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In this MATLAB code demonstration, I will showcase one application of the
SVD. This firstly decomposes a matrix A into U, V (both orthogonal matrices)
and Sigma (a rectangular diagonal matrix whose diagonal represents singular
values). Then, I will use scatterplot to represent it graphically.
clear all; close all; clc;
%generate 10000 points in 2D
N = 10000;
I firstly generate 2D Data with correlation using scatterplot
X = mvnrnd([0\ 0], [1\ .5; .5\ 1], N);
figure
colorForGraph = X(:,1)+X(:,2); %for visual reference
scatter(X(:,1),X(:,2),20,colorForGraph,'filled')
axis image
title('2D Data with Correlation');
pause
Then, by using the svd function built in MATLAB, I take the svd of the matrix.
By the formula, A = U*Sigma*V transpose, I firstly display the two singular
values, which are on the diagonal of the diagonal matrix Sigma.
[U,S,V] = svd(1/sqrt(N)*X,0);
disp(diag(S));
pause
There are two singular vectors, each of length 2.
The first one, v1, which is the red one on the figure, points to the larger
direction (dir1) of variance.
The second one, v2, which is the green one on the figure, points to the smaller
direction (dir2) of the variance.
These two singular vectors are orthogonal, and are both rescaled by singular
value (which is the largest absolute value among one's elements)
scatter(X(:,1),X(:,2),20,colorForGraph,'filled')
hold on
dir1 = V(:,1)*S(1,1);
plot([0 dir1(1)],[0 dir1(2)],'r','LineWidth',2)
dir2 = V(:,2)*S(2,2);
plot([0 dir2(1)],[0 dir2(2)], 'g', 'LineWidth',2)
axis image
title('Directions of V with Magnitude S')
pause
By the formula, A = U*Sigma*V transpose;
A*V = U*Sigma
To make the dataset uncorrelated, I multiply X by V. By the Geometric SVD
Theorem, now V and U now represents orthoNORMAL bases. The two singular
vectors, again, point to the larger and smaller direction of the variance,
but now on the uncorrelated, renormalized dataset.
figure
newData = X*V;
```

scatter(newData(:,1),newData(:,2),20,colorForGraph,'filled');

```
hold on
plot([0 S(1,1)],[0 0],'r','LineWidth',2)
plot([0 0],[0 S(2,2)],'g','LineWidth',2)
title('Renormalized Data XV')
axis image
```

This is another MATLAB code demonstration, which illustrates one more application of the SVD. This firstly takes in an image called cameraman, and performs SVD. Since the picture size is 256*256, as designated, I will represent the image using different amount of singular vectors and show how much information one singular vector contains.

```
I = double(imread('cameraman.tif'));
N = size(I,1);
figure
imagesc(I)
axis image
colormap pink
pause
[U,S,V] = svd(I);
This plots the singular values (the diagonal elements in the matrix Sigma)
in ascending order (from the biggest one). We can see that it's decaying.
The diminishing effect can be interpreted that each additional singular
vector describes less information.
figure
plot(diag(S), 'LineWidth',2)
title('Singular Values')
xlabel('i');f
ylabel('\sigma i');
pause
Now, by the formula A = sum of ((u_i)*(sigma_i)*(v_i_transpose)), I show
the effect of making A by summing up different amount of singular vectors.
I illustrate the image using 4, 8, 16, 32, 64, 128 and 256 singular vectors.
We can clearly see that as we sum up more singular vectors, the representation
of the original image becomes more accurate. Reasonably, using 256 singular
vectors gives out exactly the original image, as expected.
for i=2:log2(N)
   numKept = 2^i;
   Itmp = U(:,1:numKept)*S(1:numKept,1:numKept)*V(:,1:numKept)';
   imagesc(Itmp)
   axis image
   colormap pink
   title([num2str(numKept) ' Singular Vectors']);
   pause
end
Lastly, we see how the image would look like if we only use the first singular
vector to represent it. That is, A = sigma(1)*u(1)*v(1) transpose.
It indicates that the first singular vector (which corresponds to the biggest
eigenvalues (in absolute value)) contains a fairly large amount of
information, as the result is not too bad.
numKept = 1;
Itmp = U(:,1:numKept)*S(1:numKept,1:numKept)*V(:,1:numKept)';
imagesc(Itmp)
```