

Problem 1a)

$$J(h_t(x), \beta_t) = (e^{\beta_t} - e^{-\beta_t}) \sum_n w_t(n) \prod I[y_n \neq h_t(x_n)] + e^{\beta_t} \sum_n w_t(n)$$

We are given $\sum_n w_t(n) = 1$ & we set $\epsilon_t = \sum_n w_t(n) \prod I[y_n \neq h_t(x_n)]$

$$\text{So we can rewrite } J \text{ as: } J(h_t(x), \beta_t) = (e^{\beta_t} - e^{-\beta_t}) \epsilon_t + e^{\beta_t} (1) \\ = e^{\beta_t} (1 - \epsilon_t) + e^{-\beta_t} \epsilon_t = J$$

$$\text{Setting } \frac{dJ(h_t(x), \beta_t)}{d\beta_t} = 0$$

$$\text{we have } e^{-\beta_t} (\epsilon_t - 1) + e^{\beta_t} \epsilon_t = 0 \Rightarrow e^{-\beta_t} (1 - \epsilon_t) = e^{\beta_t} \epsilon_t$$

$$\Rightarrow -\beta_t + \ln(1 - \epsilon_t) = \beta_t + \ln(\epsilon_t) \Rightarrow 2\beta_t = \ln(1 - \epsilon_t) - \ln(\epsilon_t)$$

$$\Rightarrow \beta_t = \ln\left(\frac{1 - \epsilon_t}{\epsilon_t}\right) \cdot \frac{1}{2}$$

Problem 1b) Our predictor $h_t(x)$ for hard margin SUM is $h_t(x_n) = \text{sign}(w_t \cdot x_n + b)$

and the weighted classification error ϵ_t is $\epsilon_t = \sum_n w_t(n) \prod I[y_n \neq h_t(x_n)]$

since our data is linearly separable $\epsilon_t = 0$, SUM fits the data perfectly and no points get misclassified and when $\epsilon_t = 0$ our β_t approaches ∞

$$\text{because } \beta_t = \frac{1}{2} \ln\left(\frac{1 - 0}{0}\right) \Rightarrow \beta_t \rightarrow \infty$$

So our first iteration β_1 would approach ∞

Problem 2a) The optimum clustering for $K=3$ and $X = \{1, 2, 5, 7\}$ is:

$$\mu_1 = 1.5, \mu_2 = 5, \text{ and } \mu_3 = 7 = \text{centroids this is due to the}$$

fact that we assign points to the clusters based on the min distance which results in the clusters $(1, 2), (5), \& (7)$ so we choose the

$$\text{updated centroids } \mu^* \text{ by } \mu_k = \frac{\sum_n r_{nk} x_n}{\sum_n r_{nk}} \Rightarrow \mu_1^* = \frac{1+2}{2} = 1.5$$

$$\mu_2^* = 5/1 = 5$$

$$\mu_3^* = 7/1 = 7$$

The centroids didn't change, so we have the optimum clustering.

$$\text{The objective function is: } \sum_{n=1}^N \sum_{k=1}^K r_{nk} \|x_n - \mu_k\|_2^2 = (1-1.5)^2 + (2-1.5)^2 + (5-5)^2 + (7-7)^2 = \boxed{1/2}$$

Problem 2b) Lloyd's algorithm isn't guaranteed to converge to a global min.

For cluster assignments $\{1\}, \{2\}, \{5, 7\}$ and $\mu_1 = 1, \mu_2 = 2, \mu_3 = 6$

In the update each point is assigned to the cluster before bc the other centroids are further

We see that this is not optimal b/c our cost function:

$$\sum_{n=1}^N \sum_{k=1}^K r_{nk} \|x_n - \mu_k\|_2^2 = 0^2 + 0^2 + 1^2 + 1^2 = 2 \text{ which is greater than}$$

$1/2$ from part A. Which makes part A's clustering more optimal than this one.

$$x_1 = \|x_1 - \mu_j\|_2^2 \text{ for } \begin{matrix} j=1 \Rightarrow 0 \\ j=2 \Rightarrow 1 \\ j=3 \Rightarrow 25 \end{matrix} \rightarrow \text{assign } x_1 \text{ to cluster 1}$$

$$x_2 = \|x_2 - \mu_j\|_2^2 \text{ for } \begin{matrix} j=1 \Rightarrow 1 \\ j=2 \Rightarrow 0 \\ j=3 \Rightarrow 16 \end{matrix} \rightarrow \text{assign } x_2 \text{ to cluster 2}$$

$$x_3 = \|x_3 - \mu_j\|_2^2 \text{ for } \begin{matrix} j=1 \Rightarrow 16 \\ j=2 \Rightarrow 9 \\ j=3 \Rightarrow 1 \end{matrix} \rightarrow \text{assign } x_3 \text{ to cluster 3}$$

$$x_4 = \|x_4 - \mu_j\|_2^2 \text{ for } \begin{matrix} j=1 \Rightarrow 36 \\ j=2 \Rightarrow 16 \\ j=3 \Rightarrow 1 \end{matrix} \rightarrow \text{assign } x_4 \text{ to cluster 4}$$