

Last time: μ_n proba. meas. on E Plan extra sess:
Wednesday 14: 11am
4 p.m.

Varadhan - Donsker: I compact subsets

$$\mu_n \text{ satisfies LDP with rate } I \iff \frac{1}{n} \log \int e^{nF(x)} \mu_n(dx) = \sup_{F \in C_b(E)} (F(x) - I(x))$$

Gärtner-Ellis

Assumption: E topological v.s. (Hausdorff/regular) vector space.

μ_n proba. meas. on E

$$\frac{1}{n} \log \int e^{n\langle F, x \rangle} \mu_n(dx) \xrightarrow{G \in \mathbb{R}^d} \Lambda(F)$$

$F \in E^* \quad \varphi_n(nF)$
 $\Lambda_n(F)$

Have seen: Upper bound on compact:

$$E \text{ compact} \implies \frac{1}{n} \log \mu_n(E) \leq - \inf_{x \in E} \Lambda^*(x)$$

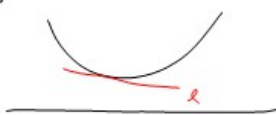
Λ^* = Legendre transform of Λ .

On \mathbb{R}^d this holds for all closed sets as soon as Λ is finite in a neighborhood of 0.

Lower bound: $x \in E$ exposed for Λ^* if

$$\Lambda^*(ly) - \Lambda^*(lx) > \langle l, y-x \rangle$$

for some l (exposing hyperplane)



Lower bound 1:

Θ open. μ_n exponentially tight.

$$\liminf \frac{1}{n} \log \mu_n(\Theta) \geq - \inf_{x \in \Theta \cap E} \Lambda^*(x)$$

$$E = \{x: x \text{ exposed by } l, \Lambda^*(lx) < \infty \text{ for } \langle l, x \rangle > 1\}$$

proof: $\nu_n = \frac{\exp(n\langle l, y \rangle) \mu_n(dy)}{\varphi_n(nl)}$

$$\mu_n(B_\delta(x)) = \int_E \mathbb{1}_{B_\delta(x)}(y) \frac{\exp(-n\langle l, y \rangle + \Lambda^*(ly))}{\nu_n(dy)}$$

$$\frac{1}{n} \log \mu_n(B_\delta(x)) \geq (\Lambda^*(lx) - \langle l, x \rangle) - \delta \|l\|_{E^*} + \liminf \frac{1}{n} \log \nu_n(B_\delta(x))$$

Let's proof that $\nu_n(B_\delta(x))$ decays to zero exponentially.

For every $N > 0$ we have a compact set $K_N \subset E$ s.t. $\liminf \frac{1}{n} \log \mu_n(K_N^c) \leq -N$.

We start by bounding $\nu_n(K_N^c \cap B_\delta^c(x))$

$$\begin{aligned} \hat{\varphi}_n(F) &:= \int_E e^{n\langle F, y \rangle} \nu_n(dy) \\ &= \int_E e^{n\langle F, y \rangle} \frac{e^{n\langle \ell, y \rangle}}{\varphi_n(\ell e)} \mu_n(dy) \\ &= \varphi_n(\ell e)^{-1} \cdot \varphi_n(n(F+\ell)) \end{aligned}$$

$$\Rightarrow \frac{1}{n} \log \hat{\varphi}_n(F) = \frac{1}{n} \log \varphi_n(n(F+\ell)) - \frac{1}{n} \log \varphi_n(\ell e)$$

by assumption $\rightarrow \Lambda(F+\ell) - \Lambda(\ell) = \hat{\Lambda}(F)$

by LD upper bound and compactness of $B_\delta^c(x) \cap K_N$ we know that $\lim_{n \rightarrow \infty} \frac{1}{n} \log \nu_n(B_\delta^c(x) \cap K_N) \leq -\inf_{x \in B_\delta^c(x) \cap K_N} \hat{\Lambda}^*(x)$

$$\begin{aligned} \hat{\Lambda}^*(y) &= \sup_{F \in E^*} \langle F, y \rangle - \hat{\Lambda}(F) \\ &= \left[\sup_{F \in E^*} \langle F, y \rangle - \Lambda(F+\ell) \right] + \Lambda(\ell) \\ &= \left(\sup_{F \in E^*} \langle F+\ell, y \rangle - \Lambda(F+\ell) \right) - \langle \ell, y \rangle \\ &= \Lambda^*(y) - \left(\langle \ell, y \rangle - \Lambda(\ell) \right) \frac{+\Lambda(\ell)}{+\langle \ell, y \rangle} \\ &\geq \Lambda^*(y) - \Lambda^*(x) + \langle \ell, x-y \rangle \\ &> 0 \quad \forall y \text{ because } x \text{ is exposed} \\ &\quad \text{with exposing hyperplane } \ell. \end{aligned}$$

The infimum of rate fun is attained on $B_\delta^c(x) \cap K_N$ (by compactness + l.s.c.) and hence positive. \Rightarrow by LD upper bound the prob. tends to zero exponentially quickly!

It remains to prove that $\nu_n(K_N^c) \rightarrow 0$

We fix $\delta > 0$. We first bound $\nu_n(K_N^c \cap \{ \ell, y \rangle > \delta \})$

$$\begin{aligned} \nu_n(K_N^c \cap \{ \ell, y \rangle > \delta \}) &= \int \mathbb{1}_{\{K_N^c \cap \{ \ell, y \rangle > \delta \}} \frac{e^{n\langle \ell, y \rangle}}{\varphi_n(\ell e)} d\mu_n(y) \\ &\leq e^{-n(\gamma-1)\delta} \varphi_n(\ell e)^{-1} \varphi_n(\gamma \ell e) \end{aligned}$$

taking $\frac{1}{n} \log$ weights

$$-(\gamma-1)\delta - \underbrace{\Lambda(\ell) + \Lambda(\gamma \ell)}_{\text{numbers}}$$

by choosing δ big enough this becomes negative and we are done!

Left: $\nu_n(K_\mu^c \cap \{e, y\} < \epsilon\}$

$$= \int_E \frac{\exp(n \langle e, y \rangle)}{\varphi_n(e)} \mathbb{1}_{\{K_\mu^c \cap \{e, y\} < \epsilon\}} \mu_n(dy)$$

$$\leq \varphi_n(e)^{-1} \exp(n\epsilon) \mu_n(K_\mu^c)$$

$$\frac{1}{n} \log \dots \leq -\Delta(e) + \epsilon - N$$

by choosing N large enough this is negative
 \Rightarrow The proba. decays exp. \Rightarrow we're done \square

Criterion for $\inf_{\partial \Omega} = \inf_{\bar{\Omega}}$!
 Try exhaustion on boundary!
 15k ±!

In \mathbb{R}^d , Δ defined on neighborhood of ∂ .

- Δ differentiable on \mathcal{D}_Ω .
- Δ steep at boundary ($x \rightarrow \partial \mathcal{D}_\Omega \Rightarrow |\nabla \Delta| \rightarrow \infty$)

I. E Banach space: Δ defined everywhere + Gateaux diff'ble!

Argument Convex Analysis:

differentiability $\xleftrightarrow[\text{Info}]{\text{Log.}}$ strict convexity!
 Reference: Rockafellar 'Convex Analysis'

Applications: (one can prove Cramér, Sauer, Schilder)

'Notions of Doob's Markov theory'

Question: Empirical distributions of Markov processes.

X_n, X_t time discrete / continuous Markov process

Empirical measures:

$$\mu_n(A) = \frac{1}{n} \sum \mathbb{1}_A(X_n)$$

$$\mu_+^t(A) = \frac{1}{t} \int_0^t \mathbb{1}_A(X_s) ds$$

IF X_n / X_t ergodic then we know that

$$\frac{1}{n} \sum_{n=1}^N F(X_n) \rightarrow \int F(y) d\mu(y)$$

$$\frac{1}{t} \int_0^t F(X_s) ds \rightarrow \int F(s) d\mu(s)$$

In particular $\mu_n / \mu_+ \xrightarrow{\text{weakly}} \mu$

Setup (the simplest possible,

Time continuous, Markov chain, on $\mathbb{Z}^d / \mathbb{N} \mathbb{Z}^d$

- exponential clock.
- jump to neighbor
- wait again ..

$\Delta_N =$ discrete Laplacian on $\mathbb{Z}^d / \mathbb{N} \mathbb{Z}^d$

$$\Delta_N(i, j) = \begin{cases} -2d & i=j \\ 1 & i \sim j \\ 0 & \text{else} \end{cases}$$

transition semigroup

$$P_t(i, j) = e^{t \Delta_N(i, j)}$$

prob to jump from i to j in time t .

See that this formula holds:

$$\tilde{\Delta}_N(i, j) = \frac{1}{2d} (\Delta_N(i, j) + 2d \text{Id})$$

$$P_+^t(i, j) = \sum_{k=0}^{\infty} P(\text{exactly } k \text{ jumps}) P(\text{embed chain jumps from } i \text{ to } j \text{ in } k \text{ steps})$$

$$= \sum_{k=0}^{\infty} \frac{(2dt)^k}{k!} e^{-2dt} (\tilde{\Delta}_N)^k(i, j)$$

$$= e^{-2dt} e^{2dt \tilde{\Delta}_N}$$

$$= e^{2dt \Delta_N}$$

Aim: look at empirical distribution:

$$\frac{1}{t} \ell_t(i, j) = \int_0^t \mathbb{1}_{(i, j)}(X_s) ds$$

Thm: $\frac{1}{t} \ell_t$ satisfy an LDP on $\mathcal{M}_1(\mathbb{Z}^d / \mathbb{N} \mathbb{Z}^d)$

The rate function is given by

$$I(\nu) = \langle \Delta_N \sqrt{\nu}, \sqrt{\nu} \rangle =: \mathcal{E}(\sqrt{\nu}, \sqrt{\nu})$$

proof: We need ① Convergence of exp. integrals D. indet form of this jump process.

② Exponential tightness **For free!**

③ Δ will be defined everywhere $+ \mathbb{C}$

We need to calculate

$$\mathbb{E} \left[\exp \langle t \eta_n, F \rangle \right]$$

$$= \mathbb{E} \left[\exp \left(\int_0^t F(X_s) ds \right) \right]$$

To treat this look at "Feynman-Kac type" semigroup

$$P_t^F f(x) = \mathbb{E} \left[\exp \left(\int_0^t F(X_s) ds \right) f(X_t) \right]$$

P_t^F is a semigroup (Markov property)
with generator $\Delta_N + F$.

$$\partial_t P_t^F f(x) \Big|_{t=0} = \mathbb{E}_x \left(\partial_t \exp \left(\int_0^t F(x_s, L_s) ds \right) f(x_t) \right) \\ + \mathbb{E}_x \left(\exp(\dots) \partial_t f(x_t) \right) \\ \stackrel{t=0}{=} F(x) + \Delta_N f(x).$$

The largest eigenvalue of $F + \Delta_N$ is isolated!

Argument: $\exists c$ such that $F + \Delta_N + c \text{Id}$ has only non-negative entries, & is irreducible.

Perron Frobenius $\Rightarrow \exists!$ maximal e.v. with multiplicity 1, eigenfunction strictly positive.

\Rightarrow The same is true for $F + \Delta_N$.

The behaviour of $e^{\Delta_N + F t}$ is governed by this largest eigenvalue.

In particular, we will have

$$\mathbb{E}_x \left(e^{\int_0^t F(x_s, L_s) ds} \right) = P_t^F \mathbb{1} \sim e^{-\lambda t}.$$

$\Rightarrow \lambda(F)$ from the theorem is given by $\lambda(F)$ "the biggest e.v."

χ ' Assumption OK.

$$\Lambda^*(\mu) = \sup_F \langle F, \mu \rangle - \lambda(F)$$

$$\lambda_F = \sup_{\ell \in \ell^2} - \langle \Delta_F \ell, \ell \rangle + \langle F, \ell, \ell \rangle \\ = \sup_{v \in \mathcal{M}_1} - \langle \Delta_F v, v \rangle + \langle F, v \rangle$$

Rest next time!