

Let R_S be the smallest hyper-rectangle in \mathbb{R}^n consistent with data

$$P(R) < \epsilon \Rightarrow P(R_S) < \epsilon \Rightarrow R(R_S) < \epsilon \quad \text{Done}$$

$$\Rightarrow \text{Assume } P(R) > \epsilon$$

Define $2n$ hyper rectangles $\Gamma_1, \Gamma_2, \dots, \Gamma_{2n}$. To create Γ_i , start with R and then decrease the size by moving a hyperplane of R (i.e. one of $\{a_1, b_1, a_2, b_2, \dots, a_n, b_n\}$) as much as possible while maintaining $P(\Gamma_i) \geq \frac{\epsilon}{2n}$.

$$\Rightarrow P(\Gamma_i) \geq \frac{\epsilon}{2n} \quad \forall i$$

$$\Rightarrow P(R) - P\left(\bigcup_{i=1}^{2n} \Gamma_i\right) < \epsilon$$

\Rightarrow If $R(R_S) > \epsilon$, then R_S must miss at least one Γ_i

$$\Rightarrow P[R(R_S) > \epsilon] \leq P\left[\bigcup_{i=1}^{2n} \{R_S \cap \Gamma_i = \emptyset\}\right]$$

$$\leq \sum_{i=1}^{2n} P[R_S \cap \Gamma_i = \emptyset] \quad (\text{by union bound})$$

$$\leq 2n \left(1 - \frac{\epsilon}{2n}\right)^M \quad \left(P(\Gamma_i) \geq \frac{\epsilon}{2n}\right)$$

$$\leq 2n \exp\left(-\frac{M\epsilon}{2n}\right) \quad (1-x \leq e^{-x})$$

$$\Rightarrow P[R(R_S) > \epsilon] \leq 2n \exp\left(-\frac{M\epsilon}{2n}\right)$$

Now for any $\delta > 0$, we want $\text{RHS} \leq 1 - \delta$

Solve for m :

$$2n \exp\left(-\frac{m\epsilon}{2n}\right) = \delta$$

$$\frac{m\epsilon}{2n} = -\log\left(\frac{\delta}{2n}\right)$$

$$m = \frac{2n}{\epsilon} \log\left(\frac{2n}{\delta}\right)$$

\Rightarrow When $m \geq \frac{2n}{\epsilon} \log\left(\frac{2n}{\delta}\right)$ we get $\mathbb{P}[R(R_S) < \epsilon] \geq 1 - \delta$

2) Algorithm: for training sample S , return hypothesis I_S . let $[a', b'] \subseteq [a, b]$, $[c', d'] \subseteq [c, d]$

If there are 2 separate sequences of positive labels return ~~the~~ $[a', b'] \cup [c', d']$ where $[a', b']$ is the smallest interval containing the first sequence of ~~the~~ positive points, and $[c', d']$ the smallest interval for the second sequence

Else return $[a', d']$ the smallest interval containing all the positive points where $[a', d'] = [a', b'] \cup [c', d']$ with $c' = b'$

Let $\epsilon > 0$, $I \in \mathcal{C}_2$

$$P(I) < \epsilon \Rightarrow P(I_S) < \epsilon \Rightarrow R(I_S) < \epsilon \quad \underline{\text{done}}$$

$$\Rightarrow P(I) > \epsilon$$

\rightarrow assume $P([a, b]) > \epsilon/3$, $P([c, d]) > \epsilon/3$

Define 4 intervals $\Gamma_1, \Gamma_2, \Gamma_3, \Gamma_4$. Γ_1 is an interval of the form $[a, b']$ where $b' \leq b$ and b' is as small as possible while maintaining $P([a, b']) \geq \frac{\epsilon}{6}$. $\Gamma_2, \Gamma_3, \Gamma_4$ are constructed in the same manner.

$$\Rightarrow P(\Gamma_i) \geq \frac{\epsilon}{6} \quad \forall i \in \{1, 2, 3, 4\}$$

If $R(I_S) > \epsilon$, I_S misses at least one Γ_i or $P((b, c)) > \frac{\epsilon}{3}$ and no sample point is in (b, c)

$$\begin{aligned} \Rightarrow P_{S \sim D^m} [R(I_S) > \epsilon] &\leq P_{S \sim D^m} \left[\bigcup_{i=1}^4 I_S \cap \Gamma_i = \emptyset \right] + \left(1 - \frac{\epsilon}{3}\right)^m \\ &\leq \sum_{i=1}^4 P_{S \sim D^m} [I_S \cap \Gamma_i = \emptyset] + \exp\left(-\frac{m\epsilon}{3}\right) \end{aligned}$$

by union bound and $1 - x \leq e^{-x}$

$$\leq 4\left(1 - \frac{\epsilon}{6}\right)^m + \exp\left(-\frac{m\epsilon}{3}\right) \quad P(\tau_c) \geq \frac{\epsilon}{6}$$

$$\leq 4\exp\left(-\frac{m\epsilon}{6}\right) + \exp\left(-\frac{m\epsilon}{3}\right) \quad 1-x < e^{-x}$$

$$\leq 5\exp\left(-\frac{m\epsilon}{6}\right)$$

$$\Rightarrow \mathbb{P}_{S \sim D^m} [R(I_S) > \epsilon] \leq 5\exp\left(-\frac{m\epsilon}{6}\right)$$

Solve for m $5\exp\left(-\frac{m\epsilon}{6}\right) = \delta$

$$\frac{m\epsilon}{6} = -\log\left(\frac{\delta}{5}\right)$$

$$m = \frac{6}{\epsilon} \log\left(\frac{5}{\delta}\right)$$

$$\Rightarrow \text{when } m \geq \frac{6}{\epsilon} \log\left(\frac{5}{\delta}\right) \text{ we get } \mathbb{P}_{S \sim D^m} [R(I_S) < \epsilon] \geq 1 - \delta$$

case C_p

Algorithm: Suppose k separate sequences of positive labels.

return $\bigcup_{i=1}^k [a_i, b_i]$ where for $i=1, \dots, k-1$ $[a_i, b_i]$ is the smallest interval containing the i^{th} sequence, and where $\bigcup_{i=1}^k [a_i, b_i] = [a_k, b_k]$ is the smallest interval containing the k^{th} sequence.

Let $\epsilon > 0$

$$P(I) < \epsilon \Rightarrow P(I_s) < \epsilon \Rightarrow R(I_s) < \epsilon \quad \underline{\text{done}}$$

$$\Rightarrow P(I) > \epsilon$$

$$\text{Assume } P([a_i, b_i]) > \frac{\epsilon}{2^{p-1}}$$

Define 2^p intervals, $\Gamma_1, \Gamma_2, \dots, \Gamma_{2^p}$. These intervals are constructed in the same way as the C_2 case (above, but with $P([a_i, b_i]) \geq \frac{\epsilon}{4^{p-2}}$.

$$\Rightarrow P(\Gamma_i) \geq \frac{\epsilon}{4^{p-2}} \quad \forall i \in [2^p]$$

If $R(I_s) > \epsilon$, I_s misses at least one Γ_i or
 $P([b_i, a_{i+1}]) > \frac{\epsilon}{2^{p-1}}$ and no sample point is in (b_i, a_{i+1})
for some $i \in \{1, \dots, p-1\}$

$$\begin{aligned} \Rightarrow P_{S \sim D^m} [R(I_s) > \epsilon] &\leq P_{S \sim D^m} \left[\bigcup_{i=1}^{2^p} I_s \cap \Gamma_i = \emptyset \right] + (p-1) \left(1 - \frac{\epsilon}{2^{p-1}}\right)^m \\ &\leq \sum_{i=1}^{2^p} P_{S \sim D^m} (I_s \cap \Gamma_i = \emptyset) + (p-1) \exp\left(\frac{-m\epsilon}{2^{p-1}}\right) \quad \left(\begin{array}{l} \text{Union bound} \\ 1-x \leq e^{-x} \end{array} \right) \\ &\leq 2^p \left(1 - \frac{\epsilon}{4^{p-2}}\right)^m + (p-1) \exp\left(\frac{-m\epsilon}{2^{p-1}}\right) \quad (P(\Gamma_i) \geq \frac{\epsilon}{4^{p-2}}) \\ &\leq 2^p \exp\left(\frac{-m\epsilon}{4^{p-2}}\right) + (p-1) \exp\left(\frac{-m\epsilon}{2^{p-1}}\right) \quad (1-x \leq e^{-x}) \\ &\leq 3^{p-1} \exp\left(\frac{-m\epsilon}{4^{p-2}}\right) \end{aligned}$$

$$\Rightarrow P_{S \sim D^m} [R(I_s) > \epsilon] \leq (3^{p-1}) \exp\left(\frac{-m\epsilon}{4^{p-2}}\right)$$

Solve for m

$$(3p-1) \exp\left(\frac{-m\epsilon}{4p-2}\right) = \delta$$

$$\frac{m\epsilon}{4p-2} = -\log\left(\frac{\delta}{3p-1}\right)$$

$$m = \frac{4p-2}{\epsilon} \log\left(\frac{3p-1}{\delta}\right)$$

\Rightarrow when $m \geq \frac{4p-2}{\epsilon} \log\left(\frac{3p-1}{\delta}\right)$ we get $\mathbb{P}_{S \sim D^m}[R(I_S) < \epsilon] \geq 1 - \delta$

our algorithm's time complexity is $O(m)$

3) we can start by using the basic lemma from class since all the conditions are still met.

$$\begin{aligned}\mathbb{E}[Q(x_{n+1}) | x_n] &\leq (1 - \mu h_n) Q(x_n) - h_n (f(x_n) - f^*) + \frac{1}{2} h_n^2 (g_n^2 + \sigma^2) \\ &= (1 - \mu h_n) Q(x_n) - h_n (f(x_n) - f^*) + \frac{1}{2} h_n^2 g_n^2 + \frac{1}{2} h_n^2 \sigma^2\end{aligned}$$

\Rightarrow we must show $-h_n (f(x_n) - f^*) + \frac{1}{2} h_n^2 g_n^2 \leq 0$ in order to get the desired inequality

$$\begin{aligned}\frac{1}{2} h_n^2 g_n^2 - h_n (f(x_n) - f^*) &\leq \frac{1}{2L} h_n g_n^2 - h_n (f(x_n) - f^*) \quad \text{by } h_n \leq \frac{1}{L} \\ &\leq h_n (f(x_n) - f^*) - h_n (f(x_n) - f^*) \quad \text{by (4)} \\ &= 0\end{aligned}$$

note: where (4) is equation (4) in the SGD notes on Arxiv that is a consequence of f being L -smooth.

$$\Rightarrow \mathbb{E}[Q(x_{n+1}) | x_n] \leq (1 - \mu h_n) Q(x_n) + \frac{1}{2} h_n^2 \sigma^2$$

$$4) 9) f(x) = \frac{1}{m} \sum_{i=1}^m \frac{(x - x_i)^2}{2}$$

$$\nabla f(x) = \frac{1}{m} \sum_{i=1}^m (x - x_i)$$

$$= \frac{1}{m} [x - x_1 + x - x_2 + \dots + x - x_m]$$

$$= \frac{1}{m} [mx - \sum x_i]$$

$$= x - \frac{1}{m} \sum_{i=1}^m x_i$$

L-Smooth

$$\begin{aligned} \|\nabla f(x) - \nabla f(y)\| &= \left\| x - \frac{1}{m} \sum_{i=1}^m x_i - \left(y - \frac{1}{m} \sum_{i=1}^m x_i \right) \right\| \\ &= \|x - y\| \end{aligned}$$

$$\Rightarrow L = 1$$

μ -Convexity

$$\nabla^2 f(x) = 1 \Rightarrow \mu = 1$$

x^*

$$\nabla f(x^*) = 0 \Rightarrow 0 = x^* - \frac{1}{m} \sum_{i=1}^m x_i$$

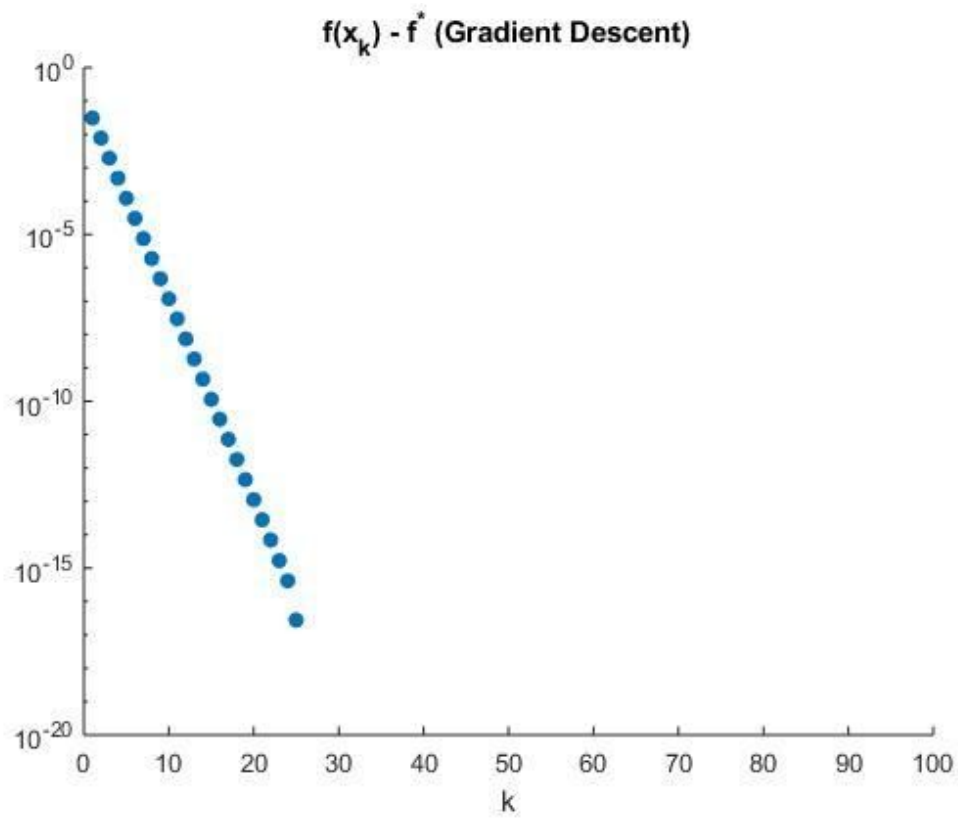
$$x^* = \frac{1}{m} \sum_{i=1}^m x_i$$

$f(x^*)$

$$f(x^*) = \frac{1}{2m} \sum_{i=1}^m (x^* - x_i)^2$$

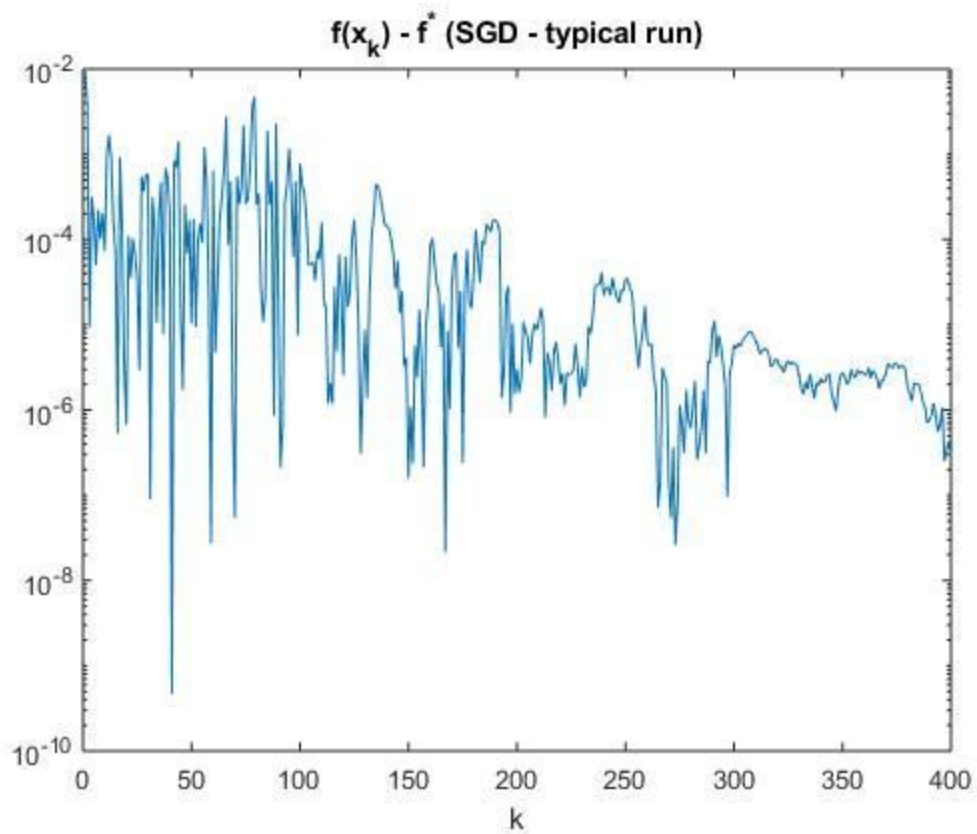
$$f(x^*) = \frac{\sigma^2}{2} \quad \text{where } \sigma^2 = \text{Var}(x_i) \quad x_i \in x_1, \dots, x_m$$

4B)

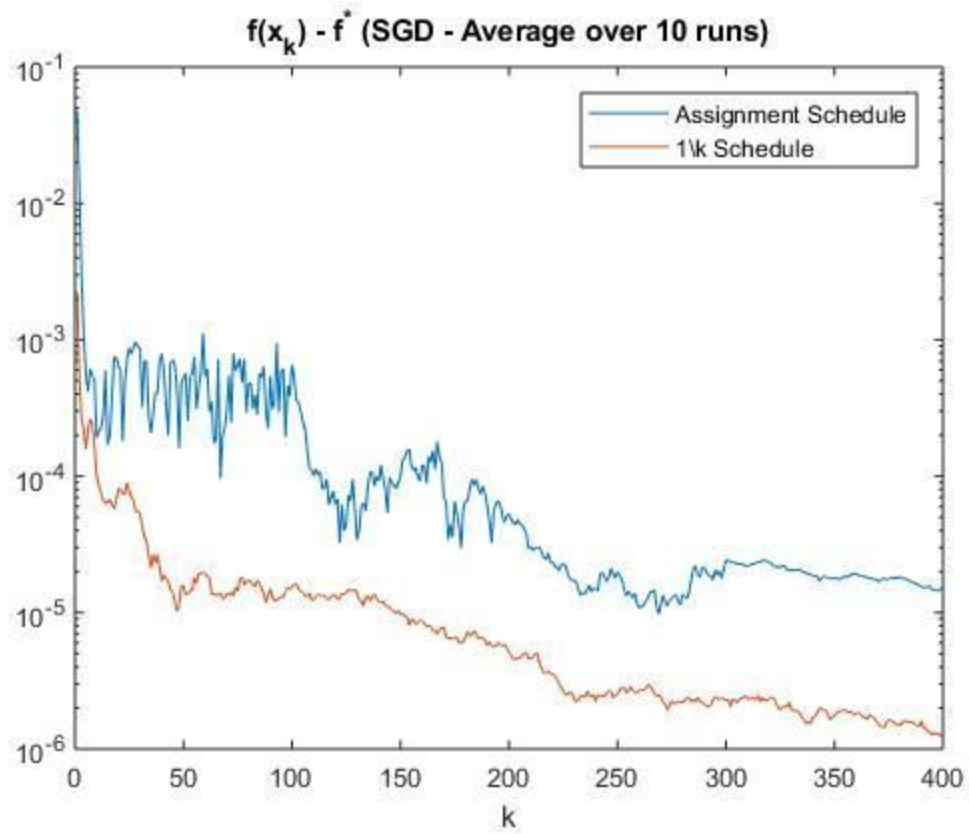


After $k=25$, MATLAB floating point precision considered $f(x_k) = f^*$. Therefore $\log(f(x_k) - f^*)$ could not be computed

4C)



4D)



I tuned SGD with a schedule of $1/k$, where k is the iteration number.

$$\begin{aligned}
 5) \quad f(x) &= \frac{\|Mx - b\|^2}{2} \\
 &= \frac{1}{2} (Mx - b)^T (Mx - b) \\
 &= \frac{1}{2} (x^T M^T - b^T) (Mx - b) \\
 &= \frac{1}{2} [x^T M^T M x - 2x^T M^T b + b^T b]
 \end{aligned}$$

$$\nabla f(x) = \frac{1}{2} [2M^T M x - 2M^T b]$$

$$= M^T M x - M^T b$$

$$\nabla^2 f(x) = M^T M$$

$M^T M$ is a Square Symmetric matrix

From class we know that the best μ -convexity and L -smoothness constants for a quadratic function

$$\begin{aligned}
 g(x) &= \frac{1}{2} x^T H x + b^T x + c \quad \text{is } \mu = \lambda_{\min}(H) \geq 0 \quad \text{and} \\
 L &= \lambda_{\max}(H)
 \end{aligned}$$

In this question we have $H = M^T M$

$$\Rightarrow \boxed{
 \begin{aligned}
 \mu &= \lambda_{\min}(M^T M) \geq 0 \\
 L &= \lambda_{\max}(M^T M)
 \end{aligned}
 }$$