

Homework 6

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Problem 1.

Solution: Compute the log likelihood of the data:

$$\ell(\boldsymbol{\mu}_k, \boldsymbol{\Sigma}_k) = \sum_k \sum_i r_{ik} \log \mathbb{P}(\mathbf{x}_i | \boldsymbol{\theta}_k) = -\frac{1}{2} \sum_i r_{ik} \left(\log |\boldsymbol{\Sigma}_k| + (\mathbf{x}_i - \boldsymbol{\mu}_k)^\top \boldsymbol{\Sigma}_k^{-1} (\mathbf{x}_i - \boldsymbol{\mu}_k) \right)$$

Taking the gradient w.r.t μ_k :

$$\frac{\partial \ell}{\partial \mu_k} = \sum_i r_{ik} \boldsymbol{\Sigma}_k^{-1} (\mathbf{x}_i - \boldsymbol{\mu}_k)$$

Since $\boldsymbol{\Sigma}_k^{-1}$ is linear:

$$\frac{\partial \ell}{\partial \mu_k} = \boldsymbol{\Sigma}_k^{-1} \sum_i r_{ik} (\mathbf{x}_i - \boldsymbol{\mu}_k) = 0 \Leftrightarrow \sum_i r_{ik} \mathbf{x}_i = \boldsymbol{\mu}_k \sum_i r_{ik}$$

as expected.

Now, taking the gradient w.r.t Σ_k :

$$\begin{aligned} \frac{\partial \ell}{\partial \Sigma_k} &= -\frac{1}{2} \sum_i r_{ik} \left(\boldsymbol{\Sigma}_k^{-1} - \boldsymbol{\Sigma}_k^{-1} (\mathbf{x}_i - \boldsymbol{\mu}_k) (\mathbf{x}_i - \boldsymbol{\mu}_k)^\top \boldsymbol{\Sigma}_k^{-1} \right) = 0 \\ &\Leftrightarrow \sum_i r_{ik} I = \left(\sum_i r_{ik} (\mathbf{x}_i - \boldsymbol{\mu}_k) (\mathbf{x}_i - \boldsymbol{\mu}_k)^\top \right) \boldsymbol{\Sigma}_k^{-1} \end{aligned}$$

Multiplying by Σ_k on the right and dividing by $r_k = \sum_i r_{ik}$, we have:

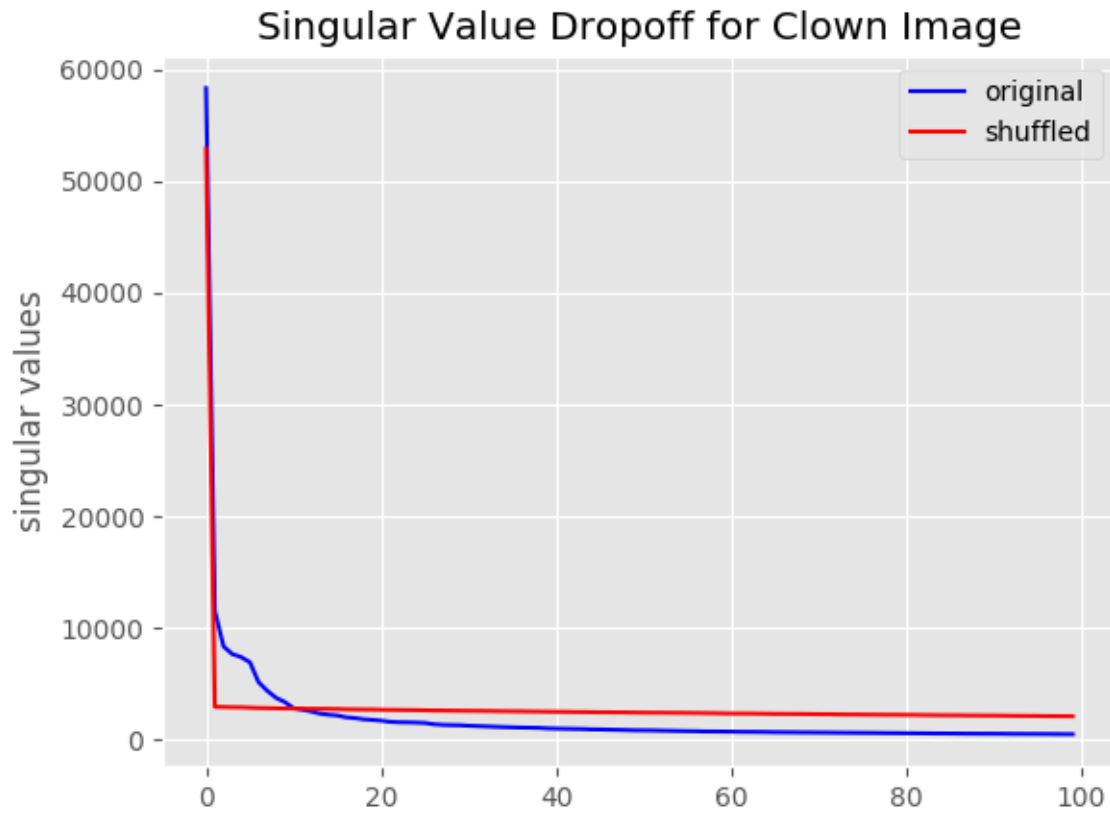
$$\boldsymbol{\Sigma}_k = \frac{1}{r_k} \sum_i r_{ik} \mathbf{x}_i \mathbf{x}_i^\top - r_k \boldsymbol{\mu}_k \boldsymbol{\mu}_k^\top$$

as expected. \square

Problem 2.

Solution: See Github repo for code.

Plot the progression of the 100 largest singular values for the original image and a randomly shuffled version of the same image (all on the same plot).



In a single figure plot a grid of four images: the original image, and a rank k truncated SVD approximation of the original image for $k \in \{2, 10, 20\}$.

Original Image



Rank 2 Approximation



Rank 10 Approximation



Rank 20 Approximation

