

# CS181 Assignment 3 - Clustering and Parameter Estimation

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## 1 High Dimensional Clustering

(a) Given that  $\rho = P(\max_m |x_m - y_m| \leq \epsilon)$ , the probability that all the  $M$  dimensions of  $\mathbf{xy}$  are between  $-\epsilon$  and  $\epsilon$ , we can find out  $\rho$  by finding the probability  $p_m$  of having each individual dimension of  $\mathbf{xy}$ , ie  $p_m = P(\epsilon \leq x_m y_m \leq \epsilon)$ . Since  $y_m$  is a uniform distribution on  $[0,1]$ , we have

$$P(-\epsilon \leq x_m - y_m \leq \epsilon) = 2\epsilon \quad (1)$$

From the independence of each component, we have

$$\rho = \prod_{m=1}^M p_m = (2\epsilon)^M \quad (2)$$

(b) In this case since  $\mathbf{x}$  is some arbitrary point in the hypercube, it is possible that the at least one of the components of  $\mathbf{x}$  is within  $\epsilon$  far away from the surface of the cube. Let the dimension that has  $x_m$  near to the bound, ie  $x_m < \epsilon$  or  $x_m > (1-\epsilon)$ , then we know that the probability of  $|y_m x_m| \leq \epsilon$  will be strictly less than  $2\epsilon$  since at least one side of the point is being truncated. Hence the total probability will be less than that of  $\rho$ .

(c) The Euclidean distance is given by

$$\|\mathbf{x} - \mathbf{y}\| = \sqrt{\sum_{m=1}^M (x_m - y_m)^2} \quad (3)$$

Let  $x_m$  and  $y_m$  be the component that maximizes  $|x_m y_m|$ , hence we have

$$\|\mathbf{x} - \mathbf{y}\| = \sqrt{(x_m - y_m)^2 + \sum_{m \neq m^*, m \in M}^M (x_m - y_m)^2} > \sqrt{(x_m - y_m)^2} = |x_m - y_m| \quad (4)$$

$$\|\mathbf{x} - \mathbf{y}\| > \max_m |x_m - y_m| \quad (5)$$

where the inequality comes from the fact that the summed square must always be bigger than or equal to zero.

Considering the geometry,  $\|\mathbf{x} - \mathbf{y}\| < \epsilon$  represents a hypersphere of radius  $\epsilon$  centered around the point  $\mathbf{x}$  and  $\max_m |x_m - y_m| < \epsilon$  represents a hypercube of side  $2\epsilon$  centered around  $\mathbf{x}$ . In this

case the probability of  $\mathbf{y}$  falling into these two different regions is just equal to the  $M$ -dimensional volume of the hypercube and hypersphere respectively. We know that the hypersphere of radius  $\epsilon$  can always be circumscribed within the hypercube of side  $2\epsilon$ . Hence we have

$$P(\|\mathbf{x} - \mathbf{y}\| < \epsilon) < P(\max_m |x_m - y_m| < \epsilon) \leq \rho \quad (6)$$

(d) Let  $p$  be the probability that the nearest neighbor of a point  $\mathbf{x}$  to be not within a radius of  $\epsilon$ , ie

$$p = 1 - P(\|\mathbf{x} - \mathbf{y}\| \leq \epsilon) \leq 1 - \rho \quad (7)$$

Since each individual point is independent of each other, hence the probability that none of the  $N$  points will have its nearest neighbour within a radius of  $\epsilon$  is  $p^N$ . Therefore, the complement of it, which is the probability that at least one of the  $N$  points will have its nearest neighbor within a radius  $\epsilon$  of it will just be  $1 - p^N$  which gives

$$1 - p^N \leq 1 - \delta \quad (8)$$

$$(1 - \rho)^N \geq \delta \quad (9)$$

$$(10)$$

$$\implies 1 - \delta \leq 1 - (1 - \rho)^N \quad (11)$$

$$\delta \geq (1 - \rho)^N \quad (12)$$

$$\frac{\log \delta}{\log (1 - \rho)} \geq N \quad (13)$$

$$N \geq \frac{\log \delta}{\log (1 - 2^M \epsilon^M)} \quad (14)$$

## 2 ML vs MAP vs FB