

# Colorado CSCI 5454: Algorithms

## Homework 9

Instructor: Bo Waggoner

Due: Friday, November 22, 2019 at 11:59pm

Turn in electronically via Gradescope.

**Remember to list the people you worked with and any outside sources used (if none, write “none”).**

### Problem 1 (12 points)

Suppose you have a database of movie recommendations stored as a matrix  $A \in \mathbb{R}^{n \times d}$ , where  $A(i, j)$  is person  $i$ 's rating of movie  $j$ , a real number between zero and one.

There are  $n$  people and  $d$  movies, so  $A$  has  $n$  rows and  $d$  columns.

Now you take the singular value decomposition,

$$A = U D V^\top$$

where (*updated*), when  $r$  is the rank of  $A$ :

- $U \in \mathbb{R}^{n \times r}$  is an orthogonal matrix<sup>1</sup>.
- $D \in \mathbb{R}^{r \times r}$  is a diagonal matrix<sup>2</sup>, and the entries are sorted from largest to smallest.
- $V \in \mathbb{R}^{d \times r}$  is an orthogonal matrix, and  $V^\top$  is its transpose.

Recall that the columns  $u_1, \dots, u_r$  of  $U$  are the *left singular vectors*, the diagonal entries  $\sigma_1, \dots, \sigma_r$  of  $D$  are the *singular values*, and the columns  $v_1, \dots, v_r$  of  $V$  are the *right singular vectors*.

Recall that we obtain a rank- $k$  approximation by taking the first  $k$  columns of  $U$  and  $V$ , along with the first  $k$  rows of  $D$ . This gives us  $U_k \in \mathbb{R}^{n \times k}$ ,  $D_k \in \mathbb{R}^{k \times k}$ , and  $V_k \in \mathbb{R}^{d \times k}$ , with

$$A_k := U_k D_k V_k^\top.$$

**In this problem, we'll show that  $A_k$  is a sum of  $k$  rank-one matrices, from “most important” to “least”. We will also bound how much accuracy is lost by dropping the “unimportant” matrices from the sum.**

**Part a (4 points)** Show that  $A_k(j, \ell) = \sum_{i=1}^k \sigma_i u_i(j) v_i(\ell)$ .

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<sup>1</sup>Every row is a unit vector, and the rows are all pairwise orthogonal; and this is also true of the columns.

<sup>2</sup>All entries are zero except the  $(i, i)$  entries.

**Solution.** Let  $B = U_k D_k$ . Then by the rules of matrix multiplication,  $B(j, i) = \sum_{o=1}^k U_k(j, o) D_k(o, i)$ . Note  $U_k(j, o) = u_o(j)$ , where  $u_o$  is the  $o$ th column. Since  $D_k(o, i) = 0$  unless  $o = i$ , in which case it is  $\sigma_i$ , we have  $B(j, i) = u_i(j) \sigma_i$ .

Then  $A_k = B V_k^\top$ . Note  $V_k^\top(i, \ell) = V_k(\ell, i) = v_i(\ell)$  where  $v_i$  is the  $i$ th column of  $V_k$ . So

$$\begin{aligned} A_k(j, \ell) &= \sum_{i=1}^k B(j, i) V_k^\top(i, \ell) \\ &= \sum_{i=1}^k B(j, i) v_i(\ell) \\ &= \sum_{i=1}^k u_i(j) \sigma_i v_i(\ell). \end{aligned}$$

**Part b (2 points)** Recall that if  $u$  and  $v$  are vectors, then their outer product  $uv^\top$  is a matrix whose  $(j, \ell)$  entry is  $u(j)v(\ell)$ . Using this and the previous part, show the following identity:

$$A_k = \sum_{i=1}^k \sigma_i u_i v_i^\top$$

That is,  $A_k$  is the sum of these  $k$  matrices, one for each set of singular value+vector.

**Solution.** Let us define  $C = \sum_{i=1}^k \sigma_i u_i v_i^\top$ . We just need to show  $C(j, \ell) = A_k(j, \ell)$  for all entries  $j, \ell$ . If we look at the matrix  $u_i v_i^\top$ , then its  $j, \ell$  entry is  $u_i(j) v_i(\ell)$ . So  $C(j, \ell) = \sum_{i=1}^k \sigma_i u_i(j) v_i(\ell)$ , which equals  $A_k(j, \ell)$  by the previous part.

**Part c (2 points)** Suppose you have computed the SVD and listed all the singular values and vectors of  $A$ . You used these to compute the approximation  $A_k$ . Using the previous part, what is a quick way to now compute the better approximation  $A_{k+1}$ ?

**Solution.** By the previous part, we can write  $A_{k+1} = A_k + \sigma_{k+1} u_{k+1} v_{k+1}^\top$ . So we just need to add this rank-one matrix to  $A_k$ .

**Part d (2 points)** When we approximate  $A$  by  $A_k$ , let the *remainder* be  $R_k := A - A_k$ . Show that  $R_k(j, \ell) = \sum_{i=k+1}^r \sigma_i u_i(j) v_i(\ell)$ .

**Solution.** If we set  $k = r$  in the previous parts, we get all of  $A$ , i.e.  $A = \sum_{i=1}^r \sigma_i u_i v_i^\top$ . So  $A - A_k = \sum_{i=k+1}^r \sigma_i u_i v_i^\top$ , which implies the claim.

**Part e (2 points)** Use the previous part to argue that  $\|A - A_k\|_F^2 \leq \sum_{i=k+1}^r \sigma_i^2$ . In other words, the total error in the approximation of  $A_k$  is bounded by the small singular values that are dropped.

(Recall that for a matrix  $R$ ,  $\|R\|_F^2 := \sum_{j,\ell} R(j,\ell)^2$ . Also recall that each  $u_i$  and  $v_i$  are unit vectors.)

**Solution.** We also need to recall that  $u_i$  is orthogonal to all  $u_{i'}$  for  $i \neq i'$ , and similarly the columns of  $V$  are orthogonal. So we can take a “brute-force” approach of expanding it out:

$$\begin{aligned} & \sum_{j,\ell} R_k(j,\ell)^2 \\ &= \sum_{j,\ell} \sum_{i=k+1}^r \sum_{i'=k+1}^r \sigma_i \sigma_{i'} u_i(j) u_{i'}(j) v_i(\ell) v_{i'}(\ell) \\ &= \sum_{i=k+1}^r \sum_{i'=k+1}^r \sigma_i \sigma_{i'} \sum_j u_i(j) u_{i'}(j) \sum_\ell v_i(\ell) v_{i'}(\ell) \\ &= \sum_{i=k+1}^r \sigma_i^2. \end{aligned}$$

The key is that  $\sum_\ell v_i(\ell) v_{i'}(\ell) = v_i \cdot v_{i'}$ , so it is zero if  $i \neq i'$ , otherwise it is one. The same goes for  $u_i$  and  $u_{i'}$ .

Note we actually get equality.

## Problem 2 (4 points)

Your friend is boasting about the following construction. “In  $m$ -dimensional space,” she says, “I put a point at  $(\frac{1}{\sqrt{2}}, 0, \dots, 0)$ . Then I put one at  $(0, \frac{1}{\sqrt{2}}, 0, \dots, 0)$ . And so on. Eventually, I have placed  $m$  points in just  $m$  dimensions, such that the distance between any pair of points is exactly one!”

“That’s nothing,” you say. “I can place  $m$  points with all pairwise distances at between 0.9 and 1.1, and I only need  $O(\text{-----})$  dimensions!”

(Fill in the blank and carefully justify your answer.)

**Solution.** We can put  $\ln(m)$  in the blank.

There are  $m$  points in our friend’s construction. The Johnson-Lindenstrauss lemma says that, if we start from our friend’s construction, we can take  $\epsilon = 0.1$  and any  $\delta < 1$  and get, with probability at least  $1 - \delta$ , all the projected points will have pairwise distance in  $[0.9, 1.1]$ , for any choice of dimension  $d \geq \frac{8}{\epsilon^2} \ln\left(\frac{m}{\delta}\right) = 800 \ln(m/\delta)$ .

Now, this holds for any  $\delta$ . So if we pick any  $\delta < 1$ , there is positive probability of being able to place the points in this manner. So there will be some way to place the points in any dimension  $d > 800 \ln(m)$ .