## 236330 - Introduction to Optimization: Homework #1 BONUS QUESTION

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## Problem:

Let:

$$A = USV^T$$

Be singular-value decomposition of A.

We want to find the gradient of:

$$f_i(A) = \sigma_i$$

## Solution:

Let  $1 \le i \le k$ .

The diagonal entries of S are the singular values of A, this implies that  $S_{ii} = \sigma_i$ . Hence:

$$f_i(A) = \sigma_i = e_i^T S e_i$$

Therefore:

$$df_i(A) = d\sigma_i = de_i^T S e_i = e_i^T dS e_i$$

Since U and V are orthogonal matrices, it follows:

$$U^T U = V^T V = I$$

Therefore:

$$dU^T U + U^T dU = 0$$

$$U^T dU = -dU^T U = -\left(U^T dU\right)^T$$

Thus,  $U^T dU$  is skew-symmetric. And:

$$dV^TV + V^TdV = 0$$

$$dV^T V = -V^T dV = -\left(dV^T V\right)^T$$

Thus  $dV^TV$  is skew-symmetric, as well.

Using the product rule of differentials on  $A = USV^T$ , we get:

$$dA = dUSV^T + UdSV^T + USdV^T$$

Left multiplying by  $U^T$  and right multiplying by V the above, yields:

$$U^T dAV = U^T dUS + dS + SdV^T V$$

Since  $U^T dU$  and  $dV^T V$  are skew-symmetric matrices, their diagonal is zero.

S is diagonal, hence dS is diagonal and therefore,

$$dS = I_k \odot \left[ U^T dAV \right]$$

where  $A \odot B$  is the Hadamard product of A and B.

Combining all together gives us:

$$df_{i}(A) = e_{i}^{T} dSe_{i}$$

$$= Tr \left(e_{i}^{T} dSe_{i}\right)$$

$$= Tr \left(e_{i}^{T} I^{k} \odot \left[U^{T} dAV\right] e_{i}\right)$$

$$= Tr \left(e_{i} e_{i}^{T} I^{k} \odot \left[U^{T} dAV\right]\right)$$

$$= Tr \left(I_{ii}^{k} \odot \left[U^{T} dAV\right]\right)$$

$$= \left[U^{T} dAV\right]_{ii}$$

$$= Tr \left(\left[U^{T} dAV\right]_{ii}\right)$$

$$= Tr \left(I_{ii}^{k} U^{T} dAV\right)$$

$$= Tr \left(VI_{ii}^{k} U^{T} dAV\right)$$

$$= Tr \left(VI_{ii}^{k} U^{T} dA\right)$$

- $(1) \forall a \in \mathbb{R}: Tr(a) = a$
- (2) Trace is invariant under cyclic permutation.
- (3)  $I_{ii}^k$  is a  $k \times k$  matrix with all entries equal to 0, except for the ii element which is equal to 1.

Using the external definition of the gradient, we get:

$$\nabla f_i(A) = UI_{ii}^k V^T$$