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Information Retrieval in High Dimensional Data Lab #5,07.06.2018

Principal Component Analysis

- Task 1. In this task, we will once again work with the MNIST training set as provided on Moodle. Choose three digit classes, e.g. 1, 2 and 3 and load N=1000 images from each of the classes to the workspace. Store the data in a floating point matrix X of shape (784, 3*N) normalized to the number range [0, 1]. Furthermore, generate a color label matrix C of dimensions (3*N, 3). Each row of C assigns an RGB color vector to the respective column of X as an indicator of the digit class. Choose [0, 0, 1], [0, 1, 0] and [1, 0, 0] for the three digit classes.
 - a) Compute the row-wise mean mu of X and subtract it from each column of X. Save the results as X c.
 - b) Use np.linalg.svd with full_matrices=False to compute the singular value decomposition [U,Sigma,VT] of X_c. Make sure the matrices are sorted in descending order with respect to the singular values.
 - c) Use reshape in order to convert mu and the first three columns of U to (28,28)-matrices. Plot the resulting images. What do you see?
 - d) Compute the matrix S=np.dot(np.diag(Sigma), VT). Note that this yields the same result as S=np.dot(U.T, X_c). The S matrix contains the 3*N scores for the principal components 1 to 784. Create a 2D scatter plot with C as its color parameter in order to plot the scores for the first two principal components of the data.
- Task 2. In this task, we consider the problem of choosing the number of principal vectors. Assuming that $\mathbf{X} \in \mathbb{R}^{p \times N}$ is the centered data matrix and $\mathbf{P} = \mathbf{U}_k \mathbf{U}_k^{\top}$ is the projector onto the k-dimensional principal subspace, the dimension k is chosen such that the fraction of overall energy contained in the projection error does not exceed ϵ , i.e.

$$\frac{\|\mathbf{X} - \mathbf{P}\mathbf{X}\|_F^2}{\|\mathbf{X}\|_F^2} = \frac{\sum_{i=1}^M \|\mathbf{x}_i - \mathbf{P}\mathbf{x}_i\|^2}{\sum_{i=1}^N \|\mathbf{x}_i\|^2} \le \epsilon,$$

where ϵ is usually chosen to be between 0.01 and 0.2.

The MIT VisTex database as provided on Moodle consists of a set of 167 RGB texture images of sizes (512,512,3). Download the ZIP file, unpack it and make yourself familiar with the directory strucutre.

- a) After preprocessing the entire image set (converting to normalized grayscale matrices), divide the images into non overlapping tiles of sizes (64,64) and create a centered data matrix X_c of size (p,N) from them, where p=64*64 and N=167*(512/64)*(512/64).
- b) Compute the SVD of X_c and make sure the singular values are sorted in descending order.
- c) Plot the fraction of signal energy contained in the projection error¹ for the principal subspace dimensions 0 to p. How many principal vectors do you need to retain 80%, 90%, 95% or 99% of the original signal energy?
- d) Discuss: Can you imagine a scenario, where signal energy is a bad measure of useful information?

Helpful Python/Numpy functions

¹Note that you do not need to evaluate any norms or projections. All you need is the result of subtask b)