

Homework 2 - Due Mon. Feb. 13th AS.110.446, EN.550.416

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Homework Policies

As in the first homework set.

Exercises

Exercise 1 (10pts). We work in \mathbb{R}^n , and fix a vector $\alpha = (\alpha_1, \dots, \alpha_n) \in \mathbb{R}_+^n$, i.e. with $\alpha_1, \dots, \alpha_n > 0$.

- Show that

$$\langle v, w \rangle_\alpha = \sum_{i=1}^n \alpha_i v_i w_i$$

defines an inner product on \mathbb{R}^n .

- Find an $n \times n$ matrix A_α (that depends on α) such that you may write the inner product above as $v^T A_\alpha w$ (thinking of vectors as column vectors).
- What is the norm $\|\cdot\|_\alpha$ associated with this inner product?
- Draw a sketch of the unit sphere $\{\|v\|_\alpha = 1\}$ corresponding to this norm, for some fixed α and for, say, $n = 2$.
- (extra question, no credit) What happens if at least one of the α_i 's is 0?

Exercise 2 (25pts). An $n \times n$ matrix A is called positive-definite if A is symmetric and $\langle Av, v \rangle \geq 0$ for all $v \in \mathbb{R}^n$, and $\langle Av, v \rangle = 0$ implies $v = 0$ (here $\langle \cdot, \cdot \rangle$ is the standard Euclidean inner product).

- Give at least 3 non-trivial and significantly different examples of 2×2 positive definite matrices.
- Was the matrix A_α in the previous exercise positive definite?
- If A is a positive definite $n \times n$ matrix, define $\langle v, w \rangle_A := \langle Av, w \rangle$ (where $\langle \cdot, \cdot \rangle$ is the standard Euclidean inner product). Show that $\langle \cdot, \cdot \rangle$ is an inner product in \mathbb{R}^n .

Exercise 3 (15pts). Let $A = \begin{bmatrix} 2 & 4 \\ 0 & 4 \end{bmatrix}$. Compute $\|A\|_1$, $\|A\|_2$, $\|A\|_\infty$.

Exercise 4 (50pts). See the script `Homework2.m` below, also available on the Wiki, also included below: follow the instructions in the script, completing it. Note the questions marked with `?????` and do Part I and Part II. See the wiki for the code (which requires a few additional scripts to load the data). Please remember to include a print out of your code, figures, etc... as per homework policies.

```

1 %% Add path to data set and helpers to load data.
2 % Change to the appropriate directory
3 addpath('../Data');
4
5 %% Load all handwritten digits in a data set
6 [X,Y] = LoadMNIST;
7 nClasses = length(unique(Y));
8
9 %% Let's look at some random data points, visualized as images
10 idxs = randperm(size(X,2),32); ...
    % Picks 32 random numbers between 1 and N=number of points
11 bigFig;
12 for k = 1:length(idxs)
13     subplot(ceil(length(idxs)/8),8,k);
14     imagesc(reshape(X(:,idxs(k)),[28,28])); ...
    % Each column vector in X is a 28x28 image
15     colormap(gray);
16 end
17
18 %% Compute the mean of the data
19 Xmean = mean(X,2);% ?????? % Compute the mean
20 % ?????? Display the mean
21 Xsubmean = bsxfun(@minus,X,Xmean); % Subtract the mean to ...
    obtain centered data. NOTE: what's the computational complexity of this command? ...
    Would you have computed Xsubmean in other ways? Would they be faster?
22 % Let's look at some random digits after subtracting the mean: make sure you ...
    understand why the images lookk like the way they do
23 idxs = randperm(size(Xsubmean,2),32);
24 bigFig;
25 for k = 1:length(idxs)
26     subplot(ceil(length(idxs)/8),8,k);
27     imagesc(reshape(Xsubmean(:,idxs(k)),[28,28]));
28     colormap(gray);
29 end
30 set(gcf, 'Name', 'Centered Data');
31
32 %% Principal Component Analysis
33 [U,S,V] = svd(Xsubmean); % ??????: This will ...
    fail: why? If it does not fail, you will wait for a very large time...
34 [U,S,-] = svd(Xsubmean,'econ'); % ??????: Run this ...
    instead: how is it different from the above?
35 % Displays some of the singular vectors
36 bigFig;h1=gcf;
37 scrsz = ...
    get(groot, 'ScreenSize');h2=figure('Position',[scrsz(3)*(1/8+3/4-3/24),scrsz(4)*(3/4),scrsz(3)*3/24,scrsz(
38 for k = 1:10
39     Xproj = U(:,k:k+2) '*X;
40     figure(h1);
41     scatter3(Xproj(1,:),Xproj(2,:),Xproj(3,:),10,Y,'filled');colorbar;
42     xlabel(num2str(k));ylabel(num2str(k+1));zlabel(num2str(k+2));
43     figure(h2); % NOTE: this helps in understanding the ...
        coordinates being used
44     for l = 1:3
45         subplot(1,3,l); imagesc(reshape(U(:,k+l-1),[28,28]));colormap(gray);
46     end
47     pause;
48 end
49
50 %% Part I : Project onto singular vectors
51 % - For each value of k=1,2,3,4,8,16,32,64,128
52 % - Project the (centered) data onto the first k singular vectors ...
    {U(:,1),U(:,2),...,U(:,k)}

```

Figure 1: Matlab code of Homework2.m

```

1 % - Compute the length of each centered data point, the length of its projection onto ...
  the first k singular vectors, and the
2 % length of the difference between the original point and this projection. What is ...
  the relationship between these 3 lengths?
3 % - Produce a figure with three rows, where in the first row you show some of an ...
  original data point, the second row shows the
4 % same data point projected onto the first k singular vectors plus the mean, and the ...
  third row shows the difference between the original
5 % data point and its projection in column two. Do this for several (random) data ...
  points, and for several values of k. Comment
6 % on how the approximations and the errors look like, how they decrease, for which ...
  value of k the approximated digits become recognizable, ...
7 % - Plot the singular values (on the diagonal of S above). You may want to switch to ...
  log_{10} scale of the singular values. What
8 % do they tell you about the error (measured how) incurred by approximating the data ...
  by k singular values?
9
10
11
12
13 %% Part II : Principal Component Analysis for each class
14 % - Pick two classes, e.g. {1,3}
15 % - Compute PCA for the data in the first class, yielding principal vectors U_1 and ...
  principal values S_1, and separately for
16 % the second class, yielding principal vectors U_2 and principal values S_2.
17 % - Plot S_1 and S_2 on the same plot, comment on their appearance, and try to provide ...
  an explanation of similarities/differences
18 % - Compare the mean squared error for:
19 %     approximating points in class 1 with their projection onto U_1(:,1:k)?
20 %     approximating points in class 2 with their projection onto U_1(:,1:k)?
21 %     approximating points in class 1 with their projection onto U_2(:,1:k)?
22 %     approximating points in class 2 with their projection onto U_2(:,1:k)?
23 % - Can you design a simple rule for assigning a point (of unknown class) to either ...
  class 1 or class 2 based on how well it i
24 % approximated by its projection onto U_1 or U_2? (be careful and don't forget about ...
  the appropriate means to subtract)
25 % - How do the results above change upon changing k?
26 % - Think about and describe all of the above geometrically

```

Figure 2: Matlab code of Homework2.m