

4.4. Some stochastic aspects in gradient algorithm. (not required for Exam.).

$$\boxed{x_{k+1} = x_k + -\gamma_k \nabla f(x_k)}$$

1. Probability space. (Ω, \mathcal{F}, P) .

- Ω a set

- \mathcal{F} : σ -field $\rightarrow \{\emptyset, \Omega\} \subseteq \mathcal{F}$

$\rightarrow A \in \mathcal{F} \Rightarrow A^c \in \mathcal{F}$

$\rightarrow \{A_n\}_{n \geq 1} \subseteq \mathcal{F} \Rightarrow \bigcup_{n \geq 1} A_n \in \mathcal{F}$.

- $P: \mathcal{F} \rightarrow [0, 1] \quad \rightarrow P[\Omega] = 1.$

$\{A_n\}_{n \geq 1} \subseteq \mathcal{F}$. s.t $A_i \cap A_j = \emptyset$. $\forall i \neq j$, then $P(\bigcup_{n \geq 1} A_n) = \sum_{n \geq 1} P[A_n]$

$$\textcircled{P[\phi \cup \Omega]} = P[\phi] + P[\Omega] \Rightarrow P[\phi] = 0.$$

2. Stochastic process. is a family of random variables.

indexed by time. $t \in [0, \infty)$

$$X: \Omega \rightarrow \mathbb{R}$$

i.e. $(X_t)_{t \in [0, \infty)}$.

$$\mathbb{E}[X] := \int_{\Omega} |X(\omega)| P(d\omega)$$

- A stochastic process $X = (X_t)_{t \in [0, \infty)}$ is called a **martingale**.

$\mathbb{E}[X_t] < \infty, \forall t \in [0, \infty)$ and. $\mathbb{E}[X_t | \mathcal{F}_s] = X_s, \forall s \leq t.$

$\{\omega : X_t^\omega \leq a\} \in \mathcal{F}_s.$

① $\mathcal{F}_s := \sigma(X_r : r \leq s)$. is the smallest σ -field w.r.t. which X_r is measurable.

② $\mathbb{E}[X_t | \mathcal{F}_s]$ is a random variable Z s.t. $\begin{cases} Z \text{ is } \mathcal{F}_s\text{-measurable} \\ \mathbb{E}[Z \cdot 1_A] = \mathbb{E}[X_t \cdot 1_A], \forall A \in \mathcal{F}_s. \end{cases}$ $\forall r \leq s.$

- $X = (X_t)_{t \in [0, \infty)}$ is called a super martingale (resp. sub martingale)

$\mathbb{E}[|X_t|] < \infty \forall t$, and $\mathbb{E}[X_t | \mathcal{F}_s] \leq X_s$. (resp. $\mathbb{E}[X_t | \mathcal{F}_s] \geq X_s$).

Doob's martingale convergence theorem. Assume that $X = (X_t)_{t \in [0, \infty)}$ is a supermartingale. s.t. $t \mapsto X_t(\omega)$ is right continuous for a.e. $\omega \in \Omega$.

and. $\sup_{t \in [0, \infty)} \mathbb{E}[X_t^-] < \infty$. ($X_t^- := \max(-X_t, 0)$)

Then. there exists a r.v. X_∞ , s.t. $X_t(\omega) \rightarrow X_\infty(\omega)$. a.e. $\omega \in \Omega$.

Remark: Given a discrete time process $(X_{t_k})_{k=0, 1, \dots}$, one can consider it as a continuous time process by setting $X_t = \underline{X_{t_k}}, \forall t \in [t_k, t_{k+1}).$
 ↳ which is right continuous. (both)

3. Example: Brownian motion. B .

A process $(B_t)_{t \geq 0}$ is called a standard B.M.

$\mathcal{F} \rightarrow B_0 = 0, t \mapsto B_t(\omega)$ is continuous
A.s.e. ω .
 $B_t - B_s \perp\!\!\!\perp \sigma(B_r : r \leq s), \forall s \leq t$.
 $B_t - B_s \sim N(0, t-s)$.

Intuition: $(\xi_k)_{k \geq 1}$ i.i.d. r.v. $\sim N(0, 1)$

$$t_k := \frac{k}{n}, B_{t_k}^n := \frac{1}{\sqrt{n}} \sum_{i=1}^{k-1} \xi_i = \underbrace{\sum_{i=1}^k}_{\text{N}(0, \frac{1}{n})} \frac{1}{\sqrt{n}} \xi_i \sim \underbrace{N(0, t_k)}_{N(0, \frac{1}{n})} \xrightarrow{n \rightarrow \infty} B_t, \text{ in some sense.}$$

Lemma: The standard B.M. is a martingale.

Proof: ① $B_t = B_t - B_0 \sim N(0, t) \Rightarrow \mathbb{E}[|B_t|] < \infty$

$$\begin{aligned} \textcircled{2} \quad \mathbb{E}[B_t | \mathcal{F}_s] &= \mathbb{E}[B_t - B_s | \mathcal{F}_s] + \mathbb{E}[B_s | \mathcal{F}_s] = B_s. \\ &\quad \mathbb{E}[B_t - B_s] = 0 \end{aligned}$$

4. Stochastic gradient algorithm.

Z is a r.v.

(P). $\min_{x \in \mathbb{R}^n} f(x), \quad \text{where } f(x) = \mathbb{E}[F(x, z)]$

Alg.1: $x_{k+1} = x_k - p_k \nabla f(x_k)$.

$$\nabla f(x) = \nabla \mathbb{E}[F(x, z)] = \mathbb{E}[\nabla_x F(x, z)]$$

Stochastic gradient algo: $x_{k+1} = x_k - p_k \nabla_x F(x, z_k)$
 where $(z_k)_{k \geq 1}$ is i.i.d sequence $\sim Z$.

Assumption: ① $\nabla_x F(x, z)$ and $\mathbb{E}[\nabla_x F(x, z)]$ is uniformly bounded.

② $\exists x^* \text{ s.t. } \langle x - x^*, \nabla f(x) \rangle > 0 \quad \forall x \neq x^*$.

③ $p_k > 0, \quad \sum_{k=1}^{\infty} p_k = +\infty, \quad \sum_{k=1}^{\infty} p_k^2 < +\infty$.

Example $p_k = \frac{1}{k}$.

Theorem. Under the above Assumption. $x_k^{(w)} \xrightarrow{k \rightarrow +\infty} x^*$. for a.e. $w \in \Omega$.

Proof. Let $\xi_{k+1} := \nabla_x F(x_k, z_{k+1}) - \nabla f(x_k)$.

Then. $x_{k+1} = x_k - p_k \nabla f(x_k) - p_k \xi_k$.

$$\mathbb{E}[\xi_{k+1} | F_k] = \mathbb{E}[\nabla_x F(x_k, z_{k+1}) | F_k] - \mathbb{E}[\nabla f(x_k) | F_k]$$

$$\textcircled{1}. \text{ Let } S_n := \sum_{k=0}^{n-1} p_{k+1}^2 \mathbb{E} \left[|\nabla_x F(X_k, Z_{k+1})|^2 \middle| \mathcal{F}_k \right]$$

$$= \mathbb{E}[f(x_k)] - \mathbb{E}[f(x_{k+1})] = 0$$

$$\leq C \cdot \sum_{k=0}^{n-1} p_{k+1}^2 \leq C \cdot \sum_{k=0}^{\infty} p_{k+1}^2 < +\infty \quad \text{a.s.}$$

- $S_n \uparrow$ in n .
- $(S_n)_{n \geq 1}$ is wif. bounded.

$$\Rightarrow \frac{S_n(\omega) \uparrow S_\infty(\omega)}{\|\sum_{k=0}^{\infty} p_{k+1}^2 \mathbb{E} [|\nabla_x F(X_k, Z_{k+1})|^2 \mid \mathcal{F}_k]\|} \text{ for a.e. } \omega.$$

$$\sum_{k=0}^{\infty} p_{k+1}^2 \mathbb{E} [|\nabla_x F(X_k, Z_{k+1})|^2 \mid \mathcal{F}_k]$$

Next, Let. $Y_n := |X_n - x^*|^2 - S_n$

Then: $\mathbb{E}[Y_{n+1} \mid \mathcal{F}_n] = \mathbb{E}[|X_{n+1} - x^*|^2 \mid \mathcal{F}_n] - \mathbb{E}[S_{n+1} \mid \mathcal{F}_n]$

$$= \mathbb{E}[|X_n - x^*|^2 \mid \mathcal{F}_n] + \mathbb{E}[\langle X_n - x^*, \nabla_x F(X_n, Z_{n+1}) \rangle \mid \mathcal{F}_n] \cdot p_n$$

$$+ p_n^2 \mathbb{E}[|\nabla_x F(X_n, Z_{n+1})|^2 \mid \mathcal{F}_n]$$

$$- \mathbb{E}[S_{n+1} \mid \mathcal{F}_n]$$

$$\langle X_n - x^*, \nabla f(x_n) \rangle \leq 0.$$

$$|X_{n+1} - x^*|^2 = |(X_n - x^*) + p_n \nabla_x F(X_n, Z_{n+1})|^2$$

$$\leq \frac{|X_n - x^*|^2 - S_n}{\underline{}} = Y_n.$$

$$\mathbb{E}[Y_{n+1} | f_h] \leq Y_n.$$

$\Rightarrow (Y_n)$ is a super martingale.

$$\text{and } \sup_n \mathbb{E}[Y_n^-] \leq \sup_n \mathbb{E}[S_n] < +\infty$$

$\Rightarrow Y_n \xrightarrow{\text{a.s.}} Y_\infty$ for some r.v. Y_∞ .

Besides: $S_n \xrightarrow{\text{a.s.}} S_\infty$.

Then: $\underbrace{|X_n - x^*|^2}_{\geq 0} \xrightarrow{\text{a.s.}} \underbrace{Y_\infty - S_\infty}_=: L \geq 0 \text{ a.s.}$

② We will prove that $\underline{L = 0}$ a.s.

Assume that $\underline{P[L > 0]} > 0$. then for some $\delta > 0$, $A_\delta := \{\omega: L(\omega) \geq \delta\}$

$$\underline{P[A_\delta]} > 0.$$

Let $\eta := \inf_{\delta \leq |x-x^*| \leq 2L} \langle f(x), x-x^* \rangle > 0$. $\forall \delta > 0$.

$$\Rightarrow \sum_{k=0}^{\infty} f_{k+1} \langle \nabla f(x_k), x_k - x^* \rangle \geq \sum_{k=0}^{\infty} f_{k+1} \cdot \eta = +\infty \text{ on } A_g.$$

$|x_k - x^*|^2 \rightarrow L$ so that $\delta \leq |x_k - x^*|^2 \leq 2L$ for k large enough.
on A_g .

$$\Rightarrow \mathbb{E} \left[\sum_{k=0}^{\infty} f_{k+1} \langle \nabla f(x_k), x_k - x^* \rangle \right] \geq \mathbb{E} [+\infty \mathbf{1}_{A_g}] = \infty$$

However, $\mathbb{E} \left[\sum_{k=0}^{\infty} f_{k+1} \langle \nabla f(x_k), x_k - x^* \rangle \right]$

$$= \sum_{k=0}^{\infty} f_{k+1} \cdot \mathbb{E} \left[\cancel{\mathbb{E}} \langle \nabla_x F(x_k, z_{k+1}), x_k - x^* \rangle \cancel{\mathbb{P}} \right]$$

$$\quad \quad \quad \langle \nabla f(x_k), x_k - x^* \rangle$$

$$= \sum_{k=0}^{\infty} \cancel{f_{k+1}} \mathbb{E} \left[\langle x_{k+1} - x_k, x_k - x^* \rangle \right]$$

$$= \frac{1}{2} \sum_{k=0}^{\infty} \mathbb{E} \left[|x_{k+1} - x^*|^2 - |x_k - x^*|^2 - |f_{k+1} \nabla_x F(x_k, z_{k+1})|^2 \right]$$

$$\quad \quad \quad |x_{k+1} - x_k + x_k - x^*|^2$$

$$\begin{aligned}
&= \frac{1}{2} \lim_{n \rightarrow \infty} \left(\sum_{k=0}^n \mathbb{E}[(X_{k+1} - x^*)^2] - \sum_{k=0}^n \mathbb{E}[f_{k+1}^2] \mathbb{E}[\nabla f(x_k, z_{k+1})^2] \right) \\
&= \frac{1}{2} \lim_{n \rightarrow \infty} \left(\mathbb{E}[|X_{n+1} - x^*|^2] - \mathbb{E}[|x_0 - x^*|^2] - \sum_{k=0}^n f_k^2 \mathbb{E}[|\nabla f(x_k, z_k)|^2] \right) \\
&= \frac{1}{2} \lim_{n \rightarrow \infty} \left(\mathbb{E}[Y_n] - \mathbb{E}[|x_0 - x^*|^2] \right). \quad < \infty
\end{aligned}$$

Since $(Y_n)_{n \in \mathbb{N}}$ is a super martingale and $\sup_n \mathbb{E}[Y_n] < \infty$

This is a contradiction.

Then $L = \emptyset$ a.s.

#

(P) $\min_{x \in \mathbb{R}^n} f(x)$.

$$x_{k+1} = x_k - \gamma \cdot \nabla f(x_k).$$

When $f: \mathbb{R}^n \rightarrow \mathbb{R}$ is not convex

Variation:

$$X_{k+1} = X_k - \Delta t \cdot \nabla f(X_k) + \sigma \sqrt{\Delta t} \xi_{k+1}$$

where $(\xi_k)_{k \geq 1}$ i.i.d. r.v. $N(0, 1)$

\Rightarrow ① $(X_k)_{k=0,1,\dots}$ is a Markov chain. invariant measure

② limit $\Delta t \downarrow 0$

$$X_{k+1} = X_0 - \sum_{i=0}^k \nabla f(X_i) \Delta t$$

$$X_t = X_0 - \int_0^t \nabla f(x_s) ds + \sigma B_t$$

Markov diffusion process (Langevin Equation)

$$\begin{aligned} &+ \sigma \sum_{i=0}^k \sqrt{\Delta t} \xi_{i+1} \\ &\rightarrow \text{B.M.} \\ &\rightarrow N(0, \sum_{i=0}^k \Delta t) \\ &= N(0, k \cdot \Delta t) \end{aligned}$$

$I(X_f)$ \rightarrow invariant measure of X .

with density.

$$\frac{1}{C(\Gamma)} \exp\left(-\frac{1}{\Gamma^2} f(x)\right)$$

$$\xrightarrow{\Gamma \rightarrow 0} \delta_{x^*}$$

Let $\varphi \in C_c^\infty(\mathbb{R}^n)$

$0 = t_0 < t_1 < \dots < t_n = t$.

$$\varphi(x_t) = \varphi(x_0) + \sum_{k=0}^{n-1} (\varphi(x_{t_{k+1}}) - \varphi(x_{t_k}))$$

$$\approx \varphi(x_0) + \sum_{k=0}^{n-1} \varphi'(x_{t_k}) (x_{t_{k+1}} - x_{t_k}) + \sum_{k=0}^{n-1} \frac{1}{2} \varphi''(x_{t_k}) (x_{t_{k+1}} - x_{t_k})^2.$$

$$\approx \varphi(x_0) - \sum_{k=0}^{n-1} \varphi'(x_{t_k}) \nabla f(x_{t_k}) \Delta t.$$

$$+ \sum_{k=0}^{n-1} \varphi'(x_{t_k}) \cdot \nabla B_{t_{k+1}} - \nabla B_{t_k} = 0$$

$$+ \sum_{k=0}^{n-1} \frac{1}{2} \varphi''(x_{t_k}) \cdot (x_{t_{k+1}} - x_{t_k})^2 \approx (B_{t_{k+1}} - B_{t_k}).$$

$$\mathbb{E}[\varphi(x_t)] = \mathbb{E}[\varphi(x_0)] - \int_0^t \mathbb{E}[\nabla \varphi(x_s) \cdot \nabla f(x_s)] ds.$$

$$+ \int_0^t \mathbb{E}[\nabla \varphi(x_s) \cdot \nabla dB_s] = 0$$

$$+ \frac{1}{2} \int_0^t \mathbb{E}[\nabla^2 \varphi(x_s)] \nabla^2 f(x_s) ds$$

$$m_t \triangleq \mathcal{L}(x_t)$$

$$\Rightarrow \int \varphi(x) m_t(x) dx = \langle \varphi, m_t \rangle.$$

$$= \langle \varphi, m_0 \rangle - \int_0^t \langle \nabla \varphi \cdot \nabla f, m_s \rangle ds + \frac{1}{2} \sigma^2 \int_0^t \langle \nabla^2 \varphi, m_s \rangle ds.$$

$$\Rightarrow \underbrace{\int_0^t \langle \varphi, \partial_t m_s \rangle ds} + \int_0^t \langle \nabla \varphi, \nabla f m_s \rangle ds - \frac{1}{2} \sigma^2 \int_0^t \langle \nabla^2 \varphi, m_s \rangle ds$$

integration by parts

$$\varphi \in C_c^\infty(\mathbb{R}^n), \quad \int_0^t \langle \varphi, \partial_t m_s \rangle ds = \int_0^t \langle \varphi, \nabla (\nabla f m_s) \rangle ds - \frac{1}{2} \sigma^2 \int_0^t \langle \varphi, \nabla^2 m_s \rangle ds, \quad \forall \varphi \in C_c^\infty$$

$$\Rightarrow \cancel{\partial_t m_s} - \nabla(\nabla f \cdot m_s) \cancel{+ \frac{1}{2} \sigma^2 \nabla^2 m_s} = 0, \quad \forall \varphi \in C$$

Fokker-Planck Equation.

Invariant measure m_∞ should satisfy

$$\nabla(\nabla f \cdot m_\infty) + \frac{1}{2} \sigma^2 \nabla^2 m_\infty = 0$$

$$\text{Let- } m_\infty(x) = \frac{1}{C(f)} \exp\left(-\frac{2}{\sigma^2} f(x)\right)$$

$$\nabla m_\infty(x) = \underline{m_\infty(x) \cdot \left(-\frac{2}{\sigma^2} \nabla f(x)\right)}$$

$$\begin{aligned} & \nabla^2 f \cdot m + \nabla f \cdot \nabla m \\ & + \frac{1}{2} \sigma^2 \nabla^2 m = 0 \end{aligned}$$

$$\begin{aligned} \nabla^2 m_\infty(x) &= \underline{m_\infty(x) \left(-\frac{2}{\sigma^2} \nabla^2 f(x)\right)} + m_\infty(x) \cdot \frac{4}{\sigma^4} \langle \nabla f, \nabla f \rangle. \end{aligned}$$

$$\Rightarrow \cancel{\nabla^2 f \cdot m} + \cancel{\nabla f \cdot m} - \cancel{\frac{2}{\sigma^2} \nabla f}$$

$$\begin{aligned}
 & + \frac{1}{2} \cancel{\sigma^2} \cdot m \cdot \cancel{\left(-\frac{2}{\sigma^2}\right)} \cdot \cancel{\nabla^2 f} \\
 & + \frac{1}{2} \cancel{\sigma^2} m \left(\frac{4}{\sigma^4} \right) \langle \nabla f, \nabla f \rangle \\
 & \approx 0
 \end{aligned}$$

$$M_{\text{iso}}(x) = \frac{1}{\sigma(\sigma)} \exp\left(-\frac{2}{\sigma^2} f(x)\right) dx \xrightarrow{\text{as } \sigma \downarrow 0} \delta_{x^*}(dx) \quad *$$