# Covariance Sensitivity Proofs

March 23, 2020

# 1 Preliminaries

**Definition 1.** Let X be a matrix of values and  $X_i$  indicate the  $i^{th}$  column of the matrix. Denote the sample mean of column  $X_i$  as  $\bar{X}_i$ , and let n be the size of  $X_i$ . Then the covariance matrix of X has  $ij^{th}$  element

$$\frac{1}{n-1} \sum_{k=1}^{n} (x_{ki} - \bar{X}_i)(x_{kj} - \bar{X}_j).$$

**Lemma 1.** Let X be a matrix of values and  $X_i$  indicate the  $i^{th}$  column of the matrix. Denote the sample mean of column  $X_i$  as  $\bar{X}_i$ , and let n be the size of  $X_i$ . Then,  $\forall i$ ,

$$\sum_{j=1}^{n} (x_{ji} - \bar{X}_i) = 0.$$

Proof.

$$\sum_{j=1}^{n} (x_{ji} - \bar{X}_i) = \sum_{j=1}^{n} x_{ji} - n\bar{X}_i,$$

$$= \sum_{j=1}^{n} x_{ji} - n \left(\frac{1}{n} \sum_{j=1}^{n} x_{ji}\right),$$

$$= 0.$$

Lemma 2. Let X be a matrix and let

$$f_{ij}(X) = \sum_{k=1}^{n} (x_{ki} - \bar{X}_i)(x_{kj} - \bar{X}_j).$$

Note that this is equivalent to the  $ij^{th}$  element of the sample covariance matrix for X, without the normalization by n-1. Consider the matrix X' equal to X with a single row

Y added, so that  $X'_i = X_i \cup \{y_i\}$ . Say  $X_i$  has size n. Let  $\bar{X}_i$ ,  $\bar{X}_j$ ,  $\bar{X}'_i$ , and  $\bar{X}'_j$  be the sample means of  $X_i, X_j, X'_i$  and  $X'_j$  respectively. Then,

$$f_{ij}(X') = f_{ij}(X) + n(\bar{X}_i - \bar{X}_i')(\bar{X}_j - \bar{X}_j') + (y_i - \bar{X}_i)(y_j - \bar{X}_j).$$

Proof. Note that

$$f_{ij}(X') = \sum_{k=1}^{n+1} (x'_{ki} - \bar{X}'_i)(x'_{kj} - \bar{X}'_j),$$

$$= \sum_{k=1}^{n} (x_{ki} - \bar{X}'_i)(x_{kj} - \bar{X}'_j) + (y_i - \bar{X}'_i)(y_j - \bar{X}'_j),$$

$$= \sum_{k=1}^{n} ((x_{ki} - \bar{X}_i) + (\bar{X}_i - \bar{X}'_i)) ((x_{kj} - \bar{X}_j) + (\bar{X}_j - \bar{X}'_j)) + (y_i - \bar{X}'_i)(y_j - \bar{X}'_j),$$

$$= \sum_{k=1}^{n} (x_{ki} - \bar{X}_i)(x_{kj} - \bar{X}_j) + (\bar{X}_j - \bar{X}'_j) \sum_{k=1}^{n} (x_{ki} - \bar{X}_i) + (\bar{X}_i - \bar{X}'_i) \sum_{k=1}^{n} (x_{kj} - \bar{X}_j),$$

$$+ \sum_{k=1}^{n} (\bar{X}_i - \bar{X}'_i)(\bar{X}_j - \bar{X}'_j) + (y_i - \bar{X}'_i)(y_j - \bar{X}'_j),$$

$$= f_{ij}(X) + n(\bar{X}_i - \bar{X}'_i)(\bar{X}_j - \bar{X}'_j) + (y_i - \bar{X}'_i)(y_j - \bar{X}'_j),$$

where the cancellation of the second and third terms in the second-to-last line is due to Lemma 1.  $\Box$ 

**Lemma 3.** Let X be a matrix of values and  $X_i$  indicate the  $i^{th}$  column of the matrix. Let  $X_i$  have size n and consider the matrix X' equal to X with a single row Y added, so that  $X'_i = X_i \cup \{y_i\}$ . Say that the space of datapoints  $X_i$  that the elements of  $X'_i$  are drawn from is bounded above by  $M_i$  and bounded below by  $m_i$ . Let  $\bar{X}_i$ ,  $\bar{X}_j$ ,  $\bar{X}'_i$ , and  $\bar{X}'_j$  be the sample means of  $X_i$ ,  $X'_j$ ,  $X'_i$  and  $X'_j$  respectively. Then,

$$n \left| (\bar{X}_i - \bar{X}_i')(\bar{X}_j - \bar{X}_j') \right| \le \frac{n}{(n+1)^2} (M_i - m_i)(M_j - m_j).$$

*Proof.* Note that

$$n \left| (\bar{X}_i - \bar{X}_i')(\bar{X}_j - \bar{X}_j') \right| = n \left| \left( \frac{1}{n} \sum_{k=1}^n x_{ki} - \frac{1}{n+1} \sum_{k=1}^{n+1} x_{ki}' \right) \left( \frac{1}{n} \sum_{k=1}^n x_{kj} - \frac{1}{n+1} \sum_{k=1}^{n+1} x_{kj}' \right) \right|,$$

$$= n \left| \left( \left( \frac{1}{n} - \frac{1}{n+1} \right) \sum_{k=1}^n x_{ki} - \frac{y_i}{n+1} \right) \left( \left( \frac{1}{n} - \frac{1}{n+1} \right) \sum_{k=1}^n x_{kj} - \frac{y_j}{n+1} \right) \right|,$$

$$= n \left| \left( \frac{1}{n(n+1)} \sum_{k=1}^n x_{ki} - \frac{y_i}{n+1} \right) \left( \frac{1}{n(n+1)} \sum_{k=1}^n x_{kj} - \frac{y_j}{n+1} \right) \right|,$$

$$= \frac{n}{(n+1)^2} \left| \left( \frac{1}{n} \sum_{k=1}^n x_{ki} - \frac{y_i}{n+1} \right) \left( \frac{1}{n} \sum_{k=1}^n x_{kj} - \frac{y_j}{n+1} \right) \right|,$$

$$\leq \frac{n}{(n+1)^2} (M_i - m_i) (M_j - m_j).$$

**Lemma 4.** Let X be a matrix of values and  $X_i$  indicate the  $i^{th}$  column of the matrix. Let  $X_i$  have size n and consider the matrix X' equal to X with a single row Y added, so that  $X'_i = X_i \cup \{y_i\}$ . Say that the space of datapoints  $X_i$  that the elements of  $X'_i$  are drawn from is bounded above by  $M_i$  and bounded below by  $m_i$ . Let  $\bar{X}_i$ ,  $\bar{X}_j$ ,  $\bar{X}'_i$ , and  $\bar{X}'_j$  be the sample means of  $X_i, X_j, X'_i$  and  $X'_j$  respectively. Then,

$$|(y_i - \bar{X}_i')(y_j - \bar{X}_j')| \le \frac{n^2}{(n+1)^2} (M_i - m_i)(M_j - m_j).$$

*Proof.* Note that

$$\begin{aligned} \left| (y_i - \bar{X}_i')(y_j - \bar{X}_j') \right| &= \left| \left( y_i - \frac{y_i + n\bar{X}_i}{n+1} \right) \left( y_j - \frac{y_j + n\bar{X}_j}{n+1} \right) \right|, \\ &= \frac{1}{(n+1)^2} \left| \left( (n+1)y_i - y_i - n\bar{X}_i \right) \left( (n+1)y_j - y_j - n\bar{X}_j \right) \right|, \\ &= \frac{n^2}{(n+1)^2} \left| (y_i - \bar{X}_i)(y_j - \bar{X}_j) \right|, \\ &\leq \frac{n^2}{(n+1)^2} (M_i - m_i)(M_j - m_j). \end{aligned}$$

# 2 NEIGHBORING DEFINITION: ADD/DROP ONE

# 2.1 $\ell_1$ -sensitivity

**Theorem 1.** Let X be a matrix of values and let  $X_i$  indicate the  $i^{th}$  column of the matrix. Let

$$f_{ij}(X) = \sum_{k=1}^{n} (x_{ki} - \bar{X}_i)(x_{kj} - \bar{X}_j).$$

Say that the space of datapoints  $\mathcal{X}_i$  that  $X_i$  is drawn from is bounded above by  $M_i$  and bounded below by  $m_i$ . Then the  $\ell_1$ -sensitivity in the add/drop-one model of  $f(\cdot)$  is bounded above by

$$\frac{n}{(n+1)}(M_i-m_i)(M_j-m_j).$$

*Proof.* We must consider both adding and removing a row from X. Adding a row:

Let  $X_i' = X_i \cup \{y_i\}$ . Then, from Lemma 2,

$$|f_{ij}(X') - f_{ij}(X)| = |n(\bar{X}_i - \bar{X}_i')(\bar{X}_j - \bar{X}_j') + (y_i - \bar{X}_i)(y_j - \bar{X}_j)|$$

$$\leq n |(\bar{X}_i - \bar{X}_i')(\bar{X}_j - \bar{X}_j')| + |(y_i - \bar{X}_i)(y_j - \bar{X}_j)|$$

$$\leq \frac{n}{(n+1)^2} (M_i - m_i)(M_j - m_j) + \frac{n^2}{(n+1)^2} (M_i - m_i)(M_j - m_j)$$
(By Lemmas 3 and 4)
$$= \frac{n}{n+1} (M_i - m_i)(M_j - m_j). \tag{2.1}$$

Removing a row:

Let Y be the last row of X, and let  $X'_i = X_i \setminus \{y_i\}$ . Note that Lemma 2 can be rewritten in this setting by parametrizing n as n-1 and swapping X and X' in its expression:

$$f_{ij}(X) = f_{ij}(X') + (n-1)(\bar{X}_i' - \bar{X}_i)(\bar{X}_j' - \bar{X}_j) + (y_i - \bar{X}_i')(y_j - \bar{X}_j').$$

Lemmas 3 and 4 may be rewritten with the same reparametrization:

$$(n-1) |(\bar{X}_i' - \bar{X}_i)(\bar{X}_j' - \bar{X}_j)| \le \frac{n-1}{n^2} (M_i - m_i)(M_j - m_j),$$

and

$$|(y_i - \bar{X}_i')(y_j - \bar{X}_j')| \le \frac{(n-1)^2}{n^2} (M_i - m_i)(M_j - m_j).$$

Then,

$$\begin{aligned}
\left| f_{ij}(X) - f_{ij}(X') \right| &= \left| (n-1)(\bar{X}_i' - \bar{X}_i)(\bar{X}_j' - \bar{X}_j) + (y_i - \bar{X}_i')(y_j - \bar{X}_j') \right|, \\
&\leq \left| (n-1)(\bar{X}_i' - \bar{X}_i)(\bar{X}_j' - \bar{X}_j) \right| + \left| (y_i - \bar{X}_i')(y_j - \bar{X}_j') \right|, \\
&\leq \frac{n-1}{n^2} (M_i - m_i)(M_j - m_j) + \frac{(n-1)^2}{n^2} (M_i - m_i)(M_j - m_j), \\
&= \frac{n-1}{n} (M_i - m_i)(M_j - m_j).
\end{aligned} \tag{2.2}$$

Note that for any  $n \geq 1$ ,

$$\frac{n}{n+1} > \frac{n-1}{n}.\tag{2.3}$$

So, the worst-case bound always occurs in the "add-one" case, and in general the  $\ell_1$  sensitivity of  $f(\cdot)$  is bounded by

$$\frac{n}{n+1}(M_i-m_i)(M_j-m_j).$$

Corollary 1. Let  $X \leftarrow \mathcal{X}$  where  $\mathcal{X}_i$  is bounded above by  $M_i$  and bounded below by  $m_i$ . Then the  $\ell_1$ -sensitivity in the add/drop-one model of the  $ij^{th}$  element of the covariance matrix for X is bounded above by

$$\frac{1}{n+1}(M_i - m_i)(M_j - m_j).$$

*Proof.* Note that the  $ij^{th}$  element of the covariance matrix for X is equal to f(x)/n.

**Corollary 2.** Let  $X \leftarrow \mathcal{X}$  where  $\mathcal{X}_i$  is bounded above by  $M_i$  and bounded below by  $m_i$ . Then the  $\ell_1$ -sensitivity in the add/drop-one model of the  $ij^{th}$  element of a sample covariance matrix for X is bounded above by

$$\frac{n}{n^2 - 1} (M_i - m_i)(M_j - m_j).$$

*Proof.* Note that the  $ij^{\text{th}}$  element of the sample covariance of X is equal to f(x)/(n-1), and that  $(n-1)(n+1)=n^2-1$ .

#### 2.2 $\ell_2$ -sensitivity

**Theorem 2.** Let  $X \leftarrow \mathcal{X}$  where  $\mathcal{X}_i$  is bounded above by  $M_i$  and bounded below by  $m_i$ . Then the  $\ell_2$ -sensitivity in the add/drop-one model of the  $ij^{th}$  element of the covariance matrix for X is bounded above by

$$\left(\frac{1}{n+1}(M_i-m_i)(M_j-m_j)\right)^2.$$

*Proof.* This follows from the bounds in Equations 2.1 and 2.2 and the inequality in Equation 2.3, and a renormalization by n from the definition of covariance.

**Corollary 3.** Let  $X \leftarrow \mathcal{X}$  where  $\mathcal{X}_i$  is bounded above by  $M_i$  and bounded below by  $m_i$ . Then the  $\ell_2$ -sensitivity in the add/drop-one model of the  $ij^{th}$  element of a sample covariance matrix for X is bounded above by

$$\left(\frac{n}{n^2-1}(M_i-m_i)(M_j-m_j)\right)^2.$$

*Proof.* The logic here is identical to the proof of Theorem 3, with a renormalization by n rather than by n-1.

## 3 Neighboring Definition: Change One

### 3.1 $\ell_1$ -sensitivity

**Theorem 3.** Let X be a matrix of values and let  $X_i$  indicate the  $i^{th}$  column of the matrix. Let

$$f_{ij}(X) = \sum_{k=1}^{n} (x_{ki} - \bar{X}_i)(x_{kj} - \bar{X}_j).$$

Say that the space of datapoints  $\mathcal{X}_i$  that  $X_i$  is drawn from is bounded above by  $M_i$  and bounded below by  $m_i$ . Then the  $\ell_1$ -sensitivity in the change-one model of  $f(\cdot)$  is bounded above by

$$\frac{2(n-1)}{n}(M_i - m_i)(M_j - m_j).$$

*Proof.* Recall from Equation 2.1 that

$$|f_{ij}(X) - f_{ij}(X')| \le \frac{n}{(n+1)} (M_i - m_i)(M_j - m_j).$$

and

$$|f_{ij}(X) - f_{ij}(X'')| \le \frac{n}{(n+1)} (M_i - m_i)(M_j - m_j).$$

Reparametrizing these equations so that n is the size of X' and X'' gives that

$$|f_{ij}(X) - f_{ij}(X')| \le \frac{n-1}{n} (M_i - m_i)(M_j - m_j).$$

and

$$|f_{ij}(X) - f_{ij}(X'')| \le \frac{n-1}{n} (M_i - m_i)(M_j - m_j).$$

It then follows from the triangle inequality that

$$|f_{ij}(X') - f_{ij}(X'')| \le \frac{2(n-1)}{n} (M_i - m_i)(M_j - m_j).$$

Corollary 4. The  $\ell_1$ -sensitivity in the change-one model of covariance is bounded above by

$$\frac{2(n-1)}{n^2}(M_i - m_i)(M_j - m_j).$$

*Proof.* Note that the  $ij^{th}$  element of the covariance of X is equal to f(x)/n.

Corollary 5. The  $\ell_1$ -sensitivity in the change-one model of sample covariance is bounded above by

$$\frac{2}{n}(M_i - m_i)(M_j - m_j).$$

*Proof.* Note that the  $ij^{th}$  element of the sample covariance of X is equal to f(x)/(n-1).  $\square$ 

## 3.2 $\ell_2$ -sensitivity

**Theorem 4.** The  $\ell_2$ -sensitivity in the change-one model of covariance is bounded above by

$$\left(\frac{2(n-1)}{n^2}(M_i - m_i)(M_j - m_j)\right)^2$$
.

*Proof.* This follows from the bounds in the proof of Theorem 3 and a renormalization by n.

Corollary 6. The  $\ell_2$ -sensitivity in the change-one model of sample covariance is bounded above by

$$\left(\frac{2}{n}(M_i-m_i)(M_j-m_j)\right)^2.$$

*Proof.* The logic here is identical to the proof of Theorem 4, with a renormalization by n-1 rather than by n.