Asymptotics of the invariant distribution in a mean-field model with jumps

Rajesh Sundaresan

Indian Institute of Science

28 February 2013 Based on joint work with Vivek S. Borkar

Wireless Local Area Network (WLAN) interactions

- ▶ *N* nodes or particles accessing the medium in a wireless LAN
- State space for each particle: $\mathcal{Z} = \{0, 1, \cdots, r-1\}$
- Transitions: From state i to either i + 1 or 0



- r: Maximum number of transmission attempts before discard
- Coupled dynamics: Transition rate for success or failure depends on empirical distribution of nodes across states

・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・

Mean field dynamics

- Empirical measure $\mu_N(t)$: Fraction of nodes in each state
 - $X_n^{(N)}(t)$: state of *n*th particle at time *t*

$$\mu_N(t) = \frac{1}{N} \sum_{n=1}^N \delta_{\{X_n^{(N)}(t)\}} \in \mathcal{M}_1(\mathcal{Z}), \text{ space of probability measures on } \mathcal{Z}$$

< ロ > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □

- A node transits from state *i* to state *j* at time *t* with rate λ_{i,j}(µ_N(t))
- ► In general, allowed transitions are specified by the directed edges *E* on the vertex set *Z*

Example rate functions

This example comes from a discrete-time (slotted-ALOHA) model

- Slot size 1/N, access probability in each slot is c_i/N when node is in state i, with c ∈ ℝ^r₊
- Assume three states r = 3.

With $\xi \in \mathcal{M}_1(\mathcal{Z})$, the rate matrix is

$$\Lambda(\xi) = \begin{bmatrix} -(\cdot) & c_1(1 - e^{-c^T\xi}) & 0\\ c_2 e^{-c^T\xi} & -(\cdot) & c_2(1 - e^{-c^T\xi})\\ c_3 e^{-c^T\xi} & 0 & -(\cdot) \end{bmatrix}.$$

Interpretation: $c^{T}\xi$ is like a load factor when $\mu_{N}(t) = \xi$. Success probability is $e^{-c^{T}\xi}$ if an attempt is made.

The Markov processes, big and small

•
$$(X_n^{(N)}(\cdot), \ 1 \le n \le N)$$
 is Markov

State space grows exponentially with N: size r^N

Study µ_N(·) instead, also a Markov process Its state space size is at most (N + 1)^r, and is a subset of M₁(Z)

・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・

• We will focus mostly on $\mu_N(\cdot)$

The smaller Markov process

• $\mu_N(\cdot)$ is a Markov process

• The transition from ξ to $\xi + \frac{1}{N}e_j - \frac{1}{N}e_i$ occurs with rate $N\xi(i)\lambda_{i,j}(\xi)$

- ▶ For large *N*, changes are small, O(1/N), at higher rates, O(N).
- Familiar setting of Kurtz's theorem where μ_N converges to a deterministic limit given by an ODE.

The conditional expected drift in μ_N

For each k,

$$\dot{\xi}_{k} = \sum_{i:i \neq k} \xi_{i} \lambda_{i,k}(\xi) - \xi_{k} \sum_{i:i \neq k} \lambda_{k,i}$$
With $\Lambda(\xi) = [\lambda_{i,j}(\xi)]$, we get

$$\lim_{h \downarrow 0} \frac{1}{h} \mathbb{E} [\mu_{N}(t+h) - \mu_{N}(t) \mid \mu_{N}(t) = \xi] = \Lambda(\xi)^{*} \xi$$

First order approximation: ignore the randomness in $\mu_N(\cdot)$, and set it to its mean evolution given by

 $\dot{\mu}(t) = \Lambda(\mu(t))^* \ \mu(t), \quad t > 0$ [McKean-Vlasov equation]

with initial condition $\mu(0) = \mu_N(0)$.

► State space is a more familiar compact set, but evolution is nonlinear

The conditional expected drift in μ_N

For each k,

$$\dot{\xi}_{k} = \sum_{i:i \neq k} \xi_{i} \lambda_{i,k}(\xi) - \xi_{k} \sum_{i:i \neq k} \lambda_{k,i}$$
With $\Lambda(\xi) = [\lambda_{i,j}(\xi)]$, we get

$$\lim_{h \downarrow 0} \frac{1}{h} \mathbb{E} [\mu_{N}(t+h) - \mu_{N}(t) \mid \mu_{N}(t) = \xi] = \Lambda(\xi)^{*} \xi$$

► First order approximation: ignore the randomness in µ_N(·), and set it to its mean evolution given by

 $\dot{\mu}(t) = \Lambda(\mu(t))^* \ \mu(t), \quad t > 0$ [McKean-Vlasov equation]

with initial condition $\mu(0) = \mu_N(0)$.

► State space is a more familiar compact set, but evolution is nonlinear

Assumptions

- ► The graph with vertex set Z and edge set E is irreducible. Holds in our WLAN setting
- There exist positive constants c > 0 and C < +∞ such that, for every (i, j) ∈ E, we have

$$c \leq \lambda_{i,j}(\cdot) \leq C$$

◆□▶ ◆□▶ ◆三▶ ◆三▶ 三三 のへぐ

• The mapping $\mu \mapsto \lambda_{i,j}(\mu)$ is Lipschitz continuous over $\mathcal{M}_1(\mathcal{Z})$

Kurtz's theorem

► Consider D([0, T], M₁(Z)), cadlag, measure-valued paths, and equip it with the metric

$$\rho_{\mathcal{T}}(\xi,\xi') = \sup_{t \in [0,T]} ||\xi(t) - \xi'(t)||_1$$

where $|| \cdot ||_1$ is the L^1 metric

Finer than Skorohod topology; not separable

Theorem Let $\mu_N(0) \rightarrow \mu(0)$ weakly. Let T > 0 be arbitrary, but finite. Then, for every $\varepsilon > 0$, we have

$$\lim_{N\to+\infty} \Pr\left\{\rho_{\mathcal{T}}(\mu_N,\mu) > \varepsilon\right\} = 0.$$

Approximation over finite time durations

Formally ...

• For any $\Phi : \mathcal{M}_1(\mathcal{Z}) \to \mathbb{R}$ that is bounded and continuous, the conditional expected drift starting from ξ

$$\begin{split} \Omega_N \Phi(\xi) &= \lim_{h \downarrow 0} \frac{1}{h} \mathbb{E} \left[\Phi(\mu_N(t+h)) - \Phi(\mu_N(t)) \mid \mu_N(t) = \xi \right] \\ &= \sum_{(i,j): j \neq i} N\xi(i) \lambda_{i,j}(\xi) \left[\Phi\left(\xi + \frac{1}{N}e_j - \frac{1}{N}e_i\right) - \Phi(\xi) \right] \\ &= \left\langle \nabla \Phi(\xi), \dot{\xi} \right\rangle + O\left(\frac{1}{N}\right) \end{split}$$

if Φ has bounded second order derivatives.

(ロ)、(型)、(E)、(E)、 E) の(の)

Back to the individual particles

- Let $\mu(\cdot)$ be the solution to the McKean-Vlasov dynamics
- ► Tag a particle.
 - It is likely to be in state *i* with probability $\mu(t)(i)$.
 - ► Its evolution is described asymptotically by a Markov process with time-dependent transition rates \(\lambda_{i,j}(\mu(t))\)
- ► Tag k particles.
 - If their states are independent at time 0, then they evolve (in the asymptotics of large N) independently of each other under the mean field $\mu(\cdot)$

(日) (日) (日) (日) (日) (日) (日) (日)

Large deviation principle?

- From simulations, exponentially fast concentration
- ► A large deviation principle holds for some class of Markov processes. Shwartz and Weiss, Freidlin and Wentzell, Leonard, and others.

The case under consideration does not satisfy the conditions assumed in these works.

Large deviation principle (LDP)

- Definition: The sequence (p^(N), N ≥ 1) of probability measures on the metric space D([0, T], M₁(Z)) satisfies the LDP with speed N and good rate function S_[0,T](µ) if
 - For every open set G and closed set F of the metric space D([0, T], M₁(Z)), we have

$$\lim_{N \to +\infty} \inf_{\substack{N \to +\infty}} \frac{\log p^{(N)}(G)}{N} \geq -\inf_{\mu \in G} S_{[0,T]}(\mu)$$
$$\lim_{N \to +\infty} \sup_{\substack{N \to +\infty}} \frac{\log p^{(N)}(F)}{N} \leq -\inf_{\mu \in F} S_{[0,T]}(\mu)$$

▶ For each $a \in [0, +\infty)$, the level sets $\{\mu : S_{[0, T]}(\mu) \leq a\}$ are compact

・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・

Relative entropy between two inhomogenous Poisson point processes

Let us understand a simpler case first ...

- P: Poisson point process on [0, T] with intensity η(t)
 Q: Poisson point process on [0, T] with intensity ζ(t)
- ▶ Sanov's theorem: Sample *N* iid paths from *Q*. The probability that the empirical measure is in a small neighbourhood near *P* is $\approx e^{-NI(P||Q)}$ where

$$I(P||Q) = \int_{[0,T]} \left[\eta(t) \log \frac{\eta(t)}{\zeta(t)} - \eta(t) + \zeta(t) \right] dt$$
$$= \int_{[0,T]} \left[\zeta(t) \ \tau^* \left(\frac{\eta(t)}{\zeta(t)} - 1 \right) \right] dt$$

where $au^*(u)=(u+1)\log(u+1)-u,\ u\geq -1$

Heuristics

• Find probability of being near a deviant path μ , a solution to

 $\dot{\mu}(t) = L(t)^* \mu(t).$

- ▶ Normal intensity for an (i, j) jump at time t is $(\mu(t)(i)) \times \lambda_{i,j}(\mu(t))$
- Empirical distribution should be near that of iid sampling from (μ(t)(i)) × λ_{i,j}(μ(t))
- But the path µ appears to have intensity for (i, j) jump at time t given by (µ(t)(i)) × l_{i,j}(t)
- ► Add up the relative entropies for each jump process indexed by (i, j) ∈ E

$$S_{[0,T]}(\mu|\nu) = \int_{[0,T]} \left[\sum_{(i,j)\in\mathcal{E}} (\mu(t)(i))\lambda_{i,j}(\mu(t)) \ \tau^* \left(\frac{l_{i,j}(t)}{\lambda_{i,j}(\mu(t))} - 1 \right) \right] dt.$$

Finite duration LDP

Theorem Suppose that the initial conditions $\nu_N \rightarrow \nu$ weakly.

Then the sequence $(p_{\nu_N}^{(N)}, N \ge 1)$ satisfies the LDP on $D([0, T], \mathcal{M}_1(\mathcal{Z}))$ (with metric ρ_T) with speed N and a good rate function $S_{[0,T]}(\mu|\nu)$.

Proof steps

- Apply Sanov's theorem to noninteracting system on path space
- Use the Laplace-Varadhan principle to extract a path space LDP
- ► Then use the contraction principle (from an LDP for the empirical measure in path space to an LDP for the law of µ_N(·)).

・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・

Corollary: $p_{\nu_N}^{(N)} o \delta_{\mu(\cdot)}$ weakly, where $\mu(\cdot)$ is the McKean-Vlasov solution

Proof steps

- Apply Sanov's theorem to noninteracting system on path space
- Use the Laplace-Varadhan principle to extract a path space LDP
- ► Then use the contraction principle (from an LDP for the empirical measure in path space to an LDP for the law of µ_N(·)).

・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・

Corollary: $p_{\nu_N}^{(N)} \to \delta_{\mu(\cdot)}$ weakly, where $\mu(\cdot)$ is the McKean-Vlasov solution

Assumptions again

- ► The graph with vertex set Z and edge set E is irreducible Holds in the our WLAN case
- There exist positive constants c > 0 and C < +∞ such that, for every (i, j) ∈ E, we have</p>

 $c \leq \lambda_{i,j}(\cdot) < C$

- The mapping $\mu \mapsto \lambda_{i,j}(\mu)$ is Lipschitz continuous over $\mathcal{M}_1(\mathcal{Z})$
- Take lim_{t→+∞} lim_{N→+∞}(···) Assume that the McKean-Vlasov equation μ̇(t) = Λ(μ(t))*μ(t)
 Has a unique equilibrium ξ₀ (i.e., Λ(ξ₀)*ξ₀ = 0)
 The equilibrium ξ₀ is globally asymptotically stable
 Then lim_{t→+∞} μ(t) = ξ₀ for any initial condition

Assumptions again

- ► The graph with vertex set Z and edge set E is irreducible Holds in the our WLAN case
- There exist positive constants c > 0 and C < +∞ such that, for every (i,j) ∈ E, we have

$$\mathsf{c} \leq \lambda_{i,j}(\cdot) < \mathsf{C}$$

- The mapping $\mu \mapsto \lambda_{i,j}(\mu)$ is Lipschitz continuous over $\mathcal{M}_1(\mathcal{Z})$
- Take lim_{t→+∞} lim_{N→+∞}(···) Assume that the McKean-Vlasov equation μ(t) = Λ(μ(t))*μ(t)
 Has a unique equilibrium ξ₀ (i.e., Λ(ξ₀)*ξ₀ = 0)
 - The equilibrium ξ_0 is globally asymptotically stable

Then $\lim_{t\to+\infty}\mu(t)=\xi_0$ for any initial condition

When $t \to +\infty$ first ... large time behaviour

Let the directed graph G(Z, E) be irreducible. Then, for a fixed N, the Markov chain µ_N is irreducible with a finite state space. It therefore has a unique stationary distribution: ℘^(N) = ℒ_{st}(µ_N(+∞))

 Does ℘^(N) → δ_{ξ0}? (Stolyar 1989, Anantharam 1991, Anantharam and Benchekroun 1993, Bordenave et al. 2005/2007, Benaim and Le Boudec 2008)

- Decoupling approximation
- Large deviations from this limit?

Large deviations for the invariant measure

If μ_N(+∞) is near ξ, then this is most likely due to an excursion that began at ξ₀, worked against the attractor ξ₀, and took the lowest cost path to ξ over all possible time durations

Looking backwards in time, the dynamics must be

$$\dot{\hat{\mu}}(t) = -\hat{L}(t)^*\hat{\mu}(t), t \ge 0$$

with $\hat{\mu}(0) = \xi$, $\lim_{t \to +\infty} \hat{\mu}(t) = \xi_0$, and $\hat{L}(t)$ is some family of rate matrices. Define

$$m{s}(\xi) = \inf_{\hat{\mu}} \int_{[0,+\infty)} \Big[\sum_{(i,j)\in\hat{\mathcal{E}}} (\hat{\mu}(t)(j)) \hat{\lambda}_{i,j}(\hat{\mu}(t)) \ au^* \left(rac{\hat{l}_{i,j}(t)}{\hat{\lambda}_{i,j}(\hat{\mu}(t))} - 1
ight) \Big] \ dt$$

Theorem

Under the stated assumptions, the sequence $(\wp^{(N)}, N \ge 1)$ satisfies the LDP with speed N and good rate function $s(\cdot)$.

Large deviations for the invariant measure

- If μ_N(+∞) is near ξ, then this is most likely due to an excursion that began at ξ₀, worked against the attractor ξ₀, and took the lowest cost path to ξ over all possible time durations
- Looking backwards in time, the dynamics must be

$$\dot{\hat{\mu}}(t) = -\hat{L}(t)^*\hat{\mu}(t), t \ge 0$$

with $\hat{\mu}(0) = \xi$, $\lim_{t \to +\infty} \hat{\mu}(t) = \xi_0$, and $\hat{L}(t)$ is some family of rate matrices. Define

$$m{s}(\xi) = \inf_{\hat{\mu}} \int_{[0,+\infty)} \Big[\sum_{(i,j)\in\hat{\mathcal{E}}} (\hat{\mu}(t)(j)) \hat{\lambda}_{i,j}(\hat{\mu}(t)) \ au^* \left(rac{\hat{l}_{i,j}(t)}{\hat{\lambda}_{i,j}(\hat{\mu}(t))} - 1
ight) \Big] \ dt$$

Theorem

Under the stated assumptions, the sequence ($\wp^{(N)}, N \ge 1$) satisfies the LDP with speed N and good rate function $s(\cdot)$.

Summary

Asymptotics of mean field limits in WLANs

A finite duration LDP

 When there is a unique globally stable equilibrium ξ₀ for the McKean-Vlasov equation, the invariant measure satisfies the LDP. The rate function s(ξ) is characterised by the cost of an optimal control that moves the system from ξ to ξ₀ in reversed time

・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・
 ・

• Extension to cases with multiple equilibria.

arXiv:1107.4142

Proof steps

• Given $\nu_N \rightarrow \nu$, extract LDP for the laws for terminal state (finite *T*), via contraction principle, with rate function

 $S_{\mathcal{T}}(\xi|\nu) = \inf \{S_{[0,\mathcal{T}]}(\mu|\nu) \mid \mu(0) = \nu, \mu(\mathcal{T}) = \xi\}$

• If the laws for initial states satisfy the LDP with a good rate function $s(\nu)$, argue that joint laws for initial and terminal states satisfy the LDP with a good rate function $s(\nu) + S_T(\xi|\nu)$. Then apply contraction principle to get that the laws for the terminal states satisfy the LDP with good rate function

$$\inf_{\nu \in \mathcal{M}_1(\mathcal{Z})} \{ s(\nu) + S_T(\xi|\nu) \}$$

The invariant measures (℘^(N), N ≥ 1) live on a compact space. So, given any subsequence, there is a further subsequential LDP with appropriate speed, and with rate function s(ξ) that satisfies

$$s(\xi) = \inf_{\nu \in \mathcal{M}_1(\mathcal{Z})} \{ s(\nu) + S_T(\xi | \nu) \}$$

Proof steps continued

By the assumption that ξ₀ is a unique equilibrium that is globally stable, we can show s(ξ₀) = 0.

• Extract a single infinite duration path $\hat{\mu}(\cdot)$ that is optimal, i.e., it attains the infimum for each duration [0, mT], $\hat{\mu}(0) = \xi$, and satisfies

$$\begin{aligned} s(\xi) &= s(\hat{\mu}(mT)) + S_{mT}(\xi|\nu), \quad \forall m \ge 1 \\ &= s(\hat{\mu}(mT)) + \int_{[0,mT]} [\cdots] dt \end{aligned}$$

▶ The integrand in the second term is nonnegative; the second term increases with *m*, and so the first term $s(\hat{\mu}(mT))$ decreases with *m*. Since $s(\cdot)$ is bounded below by 0, $s(\hat{\mu}(mT))$ must converge to a constant as $m \to +\infty$

Proof steps continued even further

▶ So the increment $\int_{mT}^{mT+T} [\cdots] dt \rightarrow 0$ in the second term, and in the limit, integrand must be 0 a.e., which is a McKean-Vlasov path in reversed time.

More precisely, $\hat{\mu}(\cdot)$ has an ω -limit set that is positively invariant to (McKean-Vlasov dynamics in reversed time)

$$\hat{\mu}(t) = -\Lambda(\hat{\mu}(t))^*\hat{\mu}(t), \quad t \geq 0$$

- This limit set is also invariant to McKean-Vlasov dynamics. It is further compact and bounded within M₁(Z). The only such set invariant set is {ξ₀}. So μ̂(mT) → ξ₀.
- Taking limit as $m \to +\infty$,

$$s(\xi) = s(\xi_0) + \int_{[0,+\infty)} [\cdots] dt = 0 + \int_{[0,+\infty)} [\cdots] dt$$

This expression is the same regardless of the initial subsequence

► Thus every subsequence has a further subsequence that satisfies the LDP with appropriate speed and the same rate function s(·).