

CS/ECE/ME 532

Unit 3 Practice Problems

1. In (a) - (e), let the SVD of a matrix be given as $\mathbf{A} = \mathbf{U}\mathbf{\Sigma}\mathbf{V}^T$, with $\Sigma_{1,1} = \sigma_1$ denoting the first singular value.
- a) σ_1 is the largest value of $\|\mathbf{A}\mathbf{x}\|_2$ for any unit norm vector \mathbf{x} .
True False
 - b) σ_1 is the largest value of $\|\mathbf{x}^T \mathbf{A}\|_2$ for any unit norm vector \mathbf{x} .
True False
 - c) σ_1 is ℓ_2 norm of the vector \mathbf{x} that maximizes $\|\mathbf{x}^T \mathbf{A}\|_2$.
True False
 - d) $\sigma_1 = \|\mathbf{A}\|_{op}$.
True False
 - e) $\sigma_1^2 = \sum_{i,j} \mathbf{A}_{i,j}^2$.
True False

SOLUTION:

- (a) True
- (b) True
- (c) False
- (d) True
- (e) False

2. You collect eight, four dimensional data points that you store as columns in a matrix \mathbf{X} :

$$\mathbf{X} = [\mathbf{x}_1 \ \mathbf{x}_2 \ \dots \ \mathbf{x}_8] \tag{1}$$

You cluster the 8 data points by running the k -means algorithm with $k = 3$, which produces cluster centers, $\mathbf{t}_1, \mathbf{t}_2, \mathbf{t}_3$:

$$\mathbf{T} = [\mathbf{t}_1 \ \mathbf{t}_2 \ \mathbf{t}_3] = \begin{bmatrix} 1 & 1 & -2 \\ -4 & -2 & 0 \\ 7 & -6 & 2 \\ 7 & -6 & 9 \end{bmatrix} \tag{2}$$

- a) The data points $\mathbf{x}_1, \mathbf{x}_2, \mathbf{x}_3$ are assigned to cluster \mathbf{t}_1 , while \mathbf{x}_4 is assigned to \mathbf{t}_2 , and the remaining data points are assigned to \mathbf{t}_3 . Specify the cluster assignment matrix \mathbf{W} , so that $\mathbf{X} \approx \mathbf{T}\mathbf{W}^T$.

SOLUTION:

$$\mathbf{W}^T = \begin{bmatrix} 1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 1 & 1 & 1 \end{bmatrix}$$

b) What is the rank of $\mathbf{T}\mathbf{W}^T$? Why?

SOLUTION: $\mathbf{T}\mathbf{W}^T$ is rank 3. Clearly \mathbf{W} is rank 3, as is \mathbf{T} since both have three linearly independent columns. Since both \mathbf{W} and \mathbf{T} are full rank, the product is equal to the rank of each matrix.

3. You are told that a 3-by-4 matrix $\mathbf{X} = \begin{bmatrix} 4 & \cdot & \cdot & \cdot \\ \cdot & -2 & \cdot & \cdot \\ \cdot & \cdot & \cdot & 2 \end{bmatrix}$ has singular-value decomposition $\mathbf{X} = \mathbf{U}\mathbf{S}\mathbf{V}^T$ where $\mathbf{S} = \begin{bmatrix} 4\sqrt{6} & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}$ and $\mathbf{V} = \frac{1}{2} \begin{bmatrix} 1 & -1 & 1 & -1 \\ 1 & 1 & 1 & 1 \\ -1 & -1 & 1 & 1 \\ -1 & 1 & 1 & -1 \end{bmatrix}$. Find the matrix \mathbf{X} . Be

sure to explain how you obtained your answer.

SOLUTION:

\mathbf{X} is a rank-1 matrix since there is only one nonzero singular value. Hence each row of \mathbf{X} must lie in the space spanned by the first row of \mathbf{V}^T , that is, must be a scalar multiple of the first row of $\frac{1}{2} \begin{bmatrix} 1 & 1 & -1 & 1 \end{bmatrix}$. Thus, to agree with the given entries, we have

$$\mathbf{X} = \begin{bmatrix} 4 & 4 & -4 & -4 \\ -2 & -2 & 2 & 2 \\ -2 & -2 & 2 & 2 \end{bmatrix}$$

4. You are given n data points in \mathbb{R}^7 , and you want to cluster them using k means, $k = 2$, with initial clusters centers \mathbf{t}_1 and \mathbf{t}_2 . Write pseudo-code for the k means algorithm. Use matrix notation: i.e, approximate $\mathbf{X} \approx \mathbf{T}_i \mathbf{W}_i^T$, where \mathbf{T}_i is the matrix of cluster centers on iteration i , and \mathbf{W}_i is the cluster assignment matrix.

SOLUTION:

set $\mathbf{T}_0 = [\mathbf{t}_1 \ \mathbf{t}_2]$.

for $j = 1, \dots, n$, set column j of \mathbf{W}_0^T as $[0 \ 1]^T$ if $\|\mathbf{x}_j - \mathbf{t}_1\| > \|\mathbf{x}_j - \mathbf{t}_2\|$, else set as $[1 \ 0]^T$

set $\mathbf{X}_0 = \mathbf{T}_0 \mathbf{W}_0^T$

set $i = 0$

while $\|\mathbf{X}_i - \mathbf{X}_{i-1}\|_F > 0$ (i.e, while not converged)

Update cluster centers: $\mathbf{t}_1 = \frac{1}{n_1} \mathbf{X} \mathbf{w}_1$ and $\mathbf{t}_2 = \frac{1}{n_2} \mathbf{X} \mathbf{w}_2$ (where $n_j = \|\mathbf{w}_j\|_1$)

for $j = 1, \dots, n$, set column j of \mathbf{W}_i^T as $[0 \ 1]^T$ if $\|\mathbf{x}_j - \mathbf{t}_1\| > \|\mathbf{x}_j - \mathbf{t}_2\|$, else set as $[1 \ 0]^T$

$i = i + 1$

set $\mathbf{X}_i = \mathbf{T}_i \mathbf{W}_i^T$

5. **The informative SVD.** Consider a data matrix \mathbf{X} , where the m rows correspond to different training examples and the n columns correspond to different features. Let \mathbf{y} be an $m \times 1$ vector with the labels for each example. Suppose the full SVD of \mathbf{X} is given by $\mathbf{X} = \mathbf{U}\mathbf{\Sigma}\mathbf{V}^T$, where:

$$\mathbf{U} = \frac{1}{7} \begin{bmatrix} 4 & 2 & 2 & -5 \\ 1 & 4 & 4 & 4 \\ 4 & -5 & 2 & 2 \\ 4 & 2 & -5 & 2 \end{bmatrix} \quad \mathbf{\Sigma} = \begin{bmatrix} 4 & 0 & 0 \\ 0 & 3 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \quad \mathbf{V} = \frac{1}{3} \begin{bmatrix} 2 & -2 & 1 \\ 1 & 2 & 2 \\ 2 & 1 & -2 \end{bmatrix}$$

Answer the following questions.

- a) For a weight vector $\mathbf{w} \in \mathbb{R}^n$, the vector $\mathbf{X}\mathbf{w}$ is its prediction of the labels. Give a basis for the set of all such prediction vectors.

SOLUTION: $\mathbf{X}\mathbf{w}$ lies in the space spanned by the first two columns of \mathbf{U} , since \mathbf{X} has rank 2 (there are only two nonzero entries in $\mathbf{\Sigma}$.)

- b) If we restrict the weight vector to satisfy $\|\mathbf{w}\|_2 \leq 1$, what is the largest possible prediction $\mathbf{X}\mathbf{w}$ (as measured in terms of its 2-norm)?

SOLUTION: The largest possible prediction is obtained when we use $\mathbf{w} = \mathbf{v}_1$. The prediction with the largest possible norm is:

$$\mathbf{X}\mathbf{v}_1 = \sigma_1 \mathbf{u}_1 = \frac{4}{7} \begin{bmatrix} 4 \\ 1 \\ 4 \\ 4 \end{bmatrix}$$

and this vector has norm $\sigma_1 = 4$. This is the operator norm of \mathbf{X} or the largest singular value.

- c) Are there weight vectors such that $\mathbf{X}\mathbf{w} = \mathbf{0}$? If so, find a basis for the set of all such vectors.

SOLUTION: Since \mathbf{X} has rank 2 columns of \mathbf{X} are linearly dependent and thus there is a \mathbf{w} satisfying $\mathbf{X}\mathbf{w} = \mathbf{0}$. The set of such \mathbf{w} must lie in the space spanned by the last column of \mathbf{V} .

- d) Write an expression for the pseudo-inverse \mathbf{X}^\dagger satisfying $\mathbf{X}^\dagger \mathbf{X} = \mathbf{I}$ (you may leave it in factored form)

SOLUTION: The pseudoinverse of $\mathbf{U}_1 \mathbf{\Sigma}_1 \mathbf{V}_1^\top$ is $\mathbf{V}_1 \mathbf{\Sigma}_1^{-1} \mathbf{U}_1^\top$. In this case, this is:

$$\mathbf{X}^\dagger = \frac{1}{3} \begin{bmatrix} 2 & -2 \\ 1 & 2 \\ 2 & 1 \end{bmatrix} \begin{bmatrix} \frac{1}{4} & 0 \\ 0 & \frac{1}{3} \end{bmatrix} \frac{1}{7} \begin{bmatrix} 4 & 2 \\ 1 & 4 \\ 4 & -5 \\ 4 & 2 \end{bmatrix}^\top$$

- e) Suppose $\mathbf{y} = \begin{bmatrix} 7 \\ 0 \\ 0 \\ 0 \end{bmatrix}$. Compute the value of $\min_{\mathbf{w}} \|\mathbf{X}\mathbf{w} - \mathbf{y}\|_2^2$.

SOLUTION: The minimum error is the projection of \mathbf{y} onto the space orthogonal to the space spanned by the columns of \mathbf{X} . The first two columns of \mathbf{U} are a basis for the space spanned by the columns of \mathbf{X} , so the last two columns of \mathbf{U} are a basis for the space orthogonal to the columns of \mathbf{X} . We can project \mathbf{y} onto this subspace easily, since we have an orthonormal basis,

and we can find the norm of the residual easily as well:

$$\begin{aligned}\|\mathbf{X}\hat{\mathbf{w}} - \mathbf{y}\|^2 &= \|\mathbf{U}_2\mathbf{U}_2^\top\mathbf{y}\|^2 \\ &= \|\mathbf{U}_2^\top\mathbf{y}\|^2 \\ &= \left\| \frac{1}{7} \begin{bmatrix} 2 & -5 \\ 4 & 4 \\ 2 & 2 \\ -5 & 2 \end{bmatrix}^\top \begin{bmatrix} 7 \\ 0 \\ 0 \\ 0 \end{bmatrix} \right\|^2 \\ &= \left\| \begin{bmatrix} 2 \\ -5 \end{bmatrix} \right\|^2 \\ &= 29\end{aligned}$$