

# **CSE 546: Homework 3**

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## 0 Collaborators and Acknowledgements

## 1 PCA and reconstruction

### 1.1 Matrix Algebra Review

1. Recall that for  $A \in \mathbb{R}^{n \times d}$  and  $C \in \mathbb{R}^{d \times n}$ ,  $(AC)_{ij} = \sum_{k=1}^d a_{ik}c_{kj}$ . Also,  $(B^T)_{ij} = B_{ji}$ . Hence

$$(AB^T)_{ij} = \sum_{k=1}^d (A)_{ik}(B^T)_{jk} = \sum_{k=1}^d a_{ik}b_{kj}.$$

Plugging this into the definition of the trace gives

$$\begin{aligned} \text{Tr}(AB^T) &= \sum_{i=1}^n \left( \sum_{k=1}^d (AB^T)_{ii} \right) \\ &= \sum_{i=1}^n \left( \sum_{k=1}^d a_{ik}b_{ik} \right). \end{aligned}$$

Similarly,

$$(B^T A)_{ij} = \sum_{k=1}^n b_{ki}a_{kj}$$

and, by switching the order of addition,

$$\begin{aligned} \text{Tr}(B^T A) &= \sum_{i=1}^d (B^T A)_{ii} \\ &= \sum_{i=1}^d \left( \sum_{k=1}^n b_{ki}a_{ki} \right) \\ &= \sum_{i=1}^n \left( \sum_{k=1}^d b_{ki}a_{ki} \right) \\ &= \text{Tr}(AB^T). \end{aligned}$$

2. The outer equality follows from the definition of the trace:

$$\begin{aligned} \text{Tr}(\Sigma) &= \text{Tr}\left(\frac{1}{n}X^T X\right) = \frac{1}{n} \sum_{i=1}^d (X^T X)_{ii} = \frac{1}{n} \sum_{i=1}^d \left( \sum_{k=1}^n x_{ik}^2 \right) \\ &= \frac{1}{n} \sum_{i=1}^d \|X_i\|^2. \end{aligned}$$

For the other equality, we need some standard linear algebra results. Since  $\Sigma$  is symmetric and real, it has a real orthogonal eigendecomposition. That is to say, there exists an orthogonal matrix  $Q$  and a diagonal matrix  $\Lambda$  with diagonal entries  $\lambda_1, \lambda_2, \dots, \lambda_d$  such that

$$\Sigma = Q\Lambda Q^T.$$

Using our result from part 1, we have

$$\text{Tr}(\Sigma) = \text{Tr}(Q\Lambda Q^T) = \text{Tr}((Q\Lambda)Q^T) = \text{Tr}(Q^T Q\Lambda) = \text{Tr}(\Lambda) = \sum_{i=1}^d \lambda_i.$$

## 2 SVMs: Hinge loss and mistake bounds

1. To show that  $\ell((x, y), w) = \max\{0, 1 - w \cdot x\}$  is convex with respect to  $w$ , we will need two observations. First, for any  $a, k \in \mathbb{R}$  with  $k \geq 0$ , we have that

$$\max\{0, ka\} = k \max\{0, a\}.$$

In the case  $ka < 0$ , both sides of the equality are 0. If  $ka \geq 0$ , then  $a \geq 0$  and the equality still holds. Next, for any  $a, b \in \mathbb{R}$ , we have

$$\max\{0, a + b\} \leq \max\{0, a\} + \max\{0, b\}.$$

If both  $a$  and  $b$  are negative, then the above is an equality. If exactly one of  $a$  and  $b$  is negative and  $a + b \leq 0$  then the inequality clearly holds. If both are nonnegative then it is also an equality.

Recall that a function  $f$  is convex if for any  $t \in [0, 1]$  and for any  $x, y$  in its domain,  $f(tx + (1 - t)y) \leq tf(x) + (1 - t)f(y)$ . We will show that  $\ell((x, y), w)$  has this property with respect to  $w$ . Let  $w_1, w_2 \in \mathbb{R}^d$  be arbitrary and let  $t \in [0, 1]$ . Then  $0 \leq (1 - t) \leq 1$ , and so

$$\begin{aligned} \ell((x, y), tw_1 + (1 - t)w_2) &= \max\{0, 1 - y(tw_1 + (1 - t)w_2) \cdot x\} \\ &= \max\{0, 1 - tyw_1 \cdot x - (1 - t)yw_2 \cdot x\} \\ &= \max\{0, 1 + (t - 1) - tyw_1 \cdot x - (1 - t)yw_2 \cdot x\} \\ &= \max\{0, [t - tyw_1 \cdot x] + [(1 - t) - (1 - t)yw_2 \cdot x]\} \\ &\leq \max\{0, t - tyw_1 \cdot x\} + \max\{(1 - t) - (1 - t)yw_2 \cdot x\} \\ &= t \max\{0, 1 - yw_1 \cdot x\} + (1 - t) \max\{0, 1 - yw_2 \cdot x\} \\ &= t\ell((x, y), w_1) + (1 - t)\ell((x, y), w_2). \end{aligned}$$

Therefore  $\ell((x, y), w)$  is convex with respect to  $w$ .

2. By its definition it is clear that  $0 \leq \ell((x, y), w)$ . If  $y_i = \text{sgn}(w \cdot x_i)$  then  $y_i w \cdot x_i \geq 0$ , implying that  $1 - y_i w \cdot x_i \leq 1$ . Hence  $\ell((x_i, y_i), w) = \max\{0, 1 - y_i w \cdot x_i\} \leq 1$ . Combining these bounds we get

$$0 \leq \ell((x_i, y_i), w) \leq 1$$

for correctly classified points.

3. Observe that if we misclassify a point (so that  $y_i = -\text{sgn}(w \cdot x_i)$ ) then  $y_i w \cdot x_i \leq 0$ . Hence  $\ell((x_i, y_i), w) \geq 1$  for misclassified points. Let  $I \subset \{1, 2, \dots, n\}$  be the indices corresponding to the data points which  $w$  misclassifies. It follows that  $|I| = M(w)$ . By the previous part we know that for correct classifications the hinge loss is bounded between 0 and 1. Putting this all together we obtain

$$M(w) = \sum_{i=1}^{M(w)} 1 = \sum_{i \in I} 1 \leq \sum_{i \in I} \ell((x_i, y_i), w) \leq \sum_{i=1}^n \ell((x_i, y_i), w) = \sum_{i=1}^n \max\{0, 1 - y_i w \cdot x_i\}.$$

Dividing both sides by  $n$  gives the desired result.