Thanks Devanshu!

So, now let me demonstrate the usefulness of Singular Value Decomposition as an illustration of PCA in exploiting redundancy and compressing the image. What you can look at the screen is a simple rangoli image of size 2301x2188x3. We extracted its pixel matrix and calculated its rank. It comes out to be a full rank matrix.

In other words, all its columns are linearly independent and hence, it has minimal redundancy. However, if we have a look at its eigenfaces that we calculated through singular value decomposition, we can observe that only some of the initial eigenfaces are the most significant or most useful to us. This is because they capture the maximum variance in the matrix data.

So , we tried and had a look on how much we can regenerate the image using the linear combination of the eigenfaces that we calculated. If you look at the 2 images at the bottom left of the slide, the first one represents the layer-1 image of size 2301x2188. We have used the entire data while plotting the image. The second one represents a compressed form of the image. It is the image generated by linear combination of the first 20 eigenfaces. And it captures, most of the information of the image with little accuracy trade-off. The 20 eigenfaces can be generated by using 20 eigenvalues and corresponding eigenvectors. So, in other words, we only require 2301x20 amount of data. With the help of 20 singular values, we are able to compress 2000 columns to just 20 columns.

This is how we can use SVD in image compression and exploiting redundancy.

//Next slide

At times, we have to know how many eigenfaces are required to capture maximum variance in our data. It varies from image to image. We can calculate it using explained variance ratio. It describes the percentage of variance explained by each of the selected components. It helps us to give a good approximation of how many components are needed to describe the data almost fully.

The graph is plotted for one of the images we have experimented with. The graph shows that with about 100 components we are able to capture data with 95% variance.

//Next slide

Now, as you can see on the screen, we have shown transformations of a hearts image. We have shown graphs of how the image looks under rotation by certain angle, horizontal and vertical reflection and scaling up and down the image. In real life, we always might not be dealing with the original image, but its transformed version. And not only just one transformation, but combinations of them along with added noise. So, in such scenarios, it becomes quite difficult to examine images properly and classify them based upon the images in our database. Our problem statement for the project is to study correlation of eigen decomposition between original and transformed images for better classifying them.

Further will be taken over by my friend Shubham Patel