;
elseif i >= 26 && i < 31 && concatFVTestLabel200(i) ~= 6
    errorclass200(6) = errorclass200(6) + 1/5;
elseif i >= 31 && i < 36 && concatFVTestLabel200(i) ~= 7
    errorclass200(7) = errorclass200(7) + 1/5;
elseif i >= 36 && i < 41 && concatFVTestLabel200(i) ~= 8
    errorclass200(8) = errorclass200(8) + 1/5;
elseif i >= 41 && i < 46 && concatFVTestLabel200(i) ~= 9
    errorclass200(9) = errorclass200(9) + 1/5;
elseif i >= 46 && i < 51 && concatFVTestLabel200(i) ~= 10
    errorclass200(10) = errorclass200(10) + 1/5;
end
end
%confusion matrix K=200
%idk if the confusionmatrix is correct
stats200 = confusionmatStats(trainlabels,concatFVTestLabel200);

```

- For histograms, I chose to draw with bar graph because it seems more accurate.



- The figure displays four histograms arranged in a 2x2 grid, showing the distribution of similarity scores for different classes. The x-axis for all plots ranges from 0 to 300, and the y-axis ranges from 0 to 15.

 - Top Left:** Similarity: class 10 Train image 46: Zebra. The distribution is highly peaked around 100, with a maximum value of approximately 11.
 - Top Right:** Similarity: class 10 Train image 47: Zebra. The distribution is more spread out, with a major peak around 250 reaching a value of approximately 11.
 - Bottom Left:** Similarity: class 1 Test image 4: baseball. The distribution is highly peaked around 150, with a maximum value of approximately 9.
 - Bottom Right:** Similarity: class 1 Test image 5: baseball. The distribution is highly peaked around 70, with a maximum value of approximately 10.

Below the histograms, the following text is displayed:

```

K = 300
Number of Train Images for each class = 5
Number of Testing Images for each class = 5

According to confusionmatStats, Average accuracy of reconizing is: 92.0%.
According to computational error I computed:
    Class1: 0.6    Class2: 0.4
    Class3: 0.6    Class4: 0.0
    Class5: 0.4    Class6: 0.6
    Class7: 0.0    Class8: 1.0
    Class9: 0.4    Class10: 0.0

ConfusionMatrix is:
ans =

     2     0     1     0     0     0     0     1     1     0
     0     3     0     0     1     0     0     0     1     0
     0     0     2     0     2     0     0     1     0     0
     0     0     0     5     0     0     0     0     0     0
     0     0     1     0     3     0     0     0     1     0
     0     2     1     0     0     2     0     0     0     0
     0     0     0     0     0     0     5     0     0     0
     0     0     2     0     3     0     0     0     0     0
     0     1     0     0     1     0     0     0     3     0
     0     0     0     0     0     0     0     0     0     5
  
```

```
K = 200
```

```
Number of Train Images for each class = 5
```

```
Number of Testing Images for each class = 5
```

```
According to confusionmatStats, Average accuracy of reconizing is: 92.0%.
```

```
According to computational error I computed:
```

```
Class1: 0.4    Class2: 0.4  
Class3: 0.8    Class4: 0.4  
Class5: 0.2    Class6: 0.4  
Class7: 0.0    Class8: 0.2  
Class9: 0.8    Class10: 0.0
```

```
ConfusionMatrix is:
```

```
ans =
```

```
3    0    1    0    1    0    0    0    0    0  
0    3    1    0    0    0    0    1    0    0  
1    0    1    0    1    0    0    2    0    0  
0    1    0    3    0    0    0    0    1    0  
0    0    0    0    4    0    0    0    1    0  
0    1    1    0    0    3    0    0    0    0  
0    0    0    0    0    0    5    0    0    0  
0    0    0    0    0    0    0    4    1    0  
2    0    0    0    0    0    0    2    1    0  
0    0    0    0    0    0    0    0    0    5
```

- Classes: Baseball, Bicycle, Butterfly, Carplate, Flower, Keyboard(piano), Leopard, Pizza, Watch, Zebra
- By computing Bag of Words with two different K values (I actually computed different K values too but too much to show in here), I learned that as K values increases, there are significantly better chance of reducing error for class 4 and class 9. Inversely, there were significantly worse chance of reducing error for class 8. Since all the images are not selected from all the interest Points; rather, picked out 100 strongest points, there might be loss of information such that not stable.
- The pictures with interestpoints <100 will not work with this code because I, purposely, chose pictures with large interestpoints.

2: PCA recognition

```
%eigs  
  
clear;  
close all;  
clc;
```

```

imgDir = '/Users/e.kim4/Documents/MATLAB/RCV_project4/vision_dataset2';
imds = imageDatastore(imgDir, 'IncludeSubfolders', true, 'LabelSource',
'foldernames');
[testFace,trainFace] = splitEachLabel(imds,5);
trainlabels = grp2idx(trainFace.Labels);
sizelabels = size(trainlabels);

for i = 1:sizelabels(1)
    % each img is N=243 x P=320 M = numberofimages = 10 per class
    % 100 for whole classes
    trainF{i} = imread(trainFace.Files{i});
    testF{i} = imread(testFace.Files{i});
    if size(trainF{i},3)== 3
        trainF{i} = rgb2gray(imread(trainFace.Files{i}));
    elseif size(testF{i},3) ==3
        testF{i} = rgb2gray(imread(testFace.Files{i}));
    end

    if i == 1
        % has (N*P)x M dimension
        trainA = zeros(prod(size(trainF{1})),sizelabels(1));
        testA = zeros(prod(size(testF{1})),sizelabels(1));
        trainMean = zeros(size(trainF{1}));
        %testMean = zeros(size(testF{1}));
    end
    %avgface has NxP dimension
    trainMean = trainMean + double(trainF{i});
    %testMean = testMean + double(trainF{i});
    trainA(:,i) = trainF{i}(:);
    testA(:,i) = testF{i}(:);
end;

%%compute averageface to show; averageface for computation
trainMean = mean(trainA,2);
%testMean = mean(testA,2);

%%compute the differences of original image - Mean face
%removing all common face features that the faces share together
%so that each face is left with each unique features
for i = 1:size(trainA,2)
    %(N*P) x M
    %subtract each column with averageface
    trainA_Mean(:,i) = trainA(:,i) - trainMean;
    testA_Mean(:,i) = testA(:,i) - trainMean;
end

%%compute covariance Matrix & get eigenvector and eigenvalues
%originalC = A_Mean * transpose(A_Mean);
%better to reduce the dimensionality to reduce noise and
%number of computation

```

```

trainReducedC = transpose(trainA_Mean)*trainA_Mean;
testReducedC = transpose(testA_Mean)*testA_Mean;

%%Choosing K using SVD
%such that  $K \leq M$  and represent whole training set
%columns of U = eigenvectors
%S = eigenvalues
[trainU,trainS,trainV] = svd(trainReducedC);
[testU,testS,testV] = svd(testReducedC);
figure(1)
subplot(1,2,1)
plot(trainS);
subplot(1,2,2)
plot(testS);
hold off;
title('Decay of Eigenvalues')
xlabel('NM')
ylabel('eignvalues')

%can choose K here.
%find rank R = K
trainK = rank(trainReducedC);
testK = rank(testReducedC);

%%get eigenvector
trainEVecReduced = trainU(:,1:trainK);
testEVecReduced = testU(:,1:testK);

%%convert reduced dimensional K eigenvectors to origianl dimensionality
%u_i = A*v_i;
trainEvecOriginal(:,1:trainK) = trainA_Mean*trainEVecReduced(:,1:trainK);
testEvecOriginal(:,1:testK) = testA_Mean*testEVecReduced(:,1:testK);

%%normalized each column
%trainEvecOriginal=normc(trainEvecOriginal);
%testEvecOriginal=normc(testEvecOriginal);

%%finding coefficient a by dotproduct
trainCoef = (trainA_Mean'*trainEvecOriginal);
testCoef = (testA_Mean'*testEvecOriginal);

%normalized each column
trainCoef = normc(trainCoef);
testCoef = normc(testCoef);

%%reconstruc with eigenfaces.
%originalFace = avgfaceForComp +
a(1)*eigvecOriginal(:,1)+'...+a(114)*eigvecOriginal(114);
testFace = [];
for i=1:trainK

```

```

    if i == 1
        testFace = repmat(trainMean',size(labels(1),1) +
testCoef(:,i)*testEvecOriginal(:,i)';
    end
    testFace = testFace + testCoef(:,i)*testEvecOriginal(:,i)';
end
figure(1)
subplot(5,2,1)
imshow(uint8(reshape(testFace(1,:),[size(testF{1})])));
title(sprintf('K = %d: trainImage 1:',testK))
subplot(5,2,2)
imshow(uint8(reshape(testFace(6,:),[size(testF{1})])));
title(sprintf('K = %d: trainImage 6:',testK))
subplot(5,2,3)
imshow(uint8(reshape(testFace(11,:),[size(testF{1})])));
title(sprintf('K = %d: trainImage 11:',testK))
subplot(5,2,4)
imshow(uint8(reshape(testFace(16,:),[size(testF{1})])));
title(sprintf('K = %d: trainImage 16:',testK))
subplot(5,2,5)
imshow(uint8(reshape(testFace(21,:),[size(testF{1})])));
title(sprintf('K = %d: trainImage 21:',testK))
subplot(5,2,6)
imshow(uint8(reshape(testFace(26,:),[size(testF{1})])));
title(sprintf('K = %d: trainImage 26:',testK))
subplot(5,2,7)
imshow(uint8(reshape(testFace(31,:),[size(testF{1})])));
title(sprintf('K = %d: trainImage 31:',testK))
subplot(5,2,8)
imshow(uint8(reshape(testFace(36,:),[size(testF{1})])));
title(sprintf('K = %d: trainImage 36:',testK))
subplot(5,2,9)
imshow(uint8(reshape(testFace(41,:),[size(testF{1})])));
title(sprintf('K = %d: trainImage 41:',testK))
subplot(5,2,10)
imshow(uint8(reshape(testFace(46,:),[size(testF{1})])));
title(sprintf('K = %d: trainImage 46:',testK))

```

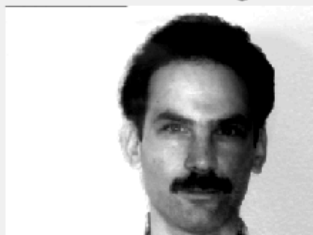
K = 49: trainImage 1:



K = 49: trainImage 6:



K = 49: trainImage 11:



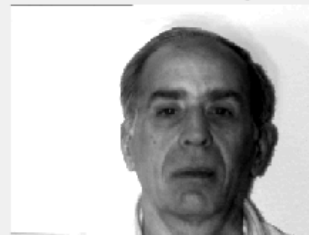
K = 49: trainImage 16:



K = 49: trainImage 21:



K = 49: trainImage 26:



K = 49: trainImage 31:



K = 49: trainImage 36:



K = 49: trainImage 41:



K = 49: trainImage 46:



K = 30: trainImage 1:



K = 30: trainImage 6:



K = 30: trainImage 11:



K = 30: trainImage 16:



K = 30: trainImage 21:



K = 30: trainImage 26:



K = 30: trainImage 31:



K = 30: trainImage 36:



K = 30: trainImage 41:



K = 30: trainImage 46:



K = 10: trainImage 1:



K = 10: trainImage 6:



K = 10: trainImage 11:



K = 10: trainImage 16:



K = 10: trainImage 21:



K = 10: trainImage 26:



K = 10: trainImage 31:



K = 10: trainImage 36:



K = 10: trainImage 41:



K = 10: trainImage 46:



- As the K decreases, I learned that the image construction will more close to mean_faces because there are not much of coefficient to represent each faces.

#3

Part1.1 Convolution

1. $H'' = H - 2$, $W'' = W - (W' - 1)$
2. Bars

Part1.1.2: Convolution by a filter bank

1. $K=3$ for this example because there are 3 filters in the convolutions.

Part1.2: Non-Linear Activation

1. Does simple linear transformation over input data.
2. Laplacian: Horizontal, ReLU: Vertical

Part2: Backpropagation

1. Maybe it is derivative of different parameter
2. Yes: for..... $dx_numerical(l,j,k,n) = (y_p - y)/deta$;

Part 2.2: Backpropagation

1. Because it's doing projective derivative of p and vl_nnconv does derivative with dy .

Part3.1

1. Convolution operator refines the images
2. The zero padding would disappear for all CNN that is layer 2~5
3. Because it is not separated by ReLUs
4. 1) 6 layers
2) support: 3 for Conv, 1 for ReLU;
NUM FIT CHANNEL: 32 for conv, n/a for ReLU
5. The size (in pixel) of the local image region that affects a particular element in a feature map. Larger receptive field size might be preferable and can be obtained with larger layers.
6. Yes.
7. It is much slower
8. Slower
9. better