

# Assignment 1: CS 215 Solutions

Neeraj Dhake  
150050022

Rohit Kumar Jena  
150050061

6th August 2016

### Honor Code:

- We pledge by our honor that we will complete the assignments in a legitimate way and will not provide or receive any unauthorized help.

### Instructions to run code:

- For Question 4, the corresponding files are *hw1\_q4.m* (to run the file and generate plots as well as give the relative errors for both the median and the mean) and *neighbours.m* (to generate the neighbours of the array at a given index i.e. if index is 14 then it will return **z(6:22)** ). To run the program, simply type *hw1\_q4* from the MATLAB command line.
- For Question 5, the corresponding files are *hw1\_q5.m* (to read the original array from the file named *input\_array.txt* and compute the mean, median, and the standard deviation). Then it prompts the user to enter the new data value. It uses the *UpdateMean.m*, *UpdateMedian.m*, and *UpdateStd.m* files to compute the new mean, new median and new standard deviation from the old values. To run the file, simply type *hw1\_q5* from the MATLAB command line. Make sure you have a file named *input\_array.txt* containing the array elements in **one line**. Or you can just use the *UpdateMean*, *UpdateMedian* and *UpdateStd* files as you wish. Make sure the array A is horizontal.

### Solutions:

1. Let  $\mu = \text{mean}$  and  $v = \text{median}$  of the dataset  $\{x_i\}_{i=1}^N$  containing  $N$  data points.

$$|\mu - v| = \left| \frac{\sum_{i=1}^N (x_i - v)}{N} \right| \leq \frac{\sum_{i=1}^N |x_i - v|}{N}$$

By Triangular Inequality,

$$\begin{aligned} \left| \frac{\sum_{i=1}^N x_i - v}{N} \right| &\leq \frac{\sum_{i=1}^N |x_i - v|}{N} \\ \Rightarrow \frac{\sum_{i=1}^N |x_i - v|}{N} &\leq \frac{\sum_{i=1}^N |x_i - \mu|}{N} \end{aligned}$$

(the value for which  $\frac{\sum_{i=1}^N |x_i - x|}{N}$  is minimum is when  $x = \text{median}$ )

Now,

$$\left( \frac{\sum_{i=1}^N |x_i - \mu|}{N} \right)^2 \leq \frac{\sum_{i=1}^N |x_i - \mu|^2}{N} \leq \frac{\sum_{i=1}^N |x_i - \mu|^2}{N-1} = \sigma^2$$

(by RMS-AM inequality)

$$\therefore |\mu - v| \leq \sigma$$

2. Given 4 datasets  $\{x_i\}_{i=1}^N$ ,  $\{y_i\}_{i=1}^N$ ,  $\{z_i\}_{i=1}^N$ , and  $\{w_i\}_{i=1}^N$  such that,

$$z_i = ax_i + b$$

$$w_i = cy_i + d$$

Using the definition of correlation coefficient, we have,

$$r(x, y) = \frac{\sum_{i=1}^N (x_i - \mu_x)(y_i - \mu_y)}{(N-1)\sigma_x\sigma_y}$$

$$r(z, w) = \frac{\sum_{i=1}^N (z_i - \mu_z)(w_i - \mu_w)}{(N-1)\sigma_z \cdot \sigma_w}$$

Now if mean of  $\{x_i\}_{i=1}^N = \mu_x$  then mean of  $\{z_i\}_{i=1}^N = a\mu_x + b$ , and similarly mean of  $\{w_i\}_{i=1}^N = a\mu_y + b$ .

Substituting the values of  $z_i, \mu_z, w_i, \mu_w$  in the second equation, we get,

$$\begin{aligned} r(z, w) &= \frac{\sum_{i=1}^N [(ax_i + b) - (a\mu_x + b)] \cdot [(cy_i + d) - (c\mu_y + d)]}{(N-1)|a|\sigma_x \cdot |c|\sigma_y} \\ &= \frac{\sum_{i=1}^N a(x_i - \mu_x) \cdot c(y_i - \mu_y)}{(N-1)|a|\sigma_x \cdot |c|\sigma_y} \\ &= \text{sgn}(ac) \cdot \frac{\sum_{i=1}^N (x_i - \mu_x)(y_i - \mu_y)}{(N-1)\sigma_x\sigma_y} \end{aligned}$$

Where  $\text{sgn}(ac)$  denotes the signum function.

Now, substituting the definition of  $r(x, y)$ , we have,

$$r(z, w) = \text{sgn}(ac) \cdot r(x, y)$$

When the sign of  $ac$  is positive, i.e. when both  $a$  and  $c$  are positive or negative, we have  $\text{sgn}(ac) = 1$ , and hence  $r(z, w) = r(x, y)$ .

When the sign of  $ac$  is negative, i.e. when the sign of  $a$  and  $c$  are opposite, we have  $\text{sgn}(ac) = -1$ , and hence  $r(z, w) = -r(x, y)$ .

3. Let  $x_i$  be the datapoints of a dataset  $\{x_i\}_{i=1}^N$  with mean  $\mu$ .

So, we have the following inequality,

$$|x_i - \mu| \leq \sqrt{\sum_{i=1}^N |x_i - \mu|^2}$$

This can easily be shown as follows:

$$|x_i - \mu|^2 \leq \sum_{i=1}^N |x_i - \mu|^2$$

Since both R.H.S and L.H.S are positive, taking square root on both sides gives the required result.

$$|x_i - \mu| \leq \sigma\sqrt{n-1}$$

Q.E.D.

4.

5. Let  $\bar{a}$  denote the mean of a dataset  $\{a_i\}_{i=1}^N$  having  $N$  datapoints.

Now, we have,

$$\bar{a} = \frac{\sum_{i=1}^N a_i}{N}$$

After we add a new element, say  $z$ , the new mean becomes,

$$\bar{a}_{new} = \frac{(\sum_{i=1}^N a_i) + z}{N+1} = \frac{N\bar{a} + z}{N+1}$$

$\therefore$  We have the value of  $\bar{a}_{new}$  in terms of  $\bar{a}, N, z$ .

For the given data, let the standard deviation be denoted by  $\sigma$ . So we have,

$$\sigma^2 = \frac{\sum_{i=1}^N (x_i - \bar{x})^2}{N-1} = \frac{(\sum_{i=1}^N x_i^2) - N\bar{x}^2}{N-1}$$

After adding a new value  $z$  to the data, we have a new value  $\sigma_{new}$  denoted by,

$$\sigma_{new}^2 = \frac{\sum_{i=1}^{N+1} (x_i - \bar{x})^2}{N} = \frac{(\sum_{i=1}^{N+1} x_i^2) - (N+1)\bar{x}_{new}^2}{N}$$

Using the value of  $\sigma^2$ , we apply the following substitution,

$$\sum_{i=1}^N x_i^2 = (N-1)\sigma^2 + N\bar{x}^2$$

We get the following equation,

$$\sigma_{new}^2 = \frac{(N-1)\sigma^2 + N\bar{x}^2 + z^2 - (N+1)\bar{x}_{new}^2}{N}$$

$\therefore$  We have the value of  $\sigma_{new}$  in terms of  $\sigma$ ,  $\bar{x}$ ,  $\bar{x}_{new}$ ,  $z$ , and  $N$ .